Royal Holloway, University of London

Department of Economics

Empirical Essays on Public and Media Attitudes to Conflict

Submitted by:

Nathan Woolley

Thesis submitted to the University of London for the degree of

Doctor of Philosophy

2018

Declaration

I, Nathan Woolley, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Signed .... (Nathan Woolley)

Date:

Abstract

The lens through which people observe and form judgements upon conflict and terrorism depends heavily on the media they consume as well as their personal circumstances. This thesis is comprised of three empirical studies; the first two investigate how media reporting of armed conflict affects both the perceptions of news consumers and the completeness of media-based datasets, the third analyses the determinants of public support for terrorism. Chapter 1 studies the factors that drive variation in the intensity of media coverage that violent events receive and the impact this will have upon consumers of news media. This is achieved by using the unique Iraq Body Count (IBC) database. Conflict events accruing intense media coverage are those that have higher numbers of fatalities and injuries, use more newsworthy weapons (e.g. explosive violence) and occur on weekdays. Events occurring further from Baghdad receive a reporting intensity penalty, particularly among the international media. Chapter 2 considers the impact of heterogenous reporting on media-based conflict event datasets. Founders of such datasets select a subset of sources from the universe of news media outlets to be monitored. This source selection affects both the overall body count as well as the dataset's event type composition. The chapter also applies multiple systems estimation (MSE) techniques to the Iraq case finding that IBC is likely missing a substantial number of events and that these are not randomly distributed across event types. The third chapter considers how an individual's support for terrorism against civilians is determined by their socio-economic and religious characteristics. The study uses 11 rounds of Pew's Global Attitudes Survey in five Muslim countries. Results show that support for terrorism generally declines as household income or religious commitment rises. Increased levels of education, however, may significantly increase support for terrorism in some countries. Finally, a concluding chapter draws out the implications from these three studies as well as the synergies between them.

Acknowledgements

I am very grateful to many people who have assisted me on this PhD journey. Firstly, to Michael Spagat, my supervisor, who has been a constant source of encouragement and inspiration and without whose time and support this thesis would not have been possible. Also to my advisor, Juan Pablo Rud, for providing very useful feedback on my work throughout.

The Department of Economics at Royal Holloway, University of London has provided an excellent environment in which to research this thesis. I would like to thank Ija Trapeznikova, Jonathan Wadsworth, Jesper Bagger and other members of academic staff who have helped shape this thesis through feedback, ideas and constructive criticism at various points during the process. I would also like to thank Annika, Florentyna and other PhD students in the department for their friendship and solidarity over the last four years.

I would also like to place on record my thanks to the Economic and Social Research Council (ESRC) who provided the funding which allowed me to carry out this research.

I am immensely grateful to my parents for their constant support and sacrifice over 26 years which has enabled me to reach this point.

Finally, thank you to my fiancée, Rebecca, for the love, patience and encouragement that you have shown me every day. This is for you.

Contents

List of Figures

List of Tables

Introduction

Over the past 70 years, the nature of conflict worldwide has changed considerably, from being mainly comprised of large inter-state or colonial wars, to being characterised by civil war and insurgency (Dupuy et al., 2017). In this thesis I examine three areas which have become salient as the nature of conflict has changed. Firstly, this transformation in conflict, in addition to various technological improvements, means that conflict news which previously flowed almost exclusively from state actors now usually comes from personal reports by journalists who have been given increasing degrees of freedom and access (Gunter, 2009). This media reporting provides the lens through which consumers' understanding of conflict is shaped. Secondly, as the prevalence of inter-state war has given way to civil war, there has been an increased reliance on NGOs and academics to carry out the documentation of conflict events which has previously been undertaken by state actors. Such organisations have often relied on the news media as the predominant (e.g. ACLED, UCDP-GED), or sole (e.g. SCAD, GDELT), source to populate their datasets. Finally, as the nature of conflict has changed, so have the types of weapons employed by actors. The use of suicide bombings has grown from being almost nonexistant before 1990 to over 500 attacks per year by 2015 (CPOST, 2016). However, little is known about the types of people who would carry out, or indeed support, such indiscriminate attacks which kill so many civlians (Iraq Body Count, n.d.(a)). This thesis is, therefore, comprised of three empirical studies which evaluate, respectively, how violent attacks against civilians are reported on by the news media, are documented by conflict datasets and may command public support.

The first chapter of this thesis considers how the news media can frame conflict through the heterogeneous intensity of news reporting afforded to different types of conflict events. The study is implemented using the media-based Iraq Body Count (IBC) data, which is unique in providing reliable linkages between conflict events and the media coverage they receive. Specifically, the study evaluates the impact of event characteristics on reporting intensity as well as how sensitivity to these characteristics changes across domestic, coalition and global media. Those events accruing more intense media coverage are those which kill and injure more civilians, take place close to the capital, occur on weekdays and involve the use of explosive weapons. International media reporting is generally more sensitive to event characteristics than that of domestic outlets, especially in terms of the event location.

In the second chapter, I assess the impact of this imperfect news reporting on the completeness and composition of media-based datasets. This study will have implications for those embarking on projects aimed at documenting war deaths, as well as for those who use such datasets for academic research. Given that monitoring media outlets is costly, those who create such datasets generally select a subset of media outlets as sources. The analysis uses the IBC data to generate pseudo-datasets based on the reporting of selected groups of media outlets. It shows that source selection has significant consequences on the overall event and fatality counts of datasets as well as their event size, temporal and locational compositions. I then progress to assess the completeness of IBC itself through the use of multiple systems estimation (MSE) techniques. Stratified estimations imply that, because of imperfect media reporting, IBC is missing around 9,500 conflict events; the majority of which are small gunfire attacks. Further analysis, based on predictions derived from military and survey data, indicates that an additional 6,000-8,000 events may have occurred outside of the media ‘ecosystem’.

The third chapter studies how both socio-economic and religious factors may impact on an individual's likelihood of claiming that the suicide bombing of civilians is a justified act. The relationship between income, education and support for terrorism has been the subject of considerable debate. Conventional wisdom, regularly conveyed by world leaders, that poverty and poor education are a root cause of violent extremism has often contrasted with academic research which has painted a weak (Shafiq and Sinno, 2010) or even inverse (Krueger, 2007) relationship. Similarly, rhetoric claiming that commitment to Islam drives people to support extremism remains empirically untested. In this study, I significantly increase the quality and quantity of data used to assess these topics. This involves the use of 11 rounds of Pew's annual Global Attitudes Survey totalling over 40,000 interviews in five predominantly Muslim countries. I show that support for terrorism generally declines as household income or religious commitment rises. Results on education are more varied with results in some countries indicating a significantly higher level of support for suicide bombing among those who are better educated.

Chapter 1

Framing of a War

Which Violent Events Grab Media Attention?

1.1 Introduction

Tens of thousands of people suffered violent deaths during the Iraq War (Iraq Body Count, n.d.(a)). Some died in events generating very limited Iraqi coverage and remained far off the radar of the typical western news consumer. Other conflict incidents triggered such a torrent of coverage that only the most isolated person could have failed to take notice. Perceptions of a conflict held by people living both inside and outside the war zone will be heavily influenced by the media coverage they consume. The news media holds the ability to 'frame' a conflict by providing the lens through which consumers view and form judgments on the violence which is occurring.

It has been shown that through the sphere of influence that the media has on public opinion, reporting can impact governmental responses to international crises (Eisensee and Strömberg, 2007). While selective coverage of only key moments within a conflict can lead to short-term emergency responses by international actors rather than the long-term preventative measures which are optimal (Jakobsen, 2000). Selective media reporting of conflict may also affect tourist flows into a conflict-affected country irrespective of the true underlying level of violence (Fielding and Shortland, 2009). Furthermore, reporting inconsistency could have a substantial impact on the accuracy of media-based conflict data. It may result in the introduction of measurement error into data commonly used to measure violence for the purposes of social science research (Weidmann, 2015). More directly, there may be significant personal costs to the friends and families of victims who have died in conflict events that do not meet certain criteria of newsworthiness, and are therefore left unreported by some media outlets. There is, therefore, a significant incentive to understand the factors affecting the intensity of reporting of conflict. The key area of research in this chapter is analysing how heterogeneity in event characteristics influences the intensity of media coverage that conflict events receive, both domestically and internationally. This heterogeneity in coverage is evaluated primarily in relation to how it will affect the knowledge of news media consumers.

This chapter contributes to the existing literature in several ways. Firstly, the analysis uses a dataset unique in directly linking specific conflict events responsible for civilian fatalities and the monitored media organisations that report upon them. These direct linkages enable claims that have been made elsewhere to be replicated but in a more robust way using a new, improved, measure of reporting intensity. Secondly, the research is original in looking at the differences in reporting between domestic (Iraqi) media, coalition media and international news agencies. Results, are found to differ significantly between these media groups. Thirdly, the chapter looks directly at the relative newsworthiness of a variety of weapon types finding that explosive weapons, and particularly those involving suicide, are more newsworthy.

1.2 Reporting of Conflict in the News Media

Media framing can be defined as "principles of selection, emphasis and presentation composed of little tacit theories about what exists, what happens and what matters" (Gitlin, 2003, p. 6). There are two types of bias emanating from media framing which affect the lens through which consumers view conflict events; description bias and selection bias (Earl et al., 2004).

Description bias is concerned with *how* an event is reported. Specifically, the bias impacts the emphasis, presentation and accuracy of news reports covering conflict events. One example of description bias involves the differences in use of emotive language in framing conflict events (Evans, 2010; Lehmann, 2005; Dimitrova and Connolly-Ahern, 2007). Another example is heterogeneity between sources in specific details about reported events such as locational information or fatality numbers (Weidmann, 2015).

Selection bias is the focus of this chapter. This refers to the decisions made by media outlets that determine *which* events are reported. A news media organisation does not report upon the entire universe of conflict events that take place, nor do they cover all the conflict events that are known to have taken place (i.e. all those reported somewhere), instead they 'frame' the conflict by choosing to cover a subset of these events. Unless this subset is entirely representative of the true events which are taking place, then news consumers of the particular media organisation will hold a skewed impression of the conflict.

The question of why certain events are selected for reporting, whilst others are not, has been at the centre of a string of research since the debate on the factors influencing the flow of international news was opened by Galtung and Ruge (1965). They established 12 conditions by which events become news; based around variables such as intensity, unpredictability, scarcity and demand. Building on this, Snyder and Kelly (1977) theorised the event selection process by using a two-sided model where the media coverage that a conflict event receives is determined by the interaction between conflict intensity and media sensitivity. In their model, intensity is determined by the size, duration and violence of conflict, while media sensitivity represents a function of the geo-political climate that each media provider is based in. This chapter builds upon this approach by using a similar, expanded, two-sided analysis. On one side, instead of the simple measure of conflict intensity, a broader range of event characteristics of conflict incidents are studied. The hypothesis that media coverage of a conflict event is significantly dependent on its intensity, in terms of magnitude and lethality, is well supported by the literature (Oliver and Myers, 1999; Weidmann, 2016). The expanded characteristics studied here also include the location and date at which an event took place, as well as the type of weapon used. On the other side, media sensitivity is studied by comparing the newsworthiness of these characteristics across media groups (e.g. domestic and international media), this allows heterogeneous sensitivity across multiple event characteristics and media providers.

As briefly outlined above in section 1.1, the chapter makes several key contributions to the existing literature. The first is the innovative use of a uniquely rich dataset, Iraq Body Count (IBC), which is detailed in section 1.4 below. A key advantage over other studies is that the version of IBC used here gives direct linkages between specific conflict events and the media coverage they received from numerous diverse sources. To be clear, IBC is not unique in its recording of media sources used in conflict event data, but instead the aim to record every reporting source from its broad list of monitored organisations. It is this data collection process which enables the analysis here in such a way that would not be possible using other media-based datasets such as ACLED, UCDP-GED or SCAD. These direct linkages provided by IBC enable the creation of a reporting intensity variable that records exactly how well reported a particular conflict event is among a set of sources. This implicitly contains more information than binary measures of coverage used by other related research (e.g. Davenport and Ball, 2002).

The main previous examples of research into the reporting of conflict using a reporting intensity measure is that of Jetter (2014) and Baum and Zhukov (2015). These papers record the change in the number of media articles mentioning the name of a country on the day following terror/conflict events occurring there. This ‘country-name intensity’ measure can be useful for analysing the relationship between event characteristics and reporting intensity for relatively infrequent events. Where it will be limited, however, is for research into a large conflict such as Iraq. For example, during the time period used in this analysis (July 2006 – November 2013) there were an average of 7.2 incidents and 20.5 fatalities per day in Iraq, with at least one event occurring on 98.5% of the days within the time frame. This frequency of events would make disentangling the impact of particular event characteristics upon reporting intensity very difficult using the ‘country-name intensity’ measure. Therefore, the precise linkages provided by IBC enable the creation of a far more accurate measure of reporting intensity than that used in previous studies.

A second key contribution here is using the unique data to compare the sensitivity of different media groups to particular event details. This sensitivity may change over time, and as a result of entirely exogenous shocks. For example, a change in sensitivity could manifest itself as a decrease in international media coverage caused by a decline in their domestic audience’s interest, which is unrelated to the level of violence within the conflict itself (Woolley, J., 2000). In this case, consumption of these media sources alone could lead consumers of news media to falsely conclude that violence has declined. A current gap in the literature exists around the reporting of domestic media due to a lack of available data. This study will assess whether the reporting of domestic media outlets in a conflict zone is generally less sensitive to event characteristics than the reporting of the international media. One specific characteristic where we may expect to see differential media sensitivity, across domestic and international media, is the event location. Previous research (Öberg and Sollenberg, 2011; Raleigh, 2012) has suggested the existence of a, within-country, centre-periphery bias. This is the idea that events taking place near to, or within, the capital city of a country are likely to be more widely reported than those taking place elsewhere. This is because the media and its sources will often only have bases in large cities. This effect is predicted to be largest for foreign media for whom leaving the safety of the capital may be dangerous and costly. This chapter will test whether this location effect exists and whether it is indeed found to be greater for the international media. It will also assess whether any locational relationship is binary (i.e. inside/outside a city) or continuous (i.e. dependent on the actual distance between the event and the nearest city).

The final key contribution to the existing conflict literature is studying the impact that the type of weapon used by a perpetrator of violence has on the media coverage that the violence receives. This topic has been previously explored in some elements of the homicide literature by studying murders involving guns (Gruenewald, Pizarro, and Chermak, 2009) or 'unusual weapons' (Buckler and Travis, 2005). In addition, Jetter (2014) finds a premium in media coverage for terror attacks which include a suicide element compared to those without suicide. However, application specifically to the media coverage of armed conflict where a far greater range of weapons are employed can ascertain the relative newsworthiness of many weapon types, as well as providing answers to several interesting research questions. One question is whether, all else equal, explosive weapons are found to be more newsworthy than other weapons, such as small arms gunfire. This may be expected because explosive violence tends to cause a higher level of collateral damage than events caused by, for example, gunfire. Some of this collateral can be controlled for in the analysis that will be undertaken here, such as the increased number of injuries accrued. Other collateral is unobserved here, such as damage to buildings and property, as well as the increased psychological damage which may come as a result of the use of explosive weapons (Article 36, 2013). Additionally, news consumers may find explosive violence more interesting and 'exotic' than other types of violence and hence media providers may be more inclined to report incidents of this type. A similar topic of interest, raised but left unanswered by Baum and Zhukov (2015), is whether there are differences in the reporting of civilian casualties between those killed by selective and indiscriminate weapons.

1.3 The Iraq War

The selection of the Iraq War as the case study for this chapter was inflenced by several factors. From the coalition invasion phase in 2003 onwards, Iraq became one of the largest media events of the 21st century, commanding front page headlines around the world over a period of more than 10 years. The war was also characterised by actors on all sides inflicting huge numbers of civilian casualties, which forms the focus of the research here. The involvement of two global and media superpowers, the US and the UK, allows for analysis of the coverage of large participating countries. Results should also translate well to other recent conflicts with western involvement, such as the war on terror in Afghanistan.

Where generalisability may be somewhat limited is when comparing international media coverage of Iraq to that of very small conflicts or those without western involvement. Results obtained on characteristics of the Iraq conflict which are unique such as interpreting results relating to event location may also be less transferable to other countries with different geographical compositions. That said, many of the event characteristics to be examined here, such as those involving event size and weapon types, should be relevant across the universe of media outlets and conflicts.

Quantitative evaluation of media coverage of the conflict in Iraq has been restricted to a few studies. Much of the academic work that has been carried out on media coverage of the Iraq war looks at the descriptive framing of the media (Dimitrova and Connolly-Ahern, 2007), analysing reports from a handful of newspapers rather than a quantitative event based approach. Additionally, the previous focus has been upon the invasion phase rather than the bulk of the conflict (Hayes and Guardino, 2010; Lehmann, 2005). The present research is unique in looking specifically at variables affecting the intensity of media reporting and also in covering the whole of Iraq over a significant time period.

Outside of academic research, anecdotal evidence shows that international journalists were restricted in their reporting capability during the Iraq conflict. This seems to be particularly prevalent for journalists covering events happening outside of Baghdad; Joe Floto, a senior producer at the BBC's Baghdad office, claimed "the situation with the roads in Iraq is so bad that our staff are largely limited to Baghdad unless there is a special operation" (Freeman, 2004). In a Pew Research Center (2007) survey of 111 Iraq-based journalists "events occurring virtually anywhere outside of Baghdad" were consistently stated to be underreported. The same survey also found that 62% of the journalists claimed that demand for stories on day-to-day violence from editors had decreased over the year before the survey was taken in late 2007, with most of this fall attributed to civilian casualties. There was also some evidence of an oversaturation effect, whereby consumers are overburdened with information about the conflict. As one journalist put it "the greatest tragedy of the war has been how the media has in some way bored its audience with the violence".

1.4 Iraq Body Count Data

Data on both conflict violence and media coverage is taken from the Iraq Body Count (IBC) project, a non-governmental organisation that documents violent deaths of civilians in Iraq. IBC's main sources of data are professional media reports originating from a range of countries including translated reports from Arabic sources. Their procedure is to “collect and reconcile every available, distinct report about each incident” (Iraq Body Count, n.d.(c)), achieved through the use of search engines and media collation services (e.g. LexisNexis). Data from these media reports are sometimes complemented with extra information from alternative sources (e.g. from hospitals and morgues). Each incident included in the data records at least one civilian death, defined as the victim either being aged under 18 or, at the time of their death, not reported as initiating deadly violence or being active members of a military or paramilitary organisation. For each unique incident in the data, IBC extracts information on the number of civilian deaths and injuries (with upper and lower bounds where sources disagree), the location (to the nearest town/village), the weapon used, and the date of each event. For some events, further information, such as victim and aggressor identities or time of day is also documented where available.

The publicly available part of the IBC database lists a subsection (generally one or two) of the media sources reporting each incident. However, the full ‘IBC Team’ database which is used here records, for data verification purposes, which of over 200 press and media outlets monitored by IBC were found to have reported each incident (Sloboda et al., 2013). This, therefore, presents a unique research opportunity to analyse the intensity of media reporting of conflict involving civilian casualties.

Although IBC has monitored civilian deaths since the coalition invasion in 2003, the data used here runs from the 1st of July 2006 through to the 10th of November 2013. This is due to a change in formatting which meant that not all media sources covering an event were correctly specified before July 2006. Events analysed are only those for which the minimum number of civilian casualties observed by IBC is greater than zero, such that all events in the data incorporate at least one confirmed civilian death. Since the exposition of the US Department of Defense’s SIGACTS database (Wikileaks, 2010) the IBC team have been amalgamating the two datasets. Due to the process being currently incomplete and inconsistent, it was necessary to remove any events in the data only recorded by SIGACTS. Events included here were also restricted to shorter duration events which occurred over a maximum period of two days. This allows for tighter more reliable linkages between specific event details such as the weapon, time and place (Hicks et al., 2009). Finally, a small number of events that were documented as aggregated reports of several separate incidents (rather than as individual events with full information) were also removed from the analysis. These include, for example, monthly body count figures from hospitals and morgues. A separate Technical Appendix (A.2) discusses the implications of removing these from the database and tests whether the reintroduction of those excluded due to being long duration or aggregations significantly affects results found in the study. These robustness checks find that these restrictions have little impact on the significance and magnitude of key results found.

After the above transformations, the data used for this research is comprised of 19,413 unique events responsible for between 54,762 and 59,584 civilian fatalities and between 88,409 and 95,877 civilian injuries. The range in these counts is due to the fact that some event entries document a minimum and maximum figure where press reports differ in their reporting of these event details. Here, the minimum count will be used throughout, however, all results are also robust to using the maximum counts.

1.4.1 Weapon Type

IBC contains detailed information about the specific weapon(s) employed by aggressors in each recorded incident, this includes multiple weapons in a small proportion of the events in the data. In order to analyse weapon types the data is coded according to the primary listed weapon and incidents are placed into one of nine weapon categories. Similar weapon types have been left separated rather than combined where they could

Table 1.1: Descriptive Statistics by Weapon

	N	Average No. of			% in
		News Reports	Fatalities	Injuries	Baghdad
Air Attack	186	7.50	5.07	6.27	31.2%
Non-Suicide Bombing	6381	5.47	2.76	7.29	32.8%
Drive-by Shooting	1321	3.59	1.44	0.61	22.1%
Execution	494	2.12	3.67	0.14	7.7%
Gunfire	9014	2.84	2.32	1.02	16.1%
Missile Fire	930	4.09	3.14	9.10	44.5%
Suicide Bomb (Foot)	299	17.28	11.77	24.03	18.4%
Suicide Bomb (Vehicle)	486	13.26	9.24	29.28	23.3%
Vehicle Accident	25	4.40	3.64	14.40	24.0%
Other	277	2.75	1.92	1.47	10.5%

be expected to lead to quantitatively different results. An example is that suicide bombings may accrue a greater level of media coverage than otherwise identical bombings without a suicide element. Some incidents involving killing by unusual methods such as stabbing, suffocation or burning, which did not fit into any of the broader weapon categories above, but had too few incidents to be listed as an independent category, were designated as 'Other'. Dichotomous variables were created for each of the 10 categories with Gunfire, as the most frequently observed weapon, being designated as the reference category throughout the following analysis.

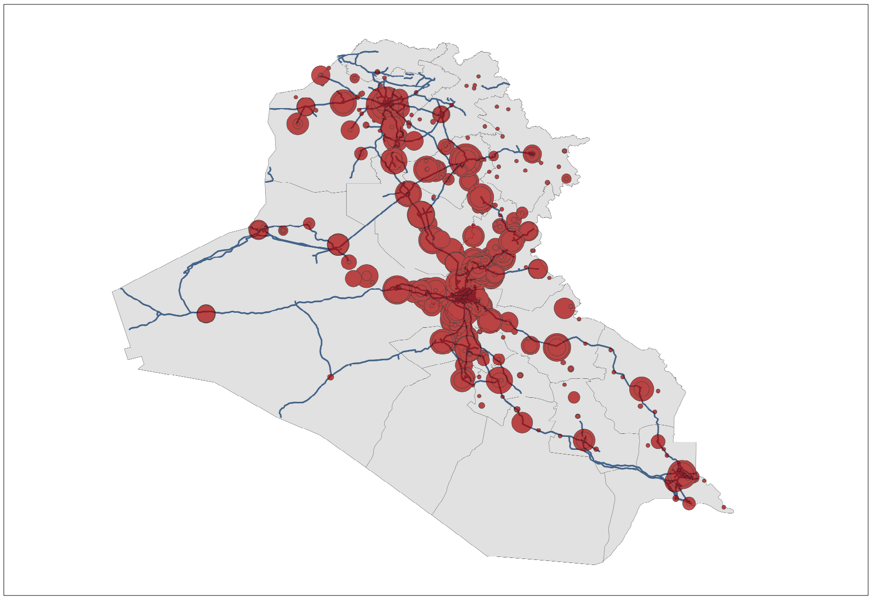
Table 1.1 shows descriptive statistics for the weapons types in the data. The table shows gunfire and bombings (non-suicide) as the most common event types. It also suggests a clear link between event intensity and media coverage with those weapon types such as bombings and aerial attacks causing a higher number of fatalities and injuries also receiving a higher average number of media reports from IBC sources.

1.4.2 Event Location

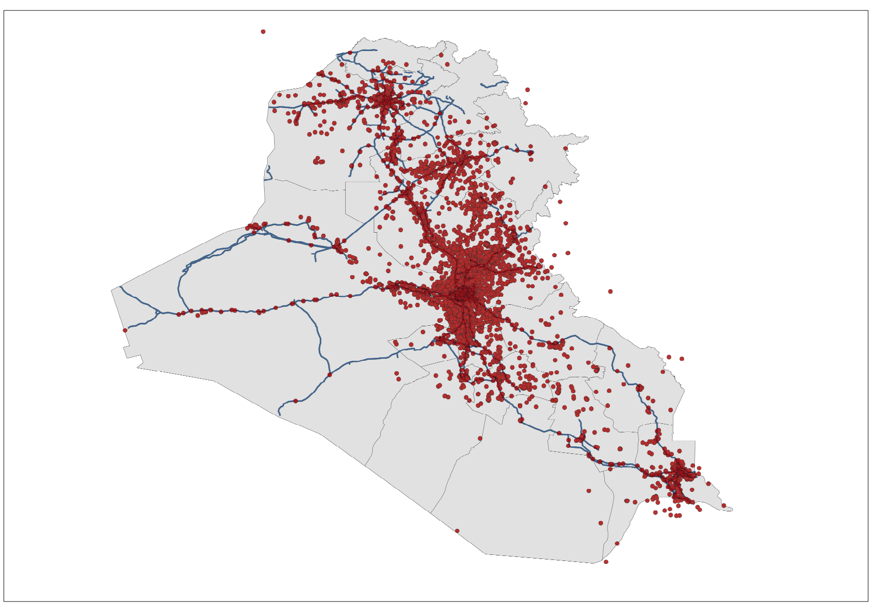
As the IBC data is not accurately georeferenced (i.e. with coordinates), it was necessary to do so manually for the incidents in the data in order to spatially analyse reporting intensity. This was achieved by using the smallest unit of locational information available across all events, the closest town. There were 691 unique location points within the IBC data and these were matched with location information from a UNOCHA and MapAction (2014) dataset providing coordinates for over 23,000 settlements in Iraq. Geo-referencing to the nearest town will lead to some inaccuracy in coordinate data by assuming all events take place in the centre of the settlement (Weidmann, 2015). However, it is assumed here however that this will be directionally unbiased overall and thus should not affect results when studying distance to events from major cities. Figure 1.1 plots the manually georeferenced IBC media-based dataset along with the US military-based SIGACTS (Wikileaks, 2010) dataset which is georeferenced at event source. The maps show events during the time period in which the two datasets overlap (July 2006 - December 2009). The size of the marker in the IBC map indicates the number of events recorded as occuring at that location. In the SIGACTS data a marker indicates one event taking place at that specific coordinate point. Whilst we would expect to see differences between the maps due to being different types of data (Weidmann, 2016) it does appear that the spatial distribution of events follow broadly similar patterns.

Distance measures were created from events to the capital and other cities to analyse whether events further from the capital do, in fact, accrue less intense media coverage. Google Maps' 'directions' feature was selected due to its ability to calculate driving time and distance using detailed information on the road networks. Driving time is expected to be superior to geodesic (as-the-crow-flies) distance because reporting intensity effects are likely to be due to journalistic decisions about whether events are worth travelling

Figure 1.1: IBC and SIGACTS Events by Location



(a) IBC Media-Based Events



(b) SIGACTS Events

to. Due to the mountainous nature of Iraq, as well as the inefficient nature of the road network, driving time is expected to give a better indication of this choice. Coordinates for all location points for individual events within the data were inputted, and expected journey time (measured in hours) was calculated to the centre of the 5 largest cities in Iraq (Baghdad, Mosul, Basra, Erbil and Kirkuk) according to the fastest driving route. This was repeated for the driving distance as well as the geodesic distance in order to perform robustness checks. There were 95 events logged as occurring in the suburbs of Baghdad, but without precise locations, these were allocated the average journey time (38 minutes) to other events occurring in the Baghdadi suburbs.

1.4.3 Media Coverage Intensity

The key measure of newsworthiness here will be a count measure of the intensity of media coverage that individual conflict events receive. This will be achieved by creating groups of news providers according to location and type and counting the number of sources within each group that reports each conflict event. This intensity measure allows the analysis to take advantage of the unique nature of the IBC data in terms of the number of media providers monitored. It implicitly carries more information than simply looking at binary measures of coverage for individual news providers. Studying the intensity of coverage also helps to avoid issues that arise due to some conflict events involving civilian casualties in Iraq never being reported on by IBC's media sources. The intensity measure means that analysis here will study why some events (all of which have been reported by at least one IBC media source) receive no or very limited coverage from a particular subsection of the sources whilst other events receive widespread coverage amongst those sources. In addition, a comparison of these results across media groups will assess the sensitivity of different types of news provider to particular characteristics of conflict events.

Groups to be used as dependent variables are as follows:

- International News Agencies: A count (0 - 3) of the number of international news agencies (Reuters, AP and AFP) reporting each event.
- Coalition Media: A count (0 - 10) of the number of coalition media outlets reporting each event. Based on the reporting of the 10 US or UK media outlets which reported the highest proportion of the conflict events in IBC.
- Iraqi Media: A count (0 - 10) of the number of Iraqi media outlets reporting each event. Based on the reporting of the 10 nationally reporting Iraqi media outlets which reported the highest proportion of the conflict events in IBC.

Table 1.2: Summary Statistics by Group

Source Group	Observations	Mean	Std. Dev.	Min	Max
News Agencies	19,413	0.860	0.978	0	3
Coalition Media	19,413	0.744	1.400	0	10
Iraqi Media	19,413	1.253	1.175	0	9

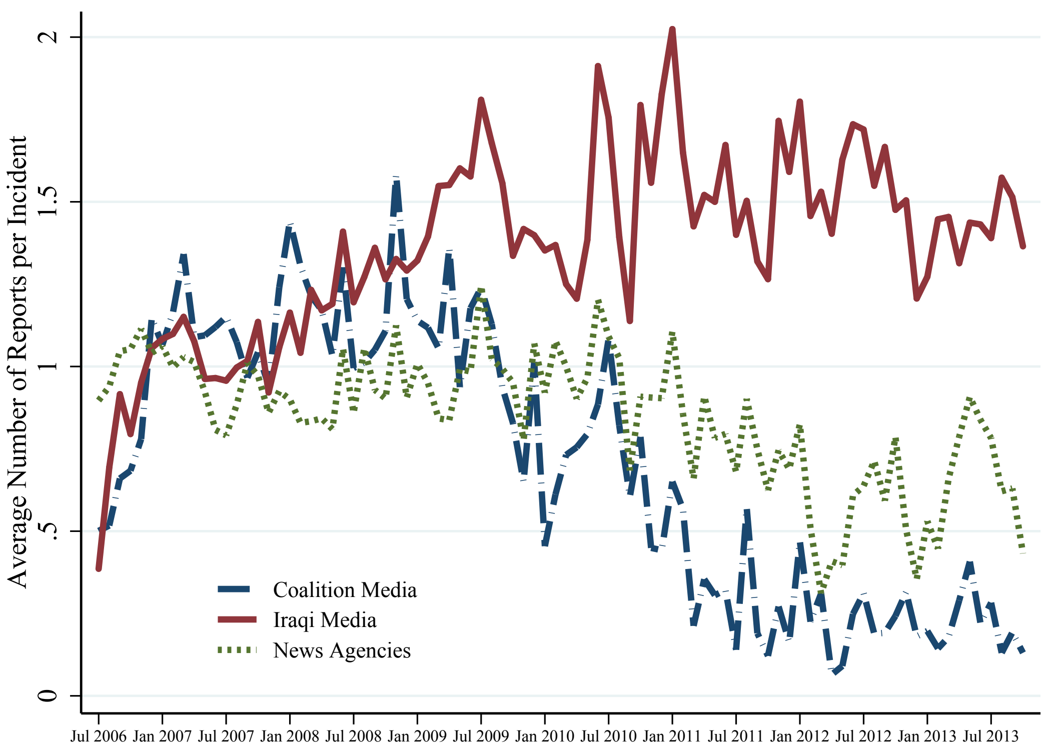
Summary statistics for each variable are presented in Table 1.2 with a list of the specific sources incorporated into each group in Table 1.3. It can be observed that the means and standard deviations differ across groups with, for example, coalition media having the lowest mean and the highest standard deviation. Figure 1.2 tracks the mean intensity of reporting across all IBC events of the source groups over time. Both a rise in the reporting of Iraqi media and a decline in reporting by coalition media and news agencies can be observed over the period. In order to allow for direct comparison of regression coefficients between the groups these variables will be standardised with a standard deviation of 1 in ordinary least squares (OLS) specifications of the models used.

Table 1.3: Media Sources by Group

Media Source	Country	Proportion[a]
International News Agencies		
Reuters	UK	0.382
Associated Press	USA	0.237
Agence France-Presse	France	0.226
Coalition Media		
McClatchy Newspapers	USA	0.203
CNN	USA	0.130
New York Times	USA	0.112
Los Angeles Times	USA	0.096
British Broadcasting Corporation	UK	0.069
Washington Post	USA	0.057
The Guardian	UK	0.019
The Times	UK	0.018
The Independent	UK	0.014
The Telegraph	UK	0.012
Iraqi Media		
National Iraqi News Agency	Iraq	0.377
Voice of Iraq	Iraq	0.319
Al-Sharqiya TV	Iraq	0.196
Al-Sumaria	Iraq	0.079
All Iraq News	Iraq	0.079
AKNews	Iraq, Kurdistan	0.070
Al-Iraq	Iraq	0.030
Mosul Observer	Iraq	0.029
Al-Shorfa	Iraq	0.028
Patriotic Union of Kurdistan Media	Iraq, Kurdistan	0.027

[a]Proportion of included IBC events reported by media source

Figure 1.2: Average Number of Reports by Source Group over Time



1.5 Analysis and Results

1.5.1 Models

The analysis here utilises both OLS and negative binomial (NB) models. The OLS models are used predominantly for comparison between the media source groups created in section 1.4.3 after standardisation. The distribution (Appendix Figures A.1-A.3) and nature (count data) of the observations within the source group variables indicate that a Poisson distribution is the most appropriate model. However, for all three source groups the variance is found to be greater than the mean, indicating the presence of overdispersion. Therefore, a negative binomial regression was chosen due to its ability to model a second parameter indicating unobserved heterogeneity, and therefore account for the overdispersion within the count data (Long, 1997, p. 230).

The zero-inflated negative binomial (ZINB) model was also considered; this model assumes that the data was generated by two independent processes (Long, 1997, p. 243). The first of which is a binary model, independent of the count model, which assumes that the count measure for some events within the dataset will be zero with probability one. This imples that in the case of this study there are events which could never have been reported by the media source group. The second is a count model restricted to those not designated as 'always zeroes'. As all of the events in the dataset were reported by at least one IBC media source the 'always zero' assumption does not seem to fit the data here. However, zero-inflated negative binomial coefficients are reported in Appendix Table A.3 as a robustness check.

1.5.2 General Results

This section presents some overall results before the following sections focus on weapon and locational effects in more detail. Table 1.4 analyses several of the key independent variables and reports negative binomial and standardised OLS regression coefficients for the three source group dependent variables created in section 1.4.3. Standardised OLS coefficients are presented as levels whilst the NB coefficients are presented as incidence rate ratios. This can be interpreted, for example in the number of fatalities variable, as follows: one additional death occured by an event will lead to, ceteris paribus, an increase in media reporting within the news agencies group of 0.02 standard deviations, according to the OLS model. The NB model implies an increase in coverage of 1.1% from the previous count. The significant coefficient on the dispersion parameter (alpha) in all three NB models confirms overdispersion and that these are better modelled within the negative binomial model rather than the alternative poisson model. All specifications include controls for year and weapon type. Year controls are important due to the changing nature of the average level of coverage between the groups across the time period (Figure 1.2). Controlling for weapon type here ensures that effects observed on event size are not actually being driven by the weapon used.

OLS coefficients in bold for coalition media or news agency groups indicate significant differences with the Iraqi media groups according to a Chi-squared test performed using stata's 'suest' command. They, therefore, indicate heterogeneity between source group sensitivity for that particular characteristic. Overall, within the results presented in this section, the reporting decisions of the international media (both coalition media and news agency reporting) are found to be significantly more sensitive to the characteristics of an event when compared to domestic media outlets. This is also backed up by R^2 levels which show that the model explains a larger proportion of reporting intensity variation in international media.

Table 1.4: Negative Binomial and Standardised OLS Group Comparison

	Coalition Media		Iraqi Media		News Agencies	
	OLS	NB	OLS	NB	OLS	NB
No. of Fatalities	**0.0389*****	1.038***	0.0146***	1.007***	**0.0200*****	1.011***
	(0.00124)	(0.00219)	(0.00141)	(0.00178)	(0.00139)	(0.00123)
No. of Injuries	0.00638***	1.012***	0.00597***	1.001**	0.00452***	1.001*
	(0.000431)	(0.000944)	(0.000493)	(0.000332)	(0.000487)	(0.000373)
Driving Time from Baghdad[a]	**-0.0612*****	0.871***	-0.00769*	0.990**	**-0.0568*****	0.929***
	(0.00307)	(0.00554)	(0.00351)	(0.00366)	(0.00346)	(0.00424)
Weekend	-0.0645***	0.886***	-0.0431**	0.959**	-0.0475**	0.947**
	(0.0134)	(0.0238)	(0.0153)	(0.0150)	(0.0151)	(0.0181)
Constant	0.341***	0.489***	0.509***	0.690***	0.913***	0.891***
	(0.0175)	(0.0171)	(0.0200)	(0.0175)	(0.0198)	(0.0212)
Alpha		0.635***		0.0291***		0.0611***
		(0.0215)		(0.0121)		(0.00880)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weapon Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19413	19413	19413	19413	19413	19413
Adjusted R^2	0.371		0.177		0.199	

Standard errors in parentheses; Dependent variables standardised in OLS models; NB coefficients given as incidence rate ratios; OLS coefficients in bold for Coalition Media and News Agencies groups indicate significant ($p < 0.01$) differences with Iraqi Media group according to a Wald chi-squared test using stata's 'suest' command; [a] Measured in hours; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As anticipated by the literature (Oliver and Myers, 1999; Weidmann, 2016), there is a strong event size effect across all specifications with a positive relationship between the number of fatalities and injuries and the intensity of media coverage received. Comparing, using the standardised OLS model, between source groups shows that this event size effect is largest for coalition media coverage, indicating that coverage decisions by coalition media are the most dependent upon event magnitude. The NB coefficient shows that for each additional death incurred by an event the intensity of coverage received in the coalition media group will rise by around 4%. While the result is statistically significant, it shows a disproportionate relationship between the number of deaths and media reports; an increase in the number of people killed, ceteris paribus, fails to generate an increase in media coverage of equal magnitude.

In terms of the other event characteristics included in the model, the weekend variable is a dummy variable indicating whether events took place during the Iraqi weekend (Friday and Saturday). A negative coefficient is observed across all specifications indicating a significant drop in reporting intensity for conflict events occurring at the weekend where less staff may be available to compile reports. The results of the driving time variable, as well as the weapon type controls, will be discussed below in sections 1.5.3 and 1.5.4, respectively.

Appendix Tables A.1 and A.2 test the robustness of the results in Table 1.4. Appendix Table A.1 repeats the analysis in Table 1.4 with the imposition of robust standard errors (Huber, 1967; White, 1980). Significant results on fatalities, driving time, and weekend are found to be very robust to this specification. However, there is a weakening in significance of coefficients on the number of injuries variable. Appendix Table A.2 tests two alternative specifications of the time controls: the addition of quarter-year dummies, and the use of a time trend variable with a squared term to allow for any nonlinearities. These are useful as both a robustness check to Table 1.4 as well as an opportunity to study how the intensity of media reporting changes over time. Firstly, in terms of robustness, results are found to be very similar to those in Table A.1, with a weakening in results on the number of injuries the only significant change. The quartile dummies test whether coverage within the media groups differs within year. Results show that time of year does not affect reporting within the Iraqi Media. For the coalition and news agency media sources, events occurring in Q2, Q3, and Q4 are less intensely reported than those in the first quarter of the year. The coefficients on the year trend and non-linearity term present a very similar picture to the data presented in Figure 1.2, showing that these trends persist when controlling for other variation. For the coalition media, the coefficients show reporting intensity rising until 2008 at which point reporting intensity decreases each year at an increasing marginal rate. For the Iraqi media, reporting intensity rises every year - albeit at a diminishing marginal rate - until 2012, before decreasing slightly in 2013. For the international news agencies, reporting intensity is relatively stable until 2009 at which point it begins to decrease, although at a lower rate than for the coalition media.

It should be noted that the standard errors, and therefore the statistical significance of coefficients, are calculated with the assumption that there is no serial correlation within the error terms. Given that the data is structured as a set of observations of documented events (with multiple events occurring on a single day in the vast majority of cases) rather than structured as event counts within set time periods this is difficult to test for. Robust standard errors, therefore, may still be too small if serial correlation is indeed affecting the IBC data.

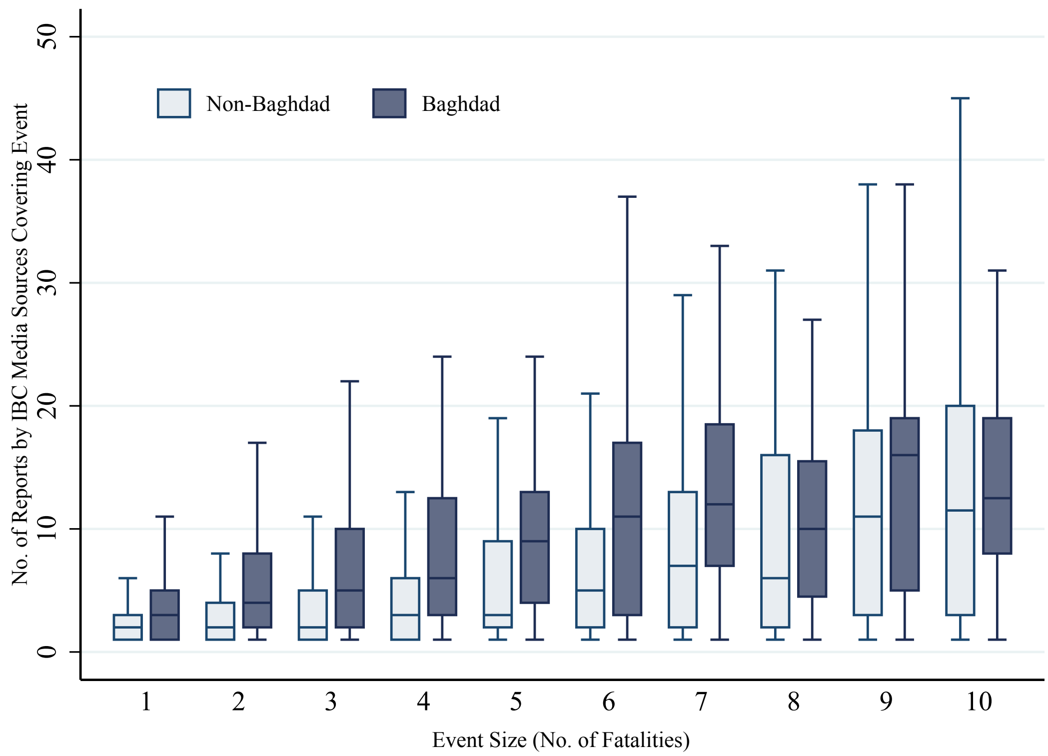
Zero-inflated negative binomial results for the coalition media group - as the group most likely to suffer from excess zeroes (Appendix Figure A.1) - are presented in Appendix Table A.3 alongside the full set of results including the control variables for Table 1.4. The ZINB coefficients are found to be very similar to the non-inflated negative binomial coefficients presented in Table 1.4.

