Decay or Resilience: The Long-Term Social Consequences of Conflict-Related Sexual Violence in Sierra Leone

—*Appendix*—

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1 Data Comparison

How do the 2011 Sierra Leone Integrated Household Survey (SLIHS) data compare with the data used in the study on Sierra Leone by Bellows and Miguel (B&M)? First of all, B&M have no data on CRSV, but only for conventionally measured violence variables (e.g. homicide, displacement, property destruction).[1] For instance, the SLIHS reports that in 32 percent of households members were killed, whereas B&M's two data sources report 44 and 20 percent, respectively. Regarding displacement, SLIHS documents 54 percent of households, whereas B&M note 39 and 97 percent, respectively. Somehow, the SLIHS data appear to lie between the two data sources B&M are using. These variations may be due to different sample sizes, different question wording and, most importantly, different times. The B&M data were collected in 2005 and 2007 whereas the SLIHS took place in 2011.

2 Figures and Expanded Tables

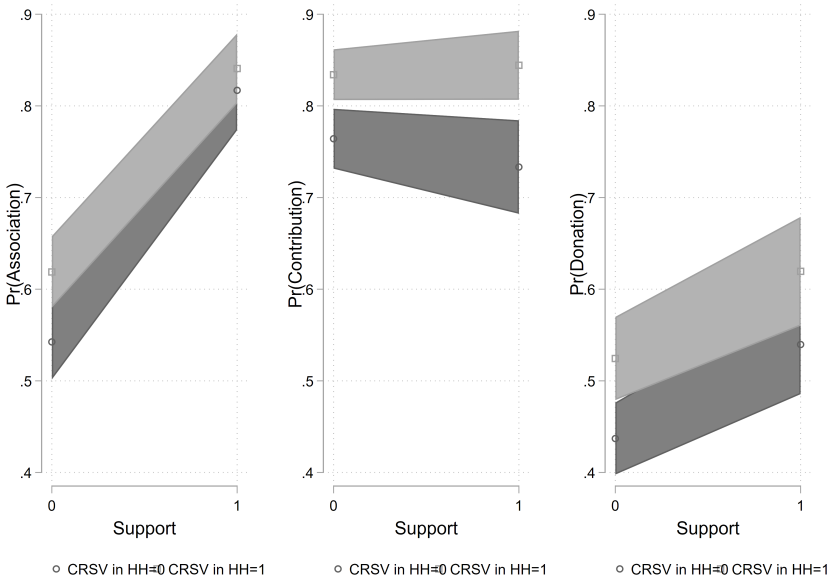
The following tables are identical to the tables in the main text but display the coefficients of all covariates: violence controls (*killed* household members, *mutilated* household members, *displaced*), household controls (*urban*, *household size*, *poverty*) and individual controls (*muslim*, *female*, *age*, *age2*).

2.1 Figures

This graph shows the conditional effect of *humanitarian aid* for unaffected and CRSV-affected households for the three outcome variables *association*, *contributions* and *donations*. The left panel shows that *humanitarian aid* substantially increases the likelihood of membership in local associations. Since the confidence intervals overlap for both types of households, there is no conditional effect. In the central panel, the effect on contributions shows that *humanitarian aid* does not significantly change the probability of contributing financially. In the right panel, the interaction effect on the outcome donations is plotted. Similarly to the left panel, there is no discernible effect on donation.

