The Long-Term Effects of Violence: How Conflict Frequency Affects Cultural Values

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Abstract

As far back as the historical record reaches, conflict has been a part of human history. It has been the rise and fall of almost every culture that exists today. The world is continuing to evolve at an exponentially increasing rate, and with it the role that violence and conflict plays in the everyday lives of the peoples of the world. According to the U.N., "The absolute number of deaths has been declining since 1946. And yet, conflict and violence are currently on the rise" (United Nations, n.d.).

This phenomenon may be due to a myriad of things. Perhaps our rapidly advancing technologies have made the organized conflicts of war safer and more predictable while also enabling chaotic individual actors more destructive power. Could it be that the conflict-steeped past has warped the cultural values to be more accepting of violence? To answer that question, I have used data from the UCDP/PRIO Armed Conflict Dataset alongside the World Values Survey Wave 7 and found that total conflict duration for countries does indeed have a tangible relationship with cultural values, but surprisingly in the opposite way I had originally assumed.

This study looks at five survey questions and their answers, as well as the total conflict duration of a country between 1946 and 2022, and other correlated factors such as military expenditure and country income classifications.

Introduction

Past research has demonstrated that for most there is no binary category that violence can fit into. Bobowik et al. (2014) summarized that in the case of WWII individuals were able to identify both positive and negative sides to the conflict. The acknowledgement “that WWII was a social catastrophe and caused the Cold War was stronger than the belief that it was a just and necessary war. However, the purpose and the burden of WWII were perceived as predominantly positive, as it was related to the reconstruction of democracy, resulting in technological advances and the creation of the United Nations”. The 36 countries that they examined attributed both positive and negative values to WWII and acknowledged complex, conflicting feelings about conflict.

It is in some party’s best interest to incite violence, as “creating a culture of violence is in the interest of both the state and insurgency movements during war since both groups need their respective support bases to support their use of violence and to extract contributions” (Steenkamp, 2005). Steenkamp concluded violence is not always an unnatural force but one perpetuated by bad actors. As these actors gain from conflict, they have more resources to then create even more conflicts, and the cycle will begin to feed itself. It is hard to imagine that kind of conflict not seeping its way into cultural values.

Previous research into these relationships has mainly focused on specific conflicts, conflict purpose, or in the case of Lansford and Dodge (2008), focused on a specific consequence of violence. They surmised that “the more frequently a society employs corporal punishment of its children, the more prevalent adult violence is at a societal level and the more adults endorse the use of violence.” The aim of this study is to depict a broader picture. How does continued conflict change someone’s cultural values? Next, I will go over the methodologies used to build the five models, a description of the data and its sources, the empirical findings, and lastly discuss the impact of this study and potential improvements that can be made in the future.

Methodology

As all the key dependent variables in this study are survey answers, and therefore ordinal, it was determined that either an ordinal probit regression or an ordinal logistic regression should be used. The majority of the survey responses are largely skewed in one direction, as shown in figure 1, so the ordinal logistic regression was chosen to attempt to alleviate the non-normal distribution. Explanations on how to interpret the ordinal logistic regression and its cumulative frequencies will be found in the empirical results section of the paper. The models were also built with robust standard errors to minimize any problems with heteroskedasticity.

Figure 1

Q191	Freq.	Percent	Cum.
1	30,042	66.45	66.45
2	4,943	10.93	77.39
3	3,097	6.85	84.24
4	1,736	3.84	88.08
5	2,465	5.45	93.53
6	922	2.04	95.57
7	581	1.29	96.85
8	476	1.05	97.91
9	251	0.56	98.46
10	696	1.54	100.00
Total	45,209	100.00	

The dependent variables the models were built around were as follows. Question 1, involving how important family is with 1 being very important and 4 being not important. Question 176, which asked respondents if they agreed or disagreed with the statement "nowadays one often has trouble deciding which moral rules are the right ones to follow?" with 1 being completely agree with the statement and 10 being completely disagree with the statement. Question 179, whether stealing property is justified, 1 being never and 10 being always. Question 191, if violence against other people is ever justified. Question 194, if political violence is either justified or never justified. These five dependent variables were then used to build five different models using the independent variables of conflict duration in days, the corruption perception index, military expenditures as a percentage of GDP, government education expenditures as a percentage of GPD, four dummy variables to denote if a country was considered low, lower middle, upper middle, or upper income, and respondent's age.