1.5.3 Locational Effects

Locational data can be used to analyse whether a centre-periphery bias exists within reporting of the conflict in Iraq where events closer to, or within, the capital are more intensely reported. Firstly, in Figure 1.3, reporting of conflict incidents by all IBC media sources are compared according to their event size and whether they took place inside or outside of Baghdad. The positive relationship between event size and intensity of media coverage, shown in Table 1.4, holds for both locations presented here. However, at all event sizes the median number (indicated by the thick horizontal lines) of media reports for events occurring in Baghdad is higher than those taking place outside the capital. An interesting extension to this shows that when the graph is extended to larger events (Appendix Figure A.5) the difference in reporting disappears. This suggests that for relatively small events a Baghdad bias exists and journalists may be unwilling to travel to report them. However, once an event passes a certain intensity threshold, this bias disappears and journalists will cover the event regardless of location. The results presented above, in Table 1.4, confirm the existence of a significant centre-periphery bias for all three media groups. For example, in the coalition media group, a one hour increase in the driving time from the location of an event to the centre of Baghdad leads to a decrease in coverage within the coalition media group of 0.0612 standard deviations in the OLS model, or of 12.9% from the previous count in the NB model. Given that some events in the data occur more than seven hours drive away from Baghdad, such events will be reported with substantially lower intensity than those inside the capital.

Given that the centre-periphery bias exists we may expect that international news reporting will be more sensitive to the bias than domestic reporting. This is because most international media were based almost exclusively in Baghdad and found leaving the capital to report events difficult (Pew Research Center, 2007). Therefore, the

Figure 1.3: Reporting of Events Inside and Outside of Baghdad by Event Size



journey time to an event is more likely to be of consequence in their coverage decisions. In contrast, domestic sources often have offices across multiple regions, meaning that they are less likely to disregard events as a result of travelling time.

This hypothesis is tested in Figure 1.4. The number of events reported by at least one of Reuters and Associated Press (the two international news agencies that reported the highest number of events) is compared by province with the number reported by at least one of the National Iraqi News Agency and Voice of Iraq (the two Iraqi news providers that reported the highest number of events). Provinces with darker colours are those where reporting by international media is more complete relative to Iraqi media. The graph indicates substantial variation between reporting. The internatio-nal news agencies reported a higher number of events in provinces close to Baghdad (denoted on the map by the octagon symbol), however, in some provinces further from the capital they reported less than 15% of the number of events reported by the Iraqi sources. These findings are supported by the regression results in Table 1.4. While the results show a universally negative relationship between coverage and distance from the capital, the effect is significantly larger in magnitude in the coalition media and news agencies groups than in the Iraqi media group (where intensity of reporting decreases by only 1% per hour). This shows that the media reporting of the international media is far more sensitive to event location.

Figure 1.4: Ratio of Event Coverage between International and Iraqi Media

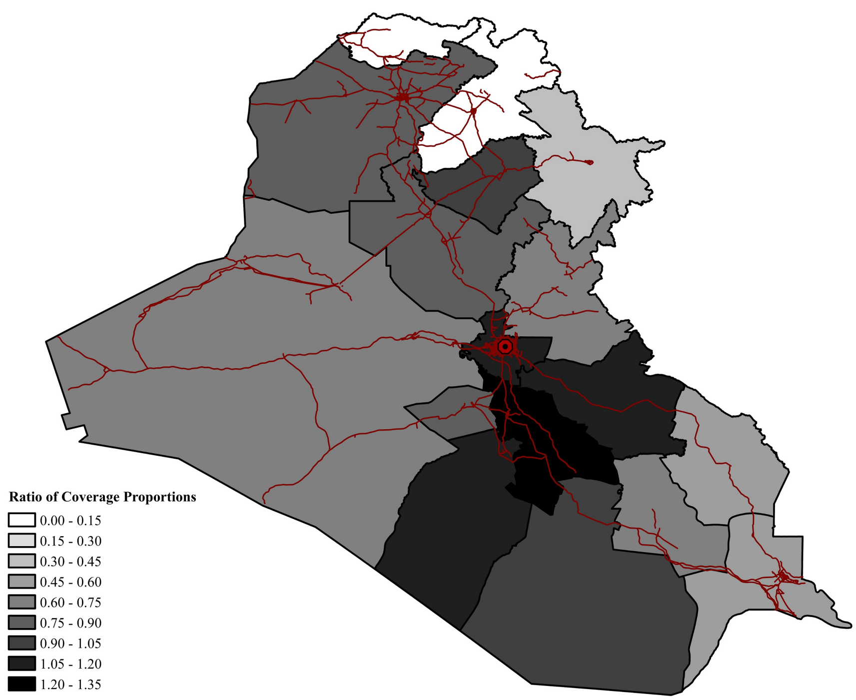


Table 1.5 dislays the results of expanded study into the impact of event location on the newsworthiness of conflict events. One research question, raised in section 1.2, is whether the centre-periphery bias found above is dependent on distance/travel time or is a binary relationship only. For this study only the coalition media group is used,

this is because Table 1.4 indicates that this group are the most likely to be influenced by location bias. The first specification is identical to that presented in column 2 of Table 1.4 and shows a decrease in reporting intensity of around 13% when the driving time to a conflict event from Baghdad increases by one hour. The second specification adds to column (1) a dummy variable indicating whether the event occurred within the city of Baghdad. The coefficient on this dummy variable is positive, significant and of considerable magnitude; events occuring in the capital obtain a substantial reporting premium. The driving time variable remains negative and is also significant, however, the size of the coefficient has now dropped to a reporting intensity decrease of 4% for a one hour increase in driving time. This suggests that, for the capital city, locational bias is partially binary, significantly depending on whether an event happens in Baghdad or elsewhere in the county. However, it is also partially continous, as when an event takes place outside of Baghdad reporting intensity decreases with the driving time. For a robustness check (Appendix Table A.5), events in Baghdad were removed from the sample and similarly significant results on driving distance to Baghdad were observed.

Another question which arises from these findings is whether the results above are specific to the capital city, Baghdad, or also hold for other major cities. We may expect that events occuring within, or close to, large cities will also recieve a reporting intensity premium for several reasons. Firstly, while most journalists in Iraq were based in Baghdad, some larger news organisations also had small regional bases or contacts operating in other large cities. Secondly, a higher population density increases the number of potential observers of conflict events and an increased proliferation of telephones and internet access increase the ability of locals, news stringers and journalists to report observed events. Finally, news stories reporting on the deaths of civilians in cities may resonate more with an international news audience whose own living standards may be closer to civilians living in urban areas compared to those living rurally.

Table 1.5: NB Regressions: Coalition Media by Locational Specification

	(1)	(2)	(3)	(4)
Driving Time from Baghdad[a]	0.871***	0.960***		
	(0.00554)	(0.00782)		
Within Baghdad City		1.797***		
		(0.0573)		
Driving Time from Nearest City[a]			0.825***	1.003
			(0.0125)	(0.0256)
Within Any City				1.445***
				(0.0571)
Constant	0.489***	0.345***	0.427***	0.313***
	(0.0171)	(0.0139)	(0.0149)	(0.0152)
Alpha	0.635***	0.592***	0.680***	0.667***
	(0.0215)	(0.0205)	(0.0223)	(0.0221)
Event Size Controls[b]	Yes	Yes	Yes	Yes
Time Controls[c]	Yes	Yes	Yes	Yes
Weapon Type Controls	Yes	Yes	Yes	Yes
Observations	19413	19413	19413	19413
Pseudo R^2	0.148	0.155	0.141	0.143

Standard errors in parentheses; Coefficients are given as incidence rate ratios
[a] Measured in hours; [b] No. of fatalities and injuries; [c] Year and weekend controls;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To test whether this hypothesis is the case, columns (3) and (4) of Table 1.5 repeat the previous analysis with an alternative measure. Here, driving time is measured from the event location to the nearest of the five largest cities in the country: Baghdad, Mosul, Basrah, Kirkuk or Erbil. Column (3) indicates that driving time to a conflict event from the nearest large city is of similar importance to driving time from Baghdad. However, in this case, when a dummy variable indicating that the event took place inside one of the large cities is added to the model, the distance measure becomes insignificant. This result is also obtained when removing those events occurring within the large cities from the sample (Appendix Table A.5).

Appendix Table A.4 reproduces the results in Table 1.5 with standard errors that are robust to heteroskedasticity (Huber, 1967; White, 1980), there is no change to the statistical significance of any coefficients.

Overall, within the reporting of coalition media sources in Iraq, there exists a clear selection bias in favour of those conflict events taking place within Baghdad and other large cities. Driving time to events from Baghdad is also found to have a significant negative effect on reporting intensity. However, driving time to events from other cities is not found to be a significant predictor of intensity of coverage. For robustness checks, all locational results were rerun, finding very similar results, using an 'as-the-crow-flies' (geodesic) measure of distance instead of the driving time measure (Appendix Table A.6).

1.5.4 Weapon Type

Whether the type of weapon employed within a conflict event will impact upon the event's newsworthiness has previously remained unstudied although indications from the homicide (e.g. Gruenewald, Pizarro, and Chermak, 2009) and terrorism (Jetter, 2014) literatures indicate that it will have a considerable effect. Figure 1.5 shows the relationship between event size and reporting within the IBC dataset comparing between gunfire and explosive weapons. Comparing these weapon types by event size is important, Table 1.1 shows bombings have a higher average death toll and Table 1.4 shows that event size is a determinant of reporting intensity. There is a large discrepancy between the median level of reporting of gunfire attacks and that of bombing events which is increasing by event size. In contrast to Figure 1.3, this gap continues to increase when event size is extended past those shown in the figure (Appendix Figure A.4). This indicates a systematic difference in the newsworthiness of these weapon types even where the number of people they kill per event is held constant.

Figure 1.5: Reporting of Gunfire and Bombing Incidents by Event Size

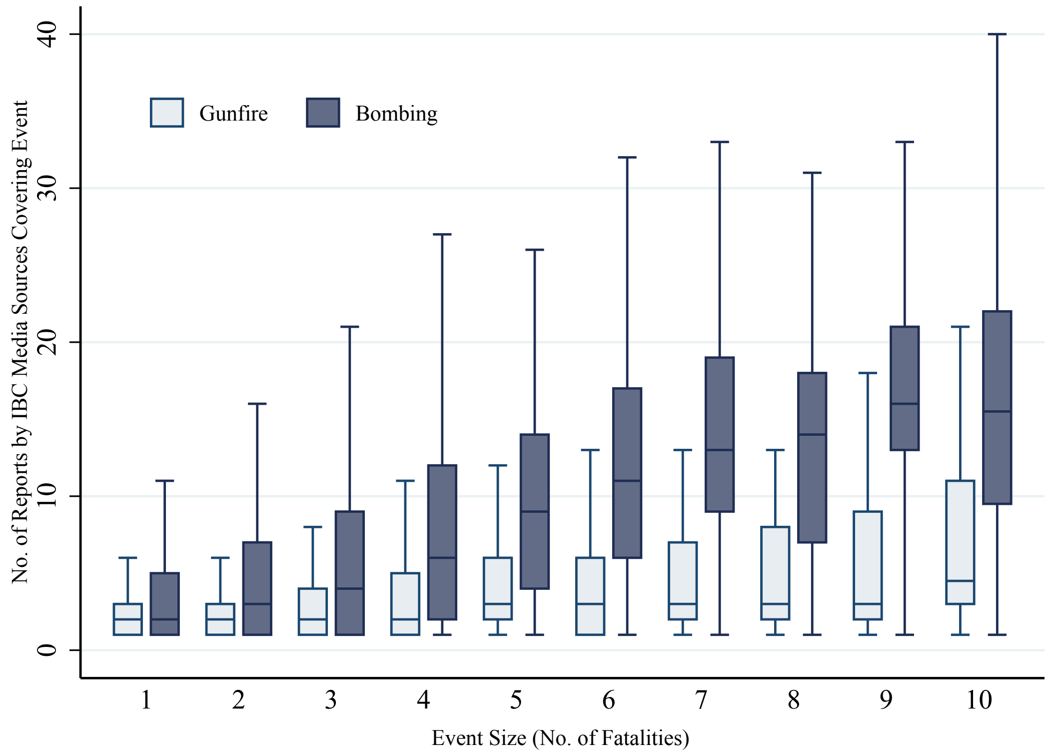
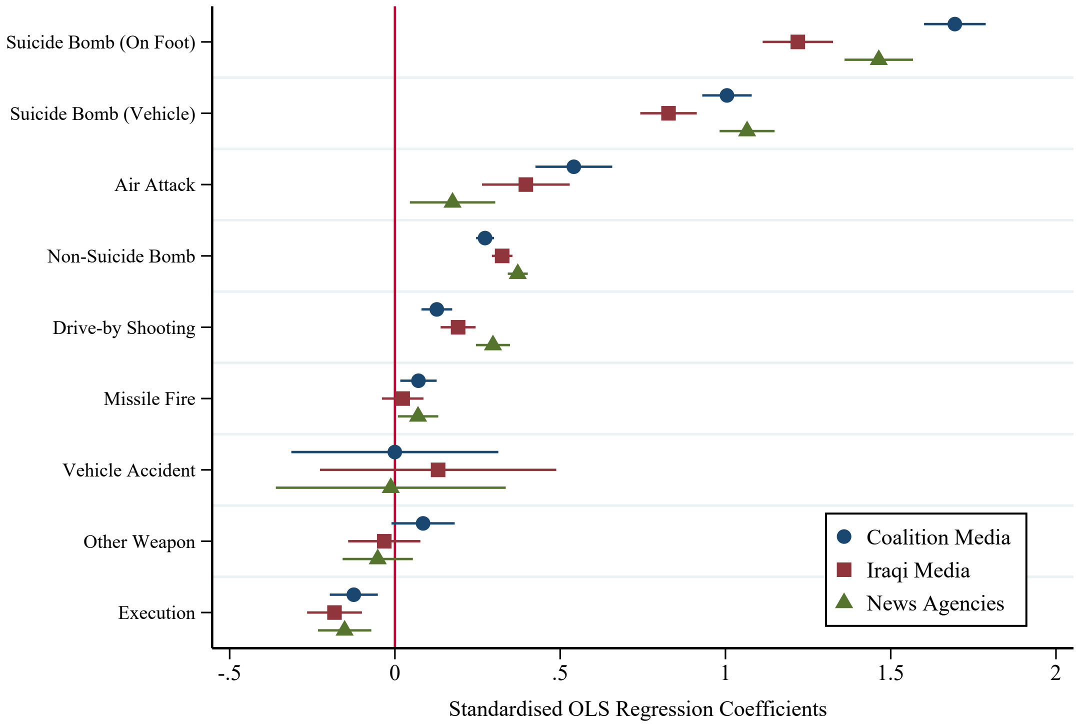


Figure 1.6 displays the coefficients from a regression analysis testing the impact of various weapon types on reporting intensity, with gunfire (the most commonly occurring weapon) as the reference category. The analysis includes a full range of controls (event size, region, time trends and weekend). The figure can be interpreted as follows: those coefficients to the left of the vertical line at zero indicate weapons which are less newsworthy than gunfire, those to the right of the line hold a reporting intensity premium over gunfire. Full negative binomial and OLS results are presented in Appendix Table A.7.

One attack type which appears to attract relatively little coverage is execution. These events receive a significantly lower intensity of coverage than gunfire across specifications despite being a particularly brutal and discriminate method of killing civilians. One reason for this could be that executions carry very little collateral damage. Also,

Figure 1.6: Standardised OLS Coefficients by Weapon Type



Note: Confidence intervals at the 95% level. Regression includes region, time and event size controls. Reference category is gunfire

despite some high profile public executions, many are carried out in secret and away from the public eye. This is in contrast to civilian deaths caused by other weapons, such as those by bombings or missile fire, which are far less likely to occur undetected. These factors may prevent news about these events ever reaching many journalists. In addition to this, if bodies are only discovered several days after an execution has taken place, some editors may no longer consider the killings as newsworthy.

The results show a significant reporting premium for explosive weapons and aerial attacks. This supports the idea that explosive violence may be considered as more ‘exotic’, and thus intrinsically more newswothy, than other forms of violence. These weapon types accrusing the highest intensity of media coverage are also those which can be considered the most indiscriminate. However, they are also more likely to kill women and children (Hicks et al., 2009), groups whose deaths are likely to be more newsworthy (Peelo et al., 2004). Therefore, it cannot be ascertained without further study whether the premium in coverage for indiscriminate weapons is as a result of the weapon type itself, or of the impact of the age or gender distribution of its victims.

The reporting intensity effect is greatest across all groups for suicide bombings and particularly those suicide attacks which are committed on foot. Such attacks receive 2.6 - 4.6 times more coverage (according to the negative binomial regressions) than, otherwise equivalent, gunfire attacks. This result runs in the same direction as that found by Jetter (2014) in his study of the media reporting of terror attacks. There could be several reasons for the observed reporting premium which suicide bombings receive. One such reason is that suicide bombing may be considered by the news media as an extreme version of the 'exotic' nature of ordinary bombing attacks, given that individuals are willing to kill themselves in their pursuit of harming others. Another possibility is that suicide attacks may be targeted at more newsworthy, high-profile, victims (Berman and Laitin, 2008) and it is partially the prescence of these which inflates intensity of coverage.

Figure 1.6 shows significant variation in reporting intensity across weapon types. However, in this case, there is comparitively little variation in the relative sensitivity of the three media source groups. The figure shows that the groups are close to unanimous in their ordering of the newsworthiness of the ten weapon types. The exception to this (i.e. a difference in ordering outside of the 95% confidence interval) is that for the international news agencies, air attacks obtain a smaller premium over gunfire attacks than non-suicide bombings. The international and coalition media groups also show a significantly larger reporting intensity premium for suicide bombings than the Iraqi media.

Appendix Figure A.6 tests whether results in Figure 1.6 are robust to heteroskedasticity. The introduction of robust standard errors (Huber, 1967; White, 1980) widens the confidence intervals (especially for rarer events such as suicide bombings). However, the significance and ordering of the weapon types is unchanged in comparison with Figure 1.6 indicating that these results are robust.

1.6 Conclusions

This chapter has made use of a unique dataset linking specific conflict events to the media sources which reported them. This data has been employed, firstly, to analyse how heterogeneity in event characteristics will affect the intensity with which events are reported by the news media and, secondly, how heterogeneous groups of news outlets differ in their sensitivity to these event characteristics.

The study has added to the existing literature on the media coverage of conflict in several ways. Firstly, the availability of an innovative dataset has presented an opportunity to test the importance of various event characteristics to the reporting of the news media. In some of these, such as an observed event size bias, this has involved quantifying an effect also predicted by other studies. Reporting intensity is found to significantly increase with event size, although, not proportionally. Other event characteristics, such as the day of the week and weapon type of an attack, have been analysed for the first time. Events occuring on weekends are covered with less intensity by the media than those which take place on weekdays. In terms of weapon types, a significant premium in media coverage has been found across source groups in the reporting of events involving explosive weapons. Those explosive weapons attacks on civilians including suicide gain an additional reporting premium. In contrast, otherwise equal conflict events involving other weapon types, such as execution, receive significantly less coverage.

Additionally, this chapter has enabled a comparison between the news reporting of domestic media, coalition media and international news agencies. In general, international media are less random in their reporting and, therefore, more sensitive to event characteristics, such as the magnitude of an event, to determine reporting. This means that the beliefs of international media consumers about the Iraq conflict are likely to have been skewed according to the biases found here. The difference between international and Iraqi media was found to be at its greatest when analysing locational bias and specifically the travelling time to an event from Baghdad. Media reporting intensity decreased with driving time from Baghdad in all media groups. However, the effect of an additional hours driving time on international reporting was 7 to 13 times that on domestic coverage. Extended analysis, specifically on the coalition media group, looked at whether the centre-periphery bias is also relevant for other cities in Iraq. Results show that the distance measure is only significant for Baghdad although events taking place within other large cities are reported more intensely.

For consumers of news media, this study has shown that relying on a few relatively homogeneous media sources for conflict news will lead to significant inaccuracies in the beliefs held about the nature of violence against civilians. For example, consumers of media from coalition countries will have observed a decline in the intensity of coverage per incident over time (Figure 1.2), which may lead them to wrongly assume a decline in violence against civilians of the same magnitude. They will also have observed a disproportionately large number of events with particularly newsworthy characteristics e.g. those involving explosive weapons and taking place within large cities. One recommendation, for those who are interested in obtaining more accurate information about civilian fatalities in conflict, is to regularly check the websites of data collators such as IBC that amalgamate information from many sources. This should give consumers a more unbiased and informed overview of the violence that is occurring. In addition to this, the news media should also be responsible for regularly updating their readers or viewers with an overview of known casualties taken from event based data, such as IBC, as well as other violence monitoring data, such as estimations from surveys.

There are of course several limitations to the analysis carried out here. Firstly, some of the results may suffer from a lack of generalisability due to this analysis being carried out on one conflict in particular. The Iraq case study was relatively unique in terms of the level of international attention it received, media reporting may be very different in smaller conflicts without western involvement. The conflict was also characterised by difficulties for journalists in travelling around the country, which may not be the case in other conflicts. That said, results from certain variables, such as event size and weapon types, should translate across conflicts and therefore can be interpreted more generally. Also, the results here were obtained using data that records events only where civilians were killed; it is possible that selection bias affecting events killing combatants could be different in nature.

A second limitation is that the IBC data, specifically the subsection of the data used here containing only fatalities reported by the media in the form of events, is not a complete list of conflict events which took place in Iraq. The chapter implemented an intensity measure of reporting (rather than a binary measure of coverage) to mitigate the impact of this. It is important to note, therefore, that results should primarily be interpreted as the impact of event characteristics upon reporting intensity amongst media reported events. The coefficients on these characteristics do, however, point to some explanations about why certain events are not reported by any media sources. Analysis here is also restricted to those event characteristics routinely recorded in the IBC database. There is likely to be heterogeneity within reporting intensity caused by event characteristics (e.g. victim and aggressor identities) that are not consistently recorded in the IBC data. There are also likely to be other event characteristics, such as damage to buildings and capital goods or political relevance of events, which affect reporting intensity but are not monitored by IBC.

This chapter has enabled a new perspective within a growing literature considering how the media 'frame' conflict through their reporting decisions. The study has also highlighted several areas where further research is necessary. One such area is for similar analyses to be carried out in alternative geo-political contexts, for example conflict zones without western involvement. This is necessary to understand whether the findings here are specific to the Iraq case, or translate to conflict in general. Another area for future research is a need to assess how other event characteristics not covered by IBC affect reporting, particularly the effect of victim or aggressor characteristics. Two final research areas which arise from the findings here are studied in Chapter 2 of this thesis. The first is how the results may impact the accuracy of the media-based conflict datasets used by many researchers engaged in empirical studies of conflict. The second considers the likely characteristics of those 'missing' events which were not picked up by any media sources.

Chapter 2

Assessing the Completeness of Media-Based Datasets

2.1 Introduction

Conflict event datasets documenting war deaths have often relied on the news media as the predominant, or sole, source used to populate their datasets. The data contained within such media-based datasets has been regularly used by politicians, journalists and other public figures to make claims regarding the intensity and lethality of conflict. This type of data also underpins much of the academic research into the empirical study of conflict and related subjects.

It is likely a mistake, however, to assume that these datasets are complete or indeed that their event type composition (e.g. geographical or locational make-up) is an accurate reflection of the true underlying compositions. This is due to two contributing factors. Firstly, Chapter 1 showed that the intensity with which the media reports upon conflict is non-uniform and determined by event characteristics. The direct consequence of this heterogeneity will be on consumers of the news media whose viewpoints will be skewed according to event newsworthiness. However, in addition to the effect upon news consumers, these findings also hold significant weight when evaluating the accuracy of media-based conflict datasets. Secondly, given that monitoring media sources is costly, those creating such datasets will only select a subset from the full set of media sources to be monitored. This reporting heterogeneity combined with a non-random source selection process will lead to a dataset comprised of a biased subsample of the universe of conflict events.

This chapter is comprised of two main sections which attempt to study these phenomena. The first section provides an overview of the literature surrounding the completeness of media-based datasets. It then proceeds to use the unique Iraq Body Count data to draw inference about the relative completeness of datasets comprised of subsets of IBC sources. The second section uses Multiple Systems Estimation (MSE) techniques to attempt to estimate the extent to which IBC itself may be incomplete.

2.2 Completeness Analysis

2.2.1 Media-Based Datasets

The use of the news media as a source for populating event datasets has increasingly become the normality in conflict documentation. Many of the most widely-used conflict event datasets use media reports as sources for their data. In some cases, such as the Social Conflict Analysis Database (SCAD) and the Global Database of Events, Language and Tone (GDELT), reporting by the news media is the sole data source. In others, such as the UCDP Georeferenced Event Dataset (UCDP-GED) and the Armed Conflict Location and Event Dataset (ACLED), news reports serve as the primary data source but may sometimes be complemented by other information (e.g. NGO reports or research articles).

Media-based conflict datasets have been used for countless academic studies into a wide range of conflict-related fields. Examples include studies looking at the relationship between conflict and climate change (Hendrix and Salehyan, 2012; O'Loughlin, Linke, and Witmer, 2014), migration (Forsberg, 2010), child welfare (Minoiu and Shemyakina, 2014) and inequality (Hegre, Østby, and Raleigh, 2009; Fjelde and Østby, 2014) among many others. The validity of many of these studies relies upon the composition of events within these datasets being an accurate reflection of the unobserved true composition of events. For example, analysis which compares child health outcomes across regions affected by heterogeneous levels of conflict will be skewed if media reporting is more sensitive to violence in particular regions. Should violence be consistently recorded by media-based datasets in such a manner this can be considered a type of neo-classical measurement error. Systematic measurement error such as this will lead to endogeneity and therefore biased coefficients where conflict is used as an independent variable in analyses.

Academic research into the completeness of such datasets has, however, been relatively sparse. While many studies acknowledge that potential inaccuracies may exist within media-based datasets (e.g. Eriksson and Wallensteen, 2004; Eck, 2012) detailed empirical analyses have been limited. Most trends which have emerged from the empirical literature suggest that the patterns in heterogeneity in coverage intensity found in Chapter 1 above may also translate to media-based datasets.

One trend to consistently emerge is an event size bias effect, where larger events will receive higher levels of media coverage. This bias is found to affect dataset completeness to various extents (Duursma, 2017; M. Price and Ball, 2014; Donnay and Filimonov, 2014). Another event characteristic shown in Chapter 1 as affecting reporting intensity is geographic location. In terms of the imact this may have on dataset completeness, O'Loughlin et al. (2010) find that the geographical distribution of conflict is highly consistent between the media-based ACLED data and the military data released by Wikileaks at the regional level. Weidmann (2013) shows, however, that consistency decreases at higher levels of geographical precision. Studies have also shown a decline in media dataset accuracy (Weidmann, 2015) or completeness (Davenport and Ball, 2002) in rural areas. The explosive weapons reporting premium found in Chapter 1 has, so far, remained unstudied in terms of the effect upon dataset completeness.

This previous research, generally based around comparing media-based and alternatively sourced conflict data, has a couple of main limitations. One is that other types of data, used for comparison, are often equally incomplete records of the conflict. For example, events in military collected data may only be recorded where troops are present and thus miss incidents of sectarian violence (Berman, Shapiro, and Felter, 2011). A second limitation is that research can be somewhat restricted by the laborious nature of coding necessary to match datasets and thus analysis can often only be undertaken using smaller samples (e.g. Siegler et al., 2008).

A consistent theme within this previous work is the consideration of media-based datasets as single entities. This bypasses the fact that they are, in fact, composed of a combination of several selected media sources. Taking this into consideration enables an alternative type of research which studies how source selection influences the completeness of a dataset. This considers how dataset creators can strive for efficiency through the selection of sources to maximise dataset completeness. Completeness here is defined as incorporating as many of the universe of media reported events and fatalities as possible. While, ideally, datasets would monitor all media sources, this is not often possible due to the marginal costs associated with monitoring each additional source. These costs may include labour, electronic subscriptions and computing power. There may also be trade-offs between data completeness and another important aim: having a distribution of events (in terms of event size, weapon type, location and time) which mirrors the underlying distribution.

The limited research that has studied this source selection process has painted a mixed picture. Doran, Pendley, and Antunes (1973) showed that event data trends based on data derived from international newspapers were often different to those in regional newspapers. However, other studies have found that source selection has only a very marginal impact on conflict documentation (Hazlewood and West, 1974; Taylor and M. C. Hudson, 1972) and that increasing the number of sources beyond two is “not likely to result in substantial changes to the overall picture” (Jackman and Boyd, 1979, p457).

The present study provides an opportunity to expand upon this ageing research through using the rich, media-based, Iraq Body Count (IBC) dataset outlined in section 1.4 above. Crucially, in IBC, media coverage can be broken-down by news outlet for each event. The IBC dataset is also composed of many media sources of various types and country origins. This enables the study of which events would have been included in a ‘pseudo dataset’, generated based on the reporting of a chosen subset of sources. Through this methodology it is possible to assess the benefits of adding further sources to a dataset, and to establish which pseudo datasets offer the most accurate documentation of the conflict relative to IBC.

In this chapter, analysis is conducted based upon a binary measure of event inclusion within a ‘pseudo dataset’ group of sources, relative to IBC. It is important to note that this measure is different to the count measure of intensity used in Chapter 1. The results in section 1.5.1 showed that newsworthiness is significantly dependent upon event characteristics. However, this will only be a problem for the completeness of a media-based conflict dataset where it results in some events not being reported on by any monitored media source. This is because only one media outlet reporting the event, among all monitored media sources, is necessary to ensure that an event is documented.

It is important to note, again, here that Iraq Body Count itself is not a complete list of conflict events and is likely to be “missing many civilian deaths from violence” (Iraq Body Count, n.d.(a)). In addition, there are other deaths, such as those found in morgue body counts, included in IBC but which are not recorded in the format of an event. This means that results here should be interpreted as assessing completeness of pseudo datasets relative to the media reported IBC data rather than to the unobserved reality (although results in section 2.3 below will point to how these results may transfer across to this). This restriction makes sense as the aim of this exercise is to understand the impact of source selection on, specifically, media datasets. The comparison with IBC shows the difference between each pseudo dataset and the ‘best case scenario’ of media data in terms of the IBC dataset.

This first section (2.2.2) is comprised of figures and simple regressions which show how these pseudo datasets will differ in their documentation of the conflict relative to the IBC dataset, comprised of the full set of media sources.

2.2.2 Dataset Creation Exercise

For the purpose of this exercise I generate four pseudo datasets which are detailed in Table 2.1 and are subsets of the full IBC database. As monitoring media sources is costly, I restrict the number of sources per group to a maximum of five sources.

Dataset (1) is comprised of the reporting of AP and AFP. These two sources were specifically chosen as a pseudo dataset grouping due to being commonly incorporated into conflict event datasets. For example, they are the sole two sources used for the Social Conflict Analysis Database (SCAD) which has been used regularly in conflict research (Salehyan et al., 2012). They are also two of the main media sources which act as a basis for the UCDP-GED Database (Croicu and Sundberg, 2015). Despite their wide use, a dataset comprised of these two sources for Iraq would only include around a third of the events within IBC while incorporating 59% of the total deaths.

The second and third pseudo datasets are comprised of the reporting of national media outlets (e.g. newspapers and websites). The sources for dataset (2) are the five US/UK media outlets that reported the highest proportion of conflict events. The third is the equivalent Iraqi group. These two datasets incorporate similar numbers of fatalities, however, dataset (2) has a considerably lower event count. The final dataset, (4), is based upon the reporting of the five largest reporting news agencies in the IBC data, combining both international and Iraqi focused agencies. This dataset incorporates around 40% more events and 30% more fatalities than the other media outlets. I would, therefore, anticipate that it will also have event type compositions which are more similar to the full IBC data.

2.2.3 Event Size

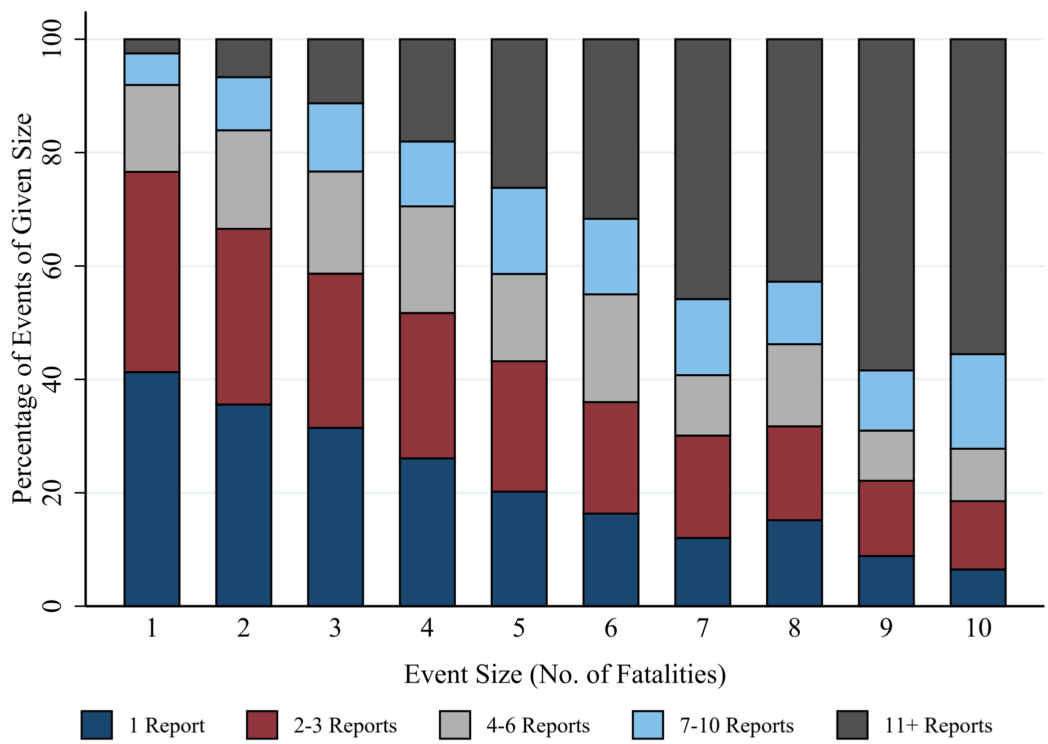
One area of key importance when implementing a data collection project aiming to document a conflict is the accuracy of the event size distribution of the dataset. Table 1.4 showed the existence of an event size bias whereby the intensity of media reporting that

Table 2.1: Pseudo Datasets by Source Composition

	Name	**Sources**	**Completeness**	
			Events	Fatalities
(1)	SCAD Sources	AP & AFP	34.25%	58.91%
(2)	US/UK Media	McClatchy Newspapers, CNN, New York Times, LA Times, BBC	26.08%	53.73%
(3)	Iraqi Media	Al-Sharqiya TV, Al-Sumaria, All Iraq News, AKNews, Al-Iraq	38.65%	55.12%
(4)	News Agencies	Reuters, AP, AFP, Voice of Iraq, National Iraqi News Agency	76.95%	85.20%

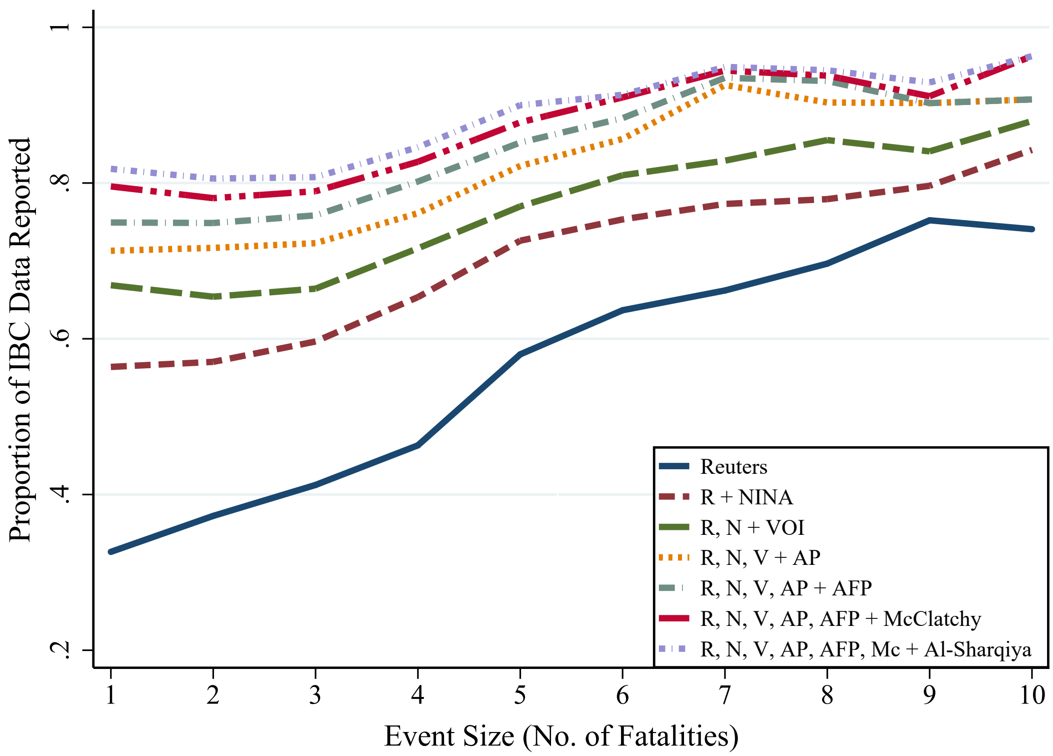
an event receives depends upon the number of fatalities which it inflicts. This is clearly presented in Figure 2.1. As event size increases, the proportion of events reported by 1 - 3 IBC monitored media sources falls from nearly 80%, for events with one death, to under 20% in events where ten people were killed. This implies that restricting the number of sources within a dataset will likely accentuate this event size bias as disproportionate numbers of smaller events will be missed for every omitted source.

Figure 2.1: Event Size Bias on Media Coverage



The assertion that smaller datasets will accentuate the event size bias is tested in Figure 2.2. The solid line represents the proportion of events reported by Reuters (the media source reporting the highest number of events) at each event size relative to the complete list of media reported events at that event size. The next six largest sources according to the number of IBC events reported are then added in turn to create an increasingly large dataset. A horizontal line would imply that a source group incorporates events in a uniform manner and thus does not have any event size bias. The steep gradient of the Reuters line means that despite covering around 75% of conflict events with 10 fatalities, only around 32% of events with a single death are included. The figure shows that adding sources tends to contribute more to the inclusion of smaller events than larger ones (where there is likely to be more crossover in reporting). Adding a further six sources contributes a percentage point increase of 21% for events of size 10 whilst increasing coverage by 49% for events of size 1. This figure shows the importance of utilising multiple media sources when recording casualties in media-based event data and that this will be particularly effective in reducing the event size bias affecting the recording of smaller events.

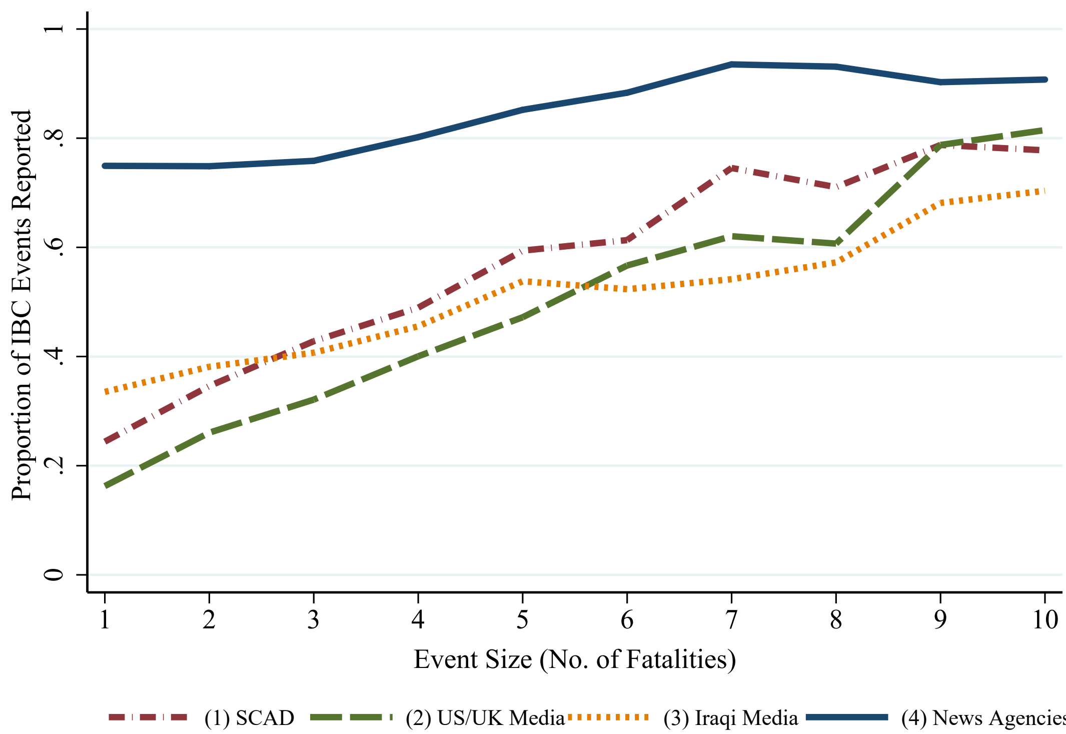
Figure 2.2: Relative Completeness by Dataset Size



In terms of the pseudo datasets outlined above in Table 2.1, Figure 2.3 presents their relative event size distributions. For all four, there is a clear oversampling of large events, albeit to differing extents. Despite reporting a lower proportion of events at each event size, dataset (3) follows a similar event size distribution to that of dataset

(4). The relative completeness of these two datasets is less dependent upon event size in comparison to datasets (1) and (2) where the event size bias effect appears to be particularly strong. This figure highlights a trade-off for dataset implementers between overall fatality coverage, which is higher in dataset (1), and event and composition accuracy, which is better in dataset (3).

Figure 2.3: Relative Completeness by Pseudo Dataset

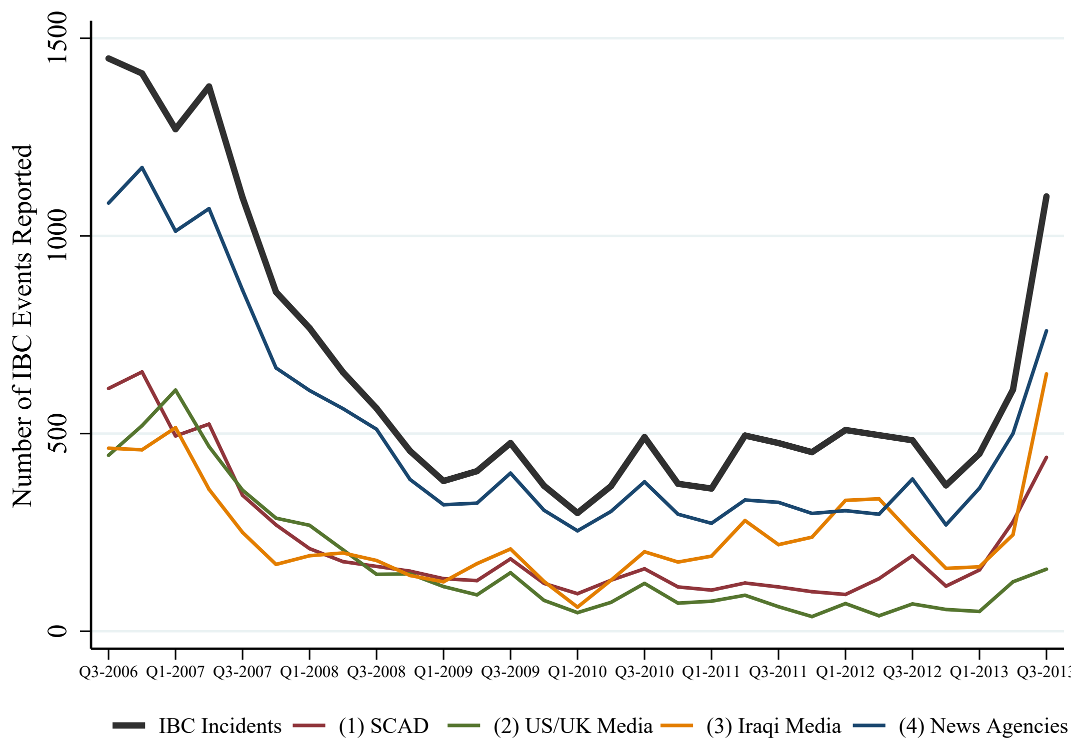


2.2.4 Dataset Performance over Time

Another important factor in maintaining an accurate record of a conflict is that the temporal fluctuations in events or fatalities are as a result of real changes in conflict intensity rather than simply a result of changes in newsworthiness.

