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Lecture 7

The Dirty War Index

Imagine a war involving several armed groups.

Almost inevitably there will be claims and counter claims about dirty behaviour by each of the groups. This debate is about groups striving to mobilize public opinion in their favour and against their enemies.

For example:

“Afghan President Hamid Karzai on Wednesday denounced the use of child suicide bombers, saying that militants who recruit them to wage terror are ‘oppressors of Islam’ and ‘oppressors of children.’” AP Story, http://news.yahoo.com/karzai-denounces-child-suicide-bombers-102442734.html

“Although civilian deaths caused by foreign troops were reportedly down, most Afghans apparently don’t believe that. The Taliban challenged UN claims that they were mostly to blame.

"Where do they get these numbers from, what sources do they have? Foreign forces are responsible for civilian casualties in bombing and firing," Taliban spokesman Qari Yusuf Ahmadi told the BBC.” Uruknet http://www.uruknet.info/?p=75748

This is a recent article that highlights many of the issues that arise. Here are some quotes:

> “The 50-day war killed more than 2,100 Palestinians, most of them civilians, and 72 people on the Israeli side, all but six of whom were soldiers.”

> “Israel’s foreign ministry rejected the report’s findings, saying Amnesty “ignores documented war crimes perpetrated by Hamas” and had produced no evidence to back up its claims.”

> ‘“The report reveals a pattern of frequent Israeli attacks using large aerial bombs to level civilian homes, sometimes killing entire families,” Amnesty said.’

> “Palestinian armed groups also committed war crimes, firing thousands of indiscriminate rockets into Israel killing six civilians including one child.”

The Dirty War Index is a tool to help sort through some of these claims by looking at certain types of simple ratios.

Here's the general definition:

$$DWI = \frac{Number\ of\ "dirty," \ i.e., \ undesirable\ or\ prohibited\ cases}{Total\ number\ of\ cases} x100$$

A few examples should make the whole idea pretty clear. See the next two tables.

DWI	Illegal Paramilitaries	Guerrillas	Government Forces
No. civilians killed	6,944	2,498	539
No. combatant opponents killed	41	2,946	659
Civilian versus opponent combatant mortality DWI calculation: No. civilians killed/Total no. of civilians and opponent combatants killed, times 100	6,944/6,985 = 0.99 × 100 = 99	2,498/5,444 = 0.46 × 100 = 46	539/1,198 = 0.45 × 100 = 45
DWI value (range 0 to 100)	99	46	45
DWI interpretation	Paramilitaries rank highest in killing the greatest absolute number of civilians. Their DWI value of 99 ranks "dirtiest," approaching the "dirtiest" theoretically possible (100). Civilians comprised 99% of victims killed and legitimate targets only 1%. The high number and high DWI suggest systematic civilian targeting.	Guerrillas rank 2nd in killing absolute numbers of civilians. Their DWI of 46 shows that civilians comprised 46% of victims killed in their attacks, a proportion that needs to be substantially lowered.	Government forces rank lowest in killing absolute numbers of civilians. However, as with the guerrillas, their DWI of 45 indicates that they need to lower substantially the proportion of civilians killed in their attacks.

This table includes deaths from one-sided, unopposed attacks by a combatant group, excluding deaths from two-sided clashes in which responsibility for death cannot be reliably assigned. Data source: CERAC's Colombia conflict database (http://www.cerac.org.co/home_english.htm) [18].

