Humanitarian Outcomes' Aid Worker Security
Database: Statistical Analysis of Data Trends,
2000-2019

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The Aid Worker Security Database (AWSD) records major incidents of violence against aid workers globally. The data, collected from public sources, aid organizations, and operational security entities, is broken down by subnational regions as well as type of attack. This report analyses this data from 2000 to 2019.

I first analyze time-trends using graphical plots, t-tests, and OLS regressions. After that, I turn to changing attack contexts and locations, demonstrating how the frequency and breakdown of these have changed across time. Subsequently, I examine the relationship between crime, the intensity of civil conflict, and attacks on aid workers. I conclude with an examination of how the means of attack have changed over time.

Time Trends

In order to examine time trends, I aggregate data on kidnappings, number of wounded, and killings by country and year, and analyze each of these datasets separately. This aggregation facilitates statistical analysis and plotting; furthermore for a study of *global* attacks, the country-year is a natural unit of analysis.

A cursory glance at the data suggests that attacks on aid workers have increased with time. Figure 1 plots kidnappings, assaults, and killings for each country in our sample. Whether we look at kidnappings, number of wounded, or killings, there has been a dramatic increase in some countries, at least since the year 2000. However, there is substantial variation in our sample, and there has been a decline in attacks in some countries in recent years. Clearly more analysis is needed.

¹Afghanistan, Syria, and South Sudan are highlighted red, blue, and orange respectively; all the other countries are highlighted in light-grey. The black line shows the mean for the entire sample, with the brown band indicating the confidence interval for this estimate.

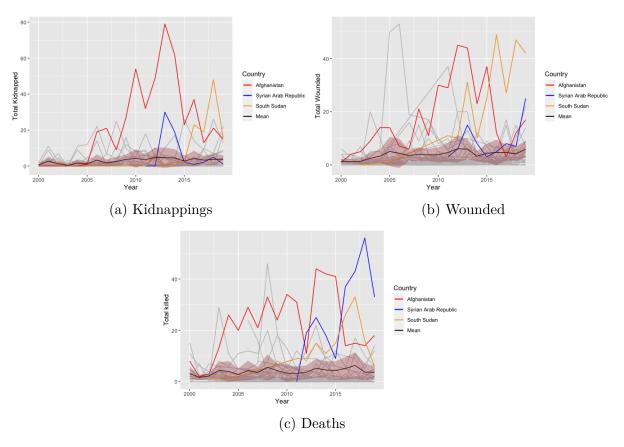


Figure 1: Time Trends

In order to systematically analyze these trends, I employ two different approaches. First, I split the sample into two periods (2000-2009 and 2010-2019), and run t-tests to examine whether there are statistically significant differences between both groups. The results, displayed in the Appendix (Tables 5-7), show that while there is no statistically significant difference between the number of aid workers killed in both periods, there has been a statistically significant increase in kidnappings and assaults.

As Figure 1 highlights, it is possible that only a handful of countries are driving the difference between both groups. Consequently, I also run OLS regressions with a time variable² and unit fixed effects. Unit fixed effects will pick up any time-invariant differences between countries.³ The results are displayed below (Table 1). While the coefficient on the time variable is positive in all three cases, the effect is not statistically significant in any case.⁴ It should be noted that this does *not* mean that attacks haven't increased with time. This simply means that once we account for variation in baseline attack rates across countries, the data cannot support any hypotheses regarding time trends. In other words, while the numbers of major attacks have unquestionably increased over time, the analysis shows the rise is driven by specific cases and is not a global phenomenon.

	Total Wounded	Total Kidnapped	Total Killed
Time	0.17	0.16	0.08
	(0.10)	(0.09)	(0.08)
Country Fixed Effects	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes
N	455	455	455

Standard errors in parentheses

Table 1: OLS Results-Time Trends

^{*} p < 0.05, ** p < 0.01, *** p < 0.001

 $^{^{2}}$ Time = Year - 2000

³Unit fixed effects generate a dummy variable for each country; when we run OLS, the estimated coefficient on this dummy gives us the mean value of the dependent variable for that country. This procedure helps us address omitted variable bias.

⁴We do note a positive time-trend for Total Wounded if we do not discard observations from before 2000.