[1] Bellows and Miguel 2009

Figure 1: Interaction Effect *CRSV in HH*humanitarian aid*



2.2 Main Regression Tables and Figures with Control Variables Presented

Table 1: Effect of CRSV on Membership in Associations

	(1) Association	(2) Association	(3) Association	(4) Association
CRSV in HH	0.377**	0.382**	0.371**	0.412**
	(0.121)	(0.120)	(0.123)	(0.135)
Humanitarian aid			1.136***	1.206***
			(0.149)	(0.190)
CRSV in HH*humanitarian aid				-0.184
				(0.254)
Homicide in HH		-0.134	-0.090	-0.092
		(0.137)	(0.138)	(0.138)
Mutilation in HH		0.686**	0.454*	0.474*
		(0.245)	(0.227)	(0.229)
HH ever displaced		-0.248+	-0.264+	-0.257+
		(0.142)	(0.144)	(0.143)
RUF camps		-0.020	-0.009	-0.010
		(0.035)	(0.035)	(0.035)
Urban	-0.927***	-0.918***	-0.957***	-0.958***
	(0.200)	(0.198)	(0.206)	(0.205)
Household size	0.064**	0.066**	0.064**	0.065**
	(0.021)	(0.021)	(0.022)	(0.022)
Poverty index	-0.188**	-0.181**	-0.244***	-0.244***
	(0.066)	(0.068)	(0.073)	(0.073)
Muslim	0.212+	0.217+	0.258*	0.258*
	(0.127)	(0.126)	(0.129)	(0.129)
Female	-0.111	-0.105	-0.114	-0.115
	(0.102)	(0.103)	(0.107)	(0.107)
Age	0.005	0.007	-0.006	-0.006
	(0.015)	(0.015)	(0.015)	(0.015)
Age2	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
District dummies	Yes	Yes	Yes	Yes
F-Stat	0.862	0.629	1.034	1.168
p-Value	0.559	0.773	0.411	0.313
Model	Logit	Logit	Logit	Logit
Observations	5475	5475	5475	5475

Note: Outcome variable *association* measures whether someone in the household is member of a community-based association.

Robust standard errors clustered by primary sampling unit in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Effect of CRSV on Prosocial Behavior

	(1) Association	(2) Contributions	(3) Donations
CRSV in HH	0.390**	0.483**	0.231+
	(0.139)	(0.158)	(0.140)
Humanitarian aid	1.314***	-0.427*	0.184
	(0.206)	(0.196)	(0.145)
CRSV in HH*humanitarian aid	-0.314	0.150	-0.088
	(0.262)	(0.264)	(0.213)
Homicide in HH	-0.189	-0.052	0.112
	(0.148)	(0.145)	(0.118)
Mutilation in HH	0.559*	0.120	-0.622***
	(0.230)	(0.278)	(0.184)
HH ever displaced	-0.154	0.160	0.221+
	(0.152)	(0.142)	(0.127)
RUF camps	-0.016	0.011	0.034
	(0.034)	(0.037)	(0.033)
Urban	-0.969***	-0.501*	0.181
	(0.212)	(0.220)	(0.189)
Household size	0.079***	0.090***	0.001
	(0.022)	(0.026)	(0.020)
Poverty index	-0.233**	-0.334***	-0.052
	(0.087)	(0.088)	(0.071)
Muslim	0.072	0.189	-0.071
	(0.143)	(0.163)	(0.152)
Female	-0.153	0.126	-0.091
	(0.104)	(0.116)	(0.092)
Age	-0.015	-0.012	0.035*
	(0.018)	(0.018)	(0.016)
Age2	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
District dummies	Yes	Yes	Yes
F-Stat	0.339	0.564	0.246
p-Value	0.962	0.827	0.987
Model	Logit	Logit	Logit
Observations	5475	5475	5475

Robust standard errors clustered by primary sampling unit in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Social Acceptance

	(1) Community Reliance	(2) Stigmatize HIV
CRSV in HH	0.025	0.078
	(0.125)	(0.109)
Homicide in HH	-0.161	-0.096
	(0.126)	(0.100)
Mutilation in HH	0.658**	0.042
	(0.249)	(0.236)
HH ever displaced	-0.402**	0.334**
	(0.145)	(0.115)
RUF camps	0.024	0.006
	(0.036)	(0.029)
Household controls	Yes	Yes
Individual controls	Yes	Yes
District dummies	Yes	Yes
F-Stat	1.000	1.437
p-Value	0.438	0.168
Model	Logit	Logit
Observations	5474	4815