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DWI	British Security Forces	Irish Republican Paramilitaries	Loyalist Paramilitaries
No. civilians + civilian political activists killed [51]	190	738	873
Total no. persons killed [51]	362	2,056	1,020
Civilian mortality DWI calculation	$190/362 = 0.52 \times 100 = 52$	$738/2{,}056 = 0.36 \times 100 = 36$	$873/1{,}020 = 0.86 \times 100 = 86$
Civilian mortality DWI value[a]	52	36	86
Combatants not wearing uniforms or distinguishing marks in attacks	Extremely low rate; British forces routinely wear uniforms in attacks.	Extremely high rate; Republican paramilitaries routinely dress as civilians in attacks.	Very high rate; Loyalist paramilitaries frequently dress as civilians during attacks.
Attacks without uniform DWI value	Approaches 0	Approaches 100	Approaches 100
Interpretation	British forces rank second dirtiest in terms of civilians constituting half their victims (DWI = 52), yet killed the lowest number of civilians ($n = 190$). British forces have a low, i.e., "clean" DWI value for attacks without uniform.	Republican paramilitaries have a high "attacks without uniform DWI" approaching 100. They thereby probably increase British forces' civilian mortality DWI by decreasing distinction between civilians and Republican combatants. Republican paramilitaries killed a high number of civilians ($n = 738$), but relative to their high number of total victims were least dirty in their civilian mortality ratio (DWI = 36). That their military opponents (British forces) wear uniforms increases their ability to distinguish civilians from combatants and to achieve a lower civilian mortality DWI.	Loyalist paramilitaries are dirtiest in terms of the civilian mortality DWI, with civilians constituting 86% of victims (DWI = 86). Loyalists also killed the highest absolute number of civilians ($n = 873$).

[a]Chi-square = 675, df = 2, $p < 0.001$.

doi:10.1371/journal.pmed.0050243.t004

The first table is on the Colombian conflict and the second is on the conflict in Northern Ireland. Interestingly, the two conflicts share a common three sided structure. There are:

1. Government forces
2. Anti-government forces
3. Illegal paramilitary forces that are anti-anti-government forces. Combining the two "anti's" we could say that they are pro-government forces except that they are illegal. Their relationship with government forces is murky and controversial.

The tables make clear that these illegal paramilitaries are much dirtier than the other groups in both conflicts. Is this a case of governments, effectively, sub-contracting out dirty work while appearing to keep their hands clean?

A few last things to notice:

1. The tables just give two examples of the same type. The analysis is at the group level (i.e, government, anti-government and illegal paramilitaries) and the other key breakdown is into civilians and combatants. But there are other possibilities and we have seen them already. Think back to "The Weapons that Kill Civilians". Here the "dirty" cases are killings of women and children and we compare different weapons with one another rather than comparing perpetrators as we do in the above examples. We will return to this subject in seminars.

2. The DWI approach does not consider the issue of intention. In the particular applications above we don't ask whether or not the different sides intended to kill civilians. We focus on what they actually do rather than what they intended to do. An advantage of the intention-free approach is that intentions are hard to discern since, ultimately, they are inside peoples' heads. Instead, we focus on predictable outcomes of, for example, using a certain weapon. So, for example, the use of explosive violence in urban areas has a predictable effect of killing relatively high proportions of women and children this is a good reason to stigmatize the practice, whether or not the people who use explosive weapons in this way consciously intend to kill women and children.

Notice that this sets the Dirty War Index apart from the Civilian Targeting Index.

They are the same type of calculation but the numerator in CTI calculations are intentional killings while the numerator in DWI calculations may or may not be intentional killings.

We think of these concepts as complementary rather than being in competition with one another.

The Costs of Conflict/The Benefits of Peace – Northern Ireland

The Besley and Mueller article looks at housing prices as a creative way of measuring the costs of conflict.

Note that Besley and Mueller present their work in terms of the benefits of peace rather than the costs of conflict. But these are really just two sides of the same coin:

1. What would be the economic benefits of ending the conflict and switching to peace? There is an implicit *counterfactual scenario* underlying this question – imagine a world that is just like the one we are living in except that there is no war. *The benefits of peace are the benefits of switching from war to no war.*

2. What would be the economic costs of switching from peace to conflict?

Why look at housing prices?

1. Housing is economically important in its own right as a major economic asset of home owners.

2. Housing prices in a neighbourhood reflect the desirability of living there. If the neighbourhood becomes more violent then prices should fall. If it becomes safer prices should rise. So housing prices can serve as a barometer of the benefits of peace and the costs of war.

What are the advantages of looking at Northern Ireland?

1. Data are very good. We have a comprehensive record of everybody killed during "The Troubles".

2. There is variation in violence over time and space including a fairly clear moment in time when the conflict ends. This means that we can investigate whether movements in house prices over time and space track the corresponding movements in violence.