Outliers

Since we are interested in cases where violence has spiked or plummeted, for each country-year, I generated a lagged variable indicating kidnappings, assaults, and killings for the previous year. Using this I simply calculate the change in attacks that year for the country in question. Figure 2 outlines the distribution of these changes for our sample. Whether we look at changes in kidnappings, assaults, or killings, the figures are consistently clustered around zero.⁵

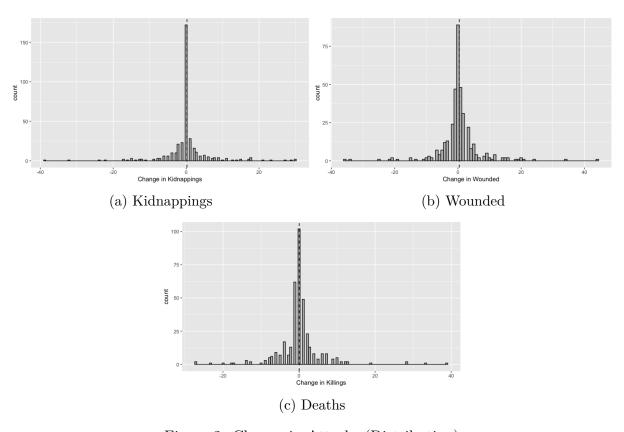


Figure 2: Change in Attacks (Distribution)

⁵The dotted line indicates the mean value.

To determine outliers, I use the IQR method. This procedure identifies outliers by breaking up the data into quartiles, calculating the difference between the cut-off values for Q3 and Q1, and adding a multiple of this difference to Q3 to identify an upper bound and substracting it from Q1 to establish a lower one.⁶. The multiple determines how extreme an outlier is: 1.5 is standard in the literature; 3 yields *extreme* outliers. For the analyses below, I used the standard approach.

The tables below (Tables 2-4) display the positive outliers associated with each type of attack. The data below conclusively establishes that the higher incidence cases also tend to be the most substantial outliers when it comes to spikes in violence against aid workers.

⁶In order to determine the interquartile range, arrange the data in ascending order, and split the data into two equal halves. The median of the lower half is labeled Q1; the median of the upper half Q3. The difference between these two values gives us the interquartile range (IQR).

Year	Country	Δ Wounded
2005	Sudan	44
2011	Nigeria	34
2016	South Sudan	24
2013	South Sudan	21
2003	Iraq	20
2018	South Sudan	20
2010	Afghanistan	19
2019	Syrian Arab Republic	18
2012	Afghanistan	16
2012	Somalia	16
2008	Afghanistan	15
2015	South Sudan	15
2015	Afghanistan	14
2007	Pakistan	14
2019	DR Congo	12
2017	Nigeria	12
2017	Somalia	12
2009	Sri Lanka	12
2018	Mali	11
2013	Jordan	10
2011	South Sudan	10
2018	Afghanistan	9
2014	Central African Republic	9
2018	DR Congo	9
2008	Somalia	9
2013	Syrian Arab Republic	9
2009	Pakistan	8
2015	Somalia	8
2007	Sri Lanka	8
2019	Central African Republic	7
2012	Kenya	7

Table 2: Δ Wounded (Positive Outliers)

Year	Country	Δ Kidnapped
2013	Afghanistan	30
2013	Syrian Arab Republic	30
2018	South Sudan	29
2010	Afghanistan	27
2015	DR Congo	23
2016	South Sudan	21
2006	Afghanistan	18
2009	Afghanistan	18
2019	Cameroon	18
2008	Somalia	18
2012	Afghanistan	17
2018	DR Congo	17
2019	Mali	15
2009	Yemen	15
2016	Afghanistan	14
2011	Pakistan	13
2006	Iraq	11
2008	Pakistan	11
2004	Sudan	11
2006	Sudan	10
2001	Burundi	9
2004	Iraq	9
2001	Somalia	9
2017	Yemen	9
2018	Afghanistan	8
2017	Somalia	8
2009	Sudan	8
2013	Sudan	8
2010	DR Congo	7
2012	Libyan Arab Jamahiriya	7
2014	Sudan	7
2019	Burkina Faso	6
2002	Chechnya	6
2007	Somalia	6
2012	South Sudan	6
2011	Yemen	6
2005	DR Congo	5
2013	DR Congo	5
2014	Mali	5
2018	Mali	5
2012	Niger	5
2017	Nigeria	5
2019	Sudan	5

Table 3: Δ Kidnapped (Positive Outliers)