Figure 2.4 presents the number of documented conflict events by quarter-year of the

Figure 2.4: Relative Event Completeness over Time



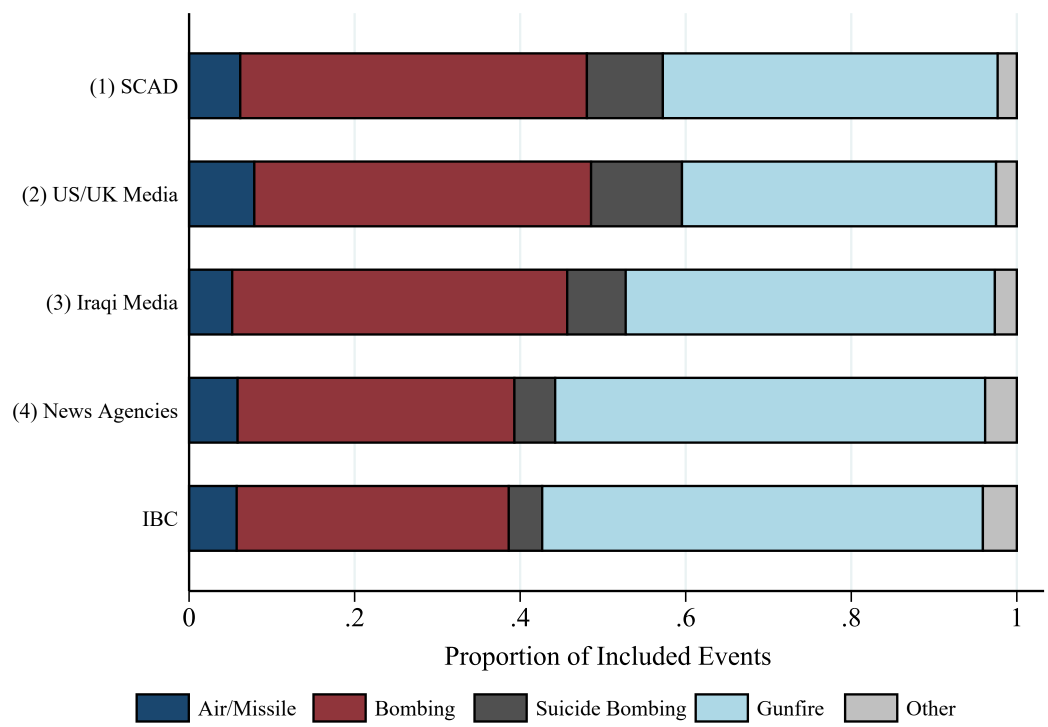
four pseudo datasets and that of IBC as a whole. As expected, dataset (4) gives by far the most accurate documentation of the timeline of the conflict relative to IBC. The other three datasets are almost identical in their recording of conflict events over the first half of the timeline, however, after Q1 of 2010 there is considerable divergence. A dataset in the form of (2) entirely fails to document the resurgence in violence towards the latter half of 2013. On the other hand, pseudo dataset (3) appears to oversample this period with the event count being around 200 events per month higher than that which it records during the IBC peak of violence during 2006 and 2007. This divergence is likely to be due to the declining interest in the conflict in Western countries as well as the increased capacity for reporting by the Iraqi media. Appendix Figure B.1 presents the results for fatalities over time. These results are very similar to those for events, albeit the differences are slightly less pronounced.

2.2.5 Weapon Type Distributions

Another important dataset characteristic is to have an accurate composition of the various types of violence employed (i.e. the weapons used). Figure 2.5 shows how the IBC weapon composition compares with the compositions contained within the pseudo datasets. (1) and (2) portray a conflict which is almost 60% comprised of incidents of explosive violence (air, missile and bombing attacks). The full IBC data suggests these types of attacks are responsible for around 42% of violence.

A similar picture is obtained in Appendix Figure B.2 showing the weapon distribution of deaths rather than events. Pseudo datasets (1), (2) and (3) show explosive weapons being responsible for around 68% of deaths while IBC shows that these should cover less than 54%. This type of bias is likely to significantly affect research undertaken using weapons data as variables.

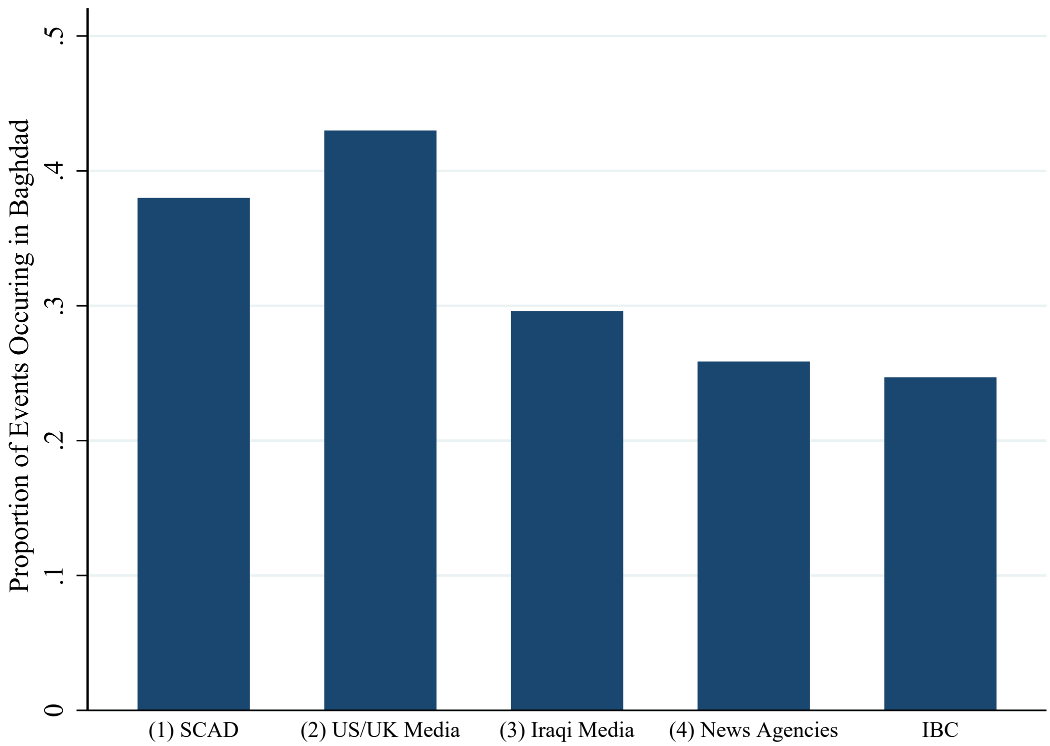
Figure 2.5: Weapon Composition by Pseudo Dataset



2.2.6 Geographical Distribution

Figure 1.3 showed how western media reporting varies with Iraqi reporting across regions. In Figure 2.6 I simply show the proportion of events which occurred in Baghdad according to the 4 pseudo datasets as well as IBC.

Figure 2.6: Proportion of Events in Baghdad by Pseudo Dataset



The group of sources chosen is shown to have a considerable impact on the proportion of events which are documented as occuring in Baghdad with all pseudo datasets oversampling Baghdad relative to IBC. For example, the sources used in SCAD overstate relative conflict intensity in Baghdad by more than 13% points. This type of dataset bias is likely to be a problem for studies using regional conflict intensity, such as Hodler and Raschky (2014) who use the UCDP GED data, and Ide et al. (2014) who use SCAD, ACLED and UCDP-GED.

2.2.7 Regression Analysis

These dataset imbalances are tested more formally in Table 2.2. Here I use a dependent variable for each pseudo dataset which is equal to 1 where an IBC event was reported by at least one of the set of media sources under analysis, and 0 otherwise. A simple linear probability (OLS) model - chosen due to the ease with which it can be interpreted - is then implemented for each pseudo dataset incorporating a range of event characteristics. Coefficients, where non-zero and significant, show that the probability of a random IBC event being included in the pseudo dataset is biased according to the event characteristic in question. For example, the probability that an event is reported by AP and/or AFP, and is thus included in dataset (1), increases by 0.724% points for every additional fatality it causes. The coefficients are presented with robust (Huber, 1967; White, 1980) standard errors in parentheses. As noted in section 1.5.2 there is a possibility that these standard errors may still be too small should serial correlation be affecting the underlying data.

The regressions confirm the findings from the above figures with all source combinations showing significant dependencies upon event characteristics when completeness is compared to the full dataset. The R^2s show, as expected, that there is a greater level of overall dependency upon event characteristics present for pseudo datasets (1) and (2), where 12.2% and 17.6% of the variation in inclusion can be attributed to the event characteristics tested here. In contrast, these event characteristics account for only 2.3% of the variation in inclusion in dataset (4) where missingness can be considered as more of a random process.

The impact on inclusion probability of each event characteristic generally moves in the same direction across pseudo datasets although there is substantial variation in magnitudes. A positive coefficient on fatalities and injuries indicates an event size bias in all pseudo datasets, albeit there is substantial variation between datasets with the

Table 2.2: Bias in Completeness of Media Source Combinations

	(1) SCAD Sources	(2) US/UK Media	(3) Iraqi Media	(4) News Agencies
No. of Fatalities	0.00724***	0.00854***	0.00540***	0.000929
	(0.00181)	(0.00195)	(0.00154)	(0.000770)
No. of Injuries	0.00119	0.00107	0.00125	0.000947**
	(0.000782)	(0.000820)	(0.000674)	(0.000363)
Baghdad Driving Time	-0.0386***	-0.0336***	-0.00672***	-0.00946***
	(0.00190)	(0.00179)	(0.00194)	(0.00168)
Year Trend	-0.00958***	-0.0367***	0.0394***	-0.0159***
	(0.00141)	(0.00119)	(0.00148)	(0.00133)
Weekend	-0.0355***	-0.0247***	-0.0248**	0.00157
	(0.00738)	(0.00654)	(0.00780)	(0.00702)
Air/Missile	0.0283	0.0603***	0.0496**	-0.00799
	(0.0159)	(0.0157)	(0.0157)	(0.0136)
Non-Suicide Bombing	0.139***	0.129***	0.0979***	0.0321***
	(0.00891)	(0.00832)	(0.00891)	(0.00739)
Suicide Bombing	0.406***	0.399***	0.282***	0.146***
	(0.0259)	(0.0276)	(0.0242)	(0.0127)
Other Weapon	-0.0750***	-0.0499***	-0.0587***	-0.0404*
	(0.0141)	(0.0131)	(0.0155)	(0.0165)
Constant	0.387***	0.400***	0.182***	0.833***
	(0.0111)	(0.0112)	(0.0103)	(0.00815)
Observations	19413	19413	19413	19413
R^2	0.122	0.176	0.087	0.023

Note: Omitted weapon category is gunfire; Driving time measured in hours; Robust standard errors in parentheses; $^*p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

coefficient on (4) insignificant when controlling for weapon type. In terms of the weapon type variables, suicide bombing attacks are between 15% and 40% more likely to be incorporated into the datasets than otherwise equivalent gunfire deaths, depending on pseudo dataset. The 'Driving Time from Baghdad' variable also shows the same pattern across datasets although the probability of inclusion declines by 4% per hour's drive in the SCAD sources while the effect is below 1% in the Iraqi media and News Agencies datasets.

One noticeable difference in the bias affecting each pseudo dataset is in the year trend variable. Inclusion probability is significantly decreasing by year, controlling for other event characteristics, over the 2006-2013 period in (1), (2) and (4), while significantly increasing in the Iraqi media dataset (3). This, again, is likely to be due to the decline in interest in the conflict internationally, especially after coalition troops started to be withdrawn. Combined with Figure 2.4, this provides strong evidence that source selection will play a significant part in determining the temporal variation in conflict datasets. For example, in dataset (2) an event occurring in 2013 had a probability of inclusion which was 26% lower than an otherwise identical event in 2006. On the other hand, in dataset (3) the probability would be 28% higher 7 years later.

Table B.1 presents robustness checks comprising alternative temporal specifications; these are the addition of a quadratic term to the time trend and the addition of dummy variables indicating the quarter of the year. The table shows that the results in Table 2.2 are very robust to these alternative specifications with no coefficients showing considerable changes in magnitude or significance. The quadratic term is significant in all specifications, although the direction depends upon the pseudo dataset. For datasets (1) and (4) the quadratic term is working in an opposing direction to the year trend. This indicates, for example for the SCAD sources, that probability of inclusion decreases over time but with diminishing marginal reductions. In datasets (2) and (3) the quadratic term indicates an exponential relationship such that for dataset (2) probability of inclusion decreases at an increasing rate (and increases at an increasing rate for dataset (3)). The coefficients for the quarter dummy variables also exhibit variation in inclusion probability between the different datasets with no consistent pattern. For the Iraqi Media group (3) there is no significant relationship between the quarter of the year and probability of coverage. For the US/UK media dataset (2) events in Q1 are significantly more likely to be included than those at other times. For dataset (1) events in Q3 have higher likelihood of inclusion, while for dataset (4) events in Q4 are less likely to be incorporated.

The results here, and those in figures 2.3-2.6, present pseudo datasets covering the same conflict which are significantly different in their size and composition. These differences are dependent upon the media outlets which are selected at the outset as data sources. The difference to the IBC data as-a-whole is smallest where the sources within a group are geographically diverse news agencies. Although the results presented in this section are specific to the Iraq case, it appears highly likely that the findings will also affect many event datasets covering other conflicts. This will impact researchers, consumers and policy makers relying on such datasets to drive their research, or to inform their beliefs about a conflict. For example, they may incorrectly assume a rise or decline in violence over time which is, in reality, a product of a change in media sensitivity.

2.3 Multiple Systems Estimation

The remainder of this chapter exploits the unique nature of IBC by implementing a multiple systems estimation (or capture-recapture) approach to the data. This is undertaken with the main aim of predicting the scale and types of conflict events which are likely missing from the media-reported IBC event data. In addition to this, the analysis should serve as a critique of the multiple systems estimation (MSE) methodology, especially where reporting of news media outlets is used as a data source.

Capture-recapture was first introduced within ecological research as a method for estimating animal populations in cases where counting full populations would be too complex or costly (Petersen, 1896; Lincoln et al., 1930). Through the capture, tagging and then recapture of animals it is possible to generate predictions of the overall population size based upon the number of animals captured each on occasion as well as the overlap. Multiple Systems Estimation (sometimes known as multiple-recapture estimation) expands upon this by implementing more complex statistical methods to allow for more than two capture occasions and various structures of overlap. These techniques have been used to estimate population sizes in a wide range of contexts such as the number of web pages on specific topics (Fienberg, Johnson, and Junker, 1999), the prevalence of HIV among drug users (Mastro et al., 1994) and lesbians among the population of Allegheny County, Pennsylvania (Aaron et al., 2003).

In recent years the technique has increasingly been used in the study of human rights abuses and, specifically, the estimation of incomplete conflict data. The technique was first used in this field by Ball (2000) to estimate the number of Guatemalans killed during the CEH mandate. It has since been used for similar projects in Bosnia (Zwierzchowski and Tabeau, 2010), Peru (Ball, Asher, et al., 2003), Kosovo (Ball, Betts, et al., 2002), Timor-Leste (Silva and Ball, 2008), Colombia (Lum, M. Price, et al., 2010) and Syria (M. Price, A. Gohdes, and Ball, 2015) among others.

These studies estimate the size and lethality of conflict by using lists of conflict events or deaths as capture occasions. These lists are generally provided by human rights organisations, governments, or other sources. Entries on each list are then matched with those on other lists by researchers using information such as date, location and weapon type, such that each unique event has a set of capture histories based on their inclusion on each list. MSE can then be used to estimate the number of events/fatalities which occurred but did not appear on any lists.

In this chapter, news media reporting will be used as the data source for the estimation. Media reporting has previously been used in several studies to generate the lists necessary for capture-recapture analysis. Eckberg (2001) uses newspaper reporting to estimate historical homicides in South Carolina. Newspaper data has also been used to generate predictions on road traffic mortality (Kraemer and Benton, 2015). However, media-based MSE in documenting conflict has been rare. The main previous example of this, which the current study aims to build on, is Hendrix and Salehyan (2015). They use a two-source capture-recapture approach to estimate the number of events which may be missing from the reporting of AP and AFP on social conflict in Africa in 2012. The present study considerably expands on their analysis by including a larger and more diverse range of media sources. This makes it possible to test how the two-source estimation which they implement compares with an estimation using multiple sources. Additionally, the availability of military and survey data in the Iraq case provides a robustness check to the MSE analysis which was not available for their study. The results in this section should complement those in section 2.2, indicating how the biases found in pseudo datasets relative to IBC may translate across to the universe of conflict events.

2.3.1 Data

The IBC data provides a unique opportunity to implement MSE and test its application to media data. The IBC team perform matching between different media sources at first capture of an event as part of their verification process. This means that all events in IBC are included along with their various capture histories across the many media source ‘lists’ which are monitored by the IBC team. The period of study here is from the 1st of July 2006 to the 31st December 2009. This interval was chosen as it covers the overlap between the IBC data (for the period in which all reporting media sources were correctly recorded) and the US military dataset SIGACTS, which will be used to check the robustness of findings. During this period the IBC dataset recorded 11,534 unique media reported conflict events which were responsible for 37,393 deaths.

As in Chapter 1, the IBC data used here is comprised exclusively of media reported deaths which were reported as events. This means that they are recorded with a full range of event characteristics such as the incident location, lethality, date and weapon type. This means that the data used here is only a subset of the full IBC, the main exclusion being the omission of deaths included in IBC as part of composite (aggregate) counts such as morgue tallies or police body counts. There are 644 composite counts in the IBC database during the 2006-2009 time period of the study comprising of 9,783 deaths. Although these deaths are not included within the MSE analysis here, one would expect that the missing events estimated by MSE would imply an additional death count of at least the 9,783 deaths which were found in composite counts. The reason for their removal is that full recording of events is the goal of any conflict documentation organisation such as IBC. Although the body counts provided by these composites can be integrated into their overall tallies, they are not covered in the same richness as the events within the data and therefore cannot easily be used for disaggregated analysis of the conflict. There are also practical reasons for their exclusion from the present analysis. Estimations generated here will be based upon the matching of events which are stratified according to event characteristics (e.g. event size), the lack of this information make this kind of estimation impossible when including the composite deaths. Additionally, the event matching by the IBC team, which underpins the SIGACTS comparison in section 2.3.5, is carried out without the inclusion of compositions.

2.3.2 Capture-Recapture Methodology

Basic two-source capture-recapture estimates can be produced using the following (Lincoln-Petersen) formula:

$$N = \frac{M \times S}{R}$$

Where M is the number of events which are 'marked' by being reported by the first media outlet, S is those 'marked' by the second media outlet and R is the number of events which were 'recaptured' i.e. those which were reported by both sources. N is, therefore, the estimated total population size including those predicted events which were not reported by either of the media outlets.

Although the estimation itself is simple, the two-source model requires a strict set of assumptions (Lum, M. E. Price, and Banks, 2013) for estimates hold. These assumptions, as well as their applications to the present context, are outlined briefly below:

(1) Closed population: That both media sources are reporting from identical populations of total conflict events. This means that they should be monitored over the same periods and should report from the same geographical areas.

(2) Homogenous probability of capture: All conflict events in the population have

an equal probability of being captured within the reporting of individual media outlets.

(3) Independent systems: An event being reported by one media outlet does not affect the probability of that event being reported by another outlet.

(4) Perfect matching: If an event is reported by multiple news agencies it should be recorded as so in the dataset.

It is reasonable to assume that assumption (1) should hold here; for this analysis I only include nationally reporting media outlets which report over the whole period of study. In terms of assumption (4), the IBC team employ a stringent data input methodology which should meet the criteria of this assumption. Specifically, they aim to record and collate every unique report from the numerous media sources which they monitor. Additionally, they only publish events which have been independently reviewed and error-checked by three team members (Iraq Body Count, n.d.(b)). There is likely to be some human error within the dataset coding although there is no evidence that this is common or systematic.

In contrast, the nature of media sources makes it highly unlikely that assumptions (2) and (3) will hold. Firstly, Chapter 1 of this thesis showed how media reporting of conflict events cannot be considered homogenous across all events. Instead, reporting will be heavily dependent upon event characteristics such as lethality and location. This implies heterogeneous probability of capture according to the population subset which events reside within, hence violating assumption (2).

Similarly, the news media are unlikely to act in a consistently independent manner from one another as required by assumption (3). They will not be operating within a vacuum, searching for events in an entirely random manner (Krüger and Lum, 2015), instead they will exhibit dependencies in several ways. Some may rely on the same sources (e.g. local stringers, witnesses or police). They may also directly rely on one another (e.g. a newspaper may only decide to report on a story when they become aware of it through the report of a news agency). Finally, groups of sources (e.g. domestic media) are likely to have similar criteria of newsworthiness; events residing within particular population subsets will be more likely to be captured by groups of media outlets. Positive list dependence, as implied here, will lead to an undercount in the population estimate for the number of conflict events.

The advantage of implementing a three-source or greater MSE approach over a simple two-source capture-recapture model is that it implicitly carries richer information (Manrique-Vallier, M. E. Price, and A. Gohdes, 2013). Data from two sources holds one of three possible states; captured by source "A", captured by source "B" or captured by both. Every additional source doubles the number of capture patterns over which to draw inference. This allows sophisticated techniques which do not require the full range of these strict assumptions to hold. For example, MSE can model a range of interactions between different source lists which means that the source independence assumption (3) is no longer required to hold. Additionally, the modelling of these source interactions will help to satisfy assumption (2), as the probability of capture can differ according to groups of source dependence.

For both two-source and multiple-source estimation there is, however, one important caveat. MSE can only estimate missing events where the probability of capture is above zero. In the present context, this means that estimations obtained here will be bounded in being only those events which could have feasibly been reported by news media outlets.

The analysis here is carried out using two methods for MSE estimation where the number of captures is greater than two. Both techniques are implemented using the data processing software 'R'. The first method, model-based MSE, obtains estimates using log-linear modelling. It derives a list of estimates based upon a full range of models controlling for various subsets of all interactions between lists. These can then be ranked according to various fit criteria such as the Bayesian Information Criterion (BIC) or Akaike Information Criterion (AIC) with the best fitting model then chosen as the central estimate. This method is implemented here using the Rcapture package (Baillargeon and Rivest, 2007) with the best estimate selected as that which minimises the BIC. This method has been used in many studies of war-related deaths (e.g. Ball, Asher, et al., 2003; A. R. Gohdes, 2015).

The second method used for this analysis is the use of 'Latent Class Models' (LCM), a new approach for MSE estimation by Manrique-Vallier (2016), implemented using the LCMCR package in R. This method works by optimally allocating all observations into an unbounded number of strata (classes) such that assumption (3) - independence- holds within each of them. One advantage of this approach over the model-based method is that the model selection step is not required. Although the method is still undergoing testing, Ball (2016) claims that the use of LCM is "probably the best option available for MSE right now." It is thus useful here as both a robustness check of results obtained using the traditional model-based methodology as well as an opportunity to test this novel method.

2.3.3 Simple MSE Results

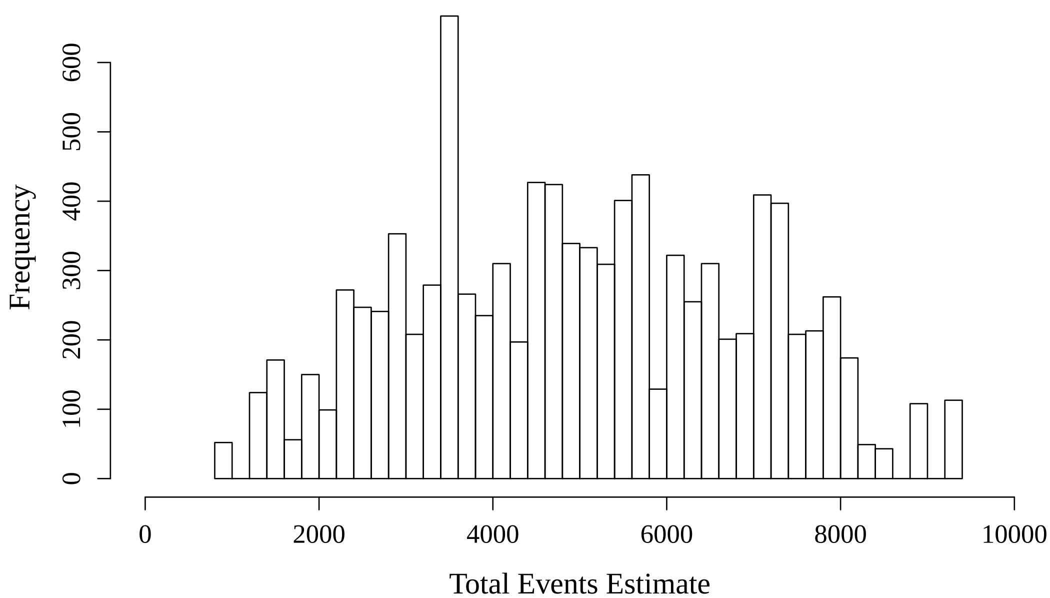
The results presented here, first, carry out an overall MSE analysis on the IBC data before proceeding in section 2.3.4 to study any compositional effects by stratifying according to event size, date and weapon type.

Two-Source and Three-Source Calculations

In order to illustrate the problems caused by not meeting the restrictions imposed by two-source capture-recapture, Figure 2.7 shows the result of estimations implemented through this method on the IBC data. This was generated by randomly drawing 10,000 pairs of news outlets from the top 20 reporting IBC media sources and estimating the total population size using the Lincoln-Petersen formula as outlined in section 2.3.2.

These results give a median estimate of 4,824 events, while no two source pairs generate

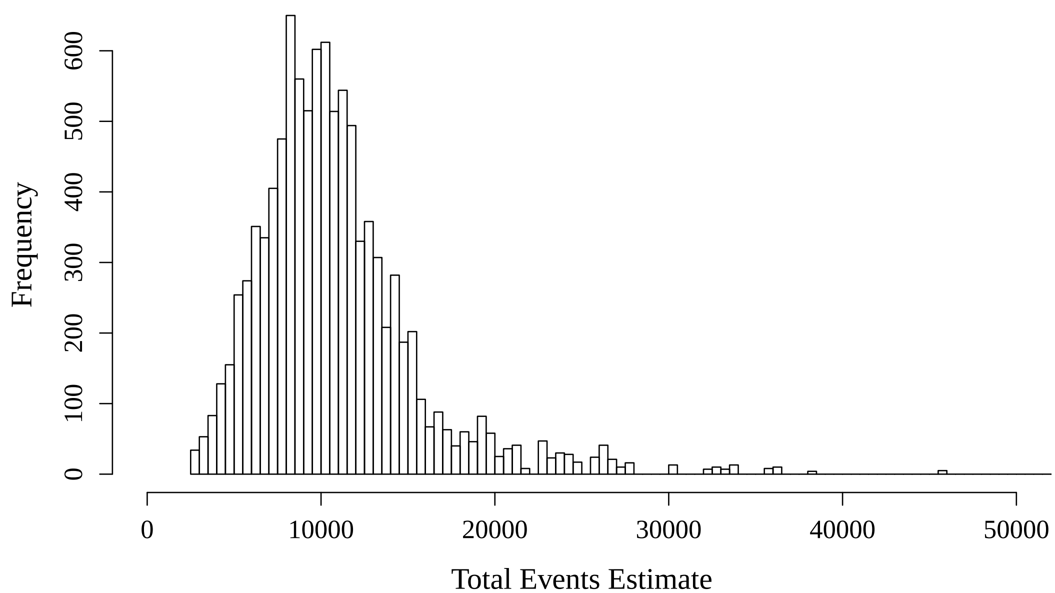
Figure 2.7: Event Population Estimates from Two-Source Capture-Recapture



a population estimate of greater than 10,000. Given that the number of events in IBC during the period of study was 11,534, all pair combinations are clearly underestimating the true population size. The most likely reason for this significant undercount is the violation of the independence assumption above which will bias estimates downwards. The results confirm that the two-source capture-recapture undertaken by Hendrix and Salehyan (2015) likely produces a significant undercount of the true rate of missingness in the SCAD datasets coverage of events in Africa. Using their two sources (AP and AFP) in the Iraq case, I calculate a capture-recapture prediction of a total of 5330 events which is less than half the observed IBC figure.

I now perform a similar analysis in Figure 2.8 however this time with the drawing of 10,000 sets of three random sources and the implementation of log-linear modelling. Moving to a three-source system moves the median estimate up to 10,096. This is still below the IBC total of 11,534 although it does now lie within the 95% confidence interval.

Figure 2.8: Event Population Estimates from Three-Source MSE



Five-Source Calculations

As outlined above, increasing the number of capture lists (sources) increases the number of possible capture patterns exponentially. This, in turn, exponentially increases the number of possible ways to model source dependency. For the remainder of this chapter I use five-source MSE. This is the maximum level of modelling complexity available within the computing constraints of this study. Here, the BIC minimising main estimate is selected from those produced by 6,893 possible source dependency patterns.

Five specific source lists are selected for the five-source MSE. These are Reuters, Associated Press, Agence France-Presse, National Iraqi News Agency and Voice of Iraq. These chosen media outlets were the top five sources in terms of reporting completeness of all events recorded by IBC monitored media sources over the period. They also, as news agencies, come closest to acting as independent news gathering bodies when compared to newspapers which may rely on agencies or wires for their stories. Finally, the source dataset comparison in section 2.2 showed that these five sources come closest to the composition and time trends of the full IBC dataset. These five sources cover 9,283

Table 2.3: Model Based MSE Estimation Results

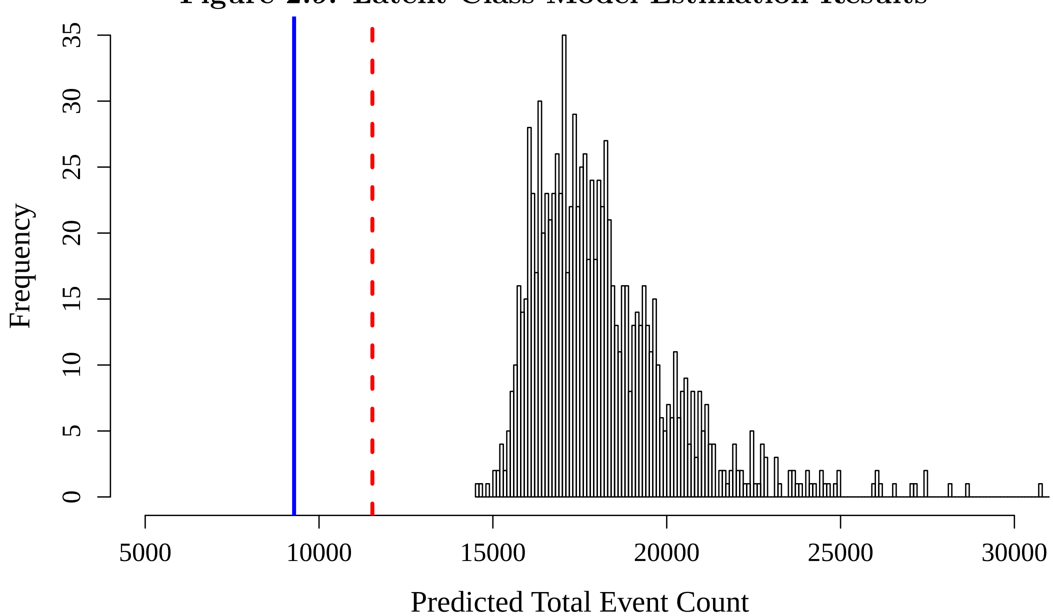
Rank	Modelled Dependencies	Estimate	Std. Err.	Bias	df	AIC	BIC
1	[12,13,14,15,23,24,25,34,35,45]	20858.1	933.8	46.9	14	263.4	384.7
2	[134,12,15,23,24,25,35,45]	20389.3	920.6	48.5	13	260.9	389.4
3	[125,13,14,23,24,34,35,45]	21136.6	973.5	51.0	13	262.8	391.2
4	[145,12,13,23,24,25,34,35]	21307.3	1070.5	60.9	13	264.3	392.8
5	[234,12,13,14,15,25,35,45]	20746.4	933.2	46.9	13	264.6	393.0
6	[245,12,13,14,15,23,34,35]	20798.5	932.7	46.9	13	264.9	393.3
7	[124,13,15,23,25,34,35,45]	20770.7	935.3	48.5	13	264.9	393.4
8	[135,12,14,23,24,25,34,45]	20689.2	958.3	51.1	13	265.0	393.4
9	[123,14,15,24,25,34,35,45]	20779.5	937.3	48.6	13	265.0	393.5
10	[235,12,13,14,15,24,34,45]	20882.3	941.3	48.2	13	265.3	393.7

of the 11,534 events in IBC during the time period of study. Running estimations using both the model-based and LCM methods yields the results presented in Table 2.3 and Figure 2.9 respectively.

Table 2.3 shows abundance (population) estimates for the top ten dependency patterns ranked according to the minimum BIC criterion. According to these results the optimal model (1) is that which models paired dependencies between all source combinations. This indicates that the reporting of none of these sources is truly independent from any other. This model estimates a total event count of 20,858, implying that IBC may be missing around 9,000 conflict events from their database. Figure 2.9 shows the results of the LCM estimation. The solid blue line represents the number of events captured by the five sources used for the estimation and the red dashed line denotes the total IBC count. The latent class model method predicts a slightly lower overall event population of 17,901 albeit with an overlapping 95% confidence interval of 15,694 to 24,122.

Assuming there is no change in the average event lethality, the model-based and LCM

Figure 2.9: Latent Class Model Estimation Results



methods estimate a total civilian death count of 67,621 and 58,035 respectively. This estimate, however, is naïve in that it assumes that missing events are just like captured events and therefore will be drawn equally from event sizes in the same composition as the captured dataset. In reality, it is highly unlikely that the composition of event characteristics of the implied missing events will be the same as those detected by IBC.

2.3.4 Stratification Results

The analysis in the previous section indicated that IBC is likely to be missing many events but provides no insight as to what kind of events these may be. The following sections use stratification techniques to partition the population according to event characteristics. Homogeneity of capture probability was one of the key assumptions outlined in section 2.3.2. Some capture heterogeneity will be accounted for by the source-dependency modelling which is possible when the number of source lists is greater than two. However, the availability of observable covariate information in the present context means that the heterogeneity can be more formally controlled for. This involves carrying out an independent MSE analysis for each stratum of the population. This means that the assumption that all events have homogeneous capture probability is now only is required to hold within each stratum. Additionally, because they are producing an independent estimate for every partition, stratification techniques provide information upon the implied change in composition of events rather than only the estimated overall total.

Event Size Stratification

Event size information is available for every event within IBC. Chapter 1 showed that the number of fatalities was one of the key contributors to differing reporting intensities. Valid MSE relies on a large enough sample to contain heterogeneity in capture histories.

Table 2.4: Model Based MSE Estimation Stratified by Event Size

Event Size	IBC		MSE Estimate	
	Events	Deaths	Events	Deaths
1	6,129	6,129	12,807 [10,980, 14,634]	12,807 [10,980, 14,634]
2-3	3,264	7,579	5,772 [4,835, 6,709]	13,403 [11,227, 15,578]
4-9	1,536	8,255	1,878 [1,745, 2,011]	10,093 [9,378, 10,808]
10-19	347	4,558	332 [320, 344]	4,361 [4,203, 4,519]
20+	258	10,872	259 [251, 267]	10,914 [10,577, 11,251]
Total	11,534	37,393	21,048 [18,131, 23,965]	51,578 [46,365, 56,790]

Note: 95% Confidence Intervals in parentheses.

Because of this, analysing each event size individually would not be plausible due to an increasingly small number of events at higher event sizes (Appendix Figure B.3). I, thus, divide the population into five event size strata; 1, 2-3, 4-9, 10-19 and 20+. MSE is then carried out for each of these strata by using the five chosen sources detailed above (i.e. Reuters, AP, AFP, NINA and VOI).

The results of this estimation using the log-linear modelling MSE estimation are displayed in Table 2.4. They show that IBC itself likely suffers from the same event size bias found in the pseudo datasets in Figure 2.3. The vast majority of estimated missing events and deaths are in the smaller event size bands (i.e. 1 and 2-3). The IBC media sources are estimated to miss around half of the deaths in these event sizes. In contrast, among the higher event sizes the MSE estimate is very close to, or even slightly lower, than the IBC observed number of events. It is possible to be lower here because these estimates are generated based upon the five top reporting sources rather than IBC as a whole. These results imply that IBC contains virtually the universe of events where 10 or more civilians were killed, but is estimated to miss a significant number of small events. The overall totals estimate that IBC contains only 54.7% of the total number of conflict events that occurred but covers (as events) 72.4% of the total estimated deaths. With the addition of the 9,783 additional composite deaths included in IBC body counts but without full event information, IBC is estimated to include 91.4% of total deaths. Results from the LCM methodology are presented in Appendix Table B.2. They show identical patterns in the composition of estimated missing events although the undercount of events of size one is estimated to be smaller.

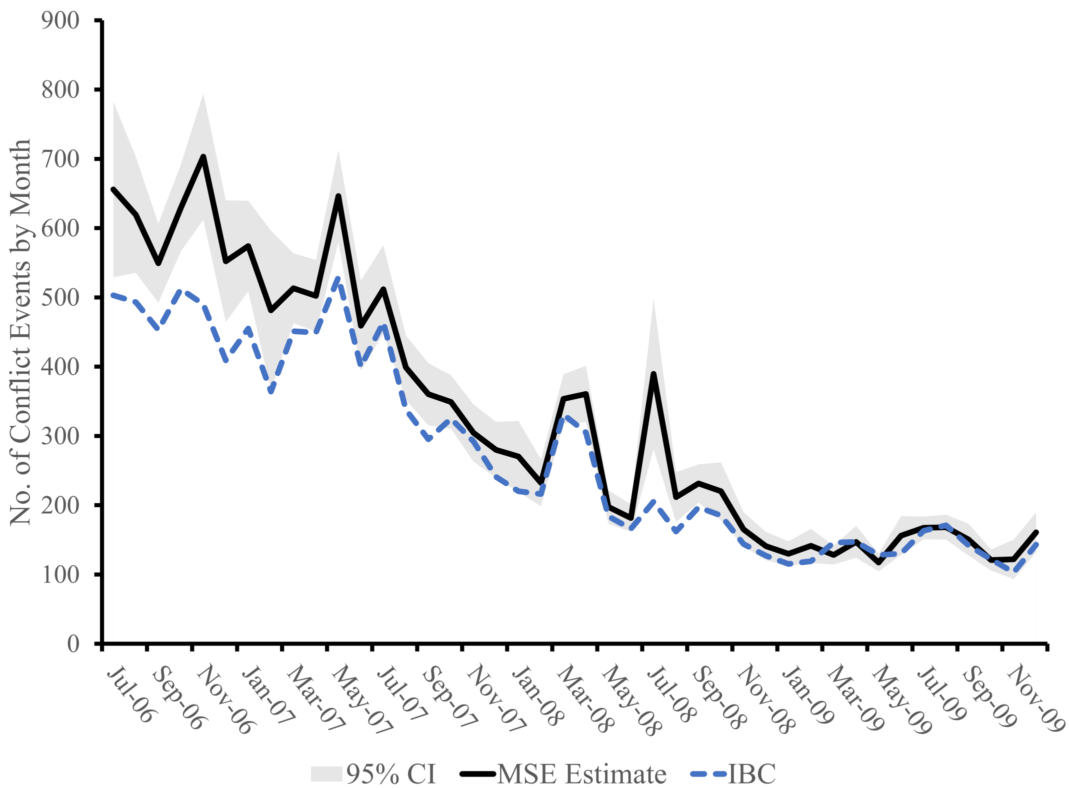
These results also shed further light upon the pseudo dataset comparison, above, in Section 2.2.3. As the event data within IBC itself is estimated to have a substantial event size bias, it appears that the bias present in the pseudo datasets (Figure 2.3) is, in fact, a lower bound of the true event size bias relative to the universe of conflict events.

Temporal Stratification

Another variable over which MSE can be stratified is the event date. The event data within Iraq Body Count has been regularly used by researchers (Lewis et al., 2012; Boyle, 2009; Deflem and Sutphin, 2006) and the media (e.g. BBC News, 2011; Dewast, 2016) to analyse trends in the intensity of conflict over time. In section 2.2.4, I showed that the selection of particular groups of sources may affect the temporal distribution of conflict. In this previous analysis these outcomes were assessed in terms of completeness against the full IBC database. It is important to note, however, that given that IBC itself is missing a considerable number of conflict events it is unlikely that the rate of omission is uniform over time.

To test this, I run individual (model-based) MSE analyses for every month of the period of study with the results displayed in Figure 2.10, along with their associated 95% confidence intervals. The total estimated event count is around 14,000 which is below that predicted in the previous section. This may be because of the lack of event size stratification which was not possible here because of the small sample sizes per stratum. Nevertheless, these results estimate that IBC misses many events from mid-2006 to mid-2007. Interestingly, this period is where the number of deaths recorded within IBC composites (e.g. morgue statistics) was also highest. This implies that the deaths caused by many of these estimated missing events are in IBCs overall body counts but not recorded in the form of events. After July 2007 the gap narrows, aside from a spike in July 2008. After September 2008 the estimated number of events by month is not significantly different from the IBC event total.

Figure 2.10: IBC and MSE Event Count Over Time



One possible reason for this decrease in the estimated missing events rate over time is the existence of a media oversaturation 'crowding out' effect which may exist when the number of events is high. Media organisations operate under constraints such as newspaper space, personnel time and financial resources. During periods of particularly intense conflict these constraints may lead to a crowding out of events whereby a conscious decision may be made that some observed events simply cannot be reported on (Delli Carpini and Williams, 1987; Davenport and Ball, 2002).

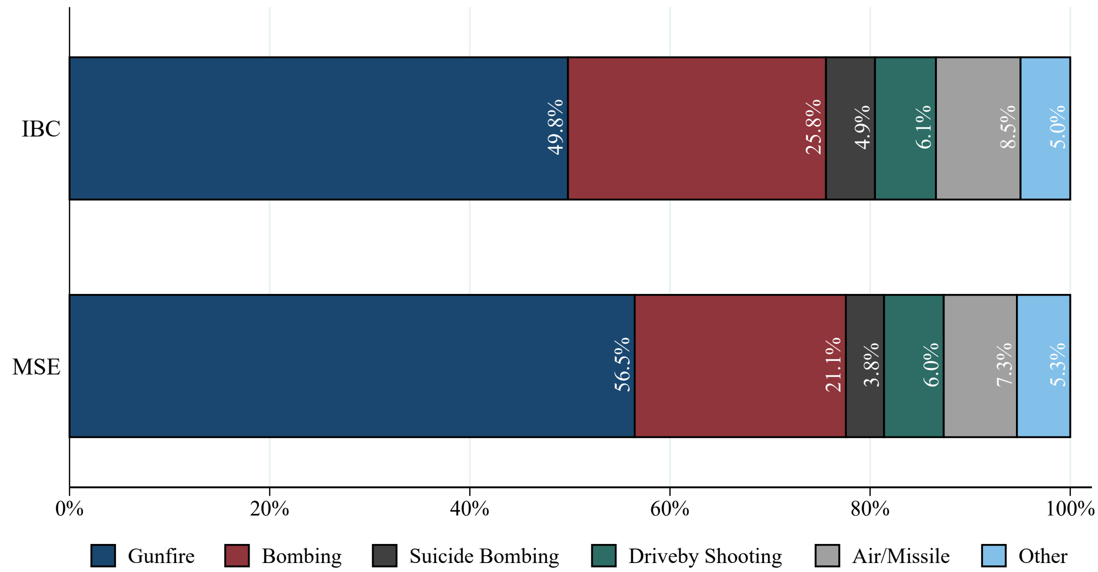
Weapon Type Stratification

Researchers have regularly used the IBC data to analyse patterns in weapon usage (e.g. Hicks et al., 2009; Boyle, 2009). If the added deaths implied by MSE are drawn from the various weapon types according to the same composition as the IBC data, then the results of these studies will remain unaffected. Should, however, these estimated missing events be drawn according to a distribution which differs from that of the rest of IBC, it can be expected that there will be implications for the conclusions of these studies. Stratifying by weapon type should also complement Figure 2.5 in showing whether IBC as a whole exhibits the same overall weapons biases as the pseudo datasets.