The Data

The data for this study came from two different datasets. The bulk of the data, including the five key dependent variables, comes from the Word Values Survey Wave 7. This is a cross-sectional survey where respondents are asked many questions about various values such as political, ethical, or family values. The second part of the data comes from the UCDP/PRIO Armed Conflict Dataset Version 23.1. This dataset tracked various conflicts from 1946 – 2022. I created a duration variable for each conflict ID found within the dataset that measures the time in days a conflict between a government and at least one other faction. These two datasets were then merged using countries to attribute the conflict duration to each individual respondent based on the country the survey took place in. Once the datasets were merged and the unmerged observations were dropped the combined dataset contained 45,209 observations.

A list of the variables used is as follows, the dependent question variables are denoted by *Q1*, *Q176*, *Q179*, *Q191* and *Q194*. The key independent variable is *conflict_duration* measured in days, and the related variables are *corrupttransp*, a corruption perception index measured on 0-100 with 0 being highly corrupt, *militaryexp*, military spending as a percentage of GDP, *educationexp*, education expense as a percentage of GDP, *low_inc*, *lmiddle_inc*, *umiddle_inc*, *upper_inc*, whether a country is considered low, lower-middle, upper-middle, and upper class income, and *Q262*, which measures the respondents age. These additional regressors were chosen to reduce omitted variable bias, as they are all correlated to *conflict_duration* to one degree or another. Summary statistics for all these regressors are found at the end of the paper. Summary statistics for the key regressor *conflict_duration* is shown in figure 6.

Figure 6

Variable	Obs	Mean	Std. dev.	Min	Max
conflict_d~n	45,209	14717.3	16221.02	0	72874

Empirical Results

The results obtained in Stata through the ordinal logistic regression were promising. Models 1-5 show the various outputs for each regression at the end of the paper. The key regressor, *conflict_duration*, was statistically significant in all five of the considered models. For explanatory purposes I will focus on the model with the strongest significant likelihood, model three, whether stealing is justified. The Stata output is shown in figure 4. The statistical model used was ordinal logistic regression. This is a model that can handle non-numeric values of the dependent variables. As to be expected with a dependent variable with a high degree of independent actors, the pseudo-R^2 value is rather low at 0.0089. This indicates there are several other factors that affect the outcome of our model that have not been accounted for. As this is a logistic regression, the various coefficients can be tricky to interpret at a glance, but the signs of the coefficients are simpler.

$$y^*(\text{Q179}) = -1.45e^{-5}\text{confict\_duration} + 8.54e^{-3}corrupttransp + 1.29e^{-5}militaryexp - 2.43e^{-5}educationexp + 0.732low\_inc - 8.15e^{-3}lmiddle\_inc - 0.845upper\_inc - 0.0086Q262$$

This model shows that the longer a country has been in conflict, the less likely the respondent is to reply to the survey question with a 10, always justifiable. These probabilities are defined by the nine tau cuts found below the coefficients. These tau cuts are used to calculate the likelihood that a particular respondent, given their independent variables, will answer with one of the 1-10 categories. Unlike ordinal probit regression, O-Logit displays a cumulative frequency as the tau cuts get higher and higher. To calculate the percentage probability, you must first calculate the y* value, convert that value into odds by e^{y*}, then take those odds and convert that to the probability, $p = \frac{odds}{1 + odds}$.

Figure 4

Ordered logistic regression

Number of obs = 45,116
Wald chi2(8) = 1012.68
Prob > chi2 = 0.0000
Log pseudolikelihood = -49536.216
Pseudo R2 = 0.0089