Robust standard errors clustered by primary sampling unit in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.3 Main Regression Tables with Unmatched Data

Table 4: Effect of CRSV on Membership in Associations (unmatched)

	(1) Association	(2) Association	(3) Association	(4) Association
CRSV in HH	0.399***	0.411***	0.392***	0.399**
	(0.115)	(0.115)	(0.116)	(0.130)
Humanitarian aid			1.127***	1.137***
			(0.132)	(0.160)
CRSV in HH*humanitarian aid				-0.031
				(0.224)
Homicide in HH		-0.144	-0.093	-0.093
		(0.131)	(0.133)	(0.133)
Mutilation in HH		0.609**	0.407+	0.410+
		(0.228)	(0.210)	(0.211)
HH ever displaced		-0.226+	-0.226+	-0.225+
		(0.136)	(0.136)	(0.136)
RUF camps		-0.002	0.007	0.007
		(0.032)	(0.032)	(0.032)
Urban	-0.969***	-0.960***	-0.997***	-0.997***
	(0.199)	(0.198)	(0.202)	(0.202)
Household size	0.061***	0.062***	0.062***	0.062***
	(0.018)	(0.018)	(0.018)	(0.019)
Poverty index	-0.237***	-0.233***	-0.286***	-0.286***
	(0.057)	(0.058)	(0.061)	(0.061)
Muslim	0.225*	0.229*	0.279**	0.280**
	(0.105)	(0.104)	(0.108)	(0.108)
Female	-0.168+	-0.163+	-0.159	-0.159
	(0.095)	(0.096)	(0.103)	(0.103)
Age	-0.002	-0.001	-0.013	-0.013
	(0.013)	(0.013)	(0.013)	(0.013)
Age2	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
District dummies	Yes	Yes	Yes	Yes
F-Stat	1.386	0.749	1.649	1.351
p-Value	0.191	0.664	0.098	0.207
Model	Logit	Logit	Logit	Logit
Observations	6694	6694	6694	6694

Robust standard errors clustered by primary sampling unit in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Effect of CRSV on Prosocial Behavior (unmatched)

	(1) Association	(2) Contributions	(3) Donations
CRSV in HH	0.399**	0.535***	0.271*
	(0.130)	(0.149)	(0.132)
Humanitarian aid	1.137***	-0.451**	0.276*
	(0.160)	(0.159)	(0.132)
CRSV in HH*humanitarian aid	-0.031	0.157	-0.150
	(0.224)	(0.244)	(0.198)
Homicide in HH	-0.093	-0.044	0.097
	(0.133)	(0.117)	(0.107)
Mutilation in HH	0.410+	0.087	-0.615***
	(0.211)	(0.263)	(0.184)
HH ever displaced	-0.225+	0.142	0.284*
	(0.136)	(0.130)	(0.120)
RUF camps	0.007	0.004	0.030
	(0.032)	(0.034)	(0.031)
Urban	-0.997***	-0.443*	0.153
	(0.202)	(0.207)	(0.188)
Household size	0.062***	0.103***	0.009
	(0.019)	(0.019)	(0.017)
Poverty index	-0.286***	-0.181**	-0.147*
	(0.061)	(0.070)	(0.057)
Muslim	0.280**	0.247*	-0.033
	(0.108)	(0.111)	(0.110)
Female	-0.159	0.126	-0.041
	(0.103)	(0.090)	(0.078)
Age	-0.013	0.006	0.026*
	(0.013)	(0.015)	(0.013)
Age2	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
District dummies	Yes	Yes	Yes
F-Stat	1.351	0.515	0.926
p-Value	0.207	0.864	0.501
Model	Logit	Logit	Logit
Observations	6694	6694	6694