The figures on the next two slides give you a sense of the data.

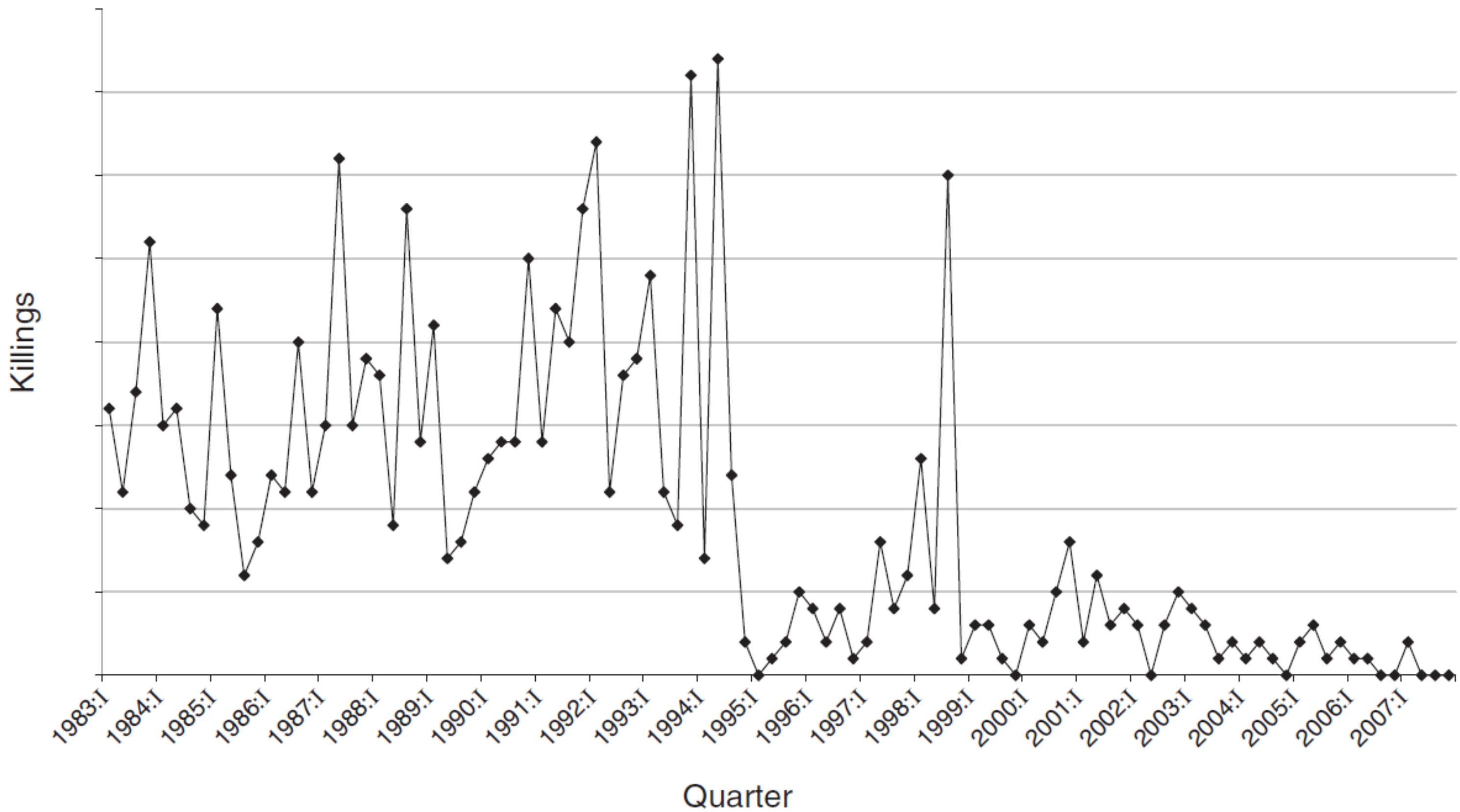


FIGURE 1. TOTAL QUARTERLY KILLINGS IN NORTHERN IRELAND

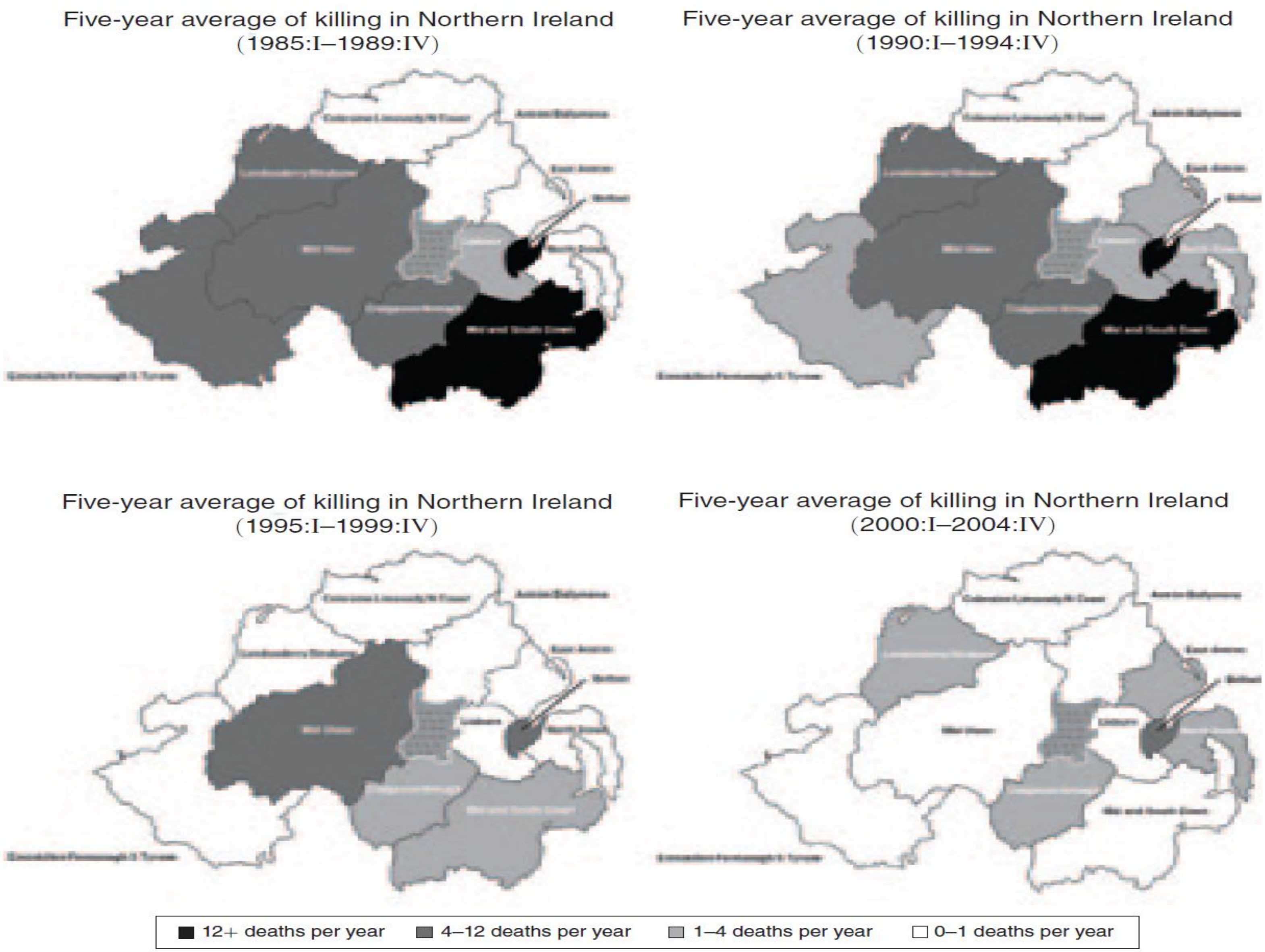

Five-year average of killing in Northern Ireland
(1985:I–1989:IV)
Five-year average of killing in Northern Ireland
(1990:I–1994:IV)
Five-year average of killing in Northern Ireland
(1995:I–1999:IV)
Five-year average of killing in Northern Ireland
(2000:I–2004:IV)
12+ deaths per year
4–12 deaths per year
1–4 deaths per year
0–1 deaths per year