In order to facilitate this analysis, events were sorted according to their primary listed weapon into one of six categories: gunfire, non-suicide bombing, suicide bombing, driveby shooting, air/missile attack, and other. The event size stratified log-linear MSE estimation (2.4) was then repeated but with the addition of weapon type stratification. Appendix Table B.3 presents the full results of these estimations broken down according to the event size bands used above. Figures 2.11 and 2.12 summarise these results by aggregating across all event size bands to show overall compositions.

Figure 2.11 presents a comparison between the weapon compositions by event of the raw IBC event data and that of the estimated event breakdown after the addition of missing events predicted by MSE. When these are incorporated we observe an increase of around 7 % points in the proportion of events categorised as gunfire. This increase has come at the expense of those categories involving explosive weapons. A similar pattern emerges in Figure 2.12 when we observe the composition of deaths, rather

Figure 2.11: IBC and MSE Estimated Event Weapon Type Composition

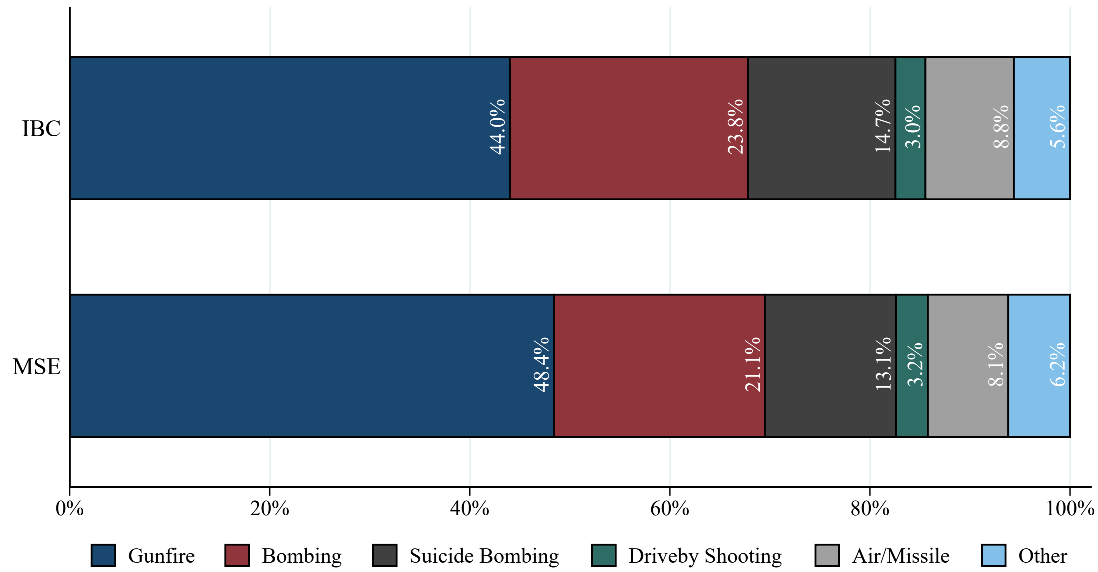


than events, with the proportion of deaths attributed to gunfire moving from 44% of the IBC deaths to 48.4% of the MSE estimated total deaths. The smaller increase in deaths compared to events is because the proportion of gunfire events is higher, and the increase implied by MSE larger, for smaller event sizes (Appendix Table B.3).

These findings, again, corroborate with the composite deaths available within IBC. Although full information is not available, many of the aggregate reports which these additional deaths are based upon contain lines such as "27 bodies found around region, most deaths caused by gunshot." It appears likely that if event details were available for these deaths, IBCs weapon breakdown would be much closer to the MSE estimate.

These results show that the bias towards explosive weapons (Figure 2.5) in the pseudo datasets in section 2.2.5 above is, again, likely to be an underestimation of the true bias. This is because Figures 2.11 and 2.12 show that IBC itself is disproportionately biased in favour of explosive violence incidents relative to other events types.

Figure 2.12: IBC and MSE Estimated Fatality Weapon Type Composition



2.3.5 Comparison With Other Data Types

Military Data Comparison

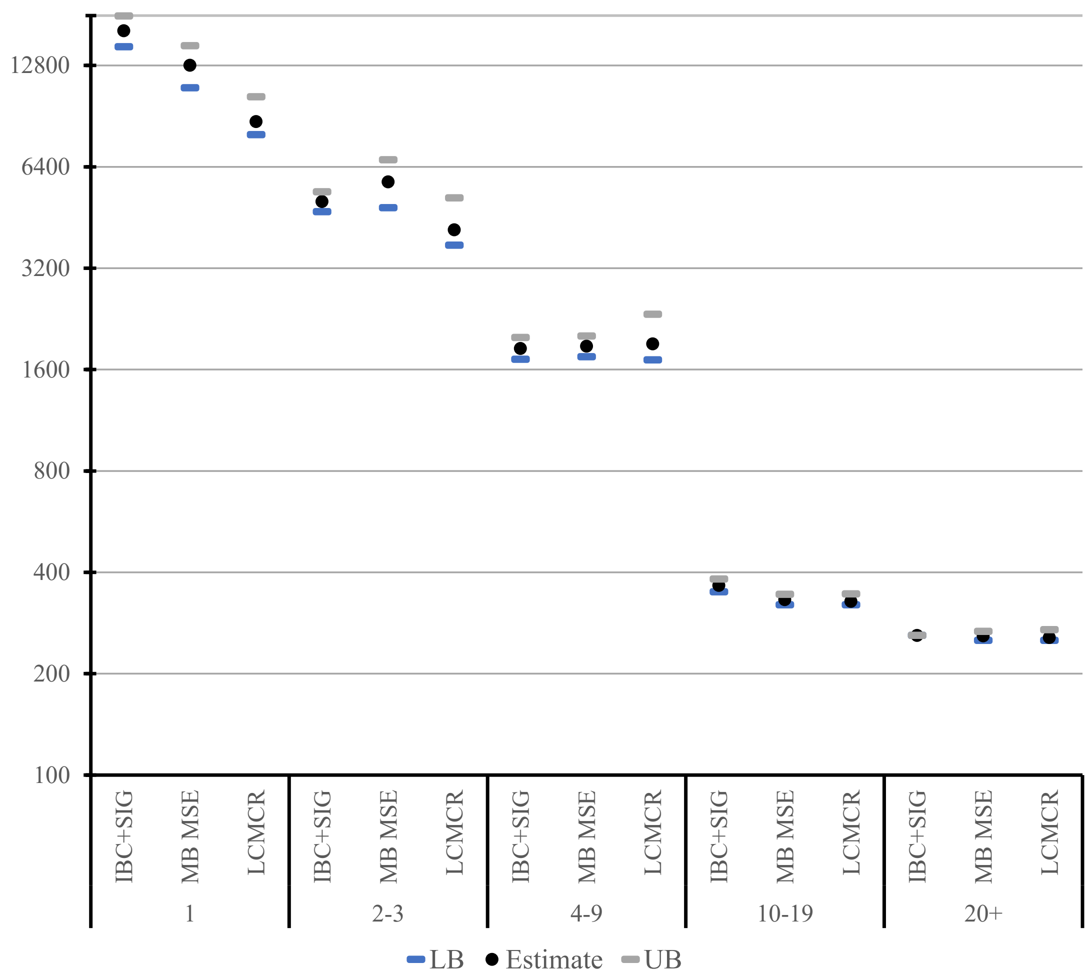
One advantage of using the Iraq case study for this analysis is that IBC was not the only data gathering project which attempted casualty recording during the period. The US military's leaked SIGACTS dataset (Wikileaks, 2010) documented 391,832 reports by US military service persons in Iraq between 2004 and 2009. Within these reports were the deaths of 66,081 civilians. While many of these events containing civilian fatalities were already documented by IBC, the leak brought to light additional conflict events which need to be incorporated into the dataset.

The complementary data within this military dataset acts as a robustness check to the above MSE analysis. We would expect that the total number of unique recorded events (which resulted in at least one civilian fatality) between both IBC and SIGACTS will be the lowest possible bound of a feasible multiple systems estimation. It is important to note that while IBC is likely a non-random subset of conflict events, this will also apply for SIGACTS. The military data here will hold its own weaknesses (Berman, Shapiro, and Felter, 2011); it captures only violence against civilians where U.S. forces are geographically close enough to compile a report and recording also may differ considerably between U.S. military units. For this reason, we should expect that the MSE estimate will be somewhat higher than this lower bound implied by IBC+SIGACTS.

At present, the IBC team are systematically working through the SIGACTS data on an event-by-event basis aiming to incorporate all new events into IBC. This process is currently incomplete and being carried out in a non-random manner meaning that the amalgamated dataset cannot yet be used. However, the IBC team have estimated the number of new events which they expect to uncover by taking a random sample across several event size bands (Iraq Body Count, 2010). The IBC team's estimation uses the IBC dataset from 2004 to 2009. As the subset of this data used here only covers the July 2006 – December 2009 period I extrapolate the matching rate found across the whole period by the IBC team to the events found within the present data range. I then use this matching rate as well as its 95% confidence interval to predict the IBC+SIGACTS event count over each event size band.

The predicted documented events from this IBC+SIGACTS matching as well as the MSE estimations from Table 2.4 and their respective 95% confidence intervals are presented in Figure 2.13 below and detailed in full in Appendix Table B.4. Note that the figure is drawn according to a logarithmic scale. The number of events in each band in the IBC+SIGACTS tally and the MSE estimates are found to be relatively consistent with one another across larger event sizes. However, for events of size one, IBC+SIGACTS predicts a total of 16,233 events, model-based MSE estimated 12,807 events, whilst the LCM methodology estimated only 8,724. There is clearly still a significant underestimation by the MSE techniques at this event size despite Table 2.4 showing that these small events were subject to the largest MSE increase.

Figure 2.13: Comparison of IBC+SIGACTS and MSE Estimates by Event Size



The results provide an opportunity to test the two MSE estimation methods alongside a benchmark. The two methods performed equally well among event sizes greater than 3. Below this, however, the model-based MSE yielded results which were significantly closer to the IBC+SIGACTS projection.

One possible reason for the underestimation of smaller events is that there are two types of events missing from IBC. The first type are those events which can be predicted by MSE. These are those which were on the radar of the news media but were not reported by the media sources monitored by IBC. Any event could be missing because of random variation in reporting. The extent to which event reporting is complete will differ according to the whether their characteristics fulfil the criteria of newsworthiness discussed in Chapter 1. A combination of stratification and source-dependency modelling means that events can be successfully estimated. The stratification results above show that these missing events are most likely to be small in terms of event size.

The second type of missing event is that which resides within the 'ecosystem' of conflict events which have no chance of ever being discovered by the news media. MSE can only produce estimates for those events for which the probability of capture is greater than zero. Chapter 1 of this thesis found that conflict events will receive an increasingly limited amount of media coverage as certain event characteristics change (e.g. as events become smaller, more rural and use non-explosive weapons). It seems very plausible (although untestable) that extreme levels of these event characteristics which drive lower reporting probabilities may be enough to give a reporting probability of zero. The gap between IBC+SIGACTS and the MSE estimates for the small event sizes in Figure 2.13 is, therefore, comprised of events with no chance of being reported by the media despite being detectable by the military.

Eventually, once the SIGACTS integration is complete, IBC will contain events which reside in this ecosystem and further multiple systems estimation should be carried out with SIGACTS included as one of the capture lists.

Survey Data Comparison

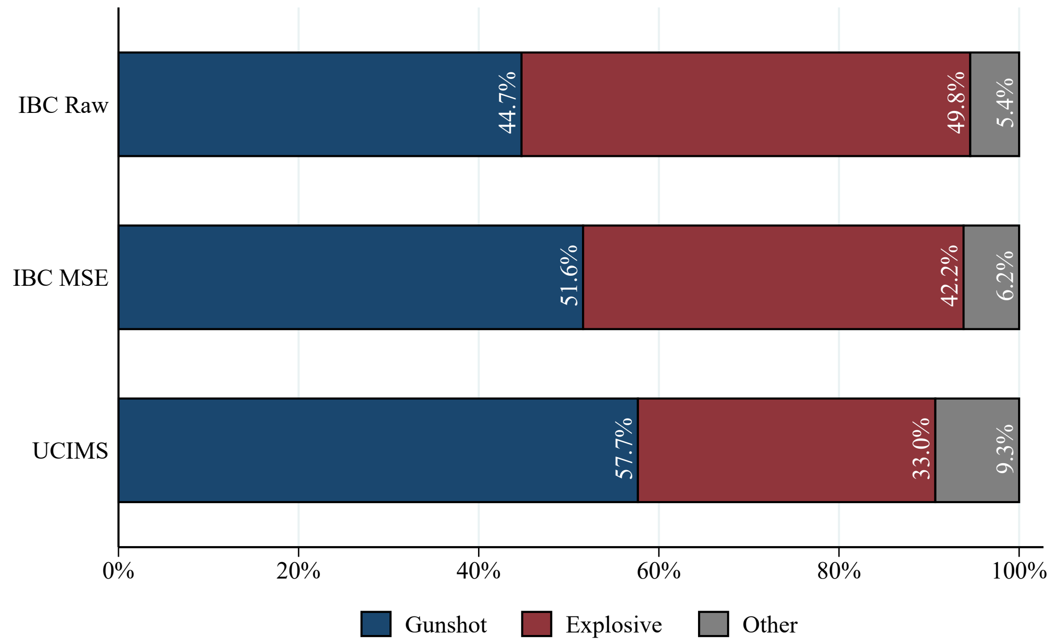
There may, however, be some further events which remain inestimable (i.e. those which reside in an ecosystem outside of the radar of both military and media sources). For these, comparing the estimated event composition with that obtained from a representative household survey may give some indications about the type of incidents these may be.

Several household surveys have attempted to estimate the number of war related deaths in Iraq (Roberts et al., 2004; Burnham et al., 2006). These studies have generally focused on the start of the Iraq War and their conclusions, and the methodologies underpinning them, have often been disputed or discredited (e.g. D. Kane, 2007; Spagat, 2010). One more recent survey by Hagopian et al. (2013), the University Collaborative Iraq Mortality Study (UCIMS), estimated a total of 405,000 excess deaths (both violent and non-violent) between 2003 and 2011. As with the earlier surveys this study has also received criticism. For example, Spagat and Weezel (2017) show that the 95% confidence interval underpinning this estimate intersects with zero. However, a benefit of the UCIMS study is that a cause of death is recorded for all violent deaths found by the survey. This data can be used to produce an estimate for the weapon composition of violent deaths across any time period. It can thus be used as a robustness check for the weapon composition predicted by the MSE analysis above.

As the UCIMS Survey and IBC have differing weapon categories, I simplify war deaths into three broad categories; gunshot deaths, explosive violence deaths and other war deaths. For the IBC plots above this means combining the gunfire and drive-by shooting events as well as the suicide bombing, non-suicide bombing and air attack/missile events. The UCIMS survey was carried out in two sections, one asking for deaths within the household and another asking for deaths among household member's siblings. For the purpose of this composition analysis I combine these to obtain the weapon composition of the 225 war deaths picked up by the survey. It should be noted that due to the relatively small sample as well as the wide confidence intervals pointed out by Spagat and Weezel (2017), the exact proportions should be treated with caution although can reasonably be considered indicative.

Figure 2.14 compares the weapon composition of raw IBC deaths, the MSE estimated deaths and that found over the same (2006-2009) time frame by the UCIMS survey. The UCIMS composition validates the direction of travel of the MSE analysis which

Figure 2.14: Comparison of IBC, MSE and UCIMS Survey Weapon Compositions



estimates an increase in the proportion of gunshot deaths at the expense of explosive violence deaths. However, while the inclusion of missing events estimated by MSE moves the gunfire percentage from 44.7% to 51.6%, the percentage found by the UCIMS survey is greater still at 57.7%.

This compositional difference appears to provide further evidence for the two event type model discussed above, whereby events of the second type are those which occurred in a different 'ecosystem' where media detection was not possible. It is these missing events which explain the compositional difference in weapons between the IBC MSE deaths and the UCIMS deaths. This difference suggests that these events are comprised predominantly of gunshot deaths. This conforms well with Figure 2.13 which showed that events in this ecosystem are mostly those with a small number of fatalities. IBC (e.g. Table 1.1) shows that gunshot events have the lowest average event size of all weapon types within IBC, with over half of events with less than four fatalities being caused by gunfire. Based upon the findings in Figure 2.10 it also seems likely, although untestable, that the number of events where the reporting probability is zero will be higher during times of intense conflict. This is due to an extreme version of oversaturation whereby journalists and stringers may be so preoccupied (e.g. with reporting large events in Baghdad) that small events occurring hundreds of miles away may never even appear on their radar.

The number of events within this ecosystem does not appear likely to be enormous, nor the number of fatalities caused by the events. Figure 2.13 suggests around 3,500 deaths reside within this ecosystem (or 7,500 when using the seemingly less successful LCM method). There could, however, be further deaths which fall outside the radar of both media and military monitoring. For the compositional analysis in Figure 2.14 an additional 6,000 gunfire deaths would bring the gunshot deaths percentages up to the 57.7% found by UCIMS, although some increase in other event types may bring the actual number of fatalities in the ecosystem slightly higher than this. From these analyses it seems reasonable to conclude that there may be somewhere in the region of 6,000 to 8,000 conflict deaths which are missing from the media-based IBC event data which could not have been picked up by media sources. However, without a truly representative, successful, survey with a large enough sample, it may be impossible to draw further inference than this educated guesswork.

2.4 Conclusions

This chapter has contributed to the previous research into the validity of media-based conflict datasets through an original approach using the unique IBC data. This approach is based around the study of the source selection process and the impact this has upon dataset completeness. I implemented this through the generation of pseudo datasets incorporating events generated from the reporting of subsets of media sources.

Results show that dataset inclusion is significantly dependent upon a range of event characteristics. One such event characteristic is the lethality of an event. Event size bias will affect dataset composition by underrepresenting smaller events. This bias will be largest where datasets are comprised of a low number of international media sources. Other important characteristics were the event date, the location and the weapon type of an event. These factors combine to generate datasets which are compositionally unbalanced relative to IBC. MSE analysis complemented this research by showing that the biases present within this comparison will likely be a lower bound of the bias between these datasets and the unobserved full set of events.

The chapter has also added to the growing literature on the use of MSE to estimate human rights abuses and conflict deaths in several ways. Firstly, in the use of media sources as the basis for the capture histories. This has only been previously attempted as a simple two-source capture-recapture (Hendrix and Salehyan, 2015). Here, I show the significant underestimation that two source models will result in and instead use a full multiple systems estimation approach to generate population predictions. Secondly, I apply the technique in a relatively unusual arena due to the existence of other types of data – military documentation and survey estimation – which act as a useful robustness checks to the findings here. Finally, in addition to the traditional log-linear modelling method, I also compare results using the new LCM technique.

Back-of-the-envelope calculations based upon the model-based MSE analysis in this chapter suggests that between July 2006 and December 2009 the media reported IBC event data is estimated as missing around 9,514 conflict events as a result of imperfect media reporting. These events were responsible for a total of 14,185 deaths. In addition to these a further 6,000 to 8,000 deaths are also likely missing which could not have feasibly been reported by media sources. IBC, in addition to its documented events, also records an additional 9,783 deaths as parts of composites (mainly within morgue counts) rather than events during the period. This implies that the missingness of IBC in terms of pure body count implied by this analysis is likely somewhere between 10,671 and 12,671.

Overall, the findings from both the pseudo dataset completeness analysis and the MSE analysis point to a few recommendations for those whom attempt to document armed conflict using media sources. Firstly, they should monitor as many outlets as possible given the resource constraints they are operating within. Increasing the number of sources grows completeness disproportionately amongst smaller, less newsworthy events (Figure 2.2) and thus works against the event size bias. Datasets monitoring conflict should also incorporate a wide range of sources including both domestic and international media. Without doing so, datasets are likely to be skewed by, for example, a decline in international interest in the conflict which could lead to incorrect assumptions that the level of conflict is also declining.

Even when undertaking these steps there will remain some events which occur and are not reported by the selected media sources and are thus omitted from the dataset. Researchers should endeavour to undertake MSE analysis, where possible, to estimate the completeness of their datasets. This technique will provide an indication of missingness; however, it will only be useful in predicting those events which the media could feasibly have reported. There are likely to be other events which will remain entirely off the radar of media sources. It should therefore be taken as a lower bound of the extent of missing events.

It is therefore recommended that, to increase data reliability, those producing conflict event datasets ensure that they utilise other sources of conflict information in addition to media sources. This could be in the form of revisiting data when new sources become available, such as IBC currently integrating the deaths from the leaked SIGACTS military data. It may also be possible to complement existing event data with further information even where data quality is less rich. For example, IBC complement their event data with additional body count data from morgue and hospitals. Finally, representative survey data, can be used to provide information about the likely composition of missing events even where full event documentation is impossible.

The findings in this chapter, as well as those in Chapter 1, also hold significance for those academics who use media-based datasets within their research. The present analysis has demonstrated the presence of systematic measurement error in the level of violence affecting Iraq between 2006 and 2013 when conflict is documented through the use of media sources. This non-classical measurement error is such that the observed level of violence - as recorded by media-based datasets - differs from the true unobserved level of violence in a non-random way through the influence of the covariates tested here. The findings also raise the likelihood of similar measurement error affecting media-based datasets documenting other conflicts.

This measurement error is likely to result in biased estimates in the many empirical academic studies which use media-recorded conflict intensity as an independent variable in their analyses. One example of a study whose results will likely be affected by the measurement error found in this chapter is analysis of the impact of conflict on education in Iraq by Diwakar (2015). The paper studies how regional conflict intensity will affect a child's years of education (or likelihood of school enrolment), where conflict intensity is measured by taking the number of events by region according to the Iraq Body Count dataset. Results in chapters 1 and 2 have showed that violence is measured with a greater degree of error (i.e. conflict intensity is more underreported) in regions which are further from Baghdad. Diwakar shows that individuals living outside the centre of Iraq - and hence further from Baghdad - have lower average levels of education. There is, therefore, a negative correlation between the unobserved size of the measurement error and the dependent variable of Diwakar's study, education. This will likely have resulted in the coefficient indicating the relationship between conflict and education being biased.

In terms of future research, there are several avenues which should be explored. Firstly, as both a robustness check and an extension to the present analysis, the estimations here should be repeated with SIGACTS as a separate source list within the MSE. This will only be possible once the IBC team completes the considerable task of integration of these new events. Post-integration we would expect this new combined dataset to be significantly closer to the universe of conflict events. Secondly, further research should be carried out on the source selection process undertaken by those establishing media-based conflict event datasets. This chapter has presented indicative results showing the importance of this process for data accuracy. Formal models should be developed to assist dataset creators with these crucially important decisions. Finally, further research should be carried out on the nature of those events which fall outside the 'ecosystem' of media coverage. Studies should assess whether this phenomena is unique to the Iraq case or also present in other conflicts.

Chapter 3

Who Supports Terrorism?

The Socio-economic and Religious Characteristics of those who Claim that the Suicide Bombing of Civilians is Justified

3.1 Introduction

This chapter studies the characteristics of those individuals who claim that the suicide bombing of civilians is justified. It aims to answer three key research questions: Are those who support terrorism living in poverty? Are they poorly educated? Are they particularly committed to Islam?

Assessing these three questions is important. Firstly, previous academic research in this area has been limited and results have painted a very mixed picture (e.g. Shafiq and Sinno, 2010), often contrasting with conventional wisdom. Secondly, understanding what drives people to support terrorist activity should have some relevance to domestic and international policymakers aiming to reduce terrorism. Terrorism does not operate in a vacuum and those groups carrying out violent attacks usually require a substantial level of localised and non-localised public support in order to successfully carry out their objectives (Pape, 2006).

This study significantly increases the data quality used to answer the key research questions above. Previous studies attempting to answer similar questions have generally relied upon data from a single year (Krueger, 2007; Shafiq and Sinno, 2010) and/or a single country (Fair, Malhotra, and Shapiro, 2010). In contrast, the present study collates survey responses from five countries over a period of 11 years (2005-2015), totalling over 40,000 interviews. This has the advantage of smoothing out random variation which can affect studies with smaller sample sizes while also better controlling for covariates (e.g. regional effects). The present data also provides an opportunity to update ageing existing research. The nature of terrorism has changed considerably over the past 15 years however most previous studies were carried out using data from the early 2000s.

While it is expected that conclusions reached here are applicable to a range of types of terrorist and insurgent activity, the focus in this research is specifically on the suicide bombing of civilians. Firstly, these types of attacks are unambiguously terrorism, defined as "the commission of criminal acts, usually violent, that target civilians or violate conventions of war when targeting military personnel; and that are committed at least partly for social, political, or religious ends" (Agnew, 2010). Chapter 1 of this thesis showed that suicide bombings also kill the most civilians and receive the most media coverage amongst tactics used by armed groups. These attacks can be thought of as a worst-case scenario which should be universally condemnable. They are also among the most difficult attacks to prevent using military means (Berman and Laitin, 2005). This is due to the ease with which bombers can blend into crowded areas as well as their instantaneous impact. This makes the prevention of these attacks, including establishing their root causes particularly important. Finally, over the period of study their use worldwide has increased substantially (CPOST, 2016). It should also be noted that, although armed groups carry out suicide bombing attacks with a variety of political, economic or religious aims, the research carried out here is particularly focused upon suicide bombing which is carried out with the aim of 'defending Islam'. Since 2011 85% of terrorism incidents worldwide occurred in majority Islamic countries (Cordesman, 2017). Islam inspired or Jihadi terrorist attacks have also been responsible for the majority of terrorism fatalities in Western Europe since 2004 (START, 2017).

3.2 Motivation

There is clear motivation in attempting to understand why people decide to support extreme ideologies and the brutal attacks which they carry out. The findings in this chapter are likely to have direct policy relevance for those governments and aid organisations who are working to reduce terrorism. It should inform the decisions they make, such as to how to target money and other resources effectively. For this to hold there should be some causal link between the extent to which citizens support terrorist activity and the quantity or lethality of terrorist events that take place, both domestically and internationally. While establishing this causal link is outside the scope of this chapter, I briefly set out how this link may work and related empirical findings.

Theoretically, there are two main causal mechanisms through which public justification for suicide bombing could lead to suicide attacks taking place. Firstly, there may be a direct correlation between those who justify attacks and those who at the time of the survey were members of armed groups. They may be currently involved in planning or carrying out attacks or may go on to do so in the future. Secondly, those who justify attacks may be more receptive to aiding armed groups. This could be in the form of passive assistance e.g. withholding information from counter-insurgency forces or willingly harbouring insurgents within their village. Alternatively, they may assist armed groups directly, this may take the form of financial or land donations. Here it is important to note that the propensity of citizens to justify attacks is not only relevant to attacks taking place in that country but also to the flow of financial resources and fighters to armed groups carrying out attacks in other countries.

Empirically, a causal relationship between public opinion and terrorism has been generally supported by the literature although there is a need for further research in this area. Sanchez-Cuenca (2007) finds that a supportive public enables terrorist groups to carry out more indiscriminate attacks and kill more civilians. Krueger and Malečková (2009) find a greater incidence of international terrorism occurs where public opinion in one country disapproves of the leadership of another.

3.3 Theoretical and Empirical Background

3.3.1 Income, Education and Terrorism

There are several theoretical channels by which income and education may affect an individual's likelihood to support or carry out terrorism. In terms of income, an ordinary rational choice model used in the crime literature (Becker, 1968) would predict that individuals will choose between working in the legal sector or illegal sector depending on what best maximises their utility while accounting for the risks which may be involved. Here, the likelihood of being involved in illegal activity will increase as legal wages decrease (Krueger and Malečková, 2003). In terms of terrorist activity, the utility derived from participation may be future financial gain or some non-pecuniary benefit such as a prestige effect felt from furthering one's political or religious ideology. In the specific case of suicide bombers, they are certainly not motivated by their own financial gain, although they may be promised payments to their family in the future

(Bahney et al., 2013). Under this type of model, we would expect that richer people would not engage in, or support, terrorism due to the increased opportunity cost of doing so. On the other hand, the relationship may in fact move in the opposite direction. For example, it could be argued that if there is little or no financial gain from terrorist activities then the poorest in society - those who have no financial cushion and whose families are living at subsistence level - have more to lose from any financial loss than those who are already wealthy. They may also expect less financial gain from any future regime change where the top jobs and power will likely go to those who are wealthier or better educated.

In terms of education, it could plausibly be assumed that higher levels of education may give people the tools (i.e. better reasoning skills) to be able to reject the ideologies behind terrorism (Berrebi, 2007). Clearly though, this depends upon not only the level of education that people receive but also the type of education. For example, five years of education at a madrassa (an Islamic religious school) may give an individual a very different ideological outlook to one provided by a western style university. It is also possible that as one's level of education increases one could become more aware of national and international political grievances while increasingly mixing among social networks with others who may hold similar views. There may also be social pressure, for example in students who are living away from their families, to join these networks and experience the solidarity which comes as being part of the group (Manzo and Wintrobe, 2009). Finally, it is possible that educated individuals may feel specific grievances if the wages they receive in the legal economy do not provide a return on their investment into education.

Political leaders and policymakers have regularly expressed views on the relationship between income, education and extreme ideologies. These include many who back up their foreign policy objectives by directly linking these factors with terrorism. Among these are former U.S. Secretary of State John Kerry who said, "We have a huge common interest in dealing with this issue of poverty, which in many cases is the root cause of terrorism" (Kerry, 2014) and former UK Prime Minister Tony Blair who claimed "Education in the 21st Century is a security issue. There is no better cause nor one more urgent" (United Nations, 2013). Assertions such as these generally conform to the conventional wisdom that reducing poverty and improving education should lead to less people choosing to support or engage in violent extremism.

However, this conventional wisdom has not always been backed up by empirical findings. The present empirical literature analysing the relationship between income, education and terrorism can be broadly categorised into three areas. The first area of research involves macroeconomic studies mapping the level of terrorism at the country level with various indicators including measures of GDP per capita and educational variables. In terms of income many studies have found either a positive relationship between GDP per capita and the level of terrorism (Kis-Katos, Liebert, and Schulze, 2011; Freytag et al., 2011) or an insignificant relationship (Abadie, 2006; Dreher and Fischer, 2011) after controlling for various geopolitical factors. Enders and Hoover (2012) find a nonlinear relationship whereby terrorism decreases with country income but only when income passes a threshold of GDP per capita. Less macroeconomic studies have included variables related to education, those that have find contrasting (Brockhoff, Krieger, and Meierrieks, 2015) or insignificant (Drakos and Gofas, 2006) results. Freytag et al. (2011) find that while terrorism is decreasing with human capital in the whole country sample, in Islamic countries this relationship is reversed. The main areas of concern with these macroeconomic studies have been the quality of the data (e.g. measuring the level of terrorism consistently over time and countries) and establishing any clear channels of causality (De Mesquita, 2008). These studies may provide an indication of the general macroeconomic conditions under which terrorism may thrive, however they cannot provide any answers on intra-country variation.

The second area of research contrasts the personal characteristics of those who carry out, or attempt to carry out, terror attacks with that of the general population. Berrebi (2007) finds that higher education and standards of living appear to be positively associated with both membership of terror organisations and becoming a suicide bomber in Pakistan. Krueger and Malečková (2003) show that members of Hezbollah are as likely to come from educated and rich families as they are to have come from poor, uneducated ones. Related research shows that changing macroeconomic circumstances will determine the quality of terrorists. Benmelech, Berrebi, and Klor (2012) show that during times of economic hardship terrorists are better educated and more experienced. The main problems with this type of research are the small sample sizes and lack of rich, consistent, data on those who have carried out, or have attempted to carry out, attacks.

The final segment of research into the relationship between income, education and terrorism is the area in which this study is placed. This is analysing the determinants of support for terrorism among a country's population by using household surveys. One advantage of survey-based analysis is that it utilises larger samples which have more accurate and consistent information than studies based on characteristics of terrorists themselves. Another advantage is that because it makes use of socioeconomic details of individuals within a population, rather than a country's macroeconomic position overall, it can pick up within country variation. For example, terrorists may thrive in general in richer countries but are they - or those whom are passively or actively supporting them - rich or poor relative to the general population? One possible drawback to this type of analysis, as discussed in the 'motivation' section above, is that it relies on the assumption that at least some of those who claim that terrorism is justified will go on to carry out attacks or assist those who do.

There have been several studies which use surveys to analyse the likelihood of support or justification for terrorism according to various characteristics. The two studies which are most closely related to this chapter are Krueger (2007, p. 23-26) and Shafiq and

Sinno (2010). These use the same data source, Pew Global Attitudes Survey (PGAS), and analyse some of the same countries as I do here. Neither of these studies find strong evidence in support of the conventional wisdom that income and education levels should be negatively correlated with support for terrorism. Krueger, using the 2004 survey, finds that "people with a higher level of education are in general more likely to say that suicide attacks against Americans and Westerners in Iraq are justified" and that the same pattern exists with attacks intended to defend Islam. He finds that there is a weak relationship between income and justification for attacks but that there is "no indication that at higher levels of income people are less likely to say that suicide bombing attacks are justified". Shafiq and Sinno, using the PGAS from 2005, find a weak and inconsistent relationship between education, income and support for suicide bombings. In terms of attacks against civilians they find that educational attainment discourages support in Indonesia and Pakistan but encourages support in Jordan. They find that greater income discourages support for suicide bombings in Jordan and Pakistan but encourages support in Morocco. Otherwise, the results they find are insignificant.

There are a few main limitations of the results of these studies which I attempt to address in this chapter. The first is that they are based on a single years' worth of data. This means that they have a relatively small sample size in each country and their results are more vulnerable to short term shocks in the dynamics of support for terrorism compared to a larger dataset which includes multiple years. Another limitation is that they use data from Spring 2004 and 2005 respectively, the nature of terrorism has clearly changed substantially between then and the final year in this study, 2015. Finally, both studies fail to fully exploit the amount of information available within the surveys. Krueger uses a simple mean comparison to show the relationship without making use of any covariates. Shafiq and Sinno, use an econometric framework but do not control for religious variables or make use of the full range of income variation, instead they separate income into quartiles. This study should complement both papers by providing an opportunity to test whether their findings remain robust when they are analysed using an expanded dataset and with alternative specifications.

Given the weak empirical evidence outlined above on education, income and terrorism I select the following hypotheses to be tested in this study:

Hypothesis 1 (H1): *There is no significant relationship between educational attainment and support for terrorism.*

Hypothesis 2 (H2): *There is no significant relationship between household income and support for terrorism.*

3.3.2 Religious Commitment and Terrorism

In a similar vein to the relationship between income, education and terrorism there is also considerable ambiguity about how an individual's commitment to Islam affects their likelihood of supporting terrorism. There are a few theoretical channels by which commitment to Islam could lead to support for terrorism. One is that radicalisation occurs directly through teaching of a narrow, fundamentalist interpretation of the Koran and Sunna, teaching potential suicide terrorists that they will die as martyrs for Allah (Thayer and V. M. Hudson, 2010). A related channel is that this radicalisation could particularly thrive when it takes place within social networks which religious commitment may create (McCauley and Moskalenko, 2008).

While politicians, such as U.S. President Donald Trump and his former Security Advisor Michael Flynn have often linked commitment to Islam with support for violent extremism (Khan, 2016), there is very weak empirical evidence of any link. Mousseau (2011) uses Pew data from 2002 and finds no relationship between religious commitment and support for terrorism. Other research has found some evidence of a relationship between mosque attendance by Palestinian Muslims and support (Ginges, Hansen, and Norenzayan, 2009) although this effect is put down mainly to a 'coalitional-commitment' effect of people meeting together rather than being directly related to religion. Fair, Malhotra, and Shapiro (2010) find that those Pakistani Muslims with a better knowledge of Islam are significantly less likely to support terrorist groups in some specifications. Again, because of the weak and contrasting empirical evidence I will test the hypothesis that:

Hypothesis 3 (H3): *There is no significant relationship between commitment to religion and support for terrorism.*

3.4 Data

The data used in this study is taken from several editions of Pew's Global Attitudes Project which is freely available on their website (Pew Research Center, 2005-2015). This takes the form of a representative household public opinion survey administered to thousands of people across a variety of countries annually. From 2002 to 2015 the following key question was asked as part of the survey to Muslims in some countries:

"Suicide bombings can be [Often/Sometimes/Rarely/Never] justified against civilian targets in order to defend Islam from its enemies?"

The answer given by respondents to this question underpins the present analysis. The question was asked to Muslims in at least one year in Bangladesh, Britain, Egypt, France, Germany, Ghana, Indonesia, Israel, Jordan, Kuwait, Lebanon, Malaysia, Mali, Morocco, Nigeria, Pakistan, Palestinian Territories, Senegal, Spain, Tanzania, Tunisia, Turkey, Uganda and Uzbekistan. Countries were then selected based upon the following criteria:

- A predominantly Muslim population.
- Good data availability through the majority of the period of study (2005-2015).
- Compatible data on education, income and region.
- Has suffered some suicide attacks against civilians during the period of study.

Taking these criteria into account the following five countries were selected for the analysis: Indonesia, Jordan, Lebanon, Pakistan, and Turkey.

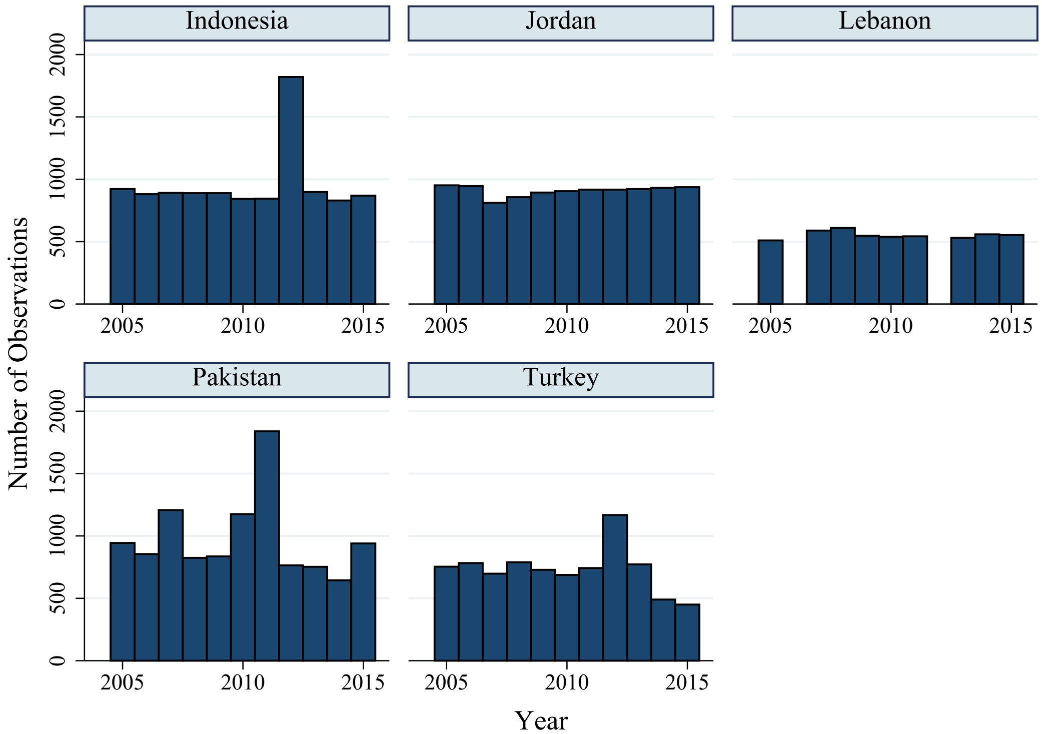
Pew follows a robust methodology (Pew Research Center, 2018) in administering their surveys to attempt to elicit honest answers from participants as well as ensuring that they sample a representative selection of the population. To ensure that participants feel comfortable, surveys are contracted out to trusted local vendors. The vendors use local people to administer the survey face-to-face in the participants own language. To ensure that the survey is representative, Pew randomly select a number of 'cluster' areas which are normally either city blocks or villages. These are chosen by first randomising at the provincial level, and then randomising at increasingly smaller territorial units, until the desired number of these clusters are identified across the country. Sometimes high-level provinces are selected with probability one, this is to ensure that at least some part of e.g. a capital city is sampled. At this point teams of local interviewers are deployed to these selected clusters. If a list of addresses is available residences are selected at random from this list. If this is not the case, interviewers perform a 'random walk' whereby they visit every third or fourth residence along a randomly set route. Participants from the adult population of these households are then selected at random, sometimes by choosing to interview the person who has had the most recent birthday. At least three attempts are made to interview the randomly chosen household/individual, at this point another household and individual are randomly selected until the desired sample size is met.

It is important to note that some small areas were excluded from random sampling in certain years where they were inaccessible or undertaking the survey may have put the interviewer in danger. In Lebanon these were comprised of a small part of Beirut under militia control and a few inaccessible villages on the Israeli border. In Turkey parts of the Doğu region were not sampled in some years due to instability. In Pakistan, small areas of several provinces were not sampled due to security concerns. In Jordan and Indonesia (excluding the autonomous Papua region) the survey covers the whole population in all areas. Omitting these areas of instability from the selection of clusters detailed above is unlikely to substantially affect results in the present analysis given that their populations cover such a tiny proportion of the country populations. However, further research – outside of the bounds of the current study – may investigate whether individuals in these areas are atypical in their support of terrorism against civilians. For example, it could be expected that areas under control of militants hold populations that are generally more supportive towards them and their methods. Alternatively, observing the violence caused by such groups first-hand may have turned the public against such acts of terrorism. Future studies may consider these questions by analysing household surveys of such areas after the conclusion of violence.

For the purpose of this research I merge the individual annual Pew datasets to create a cross-sectional panel for these five countries. This involved some transformation of key variables on education, income and region as outlined in the next section. In around 5% of interviews individuals refused to answer the suicide bombing question or claimed that they didn't know whether bombings are justified. In these cases, the individuals were removed from the analysis. Appendix Table C.1 compares the characteristics of these dropped observations to those of the full sample along with results of associated t-tests comparing the means of the groups. It finds that those who didn't answer the suicide bombing question had lower average levels of education and income in comparison to those who did. They were also significantly more likely to be female. Although these differences should be noted, I do not believe that they are significant enough to affect the overall results obtained given that they cover such a small proportion of interviewees. Furthermore, the characteristics of those who did not answer the terrorism question (i.e. more likely to be female, less well educated, and poorer) are found to be very similar to the characteristics of those who did not answer other, less contentious, questions in the survey. Column 3 of Table C.1 shows that there are no significant differences between those who did not answer questions on terrorism and those who failed to answer questions on their life dissatisfaction (aside from on the no. of children variable). This indicates that such characteristics are likely to be those of individuals who generally are less politically or socially engaged or who are cautious of surveys rather than being the specific characteristics of individuals avoiding questions on terrorism. In a very small number of observations respondents refused to answer questions on certain covariates (i.e. their education level), these observations were excluded from models including these variables.

Figure 3.1 shows the number of observations by year in each of these countries after the removal of observations with missing data. In Indonesia, Jordan, Pakistan and Turkey data is available for all 11 years. In Lebanon there are also 2 years (2006 and 2012) where the survey was not carried out. One perceived limitation to the analysis may be the relatively small sample size which the individual surveys by country rely upon. The surveys in Indonesia, Jordan and Pakistan have averages of 800-1000 responses per year, while surveys in Turkey and Lebanon rely on lower average samples (733 and 553 respectively). It is important to note, however, that the regression analysis in this chapter is not undertaken on these relatively small sample sizes. It will instead combine observations across years to create far larger samples by country. The total number of observations across all countries is 44,393.

Figure 3.1: Observations by Country and Year



3.5 Country Backgrounds

The selected countries provide the study with considerable variation and scope. Firstly, the countries cover several major world regions with Islamic populations; the Middle East, Eurasia, South Asia and Southeast Asia. In terms of population they incorporate some 550m people, ranging from Indonesia with a population of 262m to Lebanon with 6m. The countries also vary considerably in their economic development; Turkey has a GNI per capita of $11,230 while Pakistan's is just $1,500 (World Bank, n.d.). Finally, and most significantly here, they have suffered from Islamic terrorism to a variety of different extents.

3.5.1 Indonesia

Indonesia has the largest Islamic population in the world with more than 200m Muslims (BPS Census, 2010). It suffered several major attacks from radical Islamic groups on civilians during the period of study. These include suicide attacks on Westerners, Christian groups and moderate sections of Islam. The most lethal suicide attack occurred in the resorts of Jimbaran and Kuta, Bali in October 2005. The attack killed 23 people and injured over 100 and was carried out by the Al-Qaeda linked Jemaah Islamiyah (BBC News, 2005). More recently, Indonesia has been one of the world's larger exporters of Islamic State fighters with more than 500 Indonesians thought to have travelled to join them in Syria and Iraq (BNPT, 2017).