Q179	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
conflict_duration	-.0000145	8.98e-07	-16.14	0.000	-.0000163	-.0000127
corrupttransp	.0085444	.0013238	6.45	0.000	.0059499	.011139
militaryexp	.0000129	5.74e-06	2.24	0.025	1.63e-06	.0000241
educationexp	-.0000243	3.07e-06	-7.91	0.000	-.0000303	-.0000183
low_inc	.731525	.0510772	14.32	0.000	.6314155	.8316346
lmiddle_inc	-.008148	.0284521	-0.29	0.775	-.0639132	.0476171
upper_inc	-.8448635	.0516012	-16.37	0.000	-.946	-.7437271
Q262	-.0086074	.0007136	-12.06	0.000	-.0100061	-.0072086
/cut1	.6686984	.0617166			.5477361	.7896607
/cut2	1.228936	.0619715			1.107474	1.350398
/cut3	1.678775	.0623063			1.556657	1.800893
/cut4	1.984861	.0626366			1.862096	2.107627
/cut5	2.500782	.0639279			2.375486	2.626078
/cut6	2.847875	.0647573			2.720953	2.974797
/cut7	3.206043	.0661905			3.076312	3.335774
/cut8	3.6168	.0687059			3.482139	3.751461
/cut9	3.975297	.0716229			3.834919	4.115676

Put into context, every day a country was part of a conflict reduces their y* value by $1.45e^{-5}$, which means they are less likely to be found in tau cut 9 or below, holding all other things constant. This explanation holds true for all our regressors except for the dummy variables used to denote a country's income status and should be noted that since the upper-middle class dummy variable is not present in the model, it is assumed to be the baseline. The only variable found to not be statistically significant at the 5% level was the lower-middle income classification. A better version of the model could combine lower and upper middle-class indicators and test for significance again.

Conclusion

The models that were built throughout this study successfully get a look at the broad strokes picture of conflict and values. It is readily apparent that the key regressor, *conflict_duration*, has a significant impact on respondent's survey answers. What was interesting is the direction of that influence was not what was originally expected. The longer a respondent's country had been embroiled in conflict, the more likely they were to respond against justification of violence. One interpretation of this outcome is that the more an individual is exposed to violence, the better understanding they have of the gruesome and visceral nature of it. This could cause them to become more compassionate and less prone to not only violence, but any action against others.

Having a clearer understanding of the effects violence has on the core beliefs of a population can have far-reaching impacts. The more that can be understood about differing cultural values can lead to greater comradery and compassion, which in turn can help slowly ease the cycle of violence that is present today.

There is room for refinement in this subject area. One of the key problems surrounding a survey of this nature is the propensity of respondents to answer the questions with what they think they are supposed to answer with. This phenomenon is clearly demonstrated by the large skew of respondents saying that violence is never justified. This study focused on only five singular survey responses, but it could be possible to create a general value variable for each respondent based on their answers to the individual question. This would build a singular strong model as opposed to the five separate ones that were conducted during this study, as well as potentially alleviate some of the skewed answers issues. Another possible improvement could be to include a respondent's immigration status and country of birth, as those who have left their homes may have done so due to increased violence and are even more likely to think violence is unjustifiable. This paper has found that conflict duration has a significant impact on individuals ethical values surrounding violence and competition, and the more violence a person is exposed to, the less likely they will find it to be justified.

Cited Sources

Data

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Tables and Figures

Figure 1

Q191	Freq.	Percent	Cum.
1	30,042	66.45	66.45
2	4,943	10.93	77.39
3	3,097	6.85	84.24
4	1,736	3.84	88.08
5	2,465	5.45	93.53
6	922	2.04	95.57
7	581	1.29	96.85
8	476	1.05	97.91
9	251	0.56	98.46
10	696	1.54	100.00
Total	45,209	100.00	

Figure 2

Q1	Freq.	Percent	Cum.
1	41,474	91.79	91.79
2	3,360	7.44	99.23
3	266	0.59	99.81
4	84	0.19	100.00
Total	45,184	100.00	

Figure 3

Q176	Freq.	Percent	Cum.
1	6,620	14.64	14.64
2	2,579	5.70	20.35
3	3,713	8.21	28.56
4	3,738	8.27	36.83
5	7,897	17.47	54.30
6	4,987	11.03	65.33
7	4,672	10.33	75.66
8	4,235	9.37	85.03
9	2,125	4.70	89.73
10	4,643	10.27	100.00
Total	45,209	100.00	

Figure 4

Q179	Freq.	Percent	Cum.
1	32,559	72.17	72.17
2	4,350	9.64	81.81
3	2,584	5.73	87.54
4	1,334	2.96	90.49
5	1,620	3.59	94.08
6	747	1.66	95.74
7	560	1.24	96.98
8	449	1.00	97.98
9	271	0.60	98.58
10	642	1.42	100.00
Total	45,116	100.00	