FIGURE 2

The following picture captures the essence of the paper:

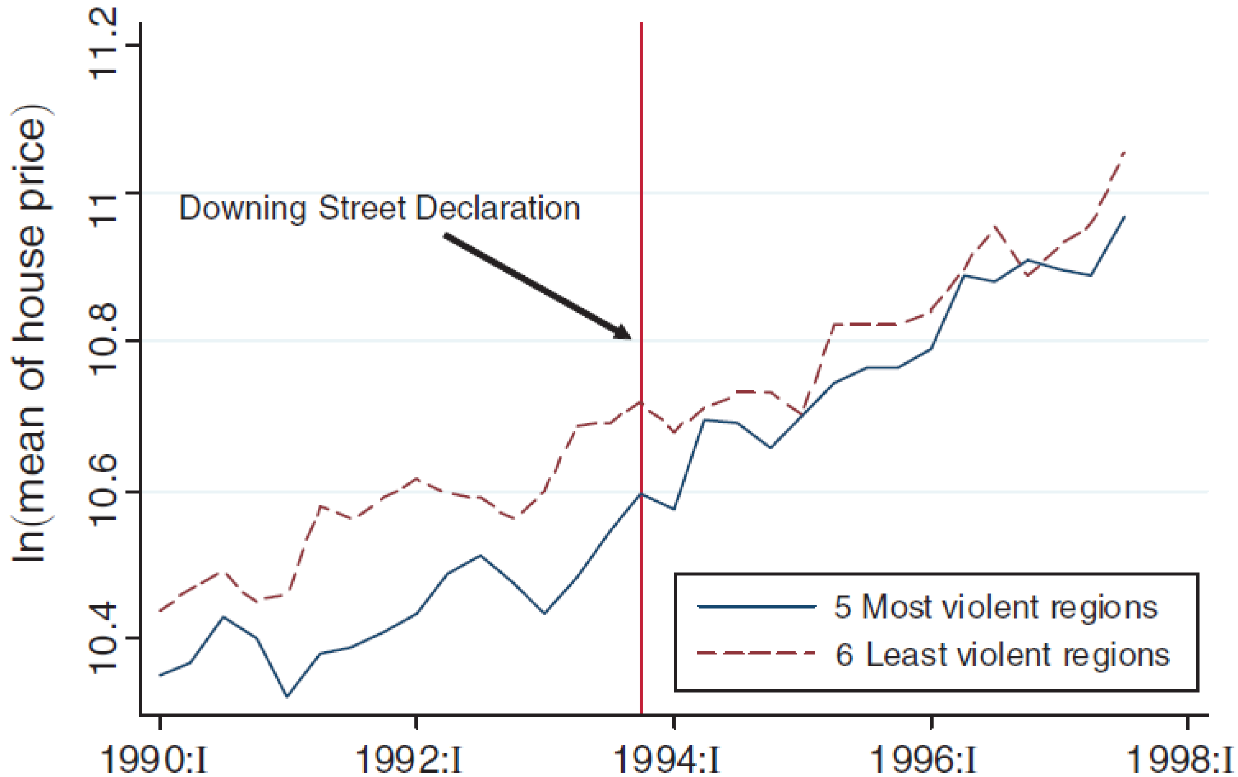


FIGURE 3. DEVELOPMENT OF HOUSE PRICES AT THE START OF THE PEACE PROCESS

Note – The Downing Street Declaration was widely (and correctly) viewed as a major step toward peace in Northern Ireland.

Notice how the gap in housing prices largely disappears after the Declaration.

This is the main point of the paper. The rest is about making this point more rigorously.

Besley and Mueller estimate the following:

$$(1) \qquad \ln(H_{rt}) = \alpha_r + \alpha_t + \beta y_{rt-1} + \varepsilon_{rt},$$

where $\ln(H_{rt})$ is the natural log of our house price index for region r at date t, y_{rt-1} is the number of killings in region r lagged one quarter, i.e., at date $t-1$, α_r are region dummies, and α_t are quarterly time dummies.[7] We estimate (1) with the

It is OK to treat the coefficient β as a causal effect of violence on the logarithm of housing prices as long as housing prices are not, themselves, a cause of violence. This is a pretty safe assumption.