3.5.2 Jordan

Jordan has generally been considered as one of the most stable and moderate countries in the Middle East (USAID, 2015). However, in recent years the country "has increasingly struggled to preserve its security and inure itself against the threat posed by homegrown extremists" (Milton-Edwards, 2017). This insecurity includes both a growing number of attacks taking place in Jordan as well as a steady stream of fighters leaving the country to fight for various jihadi groups in Syria. Suicide attacks in Jordan have been rare, however, during the period of study, the November 2005 Amman bombings carried out by Al-Qaeda in Iraq killed 60 civilians in attacks on three hotel lobbies (Ghazal, 2015).

3.5.3 Lebanon

Lebanon suffered a considerable number of attacks relative to its small population between 2005 and 2015, many of which involved a suicide element. These attacks ranged from politically motivated sectarian violence to direct attacks upon civilians. The period started with the assassination, by suicide bombing, of the former Lebanese President Rafic Hariri. The 2015 Beirut bombings carried out by Daesh were the most lethal suicide attack in the period, responsible for the deaths of 43 people with 240 recorded as wounded (International Institute for Counter-Terrorism, 2015). The period also corresponds with the transition of Hezbollah from predominantly a militant group to a political party which held ministerial office as part of a coalition deal.

3.5.4 Pakistan

Pakistan has been referred to by commentators as the "epicentre of Islamic terrorism" (Zakaria, 2010). Over the period of study 5,374 individuals were recorded by the Global Terrorism Database as killed by suicide bombing attacks (START, 2017) with the 2007 Karsaz bombing believed to have been carried out by Al-Qaeda responsible for up to 180 deaths alone. The violence in Pakistan has been multifaceted with most political parties employing military wings – some of which have allied themselves to international militant groups such as Al-Qaeda. This has led to a culture of poor governance due to the imbalance of power between civil institutions and various military groups (Nawaz, 2016).

3.5.5 Turkey

Despite its considerable standing in geo-political spheres, Turkey has suffered considerably from violence and terrorism over the past 30 years. Historically this violence has been mainly attributed to the Kurdish-Turkish conflict but in recent years there has increasingly been attacks by jihadi groups, such as Daesh. Suicide attacks have been used by both Kurdish separatists and jihadi groups during the period of study (START, 2017). The most destructive attack was the double suicide bombing of Ankara railway station in 2015 which was attributed to Daesh or its allies and killed 102 people (Guran, 2015).

3.6 Key Variables and Descriptive Statistics

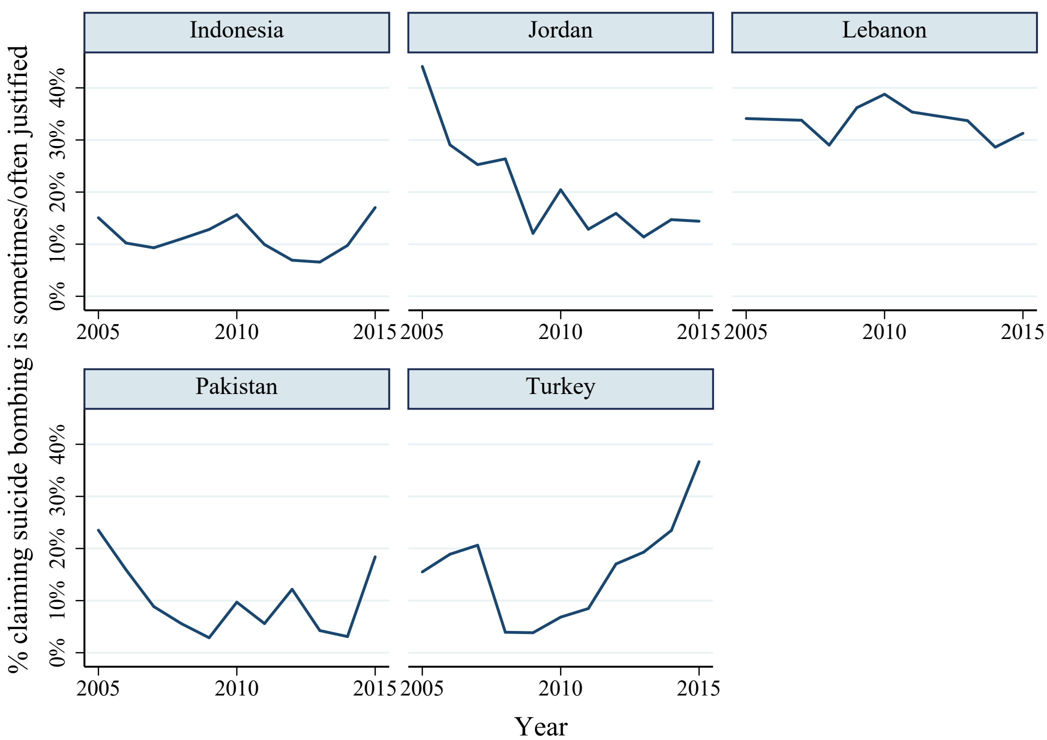
In this section I outline the transformation of key variables included in the analysis as well as presenting descriptive statistics on the temporal, socio-economic, religious and spatial distribution of public justification for terrorism. These should be seen only as initial indicative results before a range of controls are introduced in a formal econometric analysis. In this section I use a dichotomous variable equal to one if survey respondents claim that suicide bombings are 'sometimes' or 'often' justified and zero if respondents claim suicide bombings are 'rarely' or 'never' justified. This is so that results here can be simply interpreted as the percentage of people who claim that the suicide bombing of civilians is at least sometimes justified.

Within the remainder of this thesis chapter, I use language such as 'justification for suicide bombing' or 'those who justify bombing' or 'supporting suicide bombing'. To be clear, these statements are derived from the answers given to the above question; specifically, the extent to which surveyed individuals claim that suicide bombing is justified against civilians in the defence of Islam.

3.6.1 Temporal Changes

Firstly, in Figure 3.2, I plot the percentage of people claiming that suicide bombing is justified over time by country. Firstly, there is considerable variation in support across countries. Averaging over the whole period, the most supportive country was Lebanon where 33.3% of the sample believed bombing to be justified. The least supportive was Pakistan, where justification was considerably lower at 9.9%. There are few consistent temporal patterns across countries. There does appear to be an overall weakening of support in all countries from 2005 until 2007/2008, possibly related to a declining frustration about the 'War on Terror' which some Muslims interpreted as a de facto war on Islam (Cavatorta, 2012). There is also evidence of a rise in support between 2013 and 2015 in Indonesia, Pakistan and Turkey. This could be correlated with the emergence of Daesh as a major player within Syria and Iraq and the start of their expansion to other Muslim countries. Overall country specific trends show that support in Jordan declined considerably over the 11-year period, from above 40% to around 15%. In contrast in Turkey, between 2007 and 2015, the percentage of people claiming suicide bombing as justified rose from 5% to almost 40%. In Indonesia, Lebanon and Pakistan support remained relatively stable.

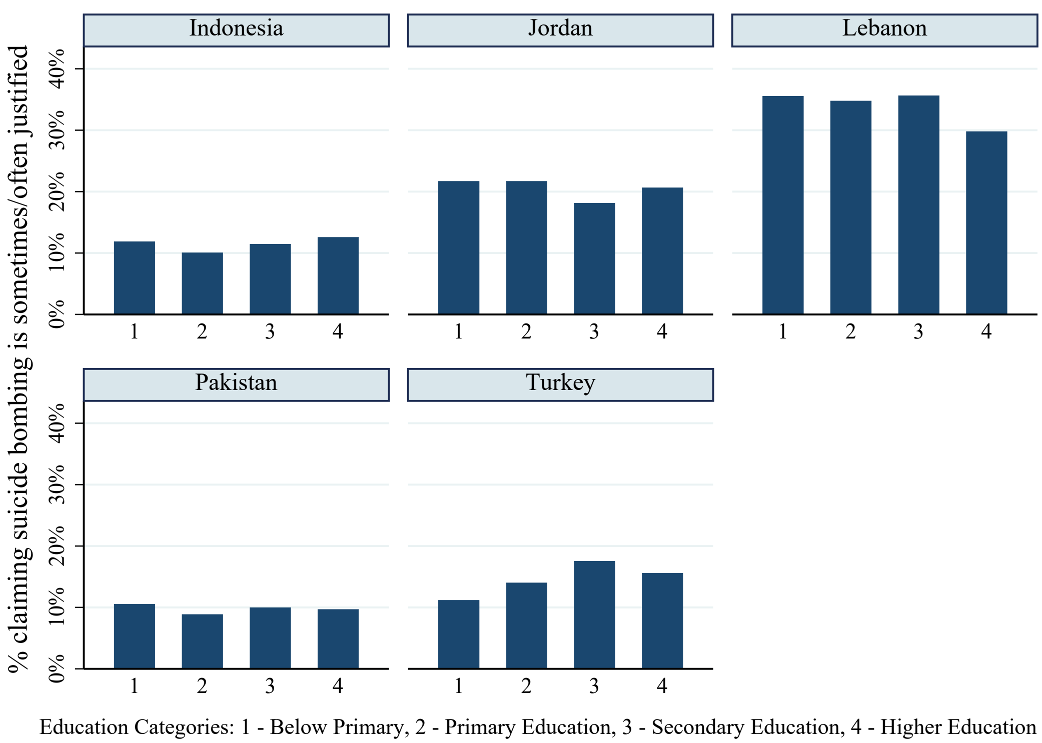
Figure 3.2: Justification for Suicide Bombing over Time



3.6.2 Education Level

There is considerable heterogeneity in educational information in the combined dataset with up to 11 different types of education in some countries and years. To simplify the analysis, as well as to ensure comparability with other studies (e.g. Krueger, 2007; Shafiq and Sinno, 2010), individuals are allocated to one of four broad categories. This is achieved using a national education framework (or equivalent) for each country and matching qualifications across years. The four categories are 'Below Primary Education', 'Completed Primary Education', 'Completed Secondary Education' and 'Some Higher Education (e.g. University or College)'.

Figure 3.3: Justification for Suicide Bombing by Education Level



Results on education are presented in Figure 3.3. The results here appear to give support to **H1** that there is no clear, consistent relationship between education and justification for suicide attacks. There is, however, some weak evidence of an increasing relationship between education and support for terrorism in Indonesia and Turkey as well as a decreasing one in Lebanon.

3.6.3 Income Level

Survey questions on monthly income are generally of the form:

"Here is a list of incomes. Which of these does your household fall into counting all wages, salaries, pensions and other incomes that come in?"

Where, in most cases, income is reported in bands, the midpoint of each band is recorded as the household income level. These bands are generally around \$25-\$100 in width (depending on country and year) and should provide a relatively good measure of household income. In the surveys administered in 2014, respondents were asked their actual monthly household income and I thus use this figure.

For the present analysis this raw income figure is transformed as follows. Firstly, I adjust the figure by using an equivalence scale. This is necessary to accurately compare income across households with a variety of different structural compositions. The consumption needs of a household grow with size but not proportionally - economies of scale mean that a family of six are unlikely to be six times poorer than an individual living alone with the same household income (OECD, n.d.). Similarly, a household comprised of two adults and four children will likely be better off than an equally financially compensated household of six adults. The scale chosen here is the 'OECD-modified scale.' This scale introduced by Hagenaars, De Vos, Asghar Zaidi, et al. (1994) attempts to model these economies of scale by using the following formula:

$$EI = \frac{RI}{0.5 + (0.5 \times a) + (0.3 \times c)}$$

Where EI is the household's equivalent income, RI is the raw income, a is the number of adults and c is the number of children living in the household. Such that for a household of size one, equivalent income is the same as raw household income. As a household increases in size, equivalent income is deflated but not in a way which weights the demands and needs of additional adults and children equally.

To provide temporal and cross-country compatibility the resulting equivalent income figure is split into income quartiles by country and year. Some models in the data, those that are within country only, use a continuous measure of income. Here, to facilitate comparison, equivalent household income by country and year is deflated to 2005 USDs.

Figure 3.4: Justification for Suicide Bombing by Income Quartile

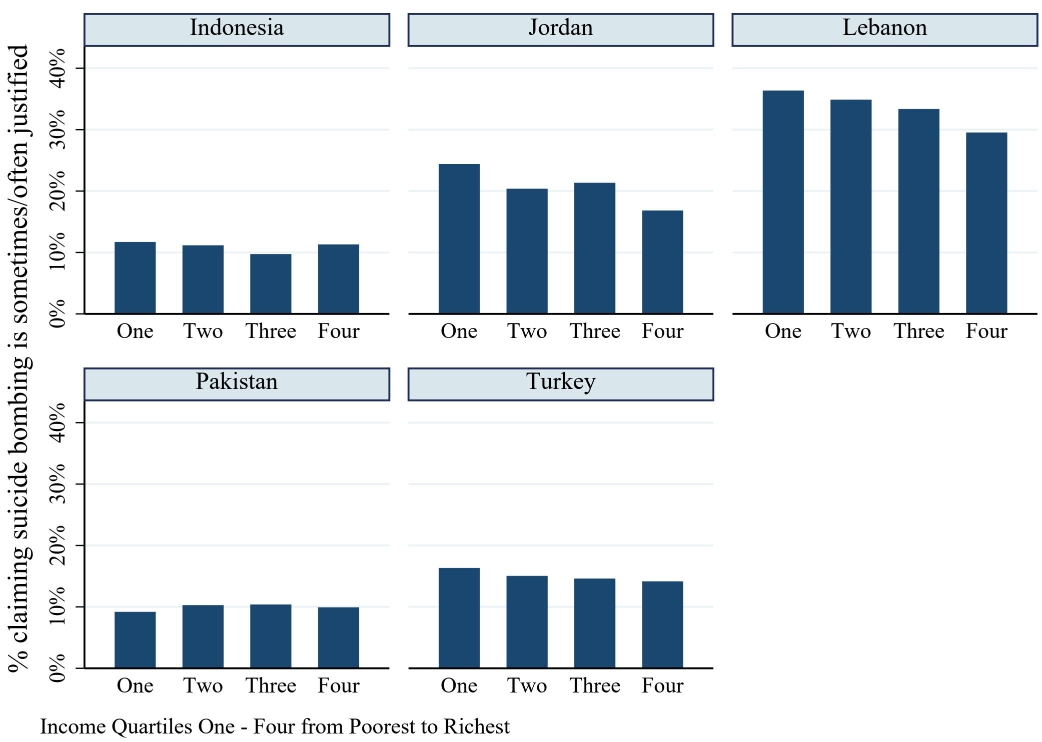


Figure 3.4 shows the level of justification by income quartile across countries. Here, we can certainly reject the notion that there is a positive relationship between in-

come and support for suicide attacks. In Jordan, Turkey and Lebanon there exists a clearly declining relationship between income quartile and support. Indonesia also exhibits an overall declining relationship albeit one which is considerably weaker and non-monotonic. In Pakistan there is little discernible relationship. We can therefore cautiously reject **H2**, that there is no relationship between income and support for terrorism, although clearly there is a need to see whether these patterns persist when controls are introduced in an econometric specification.

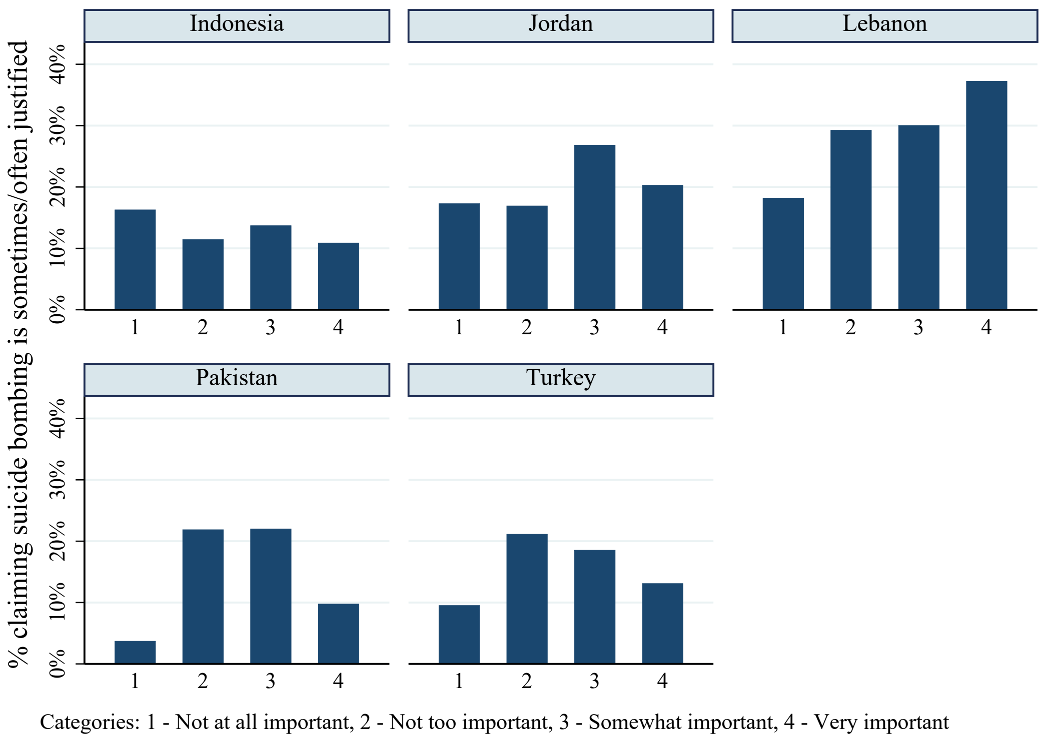
3.6.4 Religious Variables

This study uses two measures of religious commitment. Firstly, a measure of the self-declared 'importance' that individuals place upon religion. Survey respondents are asked:

"How important is religion in your life – very important, somewhat important, not too important, or not at all important?"

Figure 3.5 shows the relationship between the importance individuals place upon religion and their likelihood of justification of suicide attacks. One confounding factor here is that the suicide bombing survey question used in this study states that the justification should be 'in the defence of Islam'. This could mean that those who are not committed to Islam - and thus in the 'not at all important' or 'not too important' groups - but still believe that the suicide bombing of civilians could be justified may say that it is not justified 'in the defence of Islam'. Therefore, it is likely that the true percentage of people who would justify attacks in general in these groups is likely to be higher than that reflected in Figure 3.5. These two categories also only incorporate around 3% of the total sample. In the vast majority of surveys where individuals said that religion is somewhat or very important in their lives, there is a declining relationship in all countries except Lebanon. Overall, these graphs show a considerable amount of variation, however, there is no conclusive evidence either way as to whether we can reject **H3** that there is no impact of religion on support.

Figure 3.5: Justification for Suicide Bombing by Importance of Religion

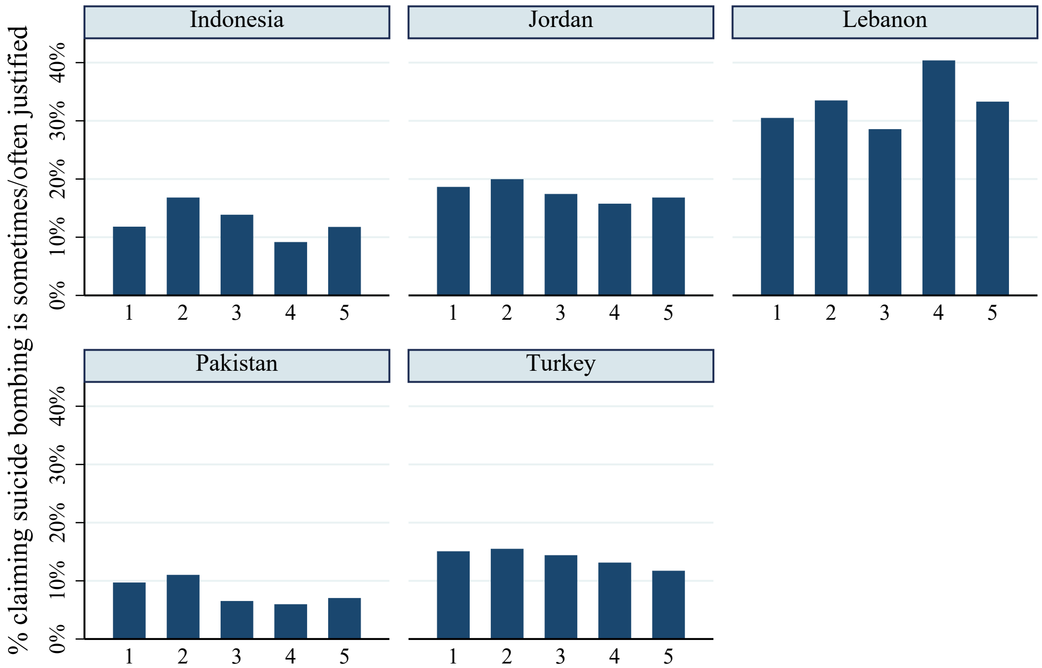


The second measure of religious commitment is a more objective indicator based upon the question:

"How often, if at all, do you pray: hardly ever, only during religious holidays, only on Fridays, only on Fridays and religious holidays, more than once a week, every day at least once, or every day five times?"

Figure 3.6 shows that, with the exception of Lebanon, as the frequency that people claim that they pray increases, the percentage claiming suicide bombing is justified decreases. Overall, this figure suggests that the hypothesis that there is no relationship can be rejected, although the direction of the relationship depends upon the country.

Figure 3.6: Justification for Suicide Bombing by Frequency of Prayer



Categories: 1 - Hardly ever, 2 - On Fridays and/or religious holidays, 3 - More than once a week, 4 - Every day, 5 - Every day five times

In order to simplify this measure for use in the regression models covered later, I convert it to a simple dichotomous variable indicating whether an individual prays at least once a day. These religious measures are not included in every econometric specification as their inclusion lowers the sample size. The religious importance question was not asked in 2014 and the frequency of prayer question was not asked in 2005, 2006 and 2012.

3.6.5 Control Variables

Several control variables are used in the econometric analysis. Most of these are individual characteristics. These include the individuals' age, their gender, their marital status, the number of children they have, and where they live. Another control variable used in some specifications is a measure of 'dissatisfaction'. This is a dummy variable equal to one if an individual answered 'dissatisfied' to the survey question: "Overall, are you satisfied or dissatisfied with the way things are going in our country at the moment?". A similar measure was introduced by Shafiq and Sinno (2010) and is intended to control for any omitted variable bias that could occur if, for example, people's willingness to support the suicide bombing of civilians is only determined as a direct result of their dissatisfaction with the way things are going in their country. In this situation results on income/education would be driven through individuals' dissatisfaction rather than having a direct impact upon one's likelihood of supporting attacks upon civilians.

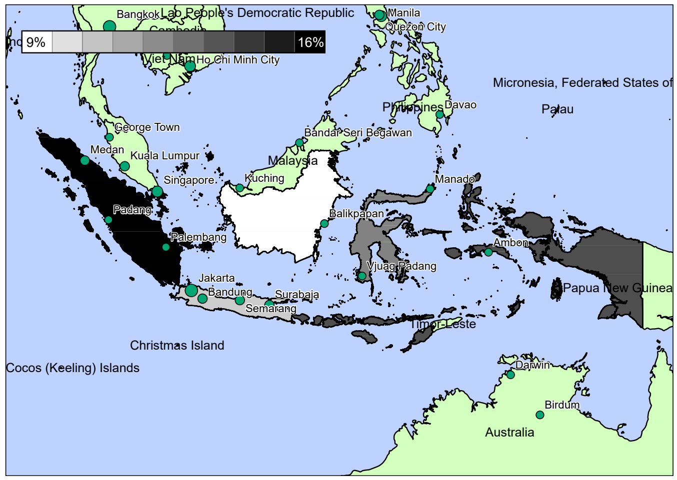
The results displayed in Table 3.1 show that factors increasing the average level of support include being male, unmarried, older and having fewer children. However, these overall trends mask considerable variation between countries. For example, contrary to the conventional wisdom, in Pakistan and Lebanon I observe a greater percentage claiming that suicide bombing is justified amongst women than men. Another interesting finding is the discrepancy in support by age groups. In Lebanon support for these attacks is more likely as age increases. In contrast, in Turkey average support is highest among young people. Trends over time in age and gender are presented in Appendix Figures C.1 and C.2. Another interesting result in Table 3.1 is that dissatisfaction with the way their country is going slightly decreases an individual's support for suicide attacks on civilians.

Table 3.1: Justification by Other Personal Characteristics

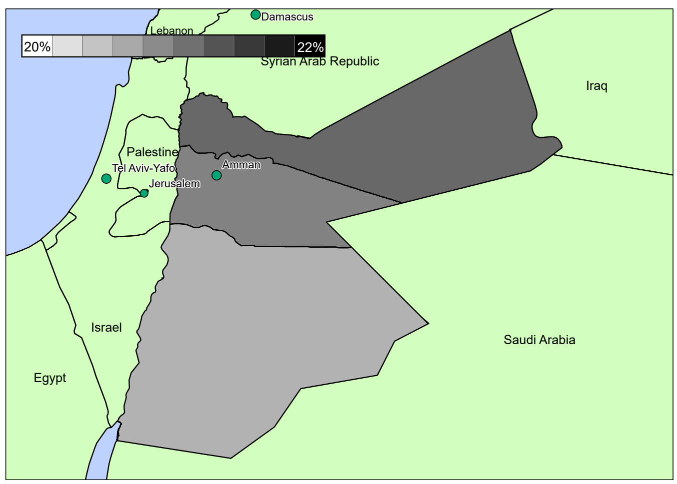
	Indonesia	Jordan	Lebanon	Pakistan	Turkey	Overall
Gender						
Female	10.26%	20.49%	34.57%	10.14%	13.29%	**15.94%**
Male	11.54%	20.63%	31.10%	9.77%	17.32%	**16.27%**
Marital Status						
Unmarried	11.85%	18.47%	31.61%	9.38%	16.98%	**17.13%**
Married	10.61%	21.65%	34.54%	10.09%	13.97%	**15.68%**
Has Children						
No Children	10.04%	28.61%	33.17%	11.34%	16.09%	**18.01%**
Children	11.16%	19.56%	33.42%	9.72%	14.16%	**15.58%**
Age Group						
18-29	10.91%	18.44%	31.66%	10.10%	18.98%	**16.04%**
Age 30-49	11.67%	21.08%	32.95%	9.47%	12.94%	**15.67%**
50-64	8.13%	24.07%	35.99%	10.92%	13.48%	**18.11%**
65+	11.90%	21.15%	44.68%	10.46%	10.02%	**13.29%**
Satisfaction						
Satisfied	12.28%	21.51%	37.75%	13.94%	18.65%	**17.90%**
Dissatisfied	10.12%	19.80%	32.69%	8.51%	11.97%	**15.12%**
Country Average	10.91%	20.62%	33.35%	9.92%	14.96%	**16.11%**
N	10,577	9,989	4,981	10,782	8,064	**44,393**

In terms of geographic variation, although some individual surveys carry data to the town level, I split observations at the regional level. This is in order to maintain geographical consistency across all years for each country. It also has the additional benefit of giving a considerable sample in every region. This means that here I can, as an original contribution, show geographically which areas of the studied countries have a higher level of support for terrorism. These regions are shown, as well as their associated levels of justification for suicide attacks, in Figure 3.7. Regional boundaries were obtained from the GADM Data project (GADM, 2018). It is important to take note of the scale in each graph i.e. in Lebanon support ranges from 30% to 40% while in Indonesia the range is from 9% to 16%. Aside from in Jordan, there is considerable variation in the average level of justification by region.

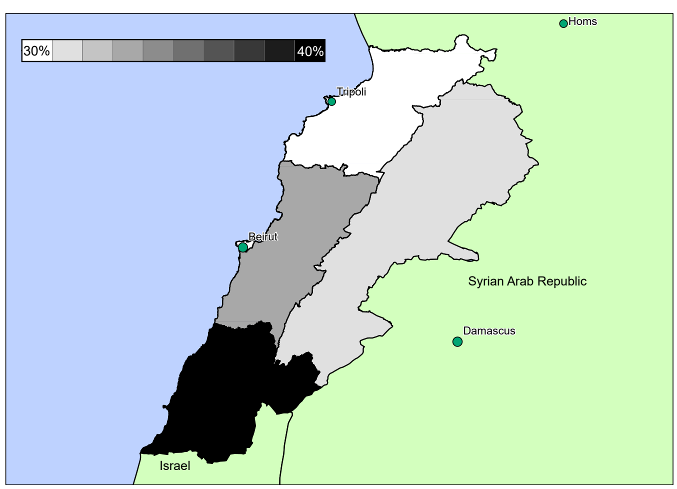
Figure 3.7: Justification for Suicide Bombing by Country Region



(a) Indonesia

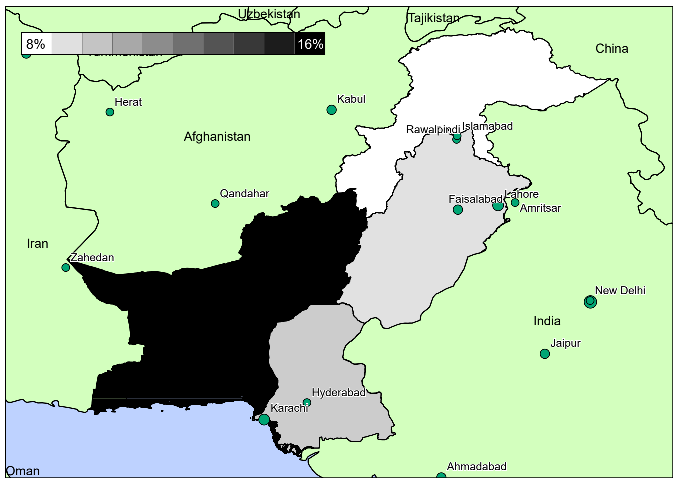


(b) Jordan

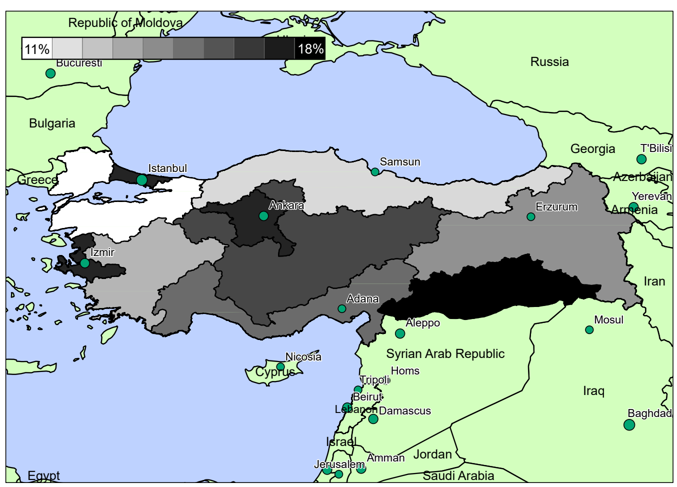


(c) Lebanon

Figure 3.7: Justification for Suicide Bombing by Country Region (cont.)



(d) Pakistan



(e) Turkey

3.7 Results and Analysis

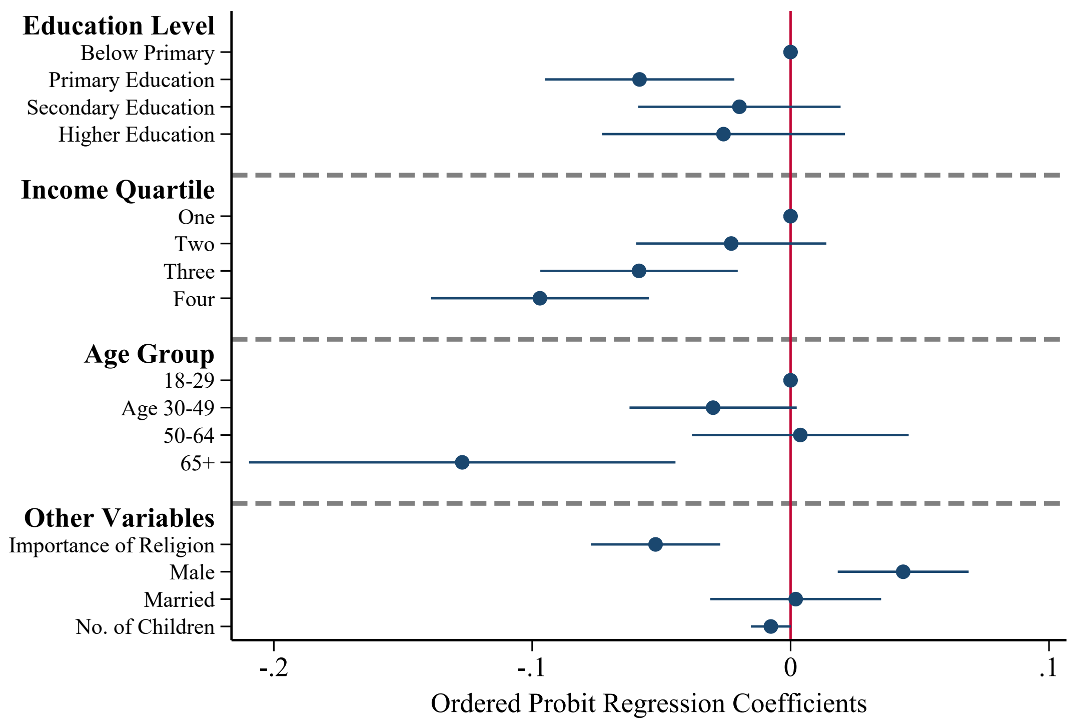
The analysis conducted in this study is split into three sections. Firstly, I present results using pooled data on all five surveyed countries. Secondly, I run individual regressions on each country to observe whether there is a consistent or differing picture. Finally, briefly summarised here but presented fully in Appendix Tables C.5 - C.9 I expand upon the findings of Shafiq and Sinno; replicating their model but adding 10 further years of data.

Most regressions presented use an ordered probit specification. The ordered probit model makes use of a natural ordering of states within a discrete random variable (Hausman, Lo, and MacKinlay, 1992). This ensures that the analysis can take advantage of the full variation in the four levels of justification (Always/ Sometimes/ Often/ Never) for suicide attacks on civilians. It works by assuming that underlying the observed ordinal response is a continuous normally distributed variable measuring propensity to justify terrorism. The distribution of this underlying variable is estimated using maximum likelihood (Daykin and Moffatt, 2002). The main advantage of using the ordered probit model over an ordinary least squares regression is that OLS implicitly assumes that the difference between each category of response is identical. This is not the case for the ordered probit model. In the appendices for robustness I repeat the analysis using alternative models and specifications including OLS and logit models.

3.7.1 Combined Country Regressions

Figure 3.8 presents ordered probit regression model coefficients and their 95% confidence intervals on the total combined sample of countries and years in my analysis. Given the considerable variation in these measures, as shown in section 3.6 above, I control for both year and regional fixed effects. I also show the omitted category for each categorical variable which will always be on the line where $X = 0$. In terms of interpreting the results; a negative coefficient, such as that on income quartile four, implies that an individual being in this category rather than the omitted category (income quartile one) has a greater likelihood of providing a lower category of answer to the bombing justification question (e.g. that suicide bombing is rarely rather than sometimes justified).

Figure 3.8: Combined Country Regression: Justification for Suicide Bombing



Note: Confidence Intervals are calculated at the 95% level; Includes Regional and Year Controls; n=38409.

These results fail to reject the hypothesis (**H1**) that there is no relationship between education and support for terrorism. While there is some evidence that those with primary education have a significantly lower level of support than those with below primary, this effect does not persist for the higher education groups where there is no significant effect at all. There does, however, appear to be a monotonically and significantly decreasing relationship between income and support for suicide attacks upon civilians. This seems to be relatively compelling evidence that the hypothesis (**H2**) that there is no relationship can be rejected. The 'importance of religion' variable also has a negative and significant coefficient. This indicates that as the importance that individuals place upon religion increases, the likelihood that they support suicide attacks on civilians decreases. The coefficients on other variables show that there is no real pattern in relation to age or marital status. However, being male (positively) and having more children (negatively) do affect an individual's level of support. Clearly, as the results here are pooling data from all countries they only indicate overall trends and may be masking some country-specific effects. This possibility is tested for in the next section.

The results reported in Figure 3.8 are coefficients. Appendix Figure C.3 repeats the analysis in Figure 3.8 using a binary probit model on the dummy measure of support which was introduced in section 3.6 above. In this graph the results are presented as marginal effects at the means (MEM) instead of ordinary probit coefficients. Presenting the results in this format makes them far easier to interpret. It involves holding all other variables at their means and observing the change in probability as a result of only changing the particular variable. For example, the coefficient of -0.046 on income quartile four means that for the average person (as determined by the means of all other variables) the impact of being in the highest income quartile compared to the lowest quartile is a decrease of 4.6% in the probability of justification for suicide bombing. Other significant results include a decrease in justification of 0.9% for every additional level of importance an individual places on religion, an increase of 0.8% for being male, and a decrease of 0.5% for every child that an individual has.

The results from Figure 3.8 and Appendix Figure C.3 are reproduced in tabular form in Appendix Table C.2. For robustness I also present two alternative specifications using OLS regression instead of the probit and ordered probit models used for the two figures.

Table C.2 shows that the results discussed above are very robust to these alternative specifications with no variables showing considerable change in sign, or significance. Additionally, the magnitude of the coefficients is very similar in the directly comparable marginal effects probit and OLS models.

3.7.2 Regression Results by Country

I now progress to setting out results by individual country. Table 3.2 includes specifications for each country both with and without the two religious variables (importance of religion and frequency of prayer). This is because of the sample size penalty which comes from including these. The other major change from Figure 3.8 is that the regressions presented in Table 3.2 use a continuous measure of income. As explained above, this is depreciated according to an equivalence scale to take into account heterogenous household dynamics and then converted to 2005 USD in order to facilitate comparison between coefficients. This continuous measure allows the models to incorporate significantly more variation than the quartile method used above and in other papers (Krueger, 2007; Shafiq and Sinno, 2010). The square of this income measure is also included to allow for any non-linear effects. These regressions include a full range of covariates as well as controls for region, year and country dissatisfaction.

The results in Table 3.2 are presented as ordered probit regression coefficients. Appendix Table C.3 presents results for the binary probit model as marginal effects at the mean (MEM). On first glance, the results in Table 3.2 add weight to the argument made by Shafiq and Sinno about the difficulty of generalising over several Muslim countries. Results observed on education, income and religion show that there are no entirely consistent relationships across all five countries and therefore it seems that a one-size-fits-all approach is not appropriate.

There was no clear relationship between education and support for the suicide bombing of civilians in the combined country analysis above. The results in Table 3.2, however, show that **H1** cannot be entirely rejected once the countries are analysed as separate entities. In Pakistan there is a non-monotonically negative relationship. Those individuals with primary or higher education are significantly less likely to justify bombings than those with 'below primary' level education, although there is no significant difference for those with Secondary education. In contrast, the results in Jordan and Turkey point in the opposite direction. Once income and the other covariates have been controlled for, it appears that the level of education in these countries has a positive, monotonic and increasingly significant effect upon support for terrorism. This gives weight to the claims of Krueger and Malečková (2003) and others who do not agree with the conventional wisdom that higher levels of education will lower support for terrorism. In Indonesia and Lebanon, it does appear that **H1** holds, there are no obvious, significant patterns.

The income relationship portrayed in Table 3.2 confirms that **H2** (no relationship between income and support for terrorism) should be rejected. In all countries, aside from Pakistan we observe negative coefficients on income variables, the majority of which are significant. In Pakistan there is a positive effect which diminishes up until the 95th percentile at which point it starts decreasing. In Jordan this transformation occurs in reverse in the 99th percentile. There is no evidence of significant nonlinearities in the other surveyed countries. Overall, these results provide backing to the popular consensus that decreasing poverty should lead to a decrease in backing for violent extremism.

Finally, the two religious variables imply that **H3** (no relationship between religious commitment and support for terrorism) should be rejected. The viewpoint professed by many, that there is a positive relationship between commitment to Islam and support for this type of terrorism, should also be rejected. All coefficients indicate that as people claim that they believe religion to be more important and their prayer becomes more frequent, the likelihood that they justify suicide bombing will decrease. This is with the exception of a positive relationship for the 'Importance of Religion' question in Lebanon. Even here though, the frequency of prayer question is working in an opposing direction. This means that only where individuals claim that religion is important to them, but fail to pray regularly, will a strong positive effect be realised. As discussed above, the suicide bombing question mentions justification in the defence of Islam. We may expect that if this was not the case the negative coefficients on 'Importance of Religion' would increase in magnitude. This is because some individuals who believe that suicide bombings are justified generally but are not religious may claim they do not believe they are justified in the defence of Islam.

The marginal effects results in Appendix Table C.3 complement the main results in Table 3.2 by providing an indication of the practical significance of results. They enable a direct comparison of the magnitude of coefficients between countries. For example, holding other variables at their means, an individual who claims that they pray daily is found to have a probability of support for terrorism which is 2.7% lower in Indonesia compared to if they prayed less frequently or never. In comparison, the probability fall in Pakistan is only 1.7%. One variable of interest where Table 3.2 indicated considerable ambiguity is the impacts of having studied higher education in comparison with having no education. The marginal effects model shows that in Jordan and Turkey the positive marginal impacts upon support for terrorism are 6% and 3.2% respectively (using the 1st model). In contrast, the negative impact on support in Pakistan is smaller in magnitude at 1.7%. This supports the earlier finding of a mixed picture, albeit one which appears stronger in support of a positive relationship than a negative one. Overall, the results in Table C.3 using a binary measure of support strongly suggests the robustness of the findings in Table 3.2.

As a robustness check and to further investigate the opposing relationships between education and income in Jordan, Turkey and Pakistan I split the country samples in two according to income and then re-estimate the results in Table 3.2. The results of this are shown in Appendix Table C.4 where for each country the left column shows results on individuals in the bottom two income quartiles and the right column shows results on individuals in the top two quartiles. The results on income and religion in this split sample regression hold up well. The religious effects are almost identical between richer and poorer groups. In terms of income, even when restricting variation to half of the distribution, all countries aside from Pakistan exhibit a negative relationship between income and support. The results on education are particularly interesting; in Jordan and Turkey the positive and significant results on education from Table 3.2 are only evident in the higher income quartiles. This exists despite an overall decreasing relationship between income and support. This means that where income is above average, and thus support is lower, higher levels of education can have an increasing effect upon support for terrorism. In Pakistan the income relationship found in Table 3.2 was positive. The split sample analysis shows that for lower income individuals increased education will increase support for suicide attacks. Conversely, for higher income individuals the education relationship is negative. These relationships hold when using other robustness checks including interactions between education and income and when splitting the data by both education and income.