Robust standard errors clustered by primary sampling unit in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.4 Alternative Outcome Variables

Table 6: Effects of CRSV on Membership in Professional and Religious Associations

	(1) Professional association
CRSV in HH	0.424*
	(0.175)
Humanitarian aid	0.198
	(0.307)
CRSV in HH*humanitarian aid	-0.453
	(0.365)
Homicide in HH	-0.181
	(0.170)
Mutilation in HH	0.455
	(0.320)
HH ever displaced	-0.271
	(0.236)
RUF camps	-0.103*
	(0.047)
Urban	0.664**
	(0.208)
Household size	0.034
	(0.035)
Poverty index	-0.169^{+}
	(0.090)
Muslim	-0.203
	(0.203)
Female	-0.060
	(0.144)
Age	0.003
	(0.025)
Age2	-0.000
	(0.000)
District dummies	Yes
F-Stat	0.817
p-Value	0.600
Model	Logit
Observations	5474

Robust standard errors clustered by primary sampling unit in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3 Instrumental Variable Approach

3.1 Theoretical Assumptions

When working with observational data, endogeneity, particularly in the form of reverse causality, is a major concern. In the main text I employed three other strategies to explore the risk of endogeneity with (a) qualitative evidence, (b) a regression on selection effects and (c) a matching procedure. Here I present the fourth strategy, an instrumental variable (IV) estimation.

IV regressions are an approach used to eliminate endogeneity by introducing an exogenous variable that affects the outcome of interest only via the explanatory variable. IV estimations allow an estimate of the local average treatment effect (LATE), the effect of the explanatory variable on the outcome for those observations (households) that respond to the instrument. This subpopulation of the sample is referred to in the literature as *compliers*. For instance, in a medical trial compliers are those subjects that comply with their assignment to either the treatment or the control group. Those in the treatment group are supposed to take the medicine, while those in the control group must abide. The LATE cannot be estimated for the following subpopulations:

- *Defiers*: those who take up the treatment (CRSV) only when they are *not* affected by the instrument
- *Always-takers*: those who take up the treatment (CRSV) even if they are not affected by the instrument
- *Never-takers*: those who never take up the treatment (CRSV) even if they are affected by the instrument

Two conditions must be fulfilled for an IV estimation to deliver unbiased results. First, the IV must be correlated with the (potentially) endogenous explanatory variable. Second, the IV must meet the exclusion restriction, i.e. the IV must not affect the outcome directly or through causal mechanisms other than the explanatory variable, unless these backdoor paths can be blocked and conditioned.[2]

3.2 Using *Distance to Mines* as Exogenous Variation of CRSV

I use the exogenous variation of two measures as an instrumental variable to predict exposure to the explanatory variable *CRSV in HH*. The first instrument *dist. from mines* measures

[2] Imbens and Angrist 1994; Pearl 2009; Morgan and Winship 2014

the distance of a chiefdom's centroid (the exact coordinates of households are unavailable) from the next diamond or gold mine.[3] The underlying idea is that the RUF, as the main perpetrator of sexual violence during the war, sought to control these mining areas. These areas should therefore have worked as magnets for what Weinstein refers to as opportunistic joiners, i.e. combatants who were drawn to the RUF not because of its (initial) ideological mission to transform the marauding political and social system,[4] but for private and materialistic benefits.[5] Building on this key aspect, Cohen argues that opportunistic groups (e.g. abductees, plus "greedy" joiners) suffer from lower levels of group cohesion than groups consisting of ideologically motivated joiners.[6] Among such low-cohesion, opportunity-driven groups, sexual violence, and particularly multiple-perpetrator rape, has commonly been used to increase bonding among combatants and thereby increase unit strength.[7] Households in chiefdoms closer to mines should therefore have had a higher risk of experiencing CRSV. The distance from mines should therefore negatively affect the risk of conflict-related sexual violence (*CRSV in HH*).