The table on the next slide summarizes the results:

Table 1—Benchmark Results

Coefficient	ln(house price) (1)	ln(house price) (2)	ln(house price) (3)	ln(house price) (4)	ln(house price) (5)	ln(house price) (6)	Pounds (millions) earned in tourist industry (7)
Killings	−0.177***	−0.212***	−0.0133***	−0.00771**		−0.0107*	−1.584***
	(0.0191)	(0.0454)	(0.00492)	(0.00295)		(0.00493)	(0.433)
Killings (lagged two quarters)					−0.0187***		
					(0.00361)		
ln(unemployment)						−0.141***	
						(0.0408)	
Observations	1,049	1,049	1,049	1,049	1,049	932	99
Region fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Region-specific time trends	No	No	No	Yes	No	No	No
R^2	0.076	0.089	0.987	0.989	0.988	0.986	0.416

Notes: The time periods are 1984:IV to 2009:I for columns 1 through 5; 1987:III to 2001:I in column 6, and 1993 to 2001 in column 7. OLS standard errors are reported in columns 1 and 7; standard errors are clustered at the region level in columns 2 through 6. All explanatory variables are lagged by one quarter. Deaths in columns 1 through 6 are normalized by their standard deviation. In column 7, the left-hand side variable is a three-year moving average from 1993 to 2001. Deaths are yearly averages lagged by four years.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Sources: Killings are conflict-related killings from Sutton (1994). Unemployment is measured using the claimant counts from the UK office for National Statistics. The house price is the average overall housing transaction price recorded by the University of Ulster. Earnings in the tourist industry is from the Northern Ireland Tourist Board.

Notice that the violence coefficients are always negative and significant.

We will assess the magnitudes of these coefficients in the next worksheet.

Sampling Rare Events

I want to return, now, to the issue of measuring the prevalence of rare events, of which conflict violence is a prime example.

The following computations serve two purposes:

1. It gives us another way to calculate and understand confidence intervals.

2. It shows how rare events can easily be mismeasured in small surveys.

We use data from the **Iraq Living Conditions Survey** 2004 (**ILCS**).

Except in Kurdistan all interviews were done between **March 22 and May 25, 2004**.

Interviews were done at **10 households** (with minor variation due to incompleteness) within each of **2,193 clusters** comprised of **70 to 200** households.

Thus, the ILCS was a **very large survey** in terms of both the number of clusters (psu's) and the number of households where interviews were conducted.

Moreover, **each cluster measurement** in the ILCS was **of just a small neighborhood**.

The ILCS recorded all household deaths: causes are classified as either: pregnancy/child birth, disease, traffic accident, war-related or “other (specify)”.

“War-related deaths” and “violent deaths” should be essentially equivalent but I will use the ILCS term “war-related deaths” for these and call everything else “non-violent”.

We have a simple two-column dataset consisting of **a list of war-related deaths in every ILCS cluster and a list of non-violent deaths in every ILCS cluster.**

Here are some interesting facts:

1. **Violence is punctuated**; Only **105 out of the 2193 (4.8%)** had positive war-related deaths, i.e., although Iraq suffered much violence during the ILCS coverage period the overwhelming majority of small neighbourhoods of 70 to 200 households do not seem to have experienced any war-related deaths.

2. **Non-violent deaths are diffuse**; 902 out of the 2193 clusters had positive non-violent deaths.