Table 3.2: Ordered Probit Regressions on Justification for Suicide Attacks by Country

	Indonesia		**Jordan**		**Lebanon**		**Pakistan**		**Turkey**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Education										
Primary	-0.0589	0.00581	0.0218	-0.0220	-0.0216	-0.0396	-0.0815**	-0.0908*	0.0662	0.113
	(0.0532)	(0.0648)	(0.0350)	(0.0434)	(0.0573)	(0.0659)	(0.0413)	(0.0522)	(0.0643)	(0.0809)
Secondary	-0.0943*	0.000727	0.0566	0.0511	0.0574	0.0994	-0.0220	-0.0256	0.126*	0.162*
	(0.0547)	(0.0677)	(0.0355)	(0.0444)	(0.0601)	(0.0685)	(0.0412)	(0.0519)	(0.0709)	(0.0901)
Higher	-0.0827	0.100	0.0984**	0.0810*	-0.0612	0.00171	-0.124**	-0.165**	0.144*	0.209**
	(0.0823)	(0.104)	(0.0390)	(0.0478)	(0.0604)	(0.0686)	(0.0619)	(0.0766)	(0.0819)	(0.105)
Income										
HH Income[a]	-0.0112	-0.164**	-0.0481***	-0.0281*	-0.0163***	-0.0189**	0.107*	0.342***	-0.0245***	-0.0202
	(0.0229)	(0.0769)	(0.0115)	(0.0145)	(0.00631)	(0.00771)	(0.0645)	(0.0860)	(0.00833)	(0.0153)
$(\text{HH Income})^2$	0.00100	0.0274	0.00245***	0.00149*	0.000260	0.0000596	-0.0257	-0.0605**	0.000191	0.000219
	(0.000694)	(0.0208)	(0.000626)	(0.000829)	(0.000177)	(0.000228)	(0.0196)	(0.0279)	(0.000224)	(0.000692)
Religion										
Importance		-0.196***		-0.0620**		0.147***		-0.393***		-0.127***
		(0.0517)		(0.0313)		(0.0298)		(0.0505)		(0.0361)
Prays Daily		-0.136**		0.0330		-0.127***		-0.0417		-0.0328
		(0.0639)		(0.0403)		(0.0428)		(0.0437)		(0.0486)
Controls[b]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cut 1	0.331***	-0.569**	-0.417***	-0.354***	-0.545***	-0.127	0.289***	-0.396*	0.500***	0.599***
Cut 2	0.884***	-0.0355	0.430***	0.547***	0.0605	0.464***	0.660***	-0.0322	0.898***	1.038***
Cut 3	1.654***	0.672***	1.254***	1.280***	0.903***	1.350***	1.082***	0.397*	1.691***	1.846***
Observations	8447	5776	8504	5587	4745	3610	9208	6637	6547	4235
Pseudo R^2	0.006	0.008	0.018	0.009	0.009	0.016	0.021	0.029	0.028	0.042

Standard errors in parentheses; Omitted Education category is 'Below Primary'; [a] Equivalent household income measured in 100's of USD; [b] Controls are gender, marital status, no. of children, age, country dissatisfaction plus regional FE and year trends; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

3.7.3 Revisiting Shafiq and Sinno

In the final section of my analysis I revisit and expand upon the findings of Shafiq and Sinno (2010) whose analysis was conducted using the PGAS data from 2005. This is to verify whether any results which they found using their model specification on one year's survey data hold up with the addition of a further 10 years' worth of data. There are, however, a couple of caveats to this. Firstly, Shafiq and Sinno run separate regressions on support for attacks on civilians and on coalition troops. In this chapter I am only able to replicate those results on civilians as subsequent Pew surveys after 2005 did not ask about attacks on troops. Secondly, they use a slightly more complex variable to model dissatisfaction than I can use here. My measure is only based on whether a person is satisfied with the way their country is going. They use this question but complement it with information on whether an individual believes that Islam is under threat. This is not possible in the expanded sample replication because, again, this question was not asked in future years.

It is also important to note that Shafiq and Sinno's regression specification is different to the one which I have used to generate the results elsewhere in this chapter (Table 3.2). I believe that the changes that I have made improve the model. The main differences are the use of a continuous measure of income depreciated according to the OECD equivalence scale, compared to using quartiles of income per capita as well as the addition of religious variables. There are also a couple of smaller changes such as increasing the number of categories of age. Where results differ slightly between the extension of Shafiq and Sinno and the results using my models presented in Table 3.2 I believe that the results of the latter should provide a better indication of any relationships.

Appendix Tables C.5 - C.9 compare the results found by Shafiq and Sinno, using 2005 data, with the results found using the same model (plus a year trend) for the full sample from 2005 through to 2015. The results in the right two columns, applying Shafiq and Sinno's methodology to the whole sample, show almost identical results to those found in Table 2 using my alternative methodology and act as a useful robustness check.

The comparison tables show some consistency between the S&S results and those from the full sample, particularly in Jordan where a negative result on income and a positive one on education was identified. However, there are several points of divergence. One is the negative and significant results on income in Lebanon and Turkey which were not picked up in the 2005 survey. In contrast, Shafiq and Sinno find a negative result on income in Pakistan while the full sample indicates that there is an overall positive relationship. Overall, these results show the importance of replicating and expanding the findings of studies such as this, especially where further data becomes available.

3.8 Discussion and Conclusions

This chapter has aimed to test the hypotheses that there is no consistent and significant relationship between education, income, religious commitment and support for terrorism using a series of surveys carried out in five Muslim countries between 2005 and 2015.

The results presented in this study have rejected the hypothesis (**H2**) that there is no relationship between income and support for terrorism. In Indonesia, Jordan, Lebanon and Turkey an increase in household income implies a reduction in an individual's justification for suicide attacks upon civilians. Conversely, in Pakistan this relationship appears to be positive although does diminish and then becomes negative for very high earning households. These results contrast with much of the previous literature in the area which has generally either concluded that there is no relationship between income and support for terrorism or that there is a positive one.

In terms of education, results are more uncertain with no overall pattern. Here, I fail to reject the hypothesis (**H1**) that there is no consistent relationship. In Lebanon and Indonesia I find no significant relationship, in Pakistan there is a non-monotonically negative relationship while in Jordan and Turkey there is a positive, significant and monotonic relationship. This positive relationship between education and support for terrorism is compatible with much of the previous empirical literature that has been carried out (e.g. Krueger (2007)). What is added to the literature here is the results observed in Appendix Table C.4. These show that individuals who are poorer are more likely to support terrorism regardless of their education. Those who are richer are less likely to support terrorism but if they are also highly educated this acts in an opposing, positive, direction compared to the income effect. One possible explanation for this could be that it is a result of the social networks these groups mix within; poorer people may often be exposed to likeminded people whose frustration with their place in life incentivises them to rebel. Those who are financially better off may not mix in social networks of discontent unless they are exposed to them within the confines of higher education. There are suggestions that the nature of education in Jordan and Turkey could lead to the formation of radicalised social networks. In Turkey, for example, the percentage of children attending religious Imam Hatip Schools rose from 2% of the secondary school age population in 2002 to 11% in 2017 (The Economist, 2017). In Jordan, the national education curriculum was changed in 2016 as the government believed that it could be driving young people towards radicalisation (Azzeh, 2016).

One caveat to the analysis in this chapter is the possibility of omitted variable bias. The R^2 values in Table 3.2 indicate that the variables included in the regression explain only some of the variation in the dependent variable, implying that there are likely to be other variables which have explanatory power that have not been incorporated. Examples of possible omitted variables which are not covered by the Pew surveys include an individual's exposure to extremism within their community, their parental background, and their type of schooling (e.g. religious or secular). Where such omitted variables are uncorrelated with incorporated independent variables, coefficients obtained on these independent variables will remain unbiased. If this is the case for all variables affecting an individual's likelihood of supporting terrorism that were not included in the model then the results in this chapter remain valid. However, where an omitted variable is correlated with one of the independent variables, the regression coefficient on this independent variable will be biased.

This analysis in this chapter incorporated as variables and controls as much individual information as was consistently available within the confines of the Pew surveys. However, despite this, it seems plausible that omitted variable bias could be affecting some coefficients in this chapter. For example, if secondary or higher education providers are more likely to teach an Islamic curriculum than primary schools then the coefficients on these education groups will be incorporating both the impact of an individual having higher levels of schooling as well as that of the omitted variable (being more likely to have received an Islamic education). In this case these two effects would be difficult to disentangle. Future surveys undertaken with the goal of producing similar analysis to the present study should ask a greater range of questions focussed upon the participants background. This may, however, come with a cost as individual's may be unwilling to discuss such personal matters and there would also be a significant time cost to the interviewer. An alternative to asking these additional questions is to collect panel data, whereby individuals are asked the same questions over a number of years. The use of repeated observations on individuals allows for time-invariant unobserved individual characteristics to be controlled for by using fixed or random effects regression. Again, however, there would be a substantial cost to implementing such a survey and, in addition, some individuals may opt out or become uncontactable part-way through the study.

Another important caveat to the analysis here is that individual's survey responses may be subject to a type of systematic measurement error, that is, they may misreport their attitudes in a non-random way. An example of this is that respondents may systematically overstate the extent to which they are committed to their religion. In this study I attempt to mitigate this risk by including a more objective proxy measure of religious commitment which is how often the survey participant prays. There are, however, further survey questions for which proxy questions are not available. The most significant for the validity of this study is whether they believe suicide bombings to be justified, the dependent variable in this analysis. It appears possible that individuals may understate the extent of their support to avoid embarrassment or because they are concerned that interviewers may pass details to law enforcement. This will be particularly problematic if this measurement error is dispersed in a non-random way amongst the sample population. For example, if older people are more likely to understate the extent of their support than younger people then results on age will likely be biased.

While outside the domain of the current study, further work could mitigate this problem using alternative survey methods. Two such methods are list experiments and endorsement experiments. Both methods employ indirect questioning techniques whereby individuals are not required to explicitly respond to sensitive questions (Blair, Imai, and Lyall, 2014). Both experimental methods randomly allocate interviewees to either the treatment or control groups. For list experiments, the control group are presented with a short list of individuals, political parties, or armed groups and asked to give the number of these which they support (without being asked to name them). The treatment group are asked to do the same with an identical list with the addition of a sensitive individual or group (such as a terrorist organisation). Researchers then analyse the difference in numerical responses between the treatment and control groups to elicit likely support for the sensitive area of study. List experiments have been previously used to study a variety of topics including the level of anti-semitism affecting support for Jewish election candidates in Florida (J. Kane, Craig, and Wald, 2004) and support for criminal organisations in Mexico (Dıaz-Cayeros et al., 2011). In endorsement experiments, respondents in the treatment group are asked about the extent of their support for a particular non-controversial policy. The control group are asked the same question, however, with the additional information that the policy is endorsed by an undesirable, or sensitive, group. The difference between the support for the policy in the treatment and control groups is therefore an indicator of the underlying level of support for the sensitive group. Endorsement experiments have previously been used to measure support for militant organisations in Pakistan (Fair, Malhotra, and Shapiro, 2012) and Afghanistan (Lyall, Blair, and Imai, 2013).

The findings outlined in this study should have policy relevance to those making decisions on how to target resources with the goal of decreasing terrorism. Firstly, policymakers should note that in neither income, education or religious commitment is there an entirely consistent relationship with support for terrorism across all countries. This should imply that one-size-fits-all policies targeted identically at all countries are unlikely to be sufficient. For example, uniformly increasing funding for educational providers is likely to have very different terrorism outcomes in some countries compared to others. This means that in some countries (e.g. Jordan and Turkey), rather than increasing funding for schools and universities policymakers should specifically target the ideologies being taught. This could be done by, for example, including mandatory peace education as part of the national curriculum. The income relationship found here should reassure policymakers that targeting poverty reduction is a worthwhile goal which should be expected to have a negative impact upon the level of support for terrorism in most countries. Finally, in terms of religion, governments should act to dampen any rhetoric linking commitment to Islam to support for terrorism. The present analysis has shown no evidence to back up these claims. However, if this populist rhetoric is allowed to shape policy it could exacerbate existing religious or political tensions causing deeper grievances which eventually lead to more terrorism.

There is a clear need for further research into several areas related to this chapter. Firstly, researchers should study empirically the causal links between support for terrorism and the level of terrorism that takes place. This should help us better understand the consequences of public support for terrorist activities and therefore the motivations for studies such as this one. Further research should also be undertaken on surveys conducted in alternative countries, this should enable further testing of any consistent patterns. In terms of education, where there is the most ambiguity, research should be carried out on the types of school people went to as well as how the social networks which they interact with affect their likelihood of radicalisation. The replication and expansion of Shafiq and Sinno's paper show that researchers should regularly revisit existing findings when further data becomes available.

Chapter 4

Thesis Conclusions

This thesis has explored three distinct research topics within the field of conflict studies. In particular, chapters have studied how conflict and terrorism may be observed through the media, documented in media-based databases, and supported by local populations. This concluding chapter draws out the main implications of these three topics individually in addition to considering further implications which may be drawn out through the synergies between them.

Chapter 1 studied the intensity with which heterogeneous conflict events are reported by the news media. This was undertaken with the main aims of understanding the relative newsworthiness of a range of conflict event characteristics, and how the importance of these characteristics varies between differing groups of news outlets (e.g. between domestic and international media). The study made use of a unique, innovative, dataset which records direct linkages between 19,413 conflict events that occurred between 2006 and 2013 in Iraq, and the specific news media outlets that reported them. Several event characteristics - such as the type of weapon employed by aggressors - were analysed for the first time in the study. Other event characteristics - such as the number of fatalities

- reported as significant by previous academic studies were reanalysed here with the benefit of a larger and more robust dataset.

The analysis in Chapter 1 resulted in several key findings. Firstly, across all media outlets, reporting intensity is found to significantly increase with event size. However, growth in coverage is not proportional; a doubling in the number of fatalities does not lead to a doubling in media coverage received by an event. Secondly, the weapon type used in a conflict event significantly impacts upon the intensity of coverage an event receives. Figure 1.6 presents the relative ordering in terms of newsworthiness of a range of weapon types. These results show that events using small arms weaponry are the least newsworthy while those utilising explosive weapons, particularly those involving a suicide element, receive a significant reporting intensity premium. These effects are not only restricted to the reporting of coalition news outlets. The relative ordering of weapons is found to be persistent across both international news agencies as well as Iraqi media outlets. Reporting is also found to be dependent upon event location. Intensity of reporting decreases as distance from the capital, Baghdad, increases. While this result is significant across domestic and international news outlets, the magnitude of the coefficient is around 13 times larger for coalition-based media than for Iraqi media.

Although Chapter 1 predominantly presented the empirical evidence for those phenomena observed, it is important to note that the results also corroborate well with the personal experiences of western journalists operating in Iraq since the outbreak of war in 2003. For example, the consistent underreporting of "events occurring virtually anywhere outside of Baghdad" was frequently cited by journalists interviewed by Pew Research Center (2007). This is explained as being caused by a combination of an increasingly dangerous security situation for journalists and the poor roads and infrastructure outside the capital city. Freeman (2004), of The Telegraph, claimed that "only the most important stories are now deemed worth leaving Baghdad for". This may offer some supporting evidence to the results in Appendix Figure A.5 which showed that the reporting gap between Baghdad and non-Baghdad events disappears for incidents where more than 20 civilians were killed.

The majority of interviewed journalists (Pew Research Center, 2007) also noted the decline in demand from editors for news stories on 'day-to-day' conflict events. This appears to support the results in Figure 1.2 showing a substantial fall over time in the average number of reports from coalition media outlets per event. This is explained as being a result of an oversaturation effect whereby "the media has in some way bored its audience with the violence". Iain Overton, a veteran reporter of more than 16 conflicts including Iraq, explained in an interview conducted for the present research (Appendix A.3) that "war reporting fatigue means that the longer a conflict goes on, the more people have to die in a 'spectacular way' to merit meaningful coverage". Additionally, anecdotal evidence from journalists corroborates those patterns of heterogenous newsworthiness of weapon types found in the chapter. For example, Overton describes how "hierarchies of reporting exist" for weaponry which determines media coverage. Suicide bombings routinely obtain "the most attention" followed by other explosive weapons which generally "trump small arms" weaponry. Although the findings of Chapter 1 are frequently cited as significant factors influencing news reporting by journalists, there are many other factors affecting the coverage that an event receives. For example, Overton claims that "the quality of the footage emerging from an event, the number of accredited journalists on the ground, the dominance of other news stories on the day, and the wider context of interest" all may also contribute in dictating the level of coverage that an event may be afforded. There is, therefore, substantial future work analysing additional variables to be carried out in this field to gain further understanding of event coverage variation.

There are several important implications of the analysis undertaken in Chapter 1. For example, the results hold substantial consequences for those individuals wishing to obtain accurate knowledge of a conflict through their consumption of the news media. Notably, relying upon a small number of relatively homogenous news outlets to gain knowledge of a conflict is likely to result in a skewed understanding of the true violence which is occurring. Such news consumers are encouraged to regularly access the websites of data collators (such as IBC) that bring together data from a variety of media (and often non-media) sources and are therefore less influenced by editors' judgements of event newsworthiness. Furthermore, news editors wishing to accurately cover the violence occurring within a conflict zone may wish to consider the significant biases detected in this study to help shape their future editorial decisions.

In addition to these direct implications, further implications requiring future study have become salient as a result of the analysis undertaken in the chapter. For example, this study has been carried out with the implicit assumption that events and their characteristics are determined exogenously from patterns of media coverage that events receive. This means, therefore, that the analysis assumes that the date, location, and nature of conflict events are selected by conflict actors in a non-reactive manner and subsequently media coverage is determined through the characteristics selected. However, previous research (e.g. Dowling, 1986) has suggested that terrorists and insurgents will plan and carry out attacks with a variety of different goals: to cause maximum fatalities and injuries, for the purpose of securing political or military advantage, for disseminating fear, or - most importantly here - with the purpose of gaining media attention for their cause. Given this, it could be considered plausible that insurgents and terror organisations may be designing their attacks in order to extort maximum media coverage. Media attention is desirable for armed groups, it gives them publicity, increases the feeling of public vulnerability, and it may offer insurgents and their grievances a type of quasi-legitimacy (Savitch and Ardashev, 2001). While conclusive evidence is weak there are several synergies between the findings of this thesis as well as those of other studies which may offer support to this theory.

One example of this can be found in the weapon type chosen by actors. Section 3.1 of this thesis set out how the use of suicide bombing has increased substantially over the past 20 years. Suicide bombings have grown from being extremely rare events responsible for between 0 and 300 deaths worldwide each year between 1980 and 2000, to averaging around 400 attacks and 4,000 deaths annually since 2005 (CPOST, 2016). Given that results in Chapter 1 showed that suicide attacks accrue the most media coverage of any weapon type, one could draw the conclusion that terror groups have increasingly moved towards this type of attack in order to maximise their media attention. This desire for attention was described in interview by journalist Iain Overton (Appendix A.3) as the 'propaganda of the deed' whereby an explosive charge is known by revolutionaries to be far more newsworthy than a bullet and thus more likely to ignite the desired social revolt.

A further example is the location of events. Chapter 1 indicated that violent events occurring in urban areas, and particularly capital cities, will accrue more coverage than otherwise equivalent events in rural areas. While conflict prevalence is declining in most countries worldwide, violence and conflict within cities is increasing (Beall, Goodfellow, and Rodgers, 2013). Savitch and Ardashev (2001) showed that terror attacks are disproportionately common in major urban areas in comparison with rural areas. They indicate several reasons for this including a higher concentration of assets, the proximity of heterogeneous social groups, and cities' role as 'nodes' in international communication. However, one key reason is that events in cities are more likely to be reported by the media; they claim that "if terrorists thrive on anything, it is media attention and widespread recognition."

There is a clear need for further research into this area, specifically studies that can successfully establish causal channels that evaluate whether armed groups select the weapons, targets, and dates of terrorism as a direct response to the reporting preferences of the media. However, should clear channels of causality be established, this should hold substantial moral implications for future reporting decisions of news editors. For example, conflict actors may have switched to using suicide bombing as a tactic due to the additional media attention, ceteris paribus, that such events accrue due to their 'exotic' nature. Given that suicide attacks are a particularly lethal type of attack (Table 1.1) it could be shown that reporting decisions of the media have inadvertently resulted in a higher number of conflict and terrorism deaths than would have otherwise been the case. An argument could be made for some type of government intervention or regulation in the media industry. This may be undertaken with the aim of preventing excess media coverage of particular groups or events where such coverage may lead to disproportionate panic amongst the general population or, indeed, encourage further attacks. However, such an intervention should be carefully evaluated against any diminishing in press freedom that it may cause. There are significant benefits to a free press, for example, investigative journalism has routinely played a positive role in exposing human rights violations by actors within conflict and has almost certainly saved lives.

Chapter 2 of this thesis considered the validity of media-based conflict datasets. Such datasets have been routinely used by NGOs to document conflict events and fatalities, particularly where conflict actors have failed to record these themselves. The chapter consisted of two main pieces of analysis. The first considered the source selection process which those planning to implement such datasets will undergo. Results, drawn from analysis using the IBC dataset, showed that source selection will hold significant implications for the accuracy of datasets. It will impact upon both the completeness of datasets (whether the total counts of events and/or fatalities are correct) and the composition (whether datasets contain proportions of different types of events which are as close as possible to the unobserved reality). There may also be trade-offs between selecting sources which provide higher completeness and those which reflect a more accurate composition. Pseudo datasets, artificially created by drawing on the reporting of particular subsets of media sources, document the Iraq conflict in systematically different ways. Examples of these substantial differences between pseudo datasets include variation in the timeline of the conflict, the event size distribution, and the weapon type composition of the datasets. The main results of this analysis should assist those embarking on the documentation of violence in selecting an optimal composition of media sources. When targeting both data completeness as well as an accurate event composition, datasets should draw predominantly upon international news agencies, complemented with the reporting of local news sources. Adding further news sources will particularly benefit datasets in correcting the imbalance of event-size bias. While this study has provided an important indication of how to increase dataset accuracy, formal models should be designed and implemented which fully evaluate the marginal costs (e.g. personnel costs and computing power) against the marginal benefits (in terms of dataset completeness and composition) of adding further sources.

The second section of analysis in Chapter 2 implemented a novel use of multiple systems estimation (MSE) techniques to the media-reported IBC dataset. The IBC dataset provided a unique opportunity to use media sources as 'capture histories' for the MSE analysis. The analysis was also complemented by the existence of other types of data - military records and household surveys - which were used as robustness checks to the MSE estimation. Analysis was undertaken with the aims of establishing the extent of completeness in IBC between July 2006 and December 2009 and gaining an understanding of the likely characteristics of those conflict events which are missing. Results found two distinct types of conflict events that are currently missing from the IBC event data. Firstly, MSE estimated around 9,500 conflict events (responsible for 14,200 fatalities) which were missed because of imperfect media reporting. Secondly, a further 6,000 to 8,000 deaths were estimated through comparing results with available military and survey data. These deaths are those which were outside the 'ecosystem' of the news media (i.e. could not have feasibly been reported upon). After discounting around 9,800 fatalities which IBC includes as body count data, the estimated missingness of IBC is estimated to be somewhere between 10,700 and 12,700 deaths. These deaths are predicted as occurring almost exclusively in very small events killing one or two people and mainly caused by gunshot wounds. The results in this section have important implications for those involved in the contested debate over the true cost - in terms of civilian lives - of the Iraq conflict. The results estimated that IBC incorporates between 73% and 77% of civilian fatalities occurring between July 2006 and December 2009 (where deaths documented in IBC as events and those recorded as part of body counts are combined). Although covering a different period, this implied rate of missingness is significantly lower than that claimed by proponents of disputed surveys (e.g. Roberts et al., 2004; Burnham et al., 2006) carried out in Iraq that estimated the number of deaths to be several times higher than the number documented by IBC.

An overall implication of the analysis in Chapter 2 is that for a large, complex, and prolonged conflict, such as Iraq, it is unlikely that any conflict data gathering methodology will be without error or bias. Although the analysis in this thesis has been particularly focussed upon omissions present in media-based datasets, other academic research has found inaccuracies in alternative data types such as military data (Berman, Shapiro, and Felter, 2011) and survey data (Spagat, 2010). This thesis recommends that organisations managing data collection projects should be open and clear about the potential flaws within their data. For example, IBC states on its database website (Iraq Body Count, n.d.(a)) that "gaps in recording and reporting suggest that even our highest totals to date may be missing many civilian deaths from violence". There should also be an onus upon journalists covering conflict to ensure that their reporting of death tolls accurately reflects the level of uncertainty present in such measures. Finally, academic researchers should acknowledge and explore where measurement error, introduced by systematic inaccuracy in the recording of conflict events, may be affecting the results of their studies.

Chapter 3 studied the socio-economic and religious characteristics which determine an individual's likelihood of claiming that terrorism against civilians is a justified act. The study analysed these topics using a larger, richer, dataset than those previously used to study similar questions. The dataset was created through the amalgamation of 11 rounds of Pew's Global Attitudes Survey, combining interviews with 44,393 individuals across five Muslim countries. Analysis was particularly focussed upon the impact of income, education, and religion on support for terrorism. Previous academic studies have painted a weak, inconsistent, picture of the impact of these variables, which has often contrasted with the conventional wisdom. In addition to a substantial increase in the sample size relative to other studies, the chapter also implemented an improved model (e.g. by using a continuous measure of income) to analyse these topics. The main chapter results indicated that there is a strong and consistently negative relationship between income and support for terrorism in Indonesia, Jordan, Lebanon, and Turkey. In Pakistan, support for terrorism increases through the lower half of the income distribution before declining for higher earners. Results on education were found to be mixed; there was no significant relationship between education and support in Indonesia and Lebanon. In Pakistan there was a negative relationship, albeit one that was non-monotonic. However, in Jordan and Turkey results indicated a positive, monotonically increasing, significant relationship between education level and support for terrorism. Religious commitment was generally found to have a negative and statistically significant impact on the extent of justification for terrorism. However, in Lebanon, the relationship is found to be positive where claims of religious commitment are not put into practice in the form of regular prayer. Covariates incorporated within the analysis indicated that unmarried men without children are the most likely group to support terrorism overall. However, this result is far from consistent across countries.

There are several key implications stemming from the analysis in Chapter 3. One such implication is that those individuals claiming that terrorism against civilians is a justified act differ systematically across countries in several ways. These include educational background, age, and gender. Policymakers should not expect that one-size-fits-all policies targeted equally at individuals across a variety of countries will necessarily be effective in suppressing support for extremism. In the present study this is particularly evidenced by results on education where well-intentioned increased funding into education might be expected to lead to a variety of different outcomes, including a rise in support for terrorism in Turkey and Jordan. Overall, poverty reduction should generally be expected to lead to a decrease in support for terrorism, however, the magnitude of this effect varies significantly across countries. Finally, results in the chapter implied that perceived positive links between commitment to Islam and support for terrorism are baseless and, generally, the relationship works in an opposing direction. Politicians and others holding influence should take note of these findings and avoid unsubstantiated rhetoric linking commitment to Islam and terrorism, which is only likely to exacerbate tensions.

The analysis in Chapter 3 also highlighted several areas where further academic research should be carried out. One such area is the application of alternative survey methods (such as list or endorsement experiments) in future analyses aiming to study similar questions. These should be implemented with the purpose of testing whether surveyed individuals answer questions honestly, especially where questions ask for viewpoints on controversial issues such as support for terrorism. Further work should also consider additional variables that may have a causal impact upon support for terrorism. Examples of such variables include the type of schooling (e.g. religious or secular) an individual has received, whether they were raised within a nuclear family unit, and their employment status. Finally, given the discussion above on whether conflict can plausibly be considered as exogenous to media coverage, synergies between chapters 1 and 3 of this thesis should be explored further. In particular, whether excess media attention received by armed groups may elicit sympathy or support for such groups and the attacks they carry out. Chapter 3 has considered those personal characteristics which increase an individual's likelihood of supporting terrorism. A possible omitted variable within this analysis may be the level of exposure that the individuals have had to the media coverage of violent events, particularly 'exotic' events such as suicide attacks known to receive excess coverage. Further work should consider whether the intensity of media coverage of violence an individual is exposed to has a significant causal effect on their likelihood of supporting violence.

Appendices

Appendix A

Framing of a War

A.1 Supplementary Figures and Tables

Figure A.1: Distribution of Coalition Media Group Variable

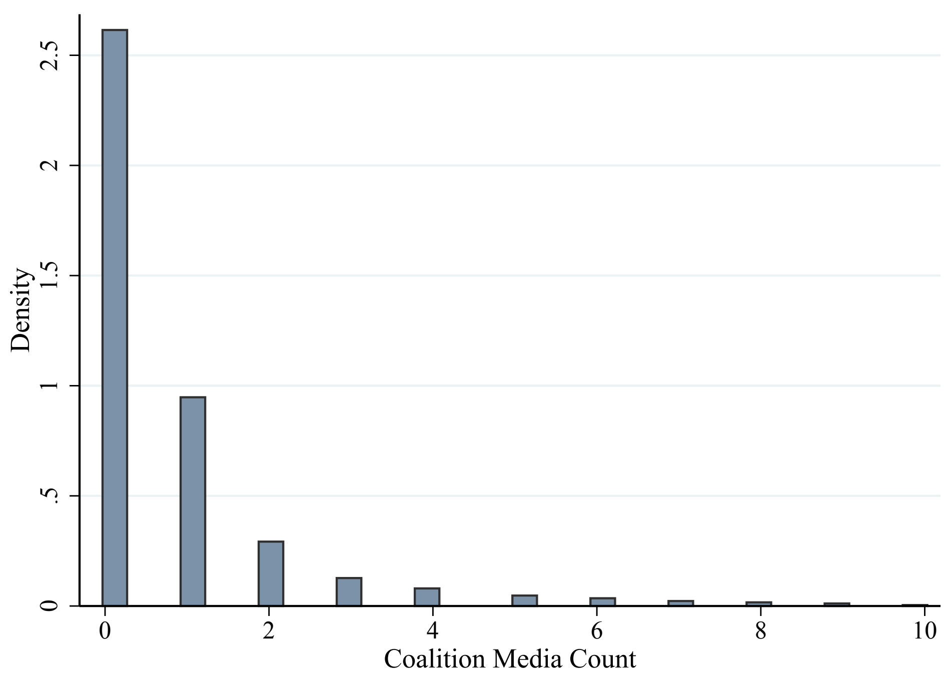


Figure A.2: Distribution of Iraqi Media Group Variable

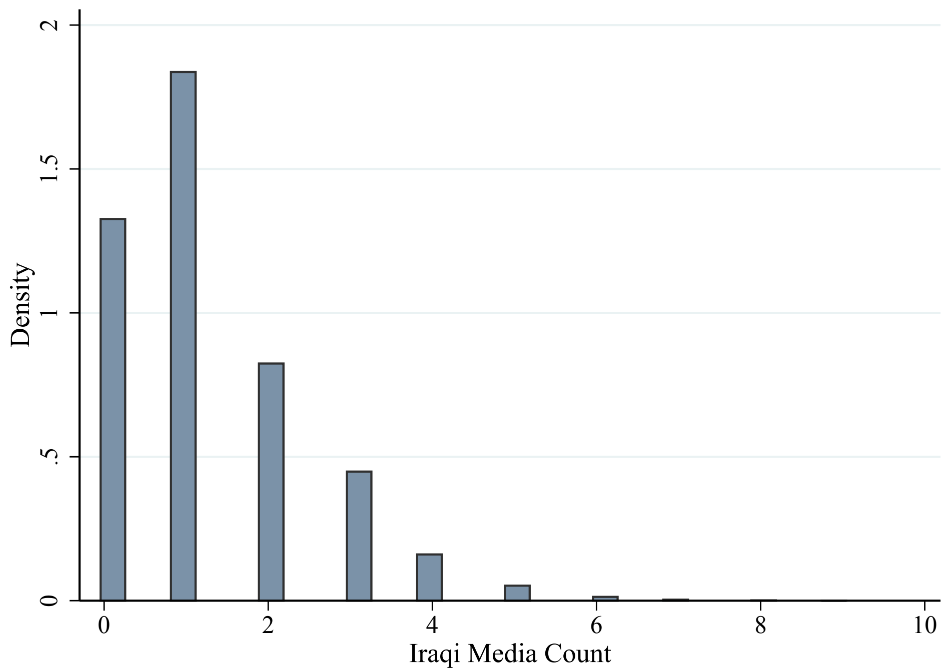


Figure A.3: Distribution of News Agencies Media Group Variable

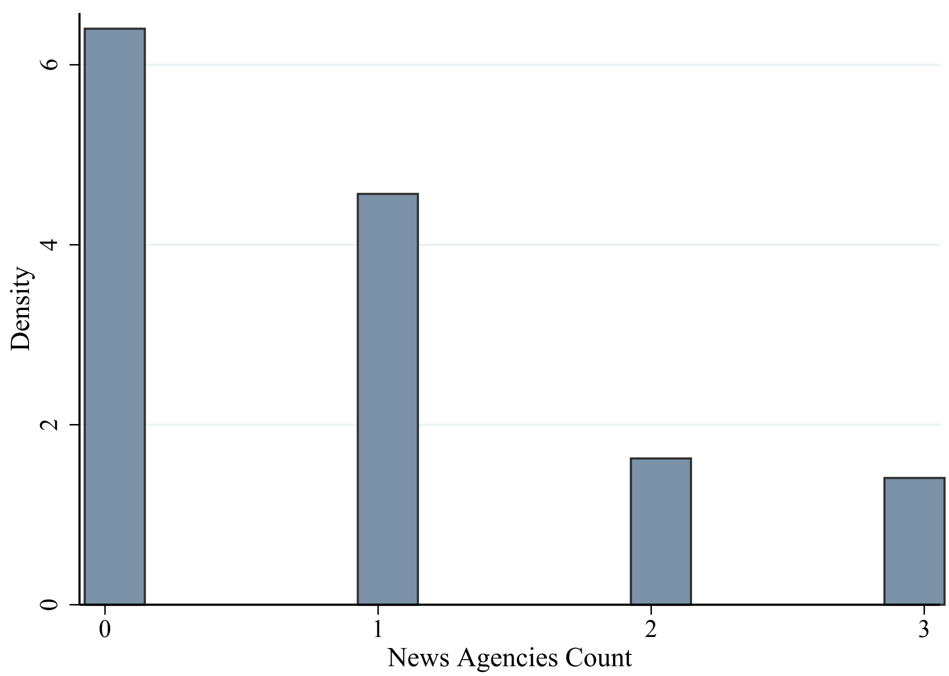


Figure A.4: Reporting of Gunfire and Bombing Attacks by Event Size

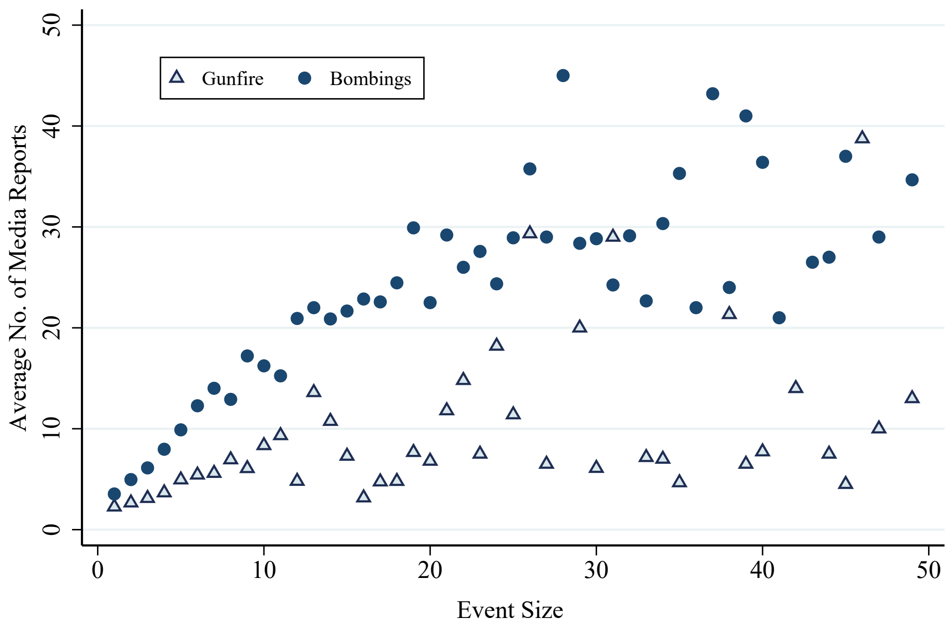


Figure A.5: Reporting Inside and Outside Baghdad by Event Size

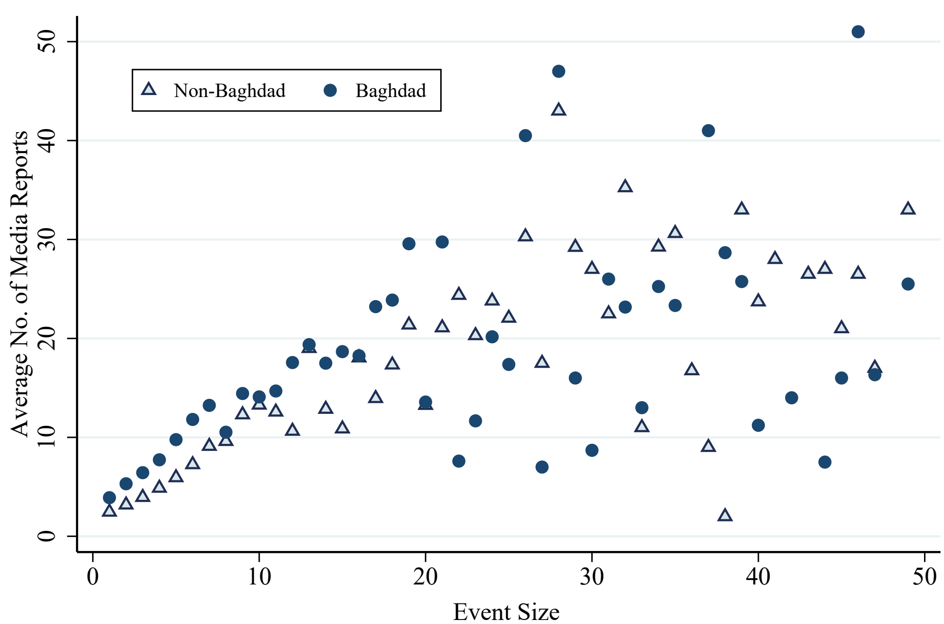
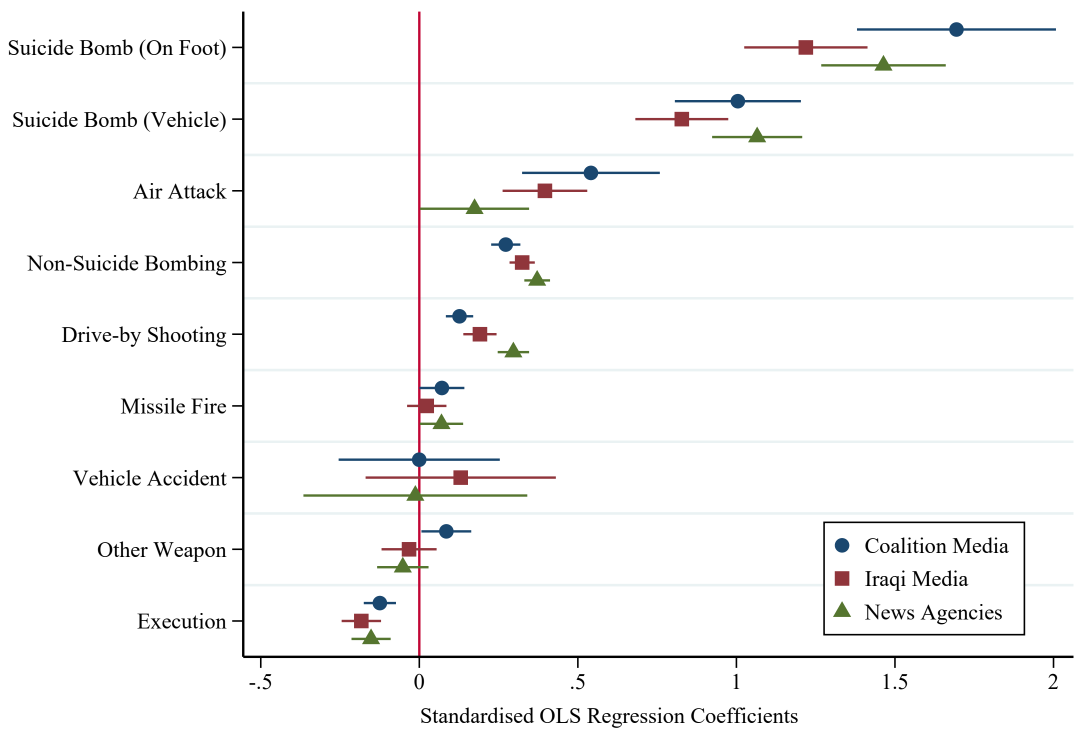


Figure A.6: Standardised OLS Coefficients by Weapon Type (Robust SEs)



Note: CIs at the 95% level and calculated using robust SEs. Regression includes region, time and event size controls. Reference category is gunfire.