Year	Country	Δ Killed
2008	Somalia	39
2013	Afghanistan	33
2003	Iraq	28
2016	Syrian Arab Republic	28
2012	Syrian Arab Republic	19
2004	Afghanistan	13
2018	Syrian Arab Republic	13
2008	Afghanistan	12
2017	Central African Republic	12
2017	Nigeria	11
2016	South Sudan	11
2003	Afghanistan	10
2010	Afghanistan	10
2009	Pakistan	10
2013	Pakistan	10
2015	Yemen	10
2006	Afghanistan	9
2011	Nigeria	9
2019	Nigeria	9
2008	Sudan	9
2018	DR Congo	7
2009	Occupied Palestinian Territories	7
2012	Pakistan	7
2011	Somalia	7
2013	Somalia	7
2011	South Sudan	7
2017	South Sudan	7
2003	Sudan	7
2002	Angola	6
2014	Central African Republic	6
2010	Iraq	6
2014	Occupied Palestinian Territories	6
2013	South Sudan	6
2013	Sudan	6
2013	Syrian Arab Republic	6
2017	Syrian Arab Republic	6
2001	DR Congo	5
2019	DR Congo	5
2009	Sri Lanka	5
2005	Sudan	5

Table 4: Δ Killed (Positive Outliers)

Attack Contexts and Locations

To examine how attack contexts and attack locations have changed with time, I pool observations across countries, split the sample into two periods (pre- and post-2010), and plot frequency charts for both groups (see Figures 3 and 5). I also generate barcharts illustrating the proportion of attacks falling under every category in each time period (see Figures 4 and 6). For both sets of analyses, I drop observations where information on the attack context or location is not available: changes in the relative popularity of certain tactics over time could simply be driven by improved data collection if we include those cases.

As the figures demonstrate, there has been a substantial increase in the number of incidents that can be traced to combat and crossfire, both in absolute and relative terms (see Figures 3 and 4). While the total number of ambushes has gone up in recent years, in relative terms it has declined in popularity. Turning to attack locations, we see that number of attacks taking place in public location has also significantly increased (see Figures 5 and 6).

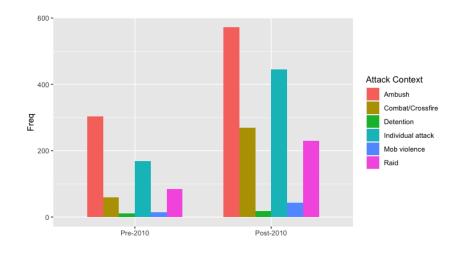


Figure 3: Attack Context (Frequency)

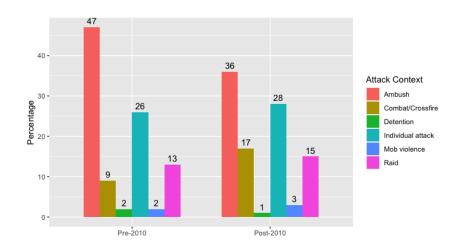


Figure 4: Attack Context (Percentage)

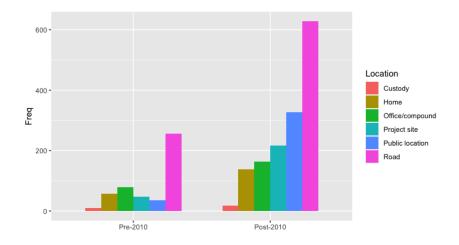


Figure 5: Location (Frequency)

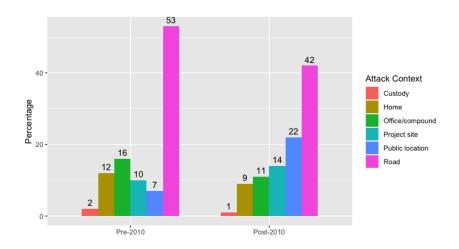


Figure 6: Location (Percentage)

Analysis - Determinants of Changing Rates

In this section, I examine the relationship between aid worker attacks, the severity of armed conflict, and crime. Gathering data on battle-related deaths and civilian fatalities from UCDP⁷ and serious assault figures from UNODC, I run OLS regressions with country fixed effects and clustered standard errors. The results displayed in the Appendix (Tables 8-10) are telling.

In none of our specifications do we see a positive, statistically significant relationship between serious assault and attacks on aid workers. However, in several specifications, we observe a positive association between attacks on aid workers and battle-related deaths and civilian fatality rates. Some of the analyses should be interpreted with caution. Simultaneously controlling for assault rates, battle-related-deaths, and civilian fatality rates (Specification 4) requires us to discard majority of the observations. Nevertheless, it does appear that attacks on aid workers are more a function of destabilizing armed conflict than the general level of crime in a country.

⁷Data on battle-related deaths comes from the UCDP Battle-Related Deaths Dataset and figures on civilian fatalities come from the UCDP One-sided Violence Dataset which gathers information of intentional attacks on civilians by governments and formally organized armed groups. For both datasets, I aggregate the variable in question by country and year.