The second instrument is related. The dummy variable *RUF*mines* has a value of 1 if a chiefdom's distance from the next diamond mine was less than 10 km and if the RUF had a medium-strong presence within that particular chiefdom. Medium-strong presence means that the RUF operated between four and seven camps per chiefdom (the maximum was 14) and proxies the idea that the RUF did not have full control of a chiefdom but apparently had a strong interest in doing so, presumably to control mines.[8] Such characteristics are likely to have attracted more opportunistic RUF fighters, since control and monitoring by RUF leadership in such areas was much less established than in RUF strongholds. Individual benefits for RUF fighters from diamonds and looting are likely to have been greater there than in established rebel-held areas where activities were more strictly monitored by the leadership.[9] Households in such chiefdoms should therefore have faced a higher likelihood of CRSV since the RUF leadership did not have the capacity to sanction combatant misbehavior.

3.3 Exclusion Restriction

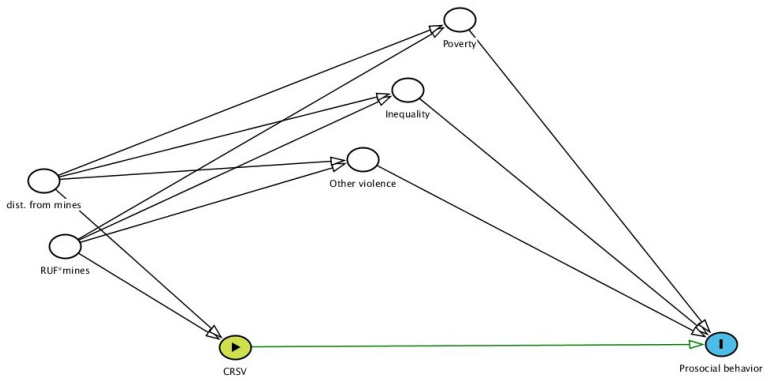
A critical component of any IV estimation is the exclusion restriction (ER) and its discussion. For an IV to deliver unbiased estimates, it must not violate the ER. The ER states that the

[3] The process of geolocating the mines is described below.
[4] Richards 1996; Peters 2011
[5] Weinstein 2005
[6] Cohen 2013
[7] Coulter 2009, 127
[8] Peters 2011, 111
[9] Peters 2011, 157

IV must not affect the outcome of interest (prosocial behavior) directly or through causal processes other than the explanatory variable.[10] In reality IVs often work through alternative channels that may then affect the outcome. The literature on IV regressions refers to this problem as a *backdoor criterion* and suggests that if these factors are observed and accounted for in the model, the IV regression delivers unbiased estimates.[11] It is important to note that there are no statistics or empirical tests with which one could determine whether the IV meets the criteria of the ER. Essentially, the validity of the ER must be theorized and discussed by the researcher.[12]

Do the instruments *dist. from mines* and *RUF*mines* meet the exclusion restriction? As described above, there is strong theoretical, empirical and anthropological evidence that both instruments are related to conflict-related sexual violence.[13] However, there are three channels through which these instrumental variables could bypass the explanatory variable *CRSV in HH* and affect the outcome prosocial behavior. Figure 2 shows these relationships with a directed acyclic graph (DAG) model, which aims to make explicit the relationships between the IVs; the explanatory variable *CRSV in HH*; the outcome; and the backdoor channels *other violence*, *poverty* and *inequality*.