Table A.1: Negative Binomial and Standardised OLS Group Comparison (Robust SE)

	Coalition Media		Iraqi Media		News Agencies	
	OLS	NB	OLS	NB	OLS	NB
No. of Fatalities	0.0389***	1.038***	0.0146**	1.007	0.0200***	1.011**
	(0.00833)	(0.00333)	(0.00504)	(0.0223)	(0.00564)	(0.00371)
No. of Injuries	0.00638	1.012***	0.00597**	1.001	0.00452	1.001
	(0.00344)	(0.00217)	(0.00222)	(0.00191)	(0.00248)	(0.00105)
Driving Time from Baghdad[a]	-0.0612***	0.871***	-0.00769	0.990	-0.0568***	0.929***
	(0.00548)	(0.00594)	(0.00441)	(0.0175)	(0.00450)	(0.00544)
Weekend	-0.0645***	0.886***	-0.0431**	0.959**	-0.0475**	0.947**
	(0.0125)	(0.0241)	(0.0149)	(0.0142)	(0.0148)	(0.0171)
Constant	0.341***	0.489***	0.509***	0.690**	0.913***	0.891***
	(0.0412)	(0.0182)	(0.0277)	(0.0849)	(0.0309)	(0.0262)
Alpha		0.635***		0.0291		0.0611***
		(0.0363)		(0.150)		(0.0164)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weapon Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19413	19413	19413	19413	19413	19413
Adjusted R^2	0.371		0.177		0.199	

Robust standard errors in parentheses; Dependent variables standardised in OLS models; NB coefficients given as incidence rate ratios; OLS coefficients in bold for Coalition Media and News Agencies groups indicate significant ($p < 0.01$) differences with Iraqi Media group according to a Wald chi-squared test using stata's 'suest' command; [a] Measured in hours; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Time Trend Robustness Checks (OLS Coefficients Table 1.4)

	Coalition Media		Iraqi Media		News Agencies	
	(1)	(2)	(3)	(4)	(5)	(6)
No. of Fatalities	0.0387***	0.0387***	0.0145**	0.0145**	0.0199***	0.0198***
	(0.00834)	(0.00835)	(0.00505)	(0.00505)	(0.00564)	(0.00567)
No. of Injuries	0.00644	0.00648	0.00601**	0.00603**	0.00454	0.00463
	(0.00343)	(0.00343)	(0.00222)	(0.00221)	(0.00247)	(0.00248)
Baghdad Driving Time	-0.0612***	-0.0580***	-0.00771	-0.00701	-0.0567***	-0.0564***
	(0.00546)	(0.00540)	(0.00440)	(0.00438)	(0.00449)	(0.00447)
Weekend	-0.0646***	-0.0620***	-0.0429**	-0.0438**	-0.0478**	-0.0476**
	(0.0124)	(0.0126)	(0.0149)	(0.0149)	(0.0148)	(0.0148)
Year Dummies	Yes	No	Yes	No	Yes	No
Year Trend		0.172***		0.304***		0.0215
		(0.0116)		(0.0138)		(0.0137)
(Year Trend)^2		-0.0282***		-0.0253***		-0.00888***
		(0.00120)		(0.00149)		(0.00148)
Q2	-0.0406*		-0.0141		-0.0100	
	(0.0179)		(0.0197)		(0.0197)	
Q3	-0.0860***		-0.0376		-0.0388*	
	(0.0182)		(0.0198)		(0.0193)	
Q4	-0.0460*		0.0123		-0.0512*	
	(0.0188)		(0.0207)		(0.0202)	
Constant	0.408***	0.306***	0.522***	0.197***	0.958***	0.849***
	(0.0497)	(0.0438)	(0.0354)	(0.0328)	(0.0384)	(0.0352)
Observations	19413	19413	19413	19413	19413	19413
R^2	0.372	0.359	0.178	0.176	0.200	0.195

Note: Omitted quarter is Q1; Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Zero-Inflated Model Comparison

	Coalition Media	
	NB	ZINB
No. of Fatalities	1.038***	1.028***
	(17.67)	(16.49)
No. of Injuries	1.012***	1.006***
	(13.08)	(8.30)
Driving Time from Baghdad[a]	0.871***	0.906***
	(-21.71)	(-13.77)
Weekend	0.886***	0.939*
	(-4.51)	(-2.18)
Aerial Attack	2.007***	2.563***
	(8.09)	(10.61)
Non-Suicide Bomb	1.759***	1.813***
	(20.07)	(19.36)
Drive-by Shooting	1.432***	1.382***
	(7.43)	(5.95)
Execution	0.758***	0.716***
	(-3.33)	(-3.52)
Missile	1.307***	1.348***
	(5.39)	(5.82)
Other Weapon	1.023	1.373*
	(0.20)	(2.46)
Suicide Bomb (On Foot)	3.576***	3.482***
	(19.32)	(21.40)
Suicide Bomb (Vehicle)	2.887***	2.824***
	(18.68)	(19.97)
Vehicle Accident	0.889	0.820
	(-0.37)	(-0.71)
Constant	0.489***	0.682***
	(-20.46)	(-9.03)
Alpha	0.635***	0.371***
	(-13.40)	(-20.38)
Observations	19413	19413
Pseudo R^2	0.148	

Standard errors in parentheses; NB coefficients are given as incidence rate ratios; Weapon reference category is gunfire; [a]Measured in hours; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: NB Regressions: Coalition Media by Locational Specification (Robust SE)

	(1)	(2)	(3)	(4)
Driving Time from Baghdad[a]	0.871***	0.960***		
	(0.00594)	(0.00800)		
Within Baghdad City		1.797***		
		(0.0561)		
Driving Time from Nearest City[a]			0.825***	1.003
			(0.0137)	(0.0273)
Within Any City				1.445***
				(0.0576)
Constant	0.489***	0.345***	0.427***	0.313***
	(0.0182)	(0.0143)	(0.0158)	(0.0155)
Alpha	0.635***	0.592***	0.680***	0.667***
	(0.0363)	(0.0358)	(0.0376)	(0.0373)
Event Size Controls[b]	Yes	Yes	Yes	Yes
Time Controls[c]	Yes	Yes	Yes	Yes
Weapon Type Controls	Yes	Yes	Yes	Yes
Observations	19413	19413	19413	19413
Pseudo R^2	0.148	0.155	0.141	0.143

Robust standard errors in parentheses; Coefficients are given as incidence rate ratios

[a] Measured in hours; [b] No. of fatalities and injuries; [c]Year and weekend controls;

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: NB Regression: Restricting Sample by Location

	(1) Full Sample	(2) Minus Baghdad[a]	(3) Full Sample	(4) Minus Cities[b]
Driving Time (Baghdad)[c]	0.871***	0.962***		
	(0.00554)	(0.00842)		
Driving Time (Any City)[c]			0.825***	0.993
			(0.0125)	(0.0262)
Constant	0.489***	0.306***	0.427***	0.283***
	(0.0171)	(0.0152)	(0.0149)	(0.0171)
Alpha	0.635***	0.775***	0.680***	0.770***
	(0.0215)	(0.0324)	(0.0223)	(0.0365)
Event Size Controls[d]	Yes	Yes	Yes	Yes
Time Controls[e]	Yes	Yes	Yes	Yes
Weapon Type Controls	Yes	Yes	Yes	Yes
Observations	19413	14867	19413	10580
Pseudo R^2	0.148	0.141	0.141	0.146

Standard errors in parentheses; Coefficients given as incidence rate ratios; [a]Events in Baghdad dropped from sample; [b]Events in Baghdad, Mosul, Basrah, Kirkuk and Erbil dropped; [c]Measured in hours; [d] No. of fatalities and injuries; [e]Year and weekend controls; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6: NB Regression: Locational Specifications 'As-the-Crow-Flies'

	(1)	(2)	(3)	(4)
Distance from Baghdad[a]	0.841***	0.957***		
	(0.00742)	(0.0102)		
Within Baghdad City		1.852***		
		(0.0559)		
Distance from Nearest City[a]			0.750***	0.985
			(0.0179)	(0.0347)
Within Any City				1.423***
				(0.0496)
Constant	0.469***	0.334***	0.420***	0.318***
	(0.0163)	(0.0130)	(0.0146)	(0.0141)
Alpha	0.645***	0.592***	0.683***	0.667***
	(0.0217)	(0.0206)	(0.0224)	(0.0221)
Event Size Controls[b]	Yes	Yes	Yes	Yes
Time Controls[c]	Yes	Yes	Yes	Yes
Weapon Type Controls	Yes	Yes	Yes	Yes
Observations	19413	19413	19413	19413
Pseudo R^2	0.146	0.155	0.141	0.143

Standard errors in parentheses; Coefficients are given as incidence rate ratios;
[a] Measured per 100km 'as the crow flies'; [b] No. of fatalities and injuries;
[c]Year and weekend controls; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Full Results by Weapon Type

	Coalition Media		Iraqi Media		News Agencies	
	OLS	NB	OLS	NB	OLS	NB
Air Attack	0.541***	2.237***	0.396***	1.550***	0.174**	1.347***
	(0.0593)	(0.197)	(0.0677)	(0.0975)	(0.0659)	(0.100)
Non-Suicide Bombing	0.273***	1.797***	0.324***	1.402***	0.372***	1.610***
	(0.0139)	(0.0513)	(0.0159)	(0.0217)	(0.0154)	(0.0308)
Drive-by Shooting	0.127***	1.417***	0.191***	1.213***	0.297***	1.432***
	(0.0237)	(0.0696)	(0.0270)	(0.0324)	(0.0263)	(0.0458)
Execution	-0.124***	0.838*	-0.183***	0.747***	-0.152***	0.827**
	(0.0371)	(0.0701)	(0.0423)	(0.0419)	(0.0412)	(0.0510)
Missile Fire	0.0712*	1.257***	0.0235	1.068	0.0700*	1.180***
	(0.0281)	(0.0634)	(0.0320)	(0.0370)	(0.0312)	(0.0441)
Suicide Bomb (On Foot)	1.694***	4.563***	1.219***	2.626***	1.464***	3.496***
	(0.0476)	(0.304)	(0.0543)	(0.101)	(0.0529)	(0.142)
Suicide Bomb (Vehicle)	1.005***	3.232***	0.828***	2.096***	1.065***	2.754***
	(0.0382)	(0.187)	(0.0436)	(0.0712)	(0.0424)	(0.102)
Vehicle Accident	-0.000307	0.954	0.131	1.258	-0.0125	1.114
	(0.160)	(0.310)	(0.182)	(0.227)	(0.177)	(0.256)
Other Weapon	0.0853	1.187	-0.0323	0.980	-0.0520	0.894
	(0.0172)	(0.0405)	(0.0197)	(0.0174)	(0.0191)	(0.0242)
Constant	0.881***	1.277***	0.663***	0.866***	1.130***	1.101***
	(0.0172)	(0.0405)	(0.0197)	(0.0174)	(0.0191)	(0.0242)
Alpha		0.680***		0.00174		3.29e-11
		(0.0227)		(0.0123)		(.)
Event Size Controls[a]	Yes	Yes	Yes	Yes	Yes	Yes
Regional Controls[b]	Yes	Yes	Yes	Yes	Yes	Yes
Time Controls[c]	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19413	19413	19413	19413	19413	19413
Adjusted R^2	0.366		0.174		0.218	

Standard errors in parentheses; Dependent variables standardised in OLS models; NB coefficients given as incidence rate ratios; Reference category is gunfire; [a]No. of fatalities & injuries; [b]Dummy variables for regions [c]Year trends and weekend controls; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Technical Appendix (Excluded Observations)

The analysis in this chapter has been focused upon the intensity of reporting received by specific conflict events recorded with a wide range of event details. This has involved attempting to remove those events included in the dataset as aggregations of several incidents and therefore with varying amounts of missing information. An example of an aggregation here may be a police report documenting that 30 bodies have been found across Baghdad over a period of time. IBC will also record which (if any) media outlets reported on this police report. Despite not being covered in the same detail as other events, these deaths are still being covered by the media in some way. Also removed from the data were events recorded as lasting more than 2 days due to these events tending to have looser linkages between specific event details. It is important however to acknowledge that the exclusion of long duration events and aggregated reports may have affected results obtained. This Technical Appendix will assess whether overall results are robust to reintroducing such events into the main dataset. The intensity of coverage in the coalition media group is used as the chosen variable for analysis. One point to note again here is that the paper analyses differences in the intensity of media coverage of conflict, rather than whether events were covered at all. This implies that in order to see large changes in the observed coefficients the added events would need to be receiving a substantially different intensity of coverage compared to events with similar compositions already in the dataset.

Technical Appendix Table A.8 presents a series of robustness checks relating to reintegrating the removed aggregations back into the dataset. As there is no information within these aggregations with which to deconstruct them into individual events, they are included as single large entries. To analyse these aggregations required some generalisations over event characteristics. These include, for example, using the mid point of a region where bodies have been found and classing all deaths as gunfire where media

Table A.8: Robustness Checks using NB Model and Coalition Media Group

	Original Data	Robustness Checks		
	(1)	(2)	(3)	(4)
Driving Time to Baghdad[a]	0.871***	0.863***	0.871***	0.849***
	(0.00554)	(0.00527)	(0.00551)	(0.00528)
No. of Fatalities	1.038***	1.041***	1.037***	1.012***
	(0.00219)	(0.00176)	(0.00216)	(0.00170)
No. of Injuries	1.012***	1.011***	1.013***	1.019***
	(0.000944)	(0.000837)	(0.000942)	(0.000920)
Weekend	0.886***	0.903***	0.885***	0.896***
	(0.0238)	(0.0229)	(0.0237)	(0.0232)
Aerial Attack	2.007***	1.889***	1.975***	1.828***
	(0.173)	(0.157)	(0.169)	(0.156)
Non-Suicide Bombing	1.759***	1.701***	1.751***	1.528***
	(0.0495)	(0.0455)	(0.0491)	(0.0419)
Drive-by Shooting	1.432***	1.379***	1.433***	1.284***
	(0.0693)	(0.0652)	(0.0692)	(0.0620)
Execution	0.758***	0.769***	0.751***	0.790**
	(0.0631)	(0.0586)	(0.0599)	(0.0581)
Missile Fire	1.307***	1.243***	1.301***	1.092
	(0.0649)	(0.0597)	(0.0645)	(0.0540)
Suicide Bomb (Foot)	3.576***	3.442***	3.563***	3.510***
	(0.236)	(0.218)	(0.235)	(0.231)
Suicide Bomb (Vehicle)	2.887***	2.800***	2.870***	2.558***
	(0.164)	(0.153)	(0.163)	(0.146)
Vehicle Accident	0.889	0.873	0.883	0.785
	(0.283)	(0.271)	(0.282)	(0.258)
Other Weapon	1.023	0.990	0.961	0.883
	(0.115)	(0.109)	(0.105)	(0.0960)
Constant	0.489***	0.505***	0.491***	0.606***
	(0.0171)	(0.0170)	(0.0171)	(0.0206)
Alpha	0.635***	0.566***	0.639***	0.661***
	(0.0215)	(0.0191)	(0.0215)	(0.0212)
Observations	19413	20026	19654	20272
Pseudo R^2	0.148	0.152	0.148	0.141

Standard errors in parentheses; Coefficients given as incidence rate ratios; [a]Measured in hours
Weapons reference category is gunfire; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

reports say that 'most show signs of gunshot wounds'. Column (1) presents the same negative binomial results using the original data as those presented in Table 1.4 and therefore should be used as a comparison for the other coefficients. Column (2) removes the restriction on events found to have been reported upon as aggregations. As can be observed, there is very little movement in the obtained coefficients. This can be explained by the composition of the observations added here. They are predominantly gunfire and they receive a slightly higher than average intensity of coverage within the coalition media group. However, they are also significantly larger in magnitude than the average event within the data. Therefore, the observed intensity of reporting - taking into account the number of fatalities incurred by these events and that they are mainly caused by gunfire - is roughly at the level predicted by the existing data.

Column (3) tests a second restriction made on the data analysed in the paper by reintroducing previously removed events that have at least some information on location and weapon type with a duration of longer than 2 days. Again, the inclusion of these events is not found to have any significant effect on the coefficients reported in the main paper.

Column (4) tests the effect of simultaneously removing the restrictions on both reporting aggregations and duration. The main consequence of this is the addition of monthly body count figures from the Baghdad morgue from July – October 2006. These enter the database as very large events (300-1000 deaths) denoted as all being caused by gunfire and that received little coverage among western media sources. As expected, adding events of this magnitude which receive a low intensity of coverage diminishes the coefficient on the effect of the number of fatalities on media intensity, though it maintains significance. Coefficients are otherwise very similar to column (1), aside from missile fire no longer holding a significant coverage premium over gunfire events.

Secondly, as an additional robustness check, Technical Appendix Table A.9 compares the coalition media results in Table 1.4 with those of a date restricted sample. This sample includes only events occurring after December 2008. This date was chosen because it roughly splits the sample in half but also because events reported as aggregations within the dataset occur almost exclusively before December 2008. Rerunning these results with the restricted time frame may provide an indication as to whether results are being driven by their inclusion/non-inclusion. It also provides another useful robustness check in ensuring that the results obtained were not being led generally by events at the start of the period. The table shows that restricting the data in this way has little impact upon the regression coefficients. In terms of weapon bias, coefficients are mostly very similar in direction and size with notable differences being that the effect of missiles, aerial attack or execution upon reporting intensity is no longer significantly distinguishable from that of gunfire. The insignificant coefficient on 'aerial attack' is due to only a handful of events of this type occurring after November 2008. One other noticeable change is a strengthening of the coefficients indicating an event size effect within the intensity of coalition media reporting.

Overall, results obtained within the paper have been shown to be very robust to the treatment of removed observations. The inclusion or exclusion of these events may be considered conceptually important in terms of defining what constitutes coverage of an event. However, empirically, their inclusion would have little effect on the impact that event characteristics have upon the intensity of media coverage that events receive.

Table A.9: Impact of Restricting Analysis Time Frame

	Full Sample	Date Restricted Sample
Driving Time to Baghdad[a]	0.871***	0.882***
	(0.00554)	(0.00973)
No. of Fatalities	1.038***	1.058***
	(0.00219)	(0.00636)
No. of Injuries	1.012***	1.017***
	(0.000944)	(0.00216)
Weekend	0.886***	0.781***
	(0.0238)	(0.0399)
Aerial Attack	2.007***	3.66e-19
	(0.173)	(9.94e-10)
Non-Suicide Bombing	1.759***	1.705***
	(0.0495)	(0.0871)
Drive-by Shooting	1.432***	1.351***
	(0.0693)	(0.117)
Execution	0.758***	0.835
	(0.0631)	(0.185)
Missile Fire	1.307***	1.085
	(0.0649)	(0.179)
Suicide Bomb (Foot)	3.576***	3.455***
	(0.236)	(0.468)
Suicide Bomb (Vehicle)	2.887***	3.095***
	(0.164)	(0.377)
Vehicle Accident	0.889	0.711
	(0.283)	(0.419)
Other Weapon	1.023	0.746
	(0.115)	(0.138)
Constant	0.489***	0.128***
	(0.0171)	(0.00891)
Alpha	0.635***	0.985
	(0.0215)	(0.0533)
Observations	19413	9635
Pseudo R^2	0.148	0.162

Standard errors in parentheses; Coefficients given as incidence rate ratios; Weapons reference category is gunfire; Date restricted sample covers events after Nov 2008; [a]Measured in hours; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.3 Interview Transcript

Electronic Communication with Iain Overton (1st February 2019)

Nathan Woolley: *Iain, as a journalist who has previously reported on various conflicts worldwide, what patterns have you observed in the newsworthiness of particular conflict events? Why do you believe that certain types of events receive disproportionate levels of media attention?*

Iain Overton: When innovations in explosive materials emerged in the late 19th century, revolutionaries from New York to Paris to St Petersburg were enthralled by the notion that societal change could be achieved through a carefully placed bomb. Inherent in this was the belief that the 'propaganda of the deed' - where an explosive charge was far more 'newsworthy' than an assassin's bullet - would ignite social revolt. The first suicide bomber targeted the Tsar of Russia in 1871, and since that time explosive weapons have garnered great media attention.

Today, hierarchies of reporting exist within explosive violence use. Suicide bombs get the most attention, followed by 'prohibited' weapons such as cluster munitions and landmines. Certain explosive weapons - such as hand grenades - barely register in conflict zones, although they would gain huge attention if used in a European city. The location and type of weapon, alongside who is targeted and the number of victims, all play a part. A mortar that kills ten schoolgirls in Afghanistan will get more traction than the same weapon if it killed ten adult, male agricultural labourers. A suicide bomber in a Western city will get as much coverage as a school mass shooter in the United States. The degree to which a story gets coverage is also influenced by other factors. War reporting fatigue means that the longer a conflict goes on, the more people have to die in a 'spectacular way' to merit meaningful coverage. The quality of the footage emerging from an event, the number of accredited journalists on the ground, the dominance of other news stories on the day, and the wider context of interest (i.e. Syria is more covered than Nigeria, for example), all dictate how many inches or minutes a report might be given. Explosive weapons in a conflict zone trump small arms, but small arms in a developed nation trump explosive weapons in a conflict zone. Within explosive weapons, the hierarchy of reporting appears to be: nuclear weapons, suicide attacks, air-strikes (with cluster munitions leading that sub-type), ground-to-ground weapons, landmines, ground-to-airs, hand-held.

Appendix B

Assessing the Completeness of Media Based Datasets

B.1 Supplementary Figures and Tables

Figure B.1: Relative Fatality Completeness over Time

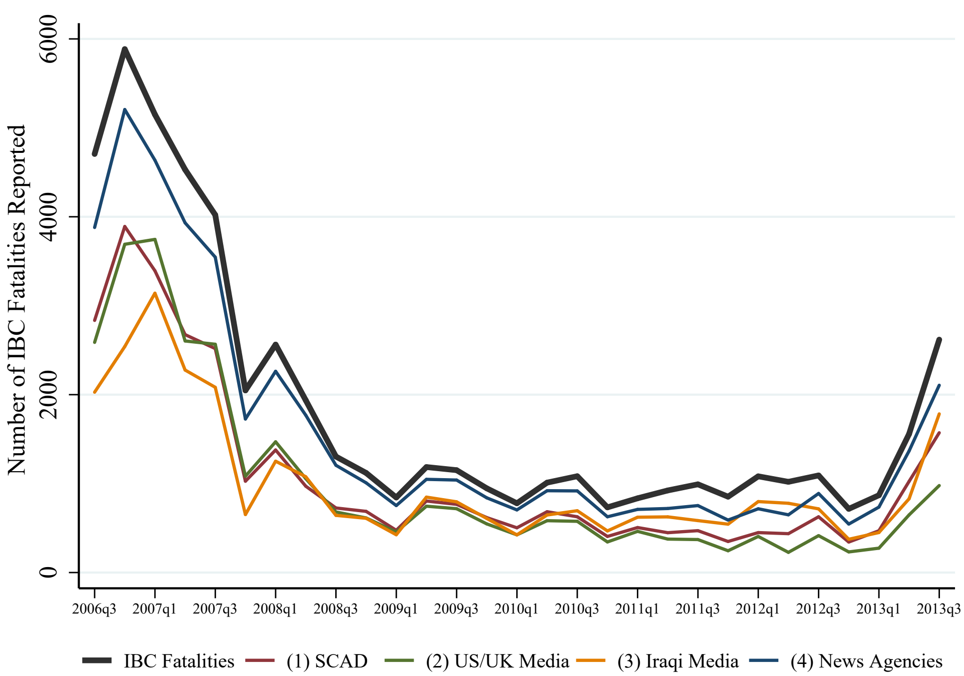


Figure B.2: Weapon Deaths Composition by Pseudo Dataset

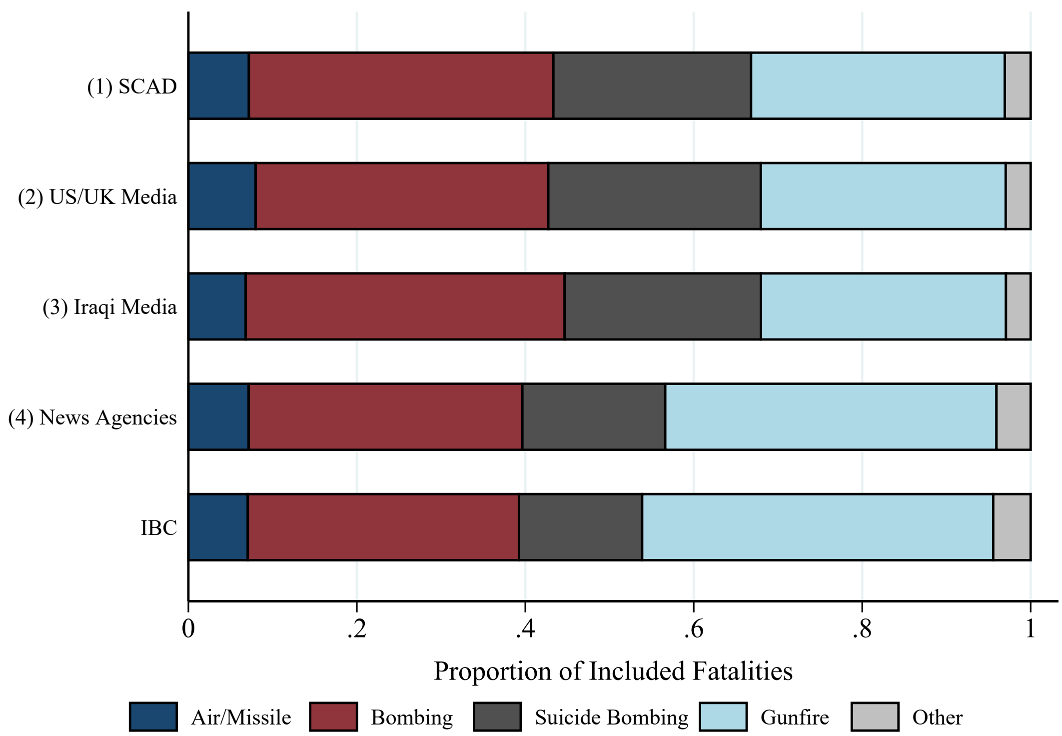


Figure B.3: No. of Events by Event Size

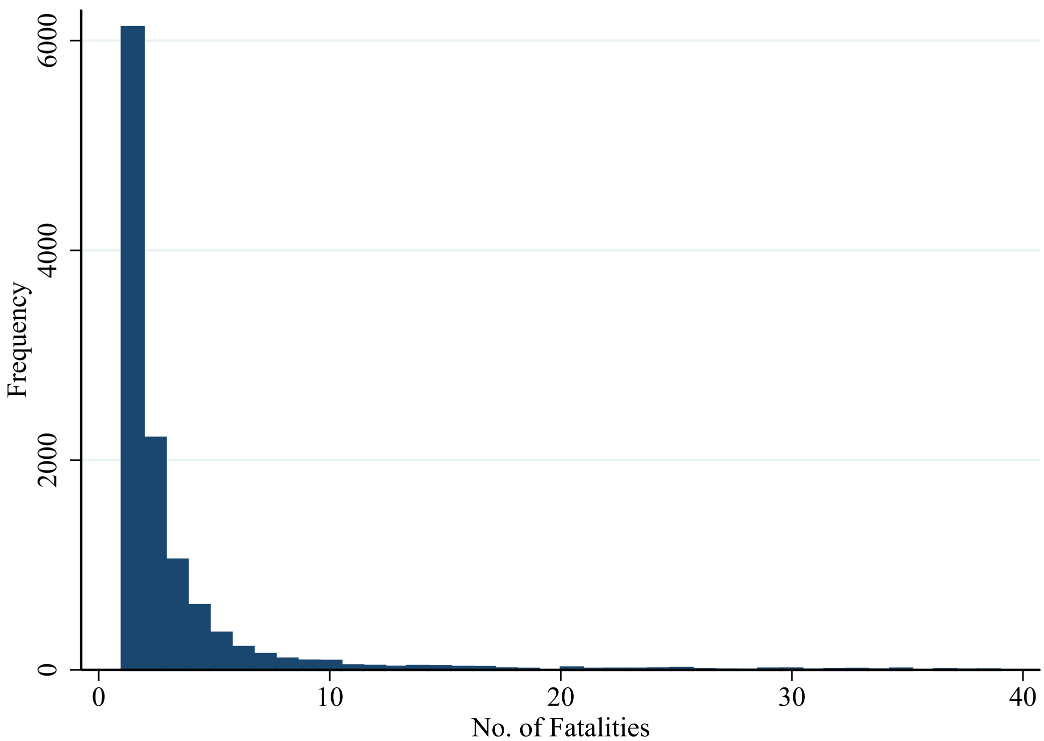


Table B.1: Time Trend Robustness Checks for Table 2.2

	(1) SCAD		(2) US/UK Media		(3) Iraqi Media		(4) News Agencies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of Fatalities	0.00730***	0.00685***	0.00842***	0.00860***	0.00542***	0.00526***	0.000905	0.00115
	(0.00182)	(0.00182)	(0.00194)	(0.00195)	(0.00155)	(0.00154)	(0.000767)	(0.000767)
No. of Injuries	0.00117	0.00131	0.00110	0.00105	0.00124	0.00129	0.000951**	0.000880*
	(0.000784)	(0.000786)	(0.000813)	(0.000819)	(0.000676)	(0.000676)	(0.000361)	(0.000360)
Baghdad Driving Time	-0.0385***	-0.0363***	-0.0338***	-0.0339***	-0.00666***	-0.00596**	-0.00954***	-0.0107***
	(0.00191)	(0.00191)	(0.00179)	(0.00180)	(0.00194)	(0.00196)	(0.00168)	(0.00169)
Weekend	-0.0354***	-0.0356***	-0.0249***	-0.0247***	-0.0246**	-0.0248**	0.00145	0.00159
	(0.00737)	(0.00734)	(0.00653)	(0.00654)	(0.00780)	(0.00780)	(0.00702)	(0.00700)
Air/Missile	0.0301	0.0256	0.0564***	0.0607***	0.0517***	0.0487**	-0.00942	-0.00646
	(0.0159)	(0.0159)	(0.0156)	(0.0156)	(0.0157)	(0.0157)	(0.0137)	(0.0136)
Bombing	0.138***	0.143***	0.130***	0.128***	0.0979***	0.0995***	0.0324***	0.0294***
	(0.00892)	(0.00890)	(0.00829)	(0.00833)	(0.00892)	(0.00892)	(0.00739)	(0.00738)
Suicide Bombing	0.407***	0.410***	0.398***	0.399***	0.283***	0.283***	0.145***	0.144***
	(0.0259)	(0.0259)	(0.0274)	(0.0276)	(0.0242)	(0.0242)	(0.0127)	(0.0127)
Other Weapon	-0.0739***	-0.0715***	-0.0529***	-0.0504***	-0.0584***	-0.0575***	-0.0411*	-0.0424*
	(0.0140)	(0.0140)	(0.0130)	(0.0131)	(0.0155)	(0.0155)	(0.0165)	(0.0165)
Year Trend	-0.00934***	-0.0836***	-0.0376***	-0.0252***	0.0397***	0.0145*	-0.0162***	0.0257***
	(0.00142)	(0.00689)	(0.00119)	(0.00606)	(0.00149)	(0.00712)	(0.00134)	(0.00619)
(Year Trend)^2		0.00817***		-0.00128*		0.00275***		-0.00459***
		(0.000741)		(0.000638)		(0.000774)		(0.000673)
Q2	0.0149		-0.0572***		-0.0117		-0.00764	
	(0.00948)		(0.00874)		(0.0102)		(0.00904)	
Q3	0.0323***		-0.0747***		0.0101		-0.0160	
	(0.00898)		(0.00831)		(0.00958)		(0.00843)	
Q4	0.0182		-0.0766***		0.00733		-0.0204*	
	(0.00940)		(0.00864)		(0.0100)		(0.00889)	
Constant	0.367***	0.498***	0.460***	0.382***	0.178***	0.219***	0.846***	0.770***
	(0.0133)	(0.0153)	(0.0134)	(0.0147)	(0.0129)	(0.0146)	(0.0102)	(0.0123)
Observations	19413	19413	19413	19413	19413	19413	19413	19413
R^2	0.123	0.128	0.180	0.176	0.087	0.087	0.023	0.025

Note: Omitted weapon type is gunfire, omitted quarter is Q1; Robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.2: LCM MSE Estimation Stratified by Event Size

Event Size	IBC		MSE Estimate	
	Events	Deaths	Events	Deaths
1	6,129	6,129	8,724 [7,966, 10,330]	8,724 [7,966, 10,330]
2-3	3,264	7,579	4,162 [3,745, 5,170]	9,664 [8,696, 12,005]
4-9	1,536	8,255	1,907 [1,709, 2,334]	10,249 [9,185, 12,544]
10-19	347	4,558	328 [320, 345]	4,308 [4,203, 4,532]
20+	258	10,872	256 [251, 270]	10,788 [10,577, 11,378]
Total	11,534	37,393	15,377 [13,991, 18,449]	43,733 [40,627, 50,789]

Note: 95% Confidence Intervals in parentheses.

Table B.3: Event Size and Weapon Stratification Breakdown

		Gunfire	Bombing	Suicide Bombing	Driveby Shooting	Air/ Missile	Other
1	IBC	3291	1534	126	505	394	279
	% IBC	53.70%	25.03%	2.06%	8.24%	6.43%	4.55%
	MSE	5193.39	1681.90	114.04	658.68	486.57	346.81
	% MSE	61.23%	19.83%	1.34%	7.77%	5.74%	4.09%
2-3	IBC	1557	911	138	158	339	161
	% IBC	47.70%	27.91%	4.23%	4.84%	10.39%	4.93%
	MSE	2088.70	937.08	143.62	176.49	349.12	228.99
	% MSE	53.23%	23.88%	3.66%	4.50%	8.90%	5.84%
4-9	IBC	672	391	156	34	185	98
	% IBC	43.75%	25.46%	10.16%	2.21%	12.04%	6.38%
	MSE	846.69	363.26	162.90	41.68	191.30	184.15
	% MSE	47.30%	20.29%	9.10%	2.33%	10.69%	10.29%
10-19	IBC	122	92	65	5	44	19
	% IBC	35.16%	26.51%	18.73%	1.44%	12.68%	5.48%
	MSE	115.12	91.52	64.10	4.00	41.20	15.00
	% MSE	34.79%	27.65%	19.37%	1.21%	12.45%	4.53%
20+	IBC	103	46	80	0	13	16
	% IBC	39.92%	17.83%	31.01%	0.00%	5.04%	6.20%
	MSE	104.61	46.00	80.02	0.00	13.00	13.00
	% MSE	40.76%	17.92%	31.18%	0.00%	5.07%	5.07%
Overall	IBC	5745	2974	565	702	975	573
	% IBC	49.81%	25.78%	4.90%	6.09%	8.45%	4.97%
	MSE	8348.50	3119.75	564.68	880.85	1081.19	787.95
	% MSE	56.47%	21.10%	3.82%	5.96%	7.31%	5.33%

Table B.4: **Full IBC+SIGACTS Matching Comparison**

Event Size		LB	Estimate	UB
1	IBC+SIGACTS	14534	16233	17932
	Model Based MSE	10980	12807	14634
	LCM Estimation	7966	8724	10330
2-3	IBC+SIGACTS	4703	5049	5394
	Model Based MSE	4835	5772	6709
	LCM Estimation	3745	4162	5170
4-9	IBC+SIGACTS	1715	1848	1990
	Model Based MSE	1745	1878	2011
	LCM Estimation	1709	1907	2334
10-19	IBC+SIGACTS	350	366	382
	Model Based MSE	320	332	344
	LCM Estimation	320	328	345
20+	IBC+SIGACTS	260	260	260
	Model Based MSE	251	259	267
	LCM Estimation	251	256	270

Appendix C

Who Supports Terrorism?

C.1 Supplementary Figures and Tables

Figure C.1: Support for Suicide Bombing over Time by Gender

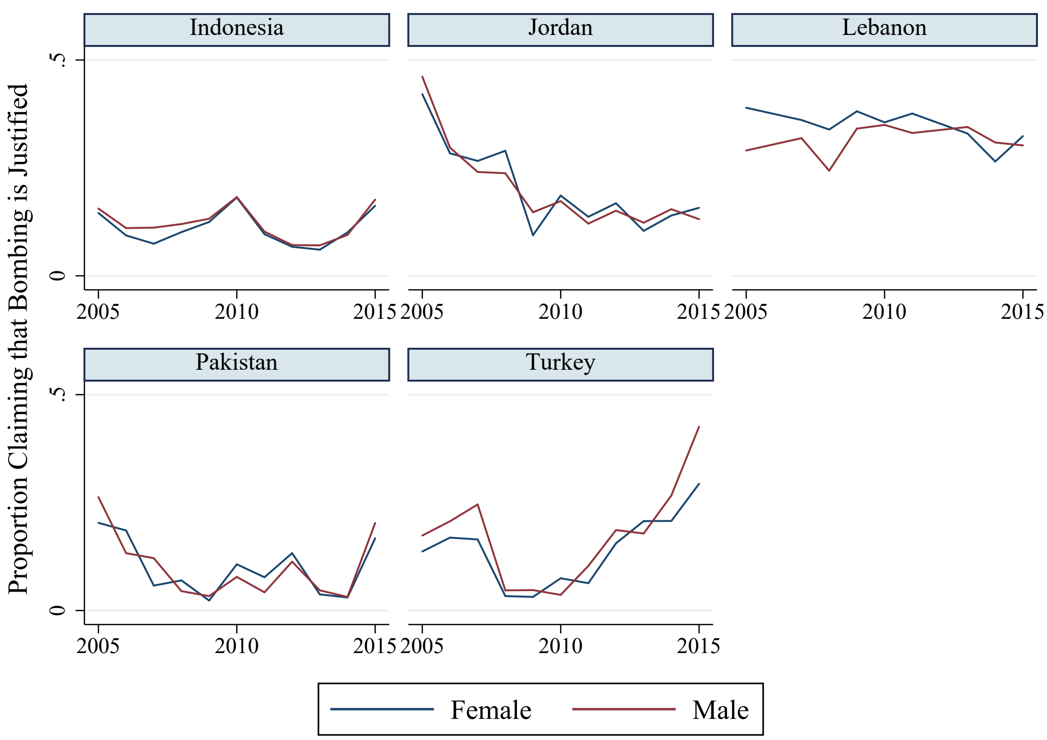


Figure C.2: Support for Suicide Bombing over Time by Age

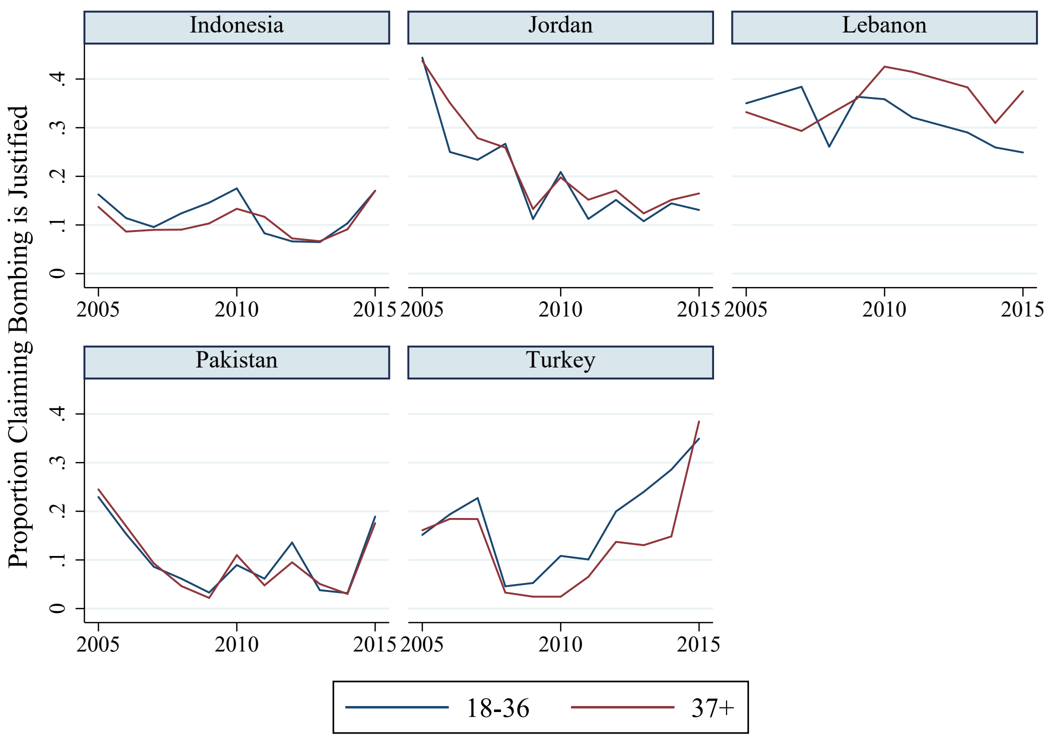


Table C.1: Comparing Dropped Observations

		Did Not Answer Question	
	Full Sample	Terrorism Support	Dissatisfaction
Below Primary	0.240	0.340†	0.345
Primary Education	0.326	0.333	0.328
Secondary Education	0.295	0.232†	0.221
Higher Education	0.140	0.095†	0.106
Income Level[a]	2.627	2.393†	2.524
Male	0.506	0.438†	0.426
Married	0.707	0.707	0.713
Age	36.246	36.463	36.588
No. of Children	2.188	2.276†	2.436*
N	44,393	2,439	1,061

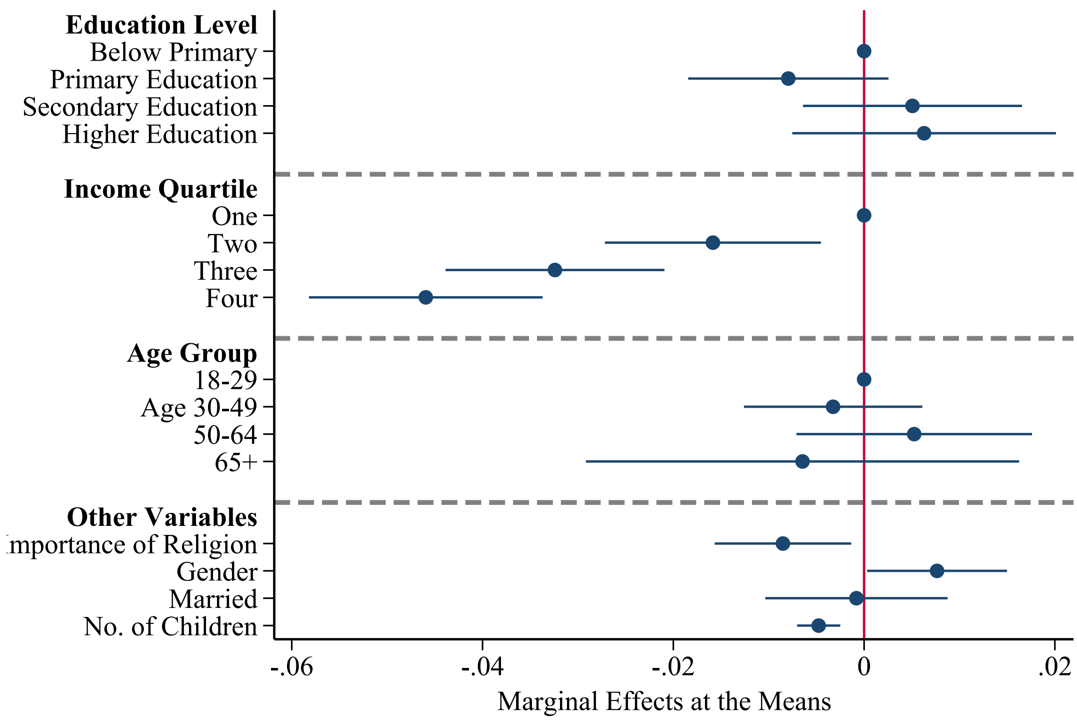
[a]Income measured in 100's 2005 USD deflated by OECD measure; † Significant ($p < 0.05$) difference with full sample; * Significant ($p < 0.05$) difference with those who did not answer terrorism question

Table C.2: **Full Results and Alternative Specifications of Figure 3.8**

	Ordinal Dependent Variable		Binary Dependent Variable	
	OProbit	OLS	Probit (MEM)	OLS
Primary Education	-0.0585***	-0.0344***	-0.00794	-0.00685
	(0.0187)	(0.0125)	(0.00536)	(0.00538)
Secondary Education	-0.0198	-0.00595	0.00507	0.00608
	(0.0200)	(0.0134)	(0.00586)	(0.00576)
Higher Education	-0.0260	-0.0113	0.00629	0.00641
	(0.0240)	(0.0164)	(0.00705)	(0.00706)
Income Q2	-0.0229	-0.0234*	-0.0158***	-0.0159***
	(0.0188)	(0.0126)	(0.00578)	(0.00543)
Income Q3	-0.0587***	-0.0507***	-0.0324***	-0.0316***
	(0.0195)	(0.0131)	(0.00586)	(0.00563)
Income Q4	-0.0970***	-0.0820***	-0.0459***	-0.0478***
	(0.0215)	(0.0144)	(0.00625)	(0.00620)
Importance of Religion	-0.0522***	-0.0304***	-0.00851**	-0.00800**
	(0.0128)	(0.00899)	(0.00365)	(0.00387)
Gender	0.0436***	0.0262***	0.00765**	0.00676*
	(0.0129)	(0.00866)	(0.00374)	(0.00373)
Married	0.00198	0.00125	-0.000803	-0.000586
	(0.0169)	(0.0113)	(0.00487)	(0.00487)
No. of Children	-0.00764*	-0.00782***	-0.00476***	-0.00500***
	(0.00396)	(0.00258)	(0.00115)	(0.00111)
Constant		0.725***		0.238***
		(0.0411)		(0.0177)
Cut 1	0.168***			
Cut 2	0.736***			
Cut 3	1.464***			
Regional Controls	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes
Age Group Controls	Yes	Yes	Yes	Yes
Pseudo R^2 / R^2	0.045	0.080		0.047
N	38409	38409	38409	38409

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure C.3: Probit Marginal Effects Regression: Justification for Suicide Bombing



Note: Confidence Intervals are calculated at the 95% level; Includes Regional and Year Controls; n=38409.