Means of Attack

The AWSD also contains information on the means of attack, i.e. the strategies and methods employed by groups or individuals targeting aid workers. Excluding the *Unknown* category used to describe cases where this information is not available, there are thirteen unique *Means of Attack*, ranging from kidnappings to body-borne IEDs to shootings. In order to identify any trends, once again, I split the sample into two groups (pre- and post-2010), and plot frequency charts for both groups (Figure 7). I also create barcharts illustrating the proportion of attacks following under each category (Figure 8).

As the barcharts demonstrate, shootings remain the most common means of attack; aerial bombardments and bodily assaults have increased the most in relative terms, going from roughly 2% to 7% of total attacks for the former, and increasing from approximately 16% to 22% of total attacks for the latter.

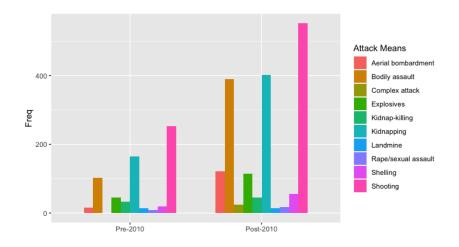


Figure 7: Attack Means (Frequency)

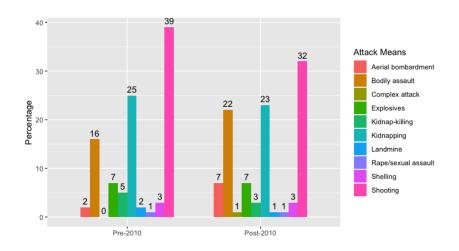


Figure 8: Attack Means (Percentage)

References

Eck, Kristine & Lisa Hultman (2007) Violence Against Civilians in War. Journal of Peace Research 44(2).

Pettersson, Therese & Magnus Öberg (2020) Organized violence, 1989-2019. Journal of Peace Research 57(4).

United Nations Office Of Drugs and Crime. (2020). Serious Assault [Data file]. Retrieved from https://dataunodc.un.org/data/crime/Serious%20assault

Appendix

	Statistic
Test statistic	-2.345897
DF	455.9008
p value	0.01940889
Mean (Pre-2010)	3.126904
Mean (Post-2010)	4.758621
Alternative hypothesis	two.sided

Welch Two Sample t-test: Pre- and Post-2010 $\,$

Table 5: Wounded (T-Test)

	Statistic
Test statistic	-2.822115
DF	387.0861
p value	0.005016869
Mean (Pre-2010)	2.000000
Mean (Post-2010)	3.938697
Alternative hypothesis	two.sided

Welch Two Sample t-test: Pre- and Post-2010

Table 6: Kidnappings (T-Test)

	Statistic
Test statistic	-0.7910416
DF	455.794
p value	0.4293312
Mean (Pre-2010)	3.705584
Mean (Post-2010)	4.268199
Alternative hypothesis	two.sided

Welch Two Sample t-test: Pre- and Post-2010

Table 7: Killings (T-Test)

	Total Killed	Total Killed	Total Killed	Total Killed
Battle Related Deaths (Logged)	1.80***			0.86
	(0.29)			(0.57)
Fatalities (Civilians) (Logged)		0.39		2.87*
		(0.69)		(1.46)
Assault Rates (Logged)			-0.13	-0.69
			(0.83)	(1.33)
State Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes
N	167	125	89	20

Standard errors in parentheses

Table 8: OLS Results-Killings (Fatalities, Battle-Related Deaths, and Assault Rates)

^{*} p < 0.05, ** p < 0.01, *** p < 0.001

	Total Kidnapped	Total Kidnapped	Total Kidnapped	Total Kidnapped
Battle Related Deaths (Logged)	1.03**			-0.90
	(0.33)			(0.90)
Fatalities (Civilians) (Logged)		-0.77		2.15
, , , , ,		(0.80)		(1.73)
Assault Rates (Logged)			-0.56	0.77
(33 /			(0.47)	(0.71)
State Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes
N	167	125	89	20

Standard errors in parentheses

Table 9: OLS Results-Kidnappings (Fatalities, Battle-Related Deaths, and Assault Rates)

	Total Wounded	Total Wounded	Total Wounded	Total Wounded
Battle Related Deaths (Logged)	0.86**			0.60
	(0.28)			(0.42)
Fatalities (Civilians) (Logged)		-0.54		1.98
, , , , ,		(0.97)		(1.29)
Assault Rates (Logged)			0.02	0.21
			(0.23)	(0.87)
State Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes
N	167	125	89	20

Standard errors in parentheses

Table 10: OLS Results-Wounded (Fatalities, Battle-Related Deaths, and Assault Rates)

^{*} p < 0.05, ** p < 0.01, *** p < 0.001

^{*} p < 0.05, ** p < 0.01, *** p < 0.001