Figure 2: Directed Acyclic Graph



First, notwithstanding the explanations provided above, one can argue that both instruments could also have affected other forms of violence such as killings, mutilation and displacement. Controlling for these should therefore block the backdoor channels (see node

[10] Imbens and Angrist 1994
[11] see, e.g., Pearl, 2009, 79; Morgan and Winship, 2014
[12] Sovey and Green 2011
[13] Weinstein 2005; Cohen 2013; Human Rights Watch 2003; Richards 1996; Gberie 2005

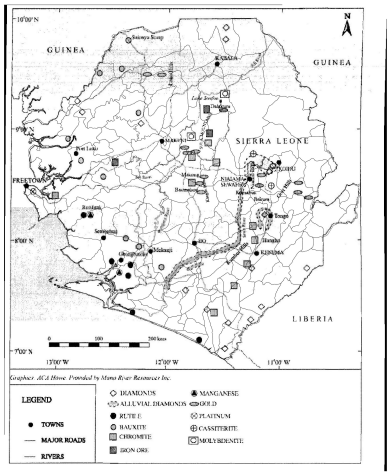
other violence in figure 2). Second, the proximity to mines could have affected the *absolute* and *perceived* economic status of a household, i.e. *poverty* and *inequality*. This effect could have gone either way. For some established households the proximity to mines and income possibilities should have resulted in higher income levels. Alternatively, mining areas were attractive for migrant workers, which could then have attracted rather poor households.[14] Both a household's absolute poverty and perceived inequality would then influence the outcome prosocial behavior since poorer households were less likely to be involved in the community (see the poverty variable in table 1 and 2 in the supplementary files). Controlling for *poverty* and perceived *inequality* should therefore close these backdoor paths (see nodes *poverty* and *inequality* in figure 2). I believe that the plausible channels through which mining could be related to prosocial behavior are exhausted by controlling for alternative forms of violence, poverty and inequality. Therefore, accounting for these alternative pathways increases the confidence that the IV estimation delivers unbiased estimates.

[14] Richards 1996

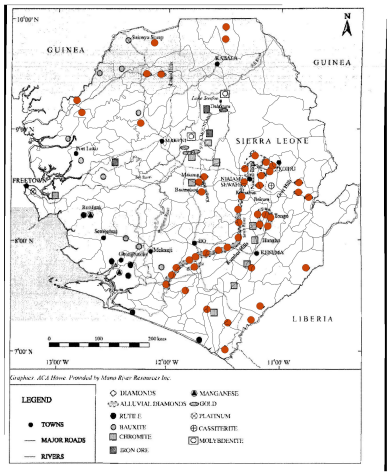
3.4 Construction of the Instrument

Figure 3: Location of Mines

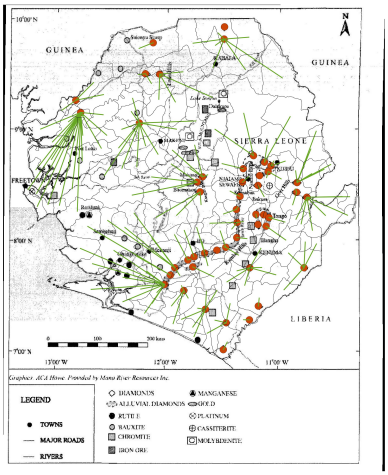
(a) Raw map of mines in Sierra Leone



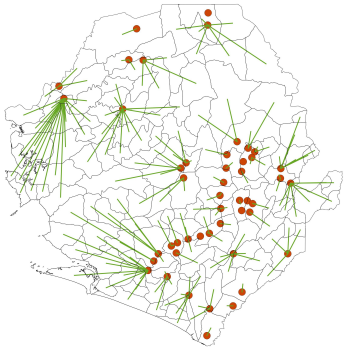
(b) Georeferencing of diamond and gold mines using qGIS



(c) Calculation of distance from mines to chiefdoms' centroids



(d) For each chiefdom, the distance to the closest mine is calculated and used as an instrument *dist. from mines*



3.5 Estimation and Results

Table 7 shows the results of the 2SLS IV estimation. Column (1) shows the results for the first stage where *CSRV* exposure is regressed on the two exogenous instruments *dist. from mines* and *RUF*mines* and the other covariates. This first stage is the same for all three outcome variables. Both instruments *dist. from mines* and *RUF*mines* are significant and point in the expected direction. First, the likelihood of *CRSV in HH* decreases with growing distance from mines, i.e. the further away a household lives from a mining area the less likely a household member will have experienced *CRSV in HH*. Second, the likelihood of *CRSV in HH* increases when diamond mines are present within a chiefdom and when the RUF holds a medium-strong presence.