Table C.3: Marginal Effects Probit Regressions on Justification for Suicide Attacks by Country

	Indonesia		**Jordan**		**Lebanon**		**Pakistan**		**Turkey**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Education										
Primary	-0.0175	-0.00489	0.0230*	0.0119	0.00258	-0.00429	-0.0135*	-0.0183**	0.00741	0.0184
	(0.0140)	(0.0152)	(0.0121)	(0.0135)	(0.0242)	(0.0276)	(0.00802)	(0.00823)	(0.0160)	(0.0178)
Secondary	-0.0148	0.00822	0.0251**	0.0210	0.0353	0.0439	-0.000947	-0.00389	0.0265	0.0314
	(0.0143)	(0.0161)	(0.0125)	(0.0143)	(0.0256)	(0.0292)	(0.00849)	(0.00889)	(0.0180)	(0.0203)
Higher	-0.00363	0.0553*	0.0603***	0.0485***	-0.0112	-0.0000401	-0.0166	-0.0248**	0.0316	0.0271
	(0.0213)	(0.0288)	(0.0147)	(0.0163)	(0.0254)	(0.0289)	(0.0115)	(0.0107)	(0.0214)	(0.0243)
Income										
HH Income[a]	-0.00310	-0.0680***	-0.0257***	-0.0176***	-0.00649**	-0.00434	0.0129	0.0611***	-0.00791***	-0.00417
	(0.00549)	(0.0185)	(0.00423)	(0.00479)	(0.00268)	(0.00363)	(0.0126)	(0.0138)	(0.00218)	(0.00394)
(HH Income)^2	0.000180	0.0122**	0.000987***	0.000751***	0.000103	-0.0000755	-0.00283	-0.0110**	0.0000798	-0.00000410
	(0.000164)	(0.00485)	(0.000227)	(0.000268)	(0.0000754)	(0.000121)	(0.00374)	(0.00451)	(0.0000556)	(0.000191)
Religion										
Importance		-0.0200		-0.0240**		0.0703***		-0.0475***		-0.0285***
		(0.0127)		(0.00986)		(0.0129)		(0.00777)		(0.00853)
Prays Daily		-0.0270*		-0.0208		-0.0289		-0.0168**		0.00586
		(0.0152)		(0.0129)		(0.0183)		(0.00688)		(0.0118)
Controls[b]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8447	5776	8504	5587	4745	3610	9208	6637	6547	4235
Pseudo R^2	0.012	0.019	0.050	0.028	0.014	0.031	0.025	0.056	0.045	0.069

Standard errors in parentheses; Omitted Education category is 'Below Primary'; [a] Equivalent household income measured in 100's of USD; [b] Controls are gender, marital status, no. of children, age, country dissatisfaction plus regional FE and year trends;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Ordered Probit Regressions by Country and Income Quartile

	Indonesia		Jordan		Lebanon		Pakistan		Turkey	
	IQ1/IQ2	IQ3/IQ4	IQ1/IQ2	IQ3/IQ4	IQ1/IQ2	IQ3/IQ4	IQ1/IQ2	IQ3/IQ4	IQ1/IQ2	IQ3/IQ4
Education										
Primary	-0.0425	0.117	-0.0198	0.00759	-0.0392	-0.0213	-0.151**	-0.0424	0.0158	0.376**
	(0.0781)	(0.122)	(0.0562)	(0.0704)	(0.0835)	(0.112)	(0.0747)	(0.0756)	(0.0982)	(0.156)
Secondary	-0.0183	0.0876	-0.0489	0.141**	0.0352	0.195*	-0.0370	-0.0343	0.102	0.399**
	(0.0853)	(0.122)	(0.0672)	(0.0641)	(0.0920)	(0.109)	(0.0834)	(0.0691)	(0.116)	(0.164)
Higher	0.153	0.171	0.0577	0.137**	-0.0129	0.0749	0.383**	-0.267***	0.124	0.449***
	(0.204)	(0.149)	(0.0792)	(0.0650)	(0.0970)	(0.107)	(0.167)	(0.0907)	(0.179)	(0.172)
Income										
HH Income[a]	-0.369	-0.123	0.0364	-0.0383**	-0.0824	-0.0163	-1.642*	0.320**	-0.308*	-0.0130
	(0.735)	(0.123)	(0.314)	(0.0195)	(0.0877)	(0.0123)	(0.924)	(0.133)	(0.163)	(0.0211)
(HH Income)^2	0.240	0.0206	-0.0719	0.00178*	0.00827	-0.00000792	4.866**	-0.0534	0.0652*	0.00000328
	(0.806)	(0.0277)	(0.131)	(0.000981)	(0.0120)	(0.000308)	(2.043)	(0.0364)	(0.0380)	(0.000844)
Religion										
Importance	-0.226***	-0.171**	-0.0906*	-0.0493	0.0818*	0.193***	-0.383***	-0.400***	-0.144**	-0.130***
	(0.0761)	(0.0714)	(0.0468)	(0.0425)	(0.0466)	(0.0394)	(0.0684)	(0.0759)	(0.0559)	(0.0483)
Prays Daily	-0.171*	-0.109	-0.0373	0.105*	-0.151**	-0.121**	-0.0515	-0.0261	-0.0486	-0.0179
	(0.0880)	(0.0940)	(0.0565)	(0.0579)	(0.0634)	(0.0583)	(0.0658)	(0.0597)	(0.0674)	(0.0717)
Controls[b]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cut 1	-0.861**	-0.282	-0.699**	-0.0927	-0.225	-0.0186	-0.582*	-0.290	0.381	0.634**
Cut 2	-0.394	0.320	0.150	0.869***	0.353	0.590***	-0.202	0.0650	0.782**	1.125***
Cut 3	0.283	1.074***	0.912***	1.577***	1.296***	1.431***	0.248	0.484	1.557***	1.984***
Observations	2772	3004	2728	2859	1614	1996	3156	3481	2127	2108
Pseudo R^2	0.014	0.008	0.014	0.009	0.008	0.026	0.044	0.024	0.047	0.058

Standard errors in parentheses; Omitted Education category is ‘Below Primary’; [a] Equivalent household income measured in 100’s of USD; [b] Controls are gender, marital status, no. of children, age, country dissatisfaction plus regional FE and year trends;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Indonesia Ordered Probit Replication/Expansion Regressions

	2005 Replication		2005-2015 Data	
Primary Education	-0.004	-0.007	-0.0650	-0.0612
	(0.149)	(0.148)	(0.0542)	(0.0542)
Secondary Education	-0.199	-0.204	-0.103*	-0.0963*
	(0.153)	(0.152)	(0.0559)	(0.0560)
Higher Education	-0.717***	-0.726***	-0.0972	-0.0843
	(0.292)	(0.291)	(0.0836)	(0.0838)
Income Quartile 2	0.064	0.063	0.0472	0.0441
	(0.138)	(0.138)	(0.0421)	(0.0421)
Income Quartile 3	-0.086	-0.087	0.0168	0.0116
	(0.135)	(0.135)	(0.0422)	(0.0422)
Income Quartile 4	0.134	0.132	0.0185	0.0126
	(0.142)	(0.143)	(0.0460)	(0.0461)
Dissatisfaction		0.019		-0.105***
		(0.064)		(0.0295)
Male	0.094	0.093	0.0688**	0.0700**
	(0.093)	(0.093)	(0.0286)	(0.0286)
Age 18 to 29	0.608***	0.609***	0.216***	0.217***
	(0.164)	(0.163)	(0.0479)	(0.0480)
Age 30 to 49	0.553***	0.553***	0.180***	0.182***
	(0.150)	(0.150)	(0.0443)	(0.0444)
Married	-0.039	-0.036	-0.0385	-0.0417
	(0.137)	(0.136)	(0.0370)	(0.0371)
No. of Children	0.064**	0.062**	-0.00488	-0.00503
	(0.042)	(0.042)	(0.0143)	(0.0143)
Cut1	0.998 ***	1.016***	0.643***	0.572***
	(0.237)	(0.241)	(0.114)	(0.116)
Cut2	1.554***	1.573***	1.196***	1.125***
	(0.238)	(0.242)	(0.114)	(0.116)
Cut3	2.569***	2.587***	1.964***	1.895***
	(0.252)	(0.263)	(0.117)	(0.119)
Year Trend	N/A	N/A	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	767	767	8447	8447
Pseudo R^2	0.031	0.031	0.004	0.005

Omitted categories: Below Primary Education, Income Quartile 1 and Age 50+; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: Jordan Ordered Probit Replication/Expansion Regressions

	2005 Replication		2005-2015 Data	
Primary Education	0.198*	0.206	0.0298	0.0291
	(0.111)	(0.110)	(0.0355)	(0.0355)
Secondary Education	0.359***	0.366***	0.0723**	0.0705**
	(0.116)	(0.116)	(0.0354)	(0.0356)
Higher Education	0.293*	0.327*	0.127***	0.124***
	(0.176)	(0.173)	(0.0385)	(0.0387)
Income Quartile 2	-0.156	-0.183	-0.0638*	-0.0638*
	(0.114)	(0.114)	(0.0361)	(0.0361)
Income Quartile 3	-0.290**	-0.285**	-0.0862**	-0.0869**
	(0.128)	(0.127)	(0.0376)	(0.0377)
Income Quartile 4	-0.562***	-0.535***	-0.238***	-0.239***
	(0.144)	(0.150)	(0.0413)	(0.0413)
Dissatisfaction		0.251***		-0.0170
		(0.063)		(0.0252)
Male	0.040	0.036	0.0307	0.0303
	(0.072)	(0.073)	(0.0246)	(0.0246)
Age 18 to 29	-0.429***	-0.440***	-0.0753*	-0.0752*
	(0.147)	(0.146)	(0.0411)	(0.0411)
Age 30 to 49	-0.166	-0.172	-0.0670*	-0.0674*
	(0.103)	(0.104)	(0.0344)	(0.0344)
Married	-0.219**	-0.215**	0.110***	0.109***
	(0.109)	(0.107)	(0.0338)	(0.0338)
No. of Children	-0.115***	-0.111***	-0.0121	-0.0121
	(0.028)	(0.028)	(0.00827)	(0.00827)
Cut1	-1.133***	-0.825 ***	-0.501***	-0.509***
	(0.158)	(0.173)	(0.0661)	(0.0671)
Cut2	-0.409***	-0.097	0.348***	0.340***
	(0.154)	(0.169)	(0.0663)	(0.0671)
Cut3	0.658***	0.988***	1.173***	1.165***
	(0.149)	(0.165)	(0.0664)	(0.0671)
Year Trend	N/A	N/A	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	887	887	8504	8504
Pseudo R^2	0.015	0.022	0.019	0.019

Omitted categories: Below Primary Education, Income Quartile 1 and Age 50+;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: Lebanon Ordered Probit Replication/Expansion Regressions

	2005 Replication		2005-2015 Data	
Primary Education	-0.145	-0.177	-0.0363	-0.0362
	(0.195)	(0.197)	(0.0577)	(0.0578)
Secondary Education	-0.139	-0.189	0.0410	0.0414
	(0.213)	(0.212)	(0.0612)	(0.0612)
Higher Education	-0.271	-0.343	-0.0866	-0.0832
	(0.260)	(0.260)	(0.0607)	(0.0608)
Income Quartile 2	-0.028	0.028	-0.000408	-0.00392
	(0.168)	(0.169)	(0.0484)	(0.0484)
Income Quartile 3	0.104	0.125	-0.0881*	-0.0900*
	(0.176)	(0.174)	(0.0475)	(0.0476)
Income Quartile 4	-0.052	-0.038	-0.114**	-0.119**
	(0.221)	(0.219)	(0.0508)	(0.0508)
Dissatisfaction		0.299***		-0.118**
		(0.072)		(0.0497)
Male	-0.111	-0.136	-0.0284	-0.0299
	(0.114)	(0.115)	(0.0324)	(0.0324)
Age 18 to 29	0.185	0.192	-0.107**	-0.108**
	(0.178)	(0.181)	(0.0533)	(0.0533)
Age 30 to 49	0.239	0.218	-0.0900**	-0.0875*
	(0.160)	(0.159)	(0.0449)	(0.0449)
Married	-0.141	-0.128	0.0172	0.0158
	(0.143)	(0.145)	(0.0400)	(0.0400)
No. of Children	-0.106*	-0.098*	-0.0129	-0.0136
	(0.057)	(0.055)	(0.0164)	(0.0164)
Cut1	-0.635***	-0.302	-0.504***	-0.587***
	(0.212)	(0.225)	(0.0976)	(0.104)
Cut2	0.112	0.457**	0.101	0.0187
	(0.210)	(0.223)	(0.0976)	(0.104)
Cut3	0.692***	1.056***	0.943***	0.861***
	(0.213)	(0.224)	(0.0990)	(0.105)
Year Trend	N/A	N/A	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	384	384	4745	4745
Pseudo R^2	0.021	0.036	0.008	0.009

Omitted categories: Below Primary Education, Income Quartile 1 and Age 50+; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.8: **Pakistan Ordered Probit Replication/Expansion Regressions**

	2005 Replication		2005-2015 Data	
Primary Education	-0.108	-0.144	-0.109***	-0.0890**
	(0.110)	(0.110)	(0.0412)	(0.0415)
Secondary Education	-0.154	-0.194	-0.0563	-0.0339
	(0.166)	(0.168)	(0.0412)	(0.0414)
Higher Education	-0.436**	-0.488***	-0.180***	-0.140**
	(0.179)	(0.183)	(0.0617)	(0.0623)
Income Quartile 2	-0.040	-0.040	0.0782*	0.0814*
	(0.139)	(0.138)	(0.0445)	(0.0447)
Income Quartile 3	-0.179	-0.181	0.0752	0.0890*
	(0.139)	(0.139)	(0.0468)	(0.0470)
Income Quartile 4	-0.316**	-0.332**	0.124**	0.142***
	(0.154)	(0.155)	(0.0511)	(0.0513)
Dissatisfaction		0.113***		-0.305***
		(0.069)		(0.0325)
Gender	0.280***	0.283***	0.0194	0.00873
	(0.099)	(0.099)	(0.0316)	(0.0318)
Age 18 to 29	-0.096	-0.099	-0.0157	-0.0195
	(0.151)	(0.150)	(0.0488)	(0.0489)
Age 30 to 49	0.085	0.079	-0.0244	-0.0230
	(0.139)	(0.139)	(0.0465)	(0.0466)
Married	0.104	0.112	0.00905	0.0120
	(0.123)	(0.122)	(0.0400)	(0.0400)
No. of Children	-0.017	-0.018	-0.00103	-0.00122
	(0.022)	(0.022)	(0.00663)	(0.00660)
Cut1	0.003	0.093	0.463***	0.321***
	(0.220)	(0.225)	(0.0923)	(0.0936)
Cut2	0.595***	0.686***	0.830***	0.691***
	(0.219)	(0.224)	(0.0927)	(0.0939)
Cut3	1.097***	1.190***	1.249***	1.114***
	(0.218)	(0.224)	(0.0935)	(0.0944)
Year Trend	N/A	N/A	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	670	670	9208	9208
Pseudo R^2	0.036	0.038	0.014	0.022

Omitted categories: Below Primary Education, Income Quartile 1 and Age 50+; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Turkey Ordered Probit Replication/Expansion Regressions

	2005 Replication		2005-2015 Data	
Primary Education	-0.268	-0.269	0.0977	0.101
	(0.229)	(0.230)	(0.0639)	(0.0642)
Secondary Education	-0.285	-0.285	0.157**	0.169**
	(0.245)	(0.245)	(0.0709)	(0.0714)
Higher Education	-0.320	-0.321	0.155*	0.169**
	(0.295)	(0.296)	(0.0809)	(0.0814)
Income Quartile 2	0.220	0.220	-0.0657	-0.0651
	(0.174)	(0.174)	(0.0502)	(0.0504)
Income Quartile 3	-0.167	-0.167	-0.166***	-0.171***
	(0.180)	(0.180)	(0.0538)	(0.0539)
Income Quartile 4	-0.308	-0.309	-0.188***	-0.187***
	(0.222)	(0.223)	(0.0576)	(0.0578)
Dissatisfaction		-0.006		-0.297***
		(0.077)		(0.0333)
Gender	0.170	0.169	0.145***	0.138***
	(0.114)	(0.114)	(0.0338)	(0.0340)
Age 18 to 29	0.318	0.319	0.226***	0.243***
	(0.202)	(0.203)	(0.0535)	(0.0539)
Age 30 to 49	0.198	0.198	0.0696	0.0790
	(0.185)	(0.185)	(0.0493)	(0.0495)
Married	0.093	0.092	-0.0211	-0.0385
	(0.154)	(0.154)	(0.0413)	(0.0415)
No. of Children	-0.023	-0.023	-0.0678***	-0.0644***
	(0.053)	(0.054)	(0.0175)	(0.0175)
Cut1	0.628*	0.621*	0.953***	0.762***
	(0.328)	(0.349)	(0.1000)	(0.102)
Cut2	1.020 ***	1.012 ***	1.346***	1.159***
	(0.327)	(0.349)	(0.101)	(0.102)
Cut3	1.874***	1.866***	2.130***	1.951***
	(0.319)	(0.343)	(0.105)	(0.106)
Year Trend	N/A	N/A	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	590	590	6547	6547
Pseudo R^2	0.061	0.061	0.019	0.027

Omitted categories: Below Primary Education, Income Quartile 1 and Age 50+; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bibliography

Aaron, D. J., Y. Chang, N. Markovic and R. LaPorte (2003). "Estimating the lesbian population: a capture-recapture approach". *Journal of Epidemiology & Community Health* 57.3, pp. 207–209.

Abadie, A. (2006). "Poverty, political freedom, and the roots of terrorism". *American Economic Review* 96.2, pp. 50–56.

Agnew, R. (2010). "A general strain theory of terrorism". *Theoretical Criminology* 14.2, pp. 131–153.

Article 36 (2013). "The impact of explosive violence on mental health and psycho-social well-being". *Article 36 Briefing Paper*. September.

Azzeh, L. (2016). "Thneibat denounces campaign against Jordanian education". *Jordan Times*. 6 October. URL: http://www.jordantimes.com/news/local/thneibat-denounces-campaign%E2%80%99-against-jordanian-education (Last Accessed: 18/09/2018).

Badan Nasional Penanggulangan Terorisme (2017). "Kalah di Irak dan Syria, Alumni ISIS Sasar Indonesia". *BNPT National News*. 28 March [Translated using Google Translate]. URL: https://www.bnpt.go.id/kalah-di-irak-dan-syria-alumni-isis-sasar-indonesia.html (Last Accessed: 18/09/2018).

Badan Pusat Statistik Census (2010). "Population by Region and Religion". *Indonesian Population Census 2010*.

Bahney, B. W., R. K. Iyengar, P. B. Johnston, D. F. Jung, J. N. Shapiro and H. J. Shatz (2013). "Insurgent compensation: Evidence from iraq". *American Economic Review* 103.3, pp. 518–22.

Baillargeon, S. and L. P. Rivest (2007). "Rcapture: loglinear models for capture-recapture in R". *Journal of Statistical Software* 19.5, pp. 1–31.

Ball, P. (2000). "The Guatemalan Commission for historical clarification: Generating analytical reports, inter-sample analysis". *American Association for the Advancement of Science*.

— (2016). "Computing Multiple Systems Estimation in R". *HRDAG*. 25 October. URL: https://hrdag.org/tech-notes/basic-mse.html (Last Accessed: 18/09/2018).

Ball, P., J. Asher, D. Sulmont and D. Manrique (2003). "How many Peruvians have died?" *American Association for the Advancement of Science*. Report to the Peruvian Commission for Truth and Justice.

Ball, P., W. Betts, F. Scheuren, J. Dudukovich and J. Asher (2002). "Killings and Refugee Flow in Kosovo March - June 1999". *American Association for the Advancement of Science*. Report to the International Criminal Tribunal for the Former Yugoslavia.

Baum, M. A. and Y. M. Zhukov (2015). "Filtering revolution: Reporting bias in international newspaper coverage of the Libyan civil war". *Journal of Peace Research* 52.3, pp. 384–400.

BBC News (2005). "Bali bombs 'were suicide attacks'". *BBC News Online*. 2 October. URL: http://news.bbc.co.uk/1/hi/world/asia-pacific/4301630.stm (Last Accessed: 18/09/2018).

— (2011). "Iraq War in Figures". *BBC News Online*. 14 December. URL: https://www.bbc.co.uk/news/world-middle-east-11107739 (Last Accessed: 18/09/2018).

Beall, J., T. Goodfellow and D. Rodgers (2013). "Cities and conflict in fragile states in the developing world". *Urban Studies* 50.15, pp. 3065–3083.

Becker, G. S. (1968). "Crime and punishment: An economic approach". *The economic dimensions of crime*. Springer, pp. 13–68.

Benmelech, E., C. Berrebi and E. F. Klor (2012). "Economic conditions and the quality of suicide terrorism". *The Journal of Politics* 74.1, pp. 113–128.

Berman, E. and D. Laitin (2005). "Hard targets: Theory and evidence on suicide attacks". *National Bureau of Economic Research Working Papers Series* 11740.

— (2008). "Religion, terrorism and public goods: Testing the club model". *Journal of Public Economics* 92.10, pp. 1942–1967.

Berman, E., J. N. Shapiro and J. H. Felter (2011). "Can hearts and minds be bought? The economics of counterinsurgency in Iraq". *Journal of Political Economy* 119.4, pp. 766–819.

Berrebi, C. (2007). "Evidence about the link between education, poverty and terrorism among Palestinians". *Peace Economics, Peace Science and Public Policy* 13.1.

Blair, G., K. Imai and J. Lyall (2014). "Comparing and combining list and endorsement experiments: Evidence from Afghanistan". *American Journal of Political Science* 58.4, pp. 1043–1063.

Boyle, M. J. (2009). "Bargaining, fear, and denial: Explaining violence against civilians in Iraq 2004–2007". *Terrorism and Political Violence* 21.2, pp. 261–287.

Brockhoff, S., T. Krieger and D. Meierrieks (2015). "Great expectations and hard times: The (nontrivial) impact of education on domestic terrorism". *Journal of Conflict Resolution* 59.7, pp. 1186–1215.

Buckler, K. and L. Travis (2005). "Assessing the newsworthiness of homicide events: An analysis of coverage in the Houston Chronicle". *Journal of Criminal Justice and Popular Culture* 12.1, pp. 1–25.

Burnham, G., R. Lafta, S. Doocy and L. Roberts (2006). "Mortality after the 2003 invasion of Iraq: a cross-sectional cluster sample survey". *The Lancet* 368.9545, pp. 1421–1428.

Cavatorta, F. (2012). “The war on terror and the transformation of political Islam”. *Religion Compass* 6.3, pp. 185–194.

Chicago Project on Security and Terrorism (2016). “Suicide Attack Database”. URL: http://cpostdata.uchicago.edu/ (Last Accessed: 18/09/2018).

Cordesman, A. H. (2017). “Islam and the Patterns in Terrorism and Violent Extremism”. *Center for Strategic & International Studies*.

Croicu, M. and R. Sundberg (2015). “UCDP georeferenced event dataset codebook version 4.0”. *Journal of Peace Research* 50.4, pp. 523–532.

Davenport, C. and P. Ball (2002). “Views to a kill: Exploring the implications of source selection in the case of Guatemalan state terror, 1977-1995”. *Journal of Conflict Resolution* 46.3, pp. 427–450.

Daykin, A. R. and P. G. Moffatt (2002). “Analyzing ordered responses: A review of the ordered probit model”. *Understanding Statistics: Statistical Issues in Psychology, Education, and the Social Sciences* 1.3, pp. 157–166.

De Mesquita, E. B. (2008). “The political economy of terrorism: A selective overview of recent work”. *The Political Economist* 10.1, pp. 1–12.

Deflem, M. and S. Sutphin (2006). “Policing post-war Iraq: Insurgency, civilian police, and the reconstruction of society”. *Sociological Focus* 39.4, pp. 265–283.

Delli Carpini, M. X. and B. A. Williams (1987). “Television and terrorism: Patterns of presentation and occurrence, 1969 to 1980”. *Western Political Quarterly* 40.1, pp. 45–64.

Dewast, L. (2016). “New UN Report Reveals Staggering Number of Casualties in Iraq in 2015”. *ABC News*. 19 January. URL: https://abcnews.go.com/International/18000-civilians-killed-iraq-2015/story?id=36372354 (Last Accessed: 18/09/2018).

Dimitrova, D. V. and C. Connolly-Ahern (2007). “A tale of two wars: Framing analysis of online news sites in coalition countries and the Arab world during the Iraq war”. *The Howard Journal of Communications* 18.2, pp. 153–168.

Diwakar, V. (2015). "The effect of armed conflict on education: evidence from Iraq". *The Journal of Development Studies* 51.12, pp. 1702–1718.

Dıaz-Cayeros, A., B. Magaloni, A. Matanock and V. Romero (2011). "Living in fear: Mapping the social embeddedness of drug gangs and violence in Mexico". *Manuscript: University of California at San Diego* 90, pp. 91–98.

Donnay, K. and V. Filimonov (2014). "Views to a war: systematic differences in media and military reporting of the war in Iraq". *EPJ Data Science* 3.1, p. 25.

Doran, C. F., R. E. Pendley and G. E. Antunes (1973). "A test of cross-national event reliability: Global versus regional data sources". *International Studies Quarterly* 17.2, pp. 175–203.

Dowling, R. E. (1986). "Terrorism and the media: A rhetorical genre". *Journal of communication* 36.1, pp. 12–24.

Drakos, K. and A. Gofas (2006). "In search of the average transnational terrorist attack venue". *Defence and Peace Economics* 17.02, pp. 73–93.

Dreher, A. and J. A. Fischer (2011). "Does government decentralization reduce domestic terror? An empirical test". *Economics Letters* 111.3, pp. 223–225.

Dupuy, K., S. Gates, H. M. Nygård, I. Rudolfsen, S. A. Rustad, H. Strand and H. Urdal (2017). "Trends in armed conflict, 1946–2016". *Conflict Trends* 2, pp. 1–4.

Duursma, A. (2017). "Counting Deaths While Keeping Peace: An Assessment of the JMAC's Field Information and Analysis Capacity in Darfur". *International Peacekeeping* 24.5, pp. 823–847.

Earl, J., A. Martin, J. D. McCarthy and S. A. Soule (2004). "The use of newspaper data in the study of collective action". *Annual Review of Sociology* 30, pp. 65–80.

Eck, K. (2012). "In data we trust? A comparison of UCDP GED and ACLED conflict events datasets". *Cooperation and Conflict* 47.1, pp. 124–141.

Eckberg, D. (2001). "Stalking the elusive homicide: A capture-recapture approach to the estimation of post-reconstruction South Carolina killings". *Social Science History* 25.1, pp. 67–91.

Eisensee, T. and D. Strömberg (2007). "News droughts, news floods, and US disaster relief". *The Quarterly Journal of Economics* 122.2, pp. 693–728.

Enders, W. and G. A. Hoover (2012). "The nonlinear relationship between terrorism and poverty". *American Economic Review* 102.3, pp. 267–72.

Eriksson, M. and P. Wallensteen (2004). "Armed Conflict, 1989–2003". *Journal of Peace Research* 41.5, pp. 625–636.

Evans, M. (2010). "Framing international conflicts: Media coverage of fighting in the Middle East". *International Journal of Media & Cultural Politics* 6.2, pp. 209–233.

Fair, C. C., N. Malhotra and J. N. Shapiro (2010). "Islam, militancy, and politics in Pakistan: Insights from a national sample". *Terrorism and Political Violence* 22.4, pp. 495–521.

— (2012). "Faith or doctrine? Religion and support for political violence in Pakistan". *Public Opinion Quarterly* 76.4, pp. 688–720.

Fielding, D. and A. Shortland (2009). "Does television terrify tourists? Effects of US television news on demand for tourism in Israel". *Journal of Risk and Uncertainty* 38.3, pp. 245–263.

Fienberg, S. E., M. S. Johnson and B. W. Junker (1999). "Classical multilevel and Bayesian approaches to population size estimation using multiple lists". *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 162.3, pp. 383–405.

Fjelde, H. and G. Østby (2014). "Socioeconomic inequality and communal conflict: A disaggregated analysis of sub-Saharan Africa, 1990–2008". *International Interactions* 40.5, pp. 737–762.

Forsberg, E. (2010). "Sons of the soil and local insurgencies: Assessing the impact of migration on civil conflicts in northeast India using the UCDP geo-coded events data". *SGIR 7th Pan-European International Relations Conference in Stockholm*, pp. 9–11.

Freeman, C. (2004). "Letter from Baghdad: Risky Business". *American Journalism Review* 67.

Freytag, A., J. J. Krüger, D. Meierrieks and F. Schneider (2011). "The origins of terrorism: Cross-country estimates of socio-economic determinants of terrorism". *European Journal of Political Economy* 27, S5–S16.

GADM (2018). "Database of Global Administrative Areas: Shapefiles for Indonesia, Jordan, Lebanon, Pakistan and Turkey". Version 3.6. URL: https://gadm.org/data.html (Last Accessed: 18/09/2018).

Galtung, J. and M. H. Ruge (1965). "The structure of foreign news. The presentation of the Congo, Cuba and Cyprus Crises in four Norwegian newspapers". *Journal of Peace Research* 2.1, pp. 64–90.

Ghazal, M. (2015). "10 years after Amman bombings, war on terror 'remains our war'". *Jordan Times*. 6 October. URL: http://www.jordantimes.com/news/local/10-years-after-amman-bombings-war-terror-remains-our-war%E2%80%99 (Last Accessed: 18/09/2018).

Ginges, J., I. Hansen and A. Norenzayan (2009). "Religion and support for suicide attacks". *Psychological science* 20.2, pp. 224–230.

Gitlin, T. (2003). "The whole world is watching: Mass media in the making and unmaking of the new left". *University of California Press*.

Gohdes, A. R. (2015). "Pulling the plug: Network disruptions and violence in civil conflict". *Journal of Peace Research* 52.3, pp. 352–367.

Gruenewald, J., J. Pizarro and S. M. Chermak (2009). "Race, gender, and the newsworthiness of homicide incidents". *Journal of Criminal Justice* 37.3, pp. 262–272.

Gunter, B. (2009). "The Public and Media Coverage of the War on Iraq". *Globalizations* 6.1, pp. 41–60.

Guran, M. (2015). "The Ankara Bombings and the Islamic State's Turkey Strategy". *CTC Sentinel* 8, p. 10.

Hagenaars, A. J., K. De Vos, M. Asghar Zaidi et al. (1994). "Poverty statistics in the late 1980s: Research based on micro-data". *Office for Official Publications of the European Communities*.

Hagopian, A., A. D. Flaxman, T. K. Takaro, S. A. E. Al Shatari, J. Rajaratnam, S. Becker, A. Levin-Rector, L. Galway, B. J. H. Al-Yasseri, W. M. Weiss, C. J. Murray and G. Burnham (2013). "Mortality in Iraq associated with the 2003–2011 war and occupation: findings from a national cluster sample survey by the University Collaborative Iraq Mortality Study". *PLoS Medicine* 10.10, pp. 1–15.

Hausman, J. A., A. W. Lo and A. C. MacKinlay (1992). "An ordered probit analysis of transaction stock prices". *Journal of financial economics* 31.3, pp. 319–379.

Hayes, D. and M. Guardino (2010). "Whose views made the news? Media coverage and the march to war in Iraq". *Political Communication* 27.1, pp. 59–87.

Hazlewood, L. A. and G. T. West (1974). "Bivariate associations, factor structures, and substantive impact: the source coverage problem revisited". *International Studies Quarterly* 18.3, pp. 317–337.

Hegre, H., G. Østby and C. Raleigh (2009). "Poverty and civil war events: A disaggregated study of Liberia". *Journal of Conflict Resolution* 53.4, pp. 598–623.

Hendrix, C. S. and I. Salehyan (2012). "Climate change, rainfall, and social conflict in Africa". *Journal of Peace Research* 49.1, pp. 35–50.

— (2015). "No news is good news: Mark and recapture for event data when reporting probabilities are less than one". *International Interactions* 41.2, pp. 392–406.

Hicks, M. H. R., H. Dardagan, G. G. Serdán, P. M. Bagnall, J. A. Sloboda and M. Spagat (2009). "The weapons that kill civilians—deaths of children and noncombatants in Iraq, 2003–2008". *New England Journal of Medicine* 360.16, pp. 1585–1588.

Hodler, R. and P. A. Raschky (2014). "Economic shocks and civil conflict at the regional level". *Economics Letters* 124.3, pp. 530–533.

Huber, P. J. (1967). "The behavior of maximum likelihood estimates under nonstandard conditions". *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability.* Vol. 1. 1. University of California Press, pp. 221–233.

Ide, T., J. Schilling, J. S. Link, J. Scheffran, G. Ngaruiya and T. Weinzierl (2014). "On exposure, vulnerability and violence: spatial distribution of risk factors for climate change and violent conflict across Kenya and Uganda". *Political Geography* 43, pp. 68–81.

International Institute for Counter-Terrorism (2015). "Summary of Terrorist Incidents and Counter-Terrorist Operations Worldwide November 2015". *ICT Incidents and Activists Database Periodic Review*.

Iraq Body Count (n.d.[a]). "Database". URL: https://www.iraqbodycount.org/database/ (Last Accessed: 18/09/2018).

— (n.d.[b]). "Methods - 3. Data Extraction". URL: https://www.iraqbodycount.org/about/methods/3 (Last Accessed: 18/09/2018).

— (n.d.[c]). "Recent Events". URL: https://www.iraqbodycount.org/database/recent/ (Last Accessed: 18/09/2018).

— (2010). "Technical Appendix to IBC Analysis". URL: https://www.iraqbodycount.org/analysis/numbers/warlogs-appendix/ (Last Accessed: 18/09/2018).

Jackman, R. W. and W. A. Boyd (1979). "Multiple sources in the collection of data on political conflict". *American Journal of Political Science*, pp. 434–458.

Jakobsen, P. V. (2000). "Focus on the CNN effect misses the point: the real media impact on conflict management is invisible and indirect". *Journal of Peace Research* 37.2, pp. 131–143.

Jetter, M. (2014). "Terrorism and the Media". *Institute for the Study of Labor (IZA) Discussion Papers* 8497.

Kane, D. (2007). "The Lancet Surveys of Mortality in Iraq". *University of Bayreuth Depository*.

Kane, J., S. C. Craig and K. D. Wald (2004). "Religion and presidential politics in Florida: A list experiment". *Social Science Quarterly* 85.2, pp. 281–293.

Kerry, J. (2014). "John Kerry Remarks After Meeting With Secretary of State of the Holy See Pietro Parolin". *U.S. Department of State*. 14 January. URL: https://

2009-2017.state.gov/secretary/remarks/2014/01/219654.htm (Last Accessed: 18/09/2018).

Khan, M. (2016). "Donald Trump National Security Adviser Mike Flynn Has Called Islam 'a Cancer'". *ABC News*. 18 November. URL: https://abcnews.go.com/Politics/donald-trump-national-security-adviser-mike-flynn-called/story?id=43575658.

Kis-Katos, K., H. Liebert and G. G. Schulze (2011). "On the origin of domestic and international terrorism". *European Journal of Political Economy* 27, pp. 17–36.

Kraemer, J. D. and C. S. Benton (2015). "Disparities in road crash mortality among pedestrians using wheelchairs in the USA: results of a capture–recapture analysis". *BMJ Open* 5.11, e008396.

Krueger, A. B. (2007). "What Makes a Terrorist." *Princeton University Press*.

Krueger, A. B. and J. Malečková (2003). "Education, poverty and terrorism: Is there a causal connection?" *Journal of Economic perspectives* 17.4, pp. 119–144.

— (2009). "Attitudes and action: Public opinion and the occurrence of international terrorism". *Science* 325.5947, pp. 1534–1536.

Krüger, J. and K. Lum (2015). "An exploration of multiple systems estimation for empirical research with conflict-related deaths".

Lehmann, I. A. (2005). "Exploring the Transatlantic Media Divide over Iraq. How and Why US and German Media Differed in Reporting on UN Weapons Inspections in Iraq, 2002-2003". *The Harvard International Journal of Press/Politics* 10.1, pp. 63–89.

Lewis, E., G. Mohler, P. J. Brantingham and A. L. Bertozzi (2012). "Self-exciting point process models of civilian deaths in Iraq". *Security Journal* 25.3, pp. 244–264.

Lincoln, F. C. et al. (1930). "Calculating waterfowl abundance on the basis of banding returns". *US Deptartment of Agriculture*.

Long, S. J. (1997). "Regression models for categorical and limited dependent variables". *Advanced quantitative techniques in the social sciences* 7.

Lum, K., M. E. Price and D. Banks (2013). "Applications of multiple systems estimation in human rights research". *The American Statistician* 67.4, pp. 191–200.

Lum, K., M. Price, T. Guberek and P. Ball (2010). "Measuring elusive populations with bayesian model averaging for multiple systems estimation: A case study on lethal violations in casanare, 1998-2007". *Statistics, Politics, and Policy* 1.1.

Lyall, J., G. Blair and K. Imai (2013). "Explaining support for combatants during wartime: A survey experiment in Afghanistan". *American Political Science Review* 107.4, pp. 679–705.

Manrique-Vallier, D. (2016). "Bayesian population size estimation using Dirichlet process mixtures". *Biometrics* 72.4, pp. 1246–1254.

Manrique-Vallier, D., M. E. Price and A. Gohdes (2013). "Multiple systems estimation techniques for estimating casualties in armed conflicts". *Counting Civilian Casualties: An Introduction to Recording and Estimating Nonmilitary Deaths in Conflict.* Ed. by T. B. Seybolt, J. D. Aronson and B. Fischhoff, pp. 165–182.

Manzo, G. and R. Wintrobe (2009). "Rational Extremism: the Political Economy of Radicalism". *Archives Européennes de Sociologie* 50.3, p. 450.

Mastro, T. D., D. Kitayaporn, B. G. Weniger, S. Vanichseni, V. Laosunthorn, T. Uneklabh, C. Uneklabh, K. Choopanya and K. Limpakarnjanarat (1994). "Estimating the number of HIV-infected injection drug users in Bangkok: a capture–recapture method." *American Journal of Public Health* 84.7, pp. 1094–1099.

McCauley, C. and S. Moskalenko (2008). "Mechanisms of political radicalization: Pathways toward terrorism". *Terrorism and political violence* 20.3, pp. 415–433.

Milton-Edwards, B. (2017). "Grappling with Islamism: Assessing Jordan's Evolving Approach". *Brookings Doha Center Analysis* 19.

Minoiu, C. and O. N. Shemyakina (2014). "Armed conflict, household victimization, and child health in Côte d'Ivoire". *Journal of Development Economics* 108, pp. 237–255.

Mousseau, M. (2011). “Urban poverty and support for Islamist terror: Survey results of Muslims in fourteen countries”. *Journal of Peace Research* 48.1, pp. 35–47.

National Consortium for the Study of Terrorism and Responses to Terrorism (START) (2017). “Global Terrorism Database”. *Department of Homeland Security, University of Maryland College Park, MD.* URL: https://www.start.umd.edu/gtd (Last Accessed: 18/09/2018).

Nawaz, S. (2016). “Countering Militancy and Terrorism in Pakistan”. *United States Institute of Peace Special Report* 393.

Öberg, M. and M. Sollenberg (2011). “Gathering conflict information using news resources”. *Understanding Peace Research: Methods and Challenges*. Ed. by K. Hoglund and M. Öberg, pp. 47–73.

OECD (n.d.). “What are Equivalence Scales?” *OECD Project on Income Distribution and Poverty*.

Oliver, P. E. and D. J. Myers (1999). “How Events Enter the Public Sphere: Conflict, Location, and Sponsorship in Local Newspaper Coverage of Public Events”. *American Journal of Sociology* 105.1, pp. 38–87.

O’Loughlin, J., A. M. Linke and F. D. Witmer (2014). “Effects of temperature and precipitation variability on the risk of violence in sub-Saharan Africa, 1980–2012”. *Proceedings of the National Academy of Sciences* 111.47, pp. 16712–16717.

O’Loughlin, J., F. D. Witmer, A. M. Linke and N. Thorwardson (2010). “Peering into the fog of war: The geography of the WikiLeaks Afghanistan war logs, 2004-2009”. *Eurasian Geography and Economics* 51.4, pp. 472–495.

Pape, R. A. (2006). “Dying to win: The strategic logic of suicide terrorism”. *Random House Incorporated*.

Peelo, M., B. Francis, K. Soothill, J. Pearson and E. Ackerley (2004). “Newspaper reporting and the public construction of homicide”. *British Journal of Criminology* 44.2, pp. 256–275.

Petersen, C. G. J. (1896). "The yearly immigration of young plaice in the Limfjord from the German sea". *Rept. Danish Biol. Sta.* 6, pp. 1–48.

Pew Research Center (2005-2015). "Data Files and Codebooks". *Pew Global Attitudes Survey.* URL: www.pewglobal.org/datasets (Last Accessed: 18/09/2018).

— (2007). "Journalists in Iraq: A Survey of Reporters on the Front Lines". *Pew Research Center: Journalism and Media Staff.* URL: http://www.journalism.org/2007/11/28/journalists-in-iraq-a-survey-of-reporters-on-the-front-lines/ (Last Accessed: 18/09/2018).

— (2018). "Methods - International Survey Research". URL: http://www.pewresearch.org/methods/international-survey-research/ (Last Accessed: 18/12/2018).

Price, M. and P. Ball (2014). "Big data, selection bias, and the statistical patterns of mortality in conflict". *SAIS Review of International Affairs* 34.1, pp. 9–20.

Price, M., A. Gohdes and P. Ball (2015). "Documents of war: Understanding the Syrian conflict". *Significance* 12.2, pp. 14–19.

Raleigh, C. (2012). "Violence against civilians: A disaggregated analysis". *International Interactions* 38.4, pp. 462–481.

Roberts, L., R. Lafta, R. Garfield, J. Khudhairi and G. Burnham (2004). "Mortality before and after the 2003 invasion of Iraq: cluster sample survey". *The Lancet* 364.9448, pp. 1857–1864.

Salehyan, I., C. S. Hendrix, J. Hamner, C. Case, C. Linebarger, E. Stull and J. Williams (2012). "Social conflict in Africa: A new database". *International Interactions* 38.4, pp. 503–511.

Sanchez-Cuenca, I. (2007). "The dynamics of nationalist terrorism: ETA and the IRA". *Terrorism and Political Violence* 19.3, pp. 289–306.

Savitch, H. V. and G. Ardashev (2001). "Does terror have an urban future?" *Urban Studies* 38.13, pp. 2515–2533.

Shafiq, M. N. and A. H. Sinno (2010). “Education, income, and support for suicide bombings: Evidence from six Muslim countries”. *Journal of Conflict Resolution* 54.1, pp. 146–178.

Siegler, A., L. Roberts, E. Balch, E. Bargues, A. Bhalla, C. Bills, E. Dzeng, Y. Epelboym, T. Foster, L. Fulton et al. (2008). “Media coverage of violent deaths in Iraq: an opportunistic capture-recapture assessment”. *Prehospital and Disaster Medicine* 23.4, pp. 369–371.

Silva, R. and P. Ball (2008). “The Demography of Conflict-Related Mortality in Timor-Leste (1974–1999): Reflections on Empirical Quantitative Measurement of Civilian Killings, Disappearances, and Famine-Related Deaths”. *Statistical Methods for Human Rights*, pp. 117–139.

Sloboda, J., H. Dardagan, M. Spagat and M. H. R. Hicks (2013). “Iraq Body Count: A Case Study in the uses of Incident-Based Conflict Casualty Data”. *Counting Civilian Casualties: An Introduction To Recording And Estimating Nonmilitary Deaths in Conflict.* Ed. by T. B. Seybolt, J. D. Aronson and B. Fischhoff.

Snyder, D. and W. R. Kelly (1977). “Conflict intensity, media sensitivity and the validity of newspaper data”. *American Sociological Review*, pp. 105–123.

Spagat, M. (2010). “Ethical and Data-Integrity Problems in the Second Lancet Survey of Mortality in Iraq”. *Defence and Peace Economics* 21.1, pp. 1–41.

Spagat, M. and S. van Weezel (2017). “Half a million excess deaths in the Iraq war: Terms and conditions may apply”. *Research & Politics* 4.4, pp. 1–8.

Taylor, C. L. and M. C. Hudson (1972). “World handbook of social and political indicators”. *New Haven: Yale University Press.*

Thayer, B. A. and V. M. Hudson (2010). “Sex and the Shaheed: Insights from the life sciences on Islamic suicide terrorism”. *International Security* 34.4, pp. 37–62.

The Economist (2017). “Erdogan vs Darwin: The decline of Turkish Schools”. *Print Edition Europe.* 30 September. URL: https://www.economist.com/europe/2017/09/30/the-decline-of-turkish-schools (Last Accessed: 18/09/2018).

United Nations (2013). “Terrorism can only be defeated by education, former British leader Blair tells UN”. *UN News*. 21 November. URL: https://news.un.org/en/story/2013/11/455992-terrorism-can-only-be-defeated-education-former-british-leader-blair-tells-un (Last Accessed: 18/09/2018).

UNOCHA and MapAction (2014). “IRAQ: Settlements (villages, towns, cities)”. *Humanitarian Response*. URL: https://www.humanitarianresponse.info/en/operations/iraq/dataset/iraq-settlements-villages-towns-cities-0.

USAID (2015). “Jordan: Country Development Strategy 2013-2017”. *United States Agency for International Development*. URL: https://www.usaid.gov/sites/default/files/documents/1883/Amended-Jordan-Country-Development-Strategy-March-2015.pdf (Last Accessed: 18/09/2018).

Weidmann, N. B. (2013). “The higher the better? The limits of analytical resolution in conflict event datasets”. *Cooperation and Conflict* 48.4, pp. 567–576.

— (2015). “On the accuracy of media-based conflict event data”. *Journal of Conflict Resolution* 59.6, pp. 1129–1149.

— (2016). “A closer look at reporting bias in conflict event data”. *American Journal of Political Science* 60.1, pp. 206–218.

White, H. (1980). “A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity”. *Econometrica: Journal of the Econometric Society*, pp. 817–838.

Wikileaks (2010). “SIGACTS Event Dataset”. *The Guardian Data Blog*. URL: https://www.theguardian.com/news/datablog/2010/oct/25/wikileaks-iraq-data (Last Accessed: 18/09/2018).

Woolley, J. T. (2000). “Using media-based data in studies of politics”. *American Journal of Political Science*, pp. 156–173.

World Bank (n.d.). “Data for Indonesia, Jordan, Lebanon, Pakistan and Turkey”. *The World Bank Databank*. URL: https://data.worldbank.org/?locations=ID-LB-PK-TR-JO (Last Accessed: 18/09/2018).

Zakaria, F. (2010). “Pakistan is ‘epicentre of Islamic terrorism’”. *CNN News*. 5 May. URL: http://edition.cnn.com/2010/OPINION/05/05/zakaria.pakistan.terror/index.html (Last Accessed: 18/09/2018).

Zwierzchowski, J. and E. Tabeau (2010). “The 1992-95 war in Bosnia and Herzegovina: Census-based multiple system estimation of casualties’ undercount”. *Households in Conlict Network*.