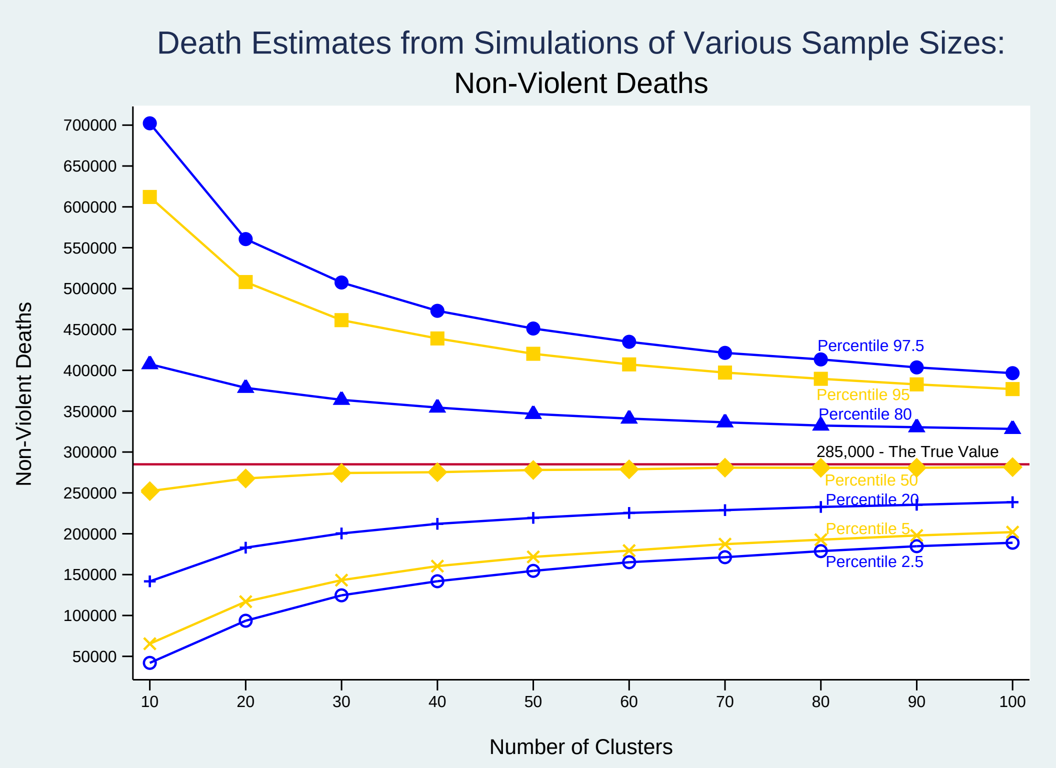
3. **Violence is concentrated**; For example, 80% of the clusters with violence had more than 10 times the average number of war-related deaths.

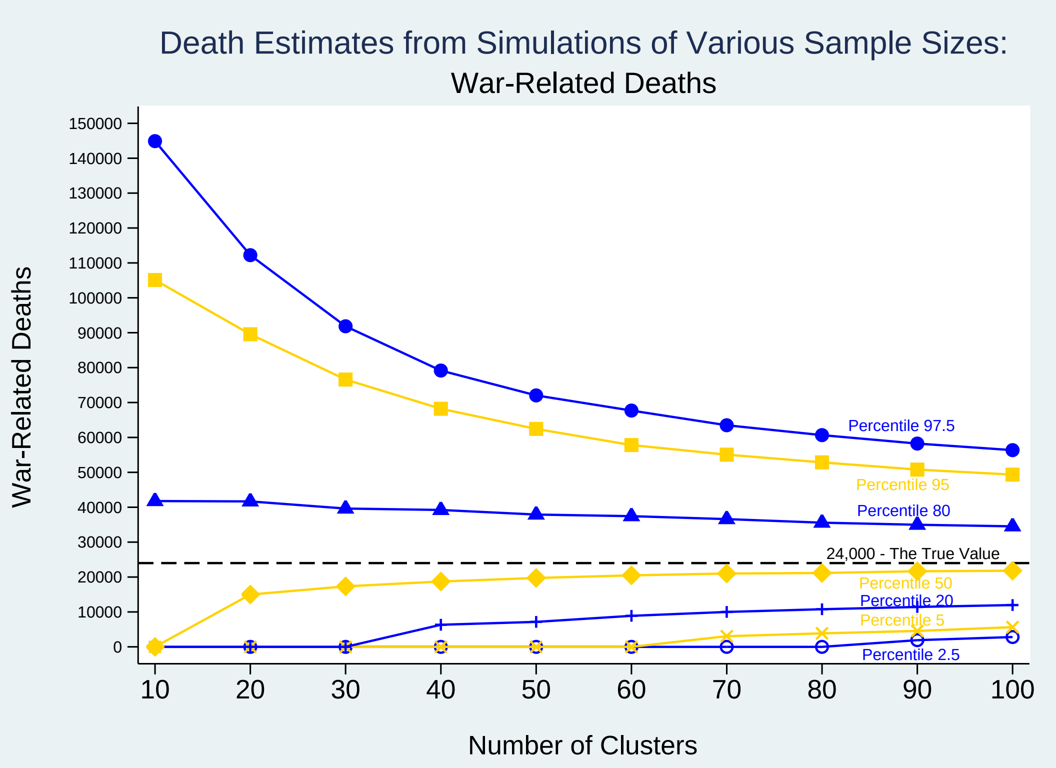
4. **Non-violent deaths are not concentrated**; only 2.5% of the clusters had more than 10 times the average number of non-violent deaths.