Columns (2) to (4) show the results of the second stage and estimates the LATE of *CRSV in HH* on the three outcomes *association*, *contribution* and *donations*. In line with the earlier results, *CRSV in HH* has a statistically significant and positive effect (below 0.1 percent) on the likelihood of being a member in a community-based *association* (column 1). Contradicting the prior results, model (2) shows that the effect of *CRSV in HH* on social *contributions* is statistically insignificant. In model (3) *CRSV in HH* has a positive and significant effect on donations (below 0.1 percent).

Overall, the statistical significance changes in all three IV models compared to the main results in table 2. The effect of *CSRV in HH* on membership in *associations* and on *donations* becomes more significant (columns [2] and [4]). However, the effect of *CRSV in HH* on *contributions* disappears in the IV models (column [3]). These slight changes in results could be the case because the IV estimation only estimates the local average treatment effect, i.e. those households that have been exposed to CRSV due to decreasing distance from mines and RUF camps (compliers).

The test statistics are supportive of the model fit. Most importantly, the F-statistic which tests the strengh of the instruments is at 40 which suggests that the instruments identify the explanatory variable *CSRV* victimization well. As a rule of thumb only F-statistics below 10 indicate a somewhat weak identification.[15] Furthermore, the low p-value of the underidentification test allows to reject the null hypothesis that the instruments are irrelevant.

Taken together, the IV results change slightly, however in two out of three models the effect of CRSV in HH remains significant. Overall, the IV results further support the resilience argument (H2) and show no signs of a decay mechanism (H1).

[15] Angrist and Pischke 2015, 113

Table 7: 2SLS IV Estimation

	First stage	Second stage		
	(1) DV: CRSV in HH	(2) DV: Association	(3) DV: Contribution	(4) DV: Donations
Dist. from mines	-0.002***			
	(0.000)			
RUF and mines	0.003***			
	(0.001)			
CRSV in HH		0.828***	-0.036	0.758***
		(0.159)	(0.105)	(0.147)
Homicide in HH	0.098***	-0.051^{+}	0.027	-0.044
	(0.017)	(0.028)	(0.018)	(0.027)
Mutilation in HH	0.328***	-0.138*	0.035	-0.347***
	(0.026)	(0.061)	(0.041)	(0.062)
HH ever displaced	0.176***	-0.152***	0.050*	-0.057
	(0.016)	(0.038)	(0.024)	(0.036)
Household size	0.004	0.007	0.017***	-0.004
	(0.003)	(0.004)	(0.003)	(0.004)
Poverty index	0.007	-0.046***	-0.051***	-0.037***
	(0.007)	(0.009)	(0.008)	(0.010)
Inequality	0.012	-0.050***	0.003	-0.002
	(0.011)	(0.014)	(0.010)	(0.014)
Urban	-0.013	-0.299***	-0.110***	0.014
	(0.017)	(0.024)	(0.016)	(0.023)
Muslim	-0.021	0.087***	0.057**	-0.022
	(0.018)	(0.022)	(0.017)	(0.022)
Female	-0.007	0.005	0.030*	-0.001
	(0.016)	(0.021)	(0.015)	(0.021)
Age	0.005^{+}	-0.002	0.000	0.009**
	(0.003)	(0.003)	(0.003)	(0.003)
Age2	-0.000^{+}	0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
N	5475.000	5475.000	5475.000	5475.000
F-Stat weak ident.		40.031	40.031	40.031
LM test underident.		70.795	70.795	70.795
Underident. p-value		0.000	0.000	0.000

Robust standard errors in parentheses.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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