Figure 5

Q194	Freq.	Percent	Cum.
1	30,419	67.29	67.29
2	4,692	10.38	77.66
3	2,846	6.30	83.96
4	1,674	3.70	87.66
5	2,408	5.33	92.99
6	953	2.11	95.10
7	594	1.31	96.41
8	548	1.21	97.62
9	310	0.69	98.31
10	765	1.69	100.00
Total	45,209	100.00	

Figure 6

Variable	Obs	Mean	Std. dev.	Min	Max
conflict_d~n	45,209	14717.3	16221.02	0	72874

Figure 7

Variable	Obs	Mean	Std. dev.	Min	Max
Q262	45,209	40.67305	15.72635	16	103

Figure 8

incomeWB	Freq.	Percent	Cum.
1	2,366	5.23	5.23
2	13,859	30.66	35.89
3	20,585	45.53	81.42
4	8,399	18.58	100.00
Total	45,209	100.00	

Model 1 – Q1

Ordered logistic regression

Number of obs = 45,184
Wald chi2(8) = 450.90
Prob > chi2 = 0.0000
Log pseudolikelihood = -13906.964
Pseudo R2 = 0.0192

Q1	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
conflict_duration	-9.02e-06	1.52e-06	-5.93	0.000	-.000012	-6.04e-06
corrupttransp	.0094287	.0019703	4.79	0.000	.005567	.0132903
militaryexp	-.0000991	.0000112	-8.83	0.000	-.0001211	-.0000771
educationexp	.0000717	5.77e-06	12.42	0.000	.0000604	.000083
low_inc	-1.036675	.1424697	-7.28	0.000	-1.31591	-.7574394
lmiddle_inc	.2632159	.0454601	5.79	0.000	.1741158	.352316
upper_inc	.2650751	.0697675	3.80	0.000	.1283333	.4018169
Q262	-.0053517	.0011836	-4.52	0.000	-.0076715	-.0030319
/cut1	2.496502	.0954964			2.309333	2.683671
/cut2	4.947568	.1043865			4.742974	5.152162
/cut3	6.382135	.1427233			6.102403	6.661868

Model 2 – Q176

```
Ordered logistic regression                         Number of obs =   45,209
                                                    Wald chi2(8)   = 1024.00
                                                    Prob > chi2    =  0.0000
Log pseudolikelihood = -100699.12                   Pseudo R2      =  0.0047
```

Q176	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
conflict_duration	-6.47e-07	6.85e-07	-0.94	0.345	-1.99e-06	6.96e-07
corrupttransp	-.0203798	.0009312	-21.89	0.000	-.0222049	-.0185548
militaryexp	.000016	4.66e-06	3.43	0.001	6.85e-06	.0000251
educationexp	-.0000157	2.37e-06	-6.61	0.000	-.0000203	-.000011
low_inc	.0271212	.0490229	0.55	0.580	-.0689619	.1232043
lmiddle_inc	-.4048315	.0223061	-18.15	0.000	-.4485506	-.3611123
upper_inc	.6295846	.0374804	16.80	0.000	.5561244	.7030448
Q262	.000052	.0005469	0.10	0.924	-.0010199	.0011239
/cut1	-2.565255	.0462727			-2.655947	-2.474562
/cut2	-2.163085	.0455241			-2.25231	-2.073859
/cut3	-1.709231	.0449348			-1.797302	-1.621161
/cut4	-1.3257	.0445608			-1.413037	-1.238362
/cut5	-.6024386	.0441522			-.6889754	-.5159018
/cut6	-.1350676	.0440486			-.2214013	-.0487339
/cut7	.3714955	.044113			.2850356	.4579554
/cut8	.9798098	.0446805			.8922376	1.067382
/cut9	1.413121	.045376			1.324186	1.502057

Model 3 – Q179

Ordered logistic regression	Number of obs = 45,116
	Wald chi2(8) = 1012.68
	Prob > chi2 = 0.0000
Log pseudolikelihood = -49536.216	Pseudo R2 = 0.0089