We study the small-sample properties of the most basic estimators of violent and non-violent conflict mortality by taking a large number of random draws of various sizes from the list of ILCS clusters following these procedures:

1. Fix a sample size of 10 clusters.
2. Draw 10,000 different samples of 10 clusters (with replacement) from the ILCS list of 2,193 clusters.
3. For each of these 10,000 samples calculate the average number of war-related deaths in this sample of 10 clusters.
4. Repeat the above steps for samples of 20, 30,…, 100, 200, 300,…2,000 clusters.
5. Repeat all of the above steps for non-violent deaths.

The next five slides present the results of these Monte Carlo simulations for clusters between the sizes of 10 and 100.


Death Estimates from Simulations of Various Sample Sizes:
Non-Violent Deaths
Non-Violent Deaths
700000
650000
600000
550000
500000
450000
400000
350000
300000
250000
200000
150000
100000
50000
10
20
30
40
50
60
70
80
90
100
Number of Clusters
Percentile 97.5
Percentile 95
Percentile 80
285,000 - The True Value
Percentile 50
Percentile 20
Percentile 5
Percentile 2.5


Death Estimates from Simulations of Various Sample Sizes:
War-Related Deaths
War-Related Deaths
Number of Clusters
Percentile 97.5
Percentile 95
Percentile 80
24,000 - The True Value
Percentile 50
Percentile 20
Percentile 5
Percentile 2.5
150000
140000
130000
120000
110000
100000
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
10
20
30
40
50
60
70
80
90
100

Non-Violent Deaths

With 30 clusters 60% of the estimates are within 30% of the true value.

With 50 clusters there is less than a 5% chance of deviating from the true value by more than 50%.

Violent Deaths

With 30 clusters more than 5% of the estimates of war-related deaths are more than triple the true value and more than 20% do not detect any deaths at all.

With 50 clusters estimates are within 50% of the true value only 46% of the time.

Summary

Non-violent deaths are estimated much more precisely than war-related deaths.

Small samples, such as the widely used 30 or 50, perform quite badly for war-related deaths; they can easily fail to detect any deaths or, on the other hand, overestimate by a factor of 3.

Notice that the ***median* estimates for war-related deaths are well below the true values in small samples,** i.e, underestimation is more likely than overestimation; the median estimate for a sample of 30 is 30% below the true value.

These simulation procedures are unbiased by design. Therefore, **overestimation tends to be larger when it occurs than is underestimation when it occurs.**

In other words, in small samples you are more likely to underestimate than overestimate but when you overestimate you are likely be farther from the true value than you are when you underestimate.

One final point.

The computer simulation method we have just used gives us another way to calculate confidence intervals – it is known as *bootstrapping*.

The idea is to use the data we have to generate a large number of simulated datasets that might have been. These many datasets give ranges of values for the variables we are interested and we construct our confidence intervals from these ranges.

In my opinion the idea behind bootstrapping is more intuitive than the idea behind the standard method that I taught you earlier in the course (standard deviation, standard error, 2 times the standard error). However, you need a computer to implement the bootstrapping technique even in simple cases whereas simple cases can be worked out with paper and pencil for the standard technique.