Q179	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
conflict_duration	-.0000145	8.98e-07	-16.14	0.000	-.0000163	-.0000127
corrupttransp	.0085444	.0013238	6.45	0.000	.0059499	.011139
militaryexp	.0000129	5.74e-06	2.24	0.025	1.63e-06	.0000241
educationexp	-.0000243	3.07e-06	-7.91	0.000	-.0000303	-.0000183
low_inc	.731525	.0510772	14.32	0.000	.6314155	.8316346
lmiddle_inc	-.008148	.0284521	-0.29	0.775	-.0639132	.0476171
upper_inc	-.8448635	.0516012	-16.37	0.000	-.946	-.7437271
Q262	-.0086074	.0007136	-12.06	0.000	-.0100061	-.0072086
/cut1	.6686984	.0617166			.5477361	.7896607
/cut2	1.228936	.0619715			1.107474	1.350398
/cut3	1.678775	.0623063			1.556657	1.800893
/cut4	1.984861	.0626366			1.862096	2.107627
/cut5	2.500782	.0639279			2.375486	2.626078
/cut6	2.847875	.0647573			2.720953	2.974797
/cut7	3.206043	.0661905			3.076312	3.335774
/cut8	3.6168	.0687059			3.482139	3.751461
/cut9	3.975297	.0716229			3.834919	4.115676

Model 4 – Q191

```
Ordered logistic regression                          Number of obs = 45,209
                                                     Wald chi2(8)  = 729.27
                                                     Prob > chi2   = 0.0000
Log pseudolikelihood = -56505.173                    Pseudo R2     = 0.0060
```

Q191	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
conflict_duration	-9.31e-06	8.50e-07	-10.95	0.000	-.000011	-7.64e-06
corrupttransp	.0138326	.0012096	11.44	0.000	.0114619	.0162034
militaryexp	-.0000246	5.57e-06	-4.42	0.000	-.0000355	-.0000137
educationexp	-.0000143	2.89e-06	-4.95	0.000	-.0000199	-8.62e-06
low_inc	.2761893	.0500862	5.51	0.000	.1780222	.3743564
lmiddle_inc	.1065033	.0262695	4.05	0.000	.0550162	.1579905
upper_inc	-.7146227	.0469254	-15.23	0.000	-.8065947	-.6226507
Q262	-.008805	.0006591	-13.36	0.000	-.0100967	-.0075132
/cut1	.7016023	.056818			.5902412	.8129635
/cut2	1.255685	.0570232			1.143921	1.367448
/cut3	1.705065	.0574799			1.592407	1.817724
/cut4	2.030677	.0578628			1.917268	2.144086
/cut5	2.704366	.0591508			2.588432	2.820299
/cut6	3.105414	.0601267			2.987567	3.22326
/cut7	3.461859	.0613268			3.341661	3.582057
/cut8	3.880479	.0637553			3.755521	4.005437
/cut9	4.194329	.0665389			4.063915	4.324743

Model 5 – Q194

```
Ordered logistic regression                        Number of obs = 45,209
                                                   Wald chi2(8)  = 481.44
                                                   Prob > chi2   = 0.0000
Log pseudolikelihood = -56246.69                   Pseudo R2     = 0.0039
```

Q194	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
conflict_duration	-.0000102	8.60e-07	-11.85	0.000	-.0000119	-8.51e-06
corrupttransp	.0038728	.0012036	3.22	0.001	.0015137	.0062319
militaryexp	4.23e-06	5.50e-06	0.77	0.442	-6.54e-06	.000015
educationexp	-.0000181	2.90e-06	-6.24	0.000	-.0000238	-.0000124
low_inc	.3742241	.0503807	7.43	0.000	.2754796	.4729685
lmiddle_inc	-.0771681	.0264811	-2.91	0.004	-.1290701	-.0252661
upper_inc	-.5045227	.0472076	-10.69	0.000	-.597048	-.4119975
Q262	-.0065674	.0006615	-9.93	0.000	-.0078639	-.0052709
/cut1	.4028922	.0567155			.2917318	.5140525
/cut2	.9327231	.0568519			.8212953	1.044151
/cut3	1.343632	.057158			1.231604	1.455659
/cut4	1.65032	.0574891			1.537644	1.762997
/cut5	2.276042	.0587645			2.160866	2.391218
/cut6	2.65656	.0597206			2.53951	2.77361
/cut7	2.982463	.0608952			2.863111	3.101816
/cut8	3.407165	.0632023			3.283291	3.531039
/cut9	3.754449	.0658304			3.625424	3.883475