Online Appendix

A latent variable approach to measuring wartime sexual violence

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Contents

Introduction to Online Appendix

This online appendix accompanies the main article *A latent variable approach to measuring wartime sexual violence*. In Section A, we explain our strategy and reasoning for aggregating conflict-actor-year observations. We show that our aggregation results in a minor improvement with regard to decreasing the number of zero-value observations. In Section B, we provide the reported prevalence of wartime sexual violence by both types of conflict actors. This expands upon our selective visual illustration provided in Figure 2 in the main article in order to enable a more direct comparison across actor types. In Section C, we present and discuss temporal variation in the correlation between human rights indicators, by year and conflict actor group. This adds to our presentation of the temporal variation in the correlation between human rights indicators regardless of actor type for all conflict-actor-year observations in Figure 3 in the main article. In Section D, we provide visual empirical evidence that both the static and the dynamic latent variable models featured in the main article converged successfully. In Section E, we provide a table of the estimates of the α and β parameters for the static and dynamic model, respectively. In Section F, we provide estimates of latent SVAC prevalence comparatively across both types of conflict actors. In particular, we highlight how our latent estimates challenge our previous understanding of SVAC in the Colombian case in comparison to purely observational data. In Section G, we provide empirical results of the correlation between our three observational human rights indicators and the static and dynamic latent estimates, respectively. Finally, in Section H, we examine the predictive validity of the static and dynamic estimates of the latent prevalence of wartime sexual violence in empirical support of Section "*Latent estimates express observational uncertainty*" in the main article. In this context, we also describe the multiple imputation strategy we adopted in the effort to account for the statistical uncertainty inherent in the latent estimates of both models.

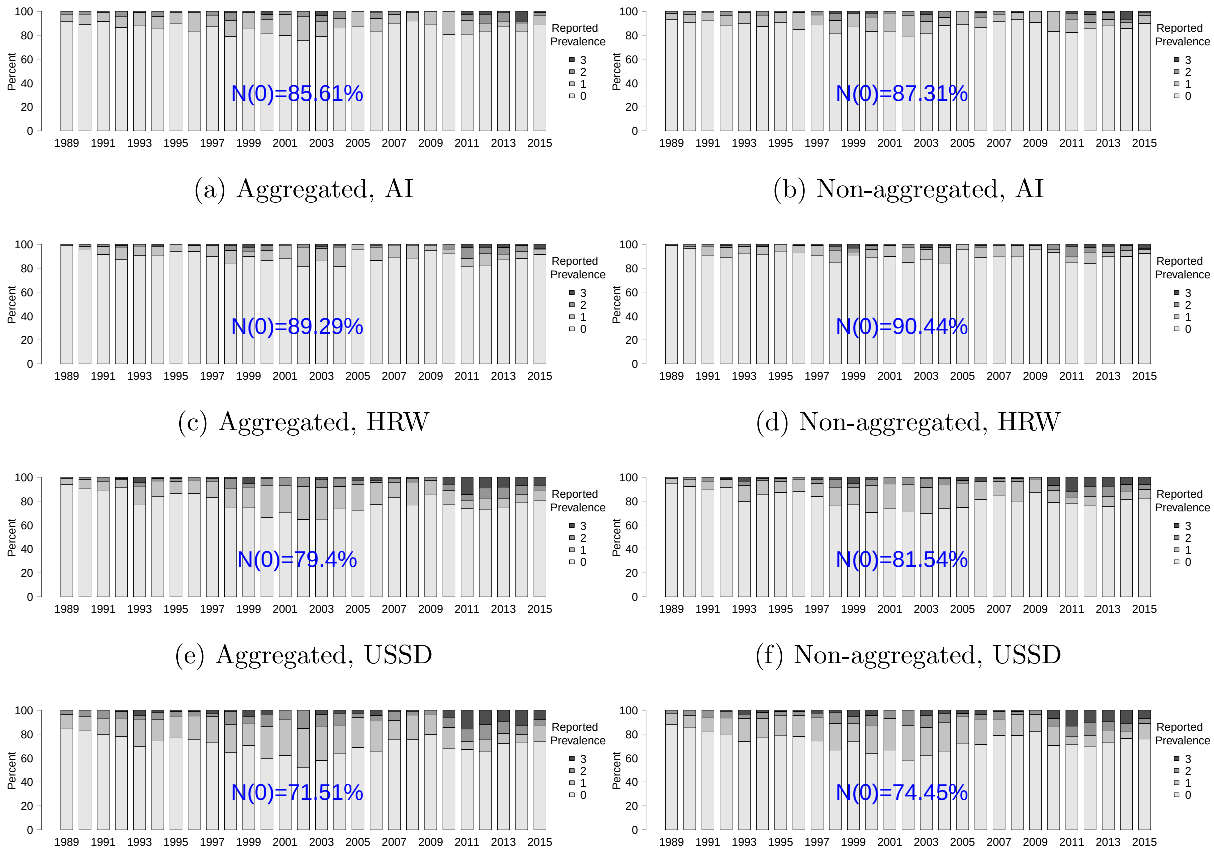
A Aggregating non-state actor observations into rebel-conflict years

In the empirical analysis in the main article, we aggregate all conflict-actor-year observations across all rebel groups active in a given conflict into a single rebel-conflict-year observation by preserving the maximum reported value across the groups for each categorical SVAC prevalence indicator (i.e., AI, HRW, USSD). Following this measurement strategy, we obtain a total of 2,092 conflict-actor-year observations for analytical purposes. Here, we explain our aggregation strategy and the reasoning behind it.

Generally, the SVAC data consists of many zero-value observations. By aggregating observations across rebel groups active in each conflict-year, our main goal was to reduce the percentage of zero-value observations. Figure 1 shows the comparative distribution of zeros in the (rebel) aggregated and (rebel) non-aggregated data (we are keeping government related observation the same both times) for each individual human rights indicator (i.e., AI, HRW, USSD), as well as for the maximum observed value across these three data sources. For the rebel non-aggregated data, the total number of conflict-actor-year observations is 2,427.

Looking at Figure 1, we find consistently that the percentage of zero values is higher when the data are not aggregated. Indicative of the difficulty of observing conflict-related sexual violence, we generally do not know whether a zero value indicates that a conflict actor did not engage in sexual violence or whether it was simply not observed when it engaged in such activity. In order to reduce this uncertainty, keep more variation in the data and hence pull the latent variable estimates away from zero, we decided to increase the number of non-zero value observations by aggregating conflict-year observations across rebel groups for the analysis in the main article.

Once it is identified that a rebel-related country-year has prevalence, future researchers may be interested in parsing out to which particular rebel groups these violations are attributed to. In addition, Figure 1 shows that the percentage difference of zero-value observations between the rebel aggregated and non-aggregated data is small. Interested scholars will therefore be able to produce latent variable estimates for each individual conflict-actor-year if they so desire.



(a) Aggregated, AI

(b) Non-aggregated, AI

(c) Aggregated, HRW

(d) Non-aggregated, HRW

(e) Aggregated, USSD

(f) Non-aggregated, USSD

(g) Aggregated, maximum observed value

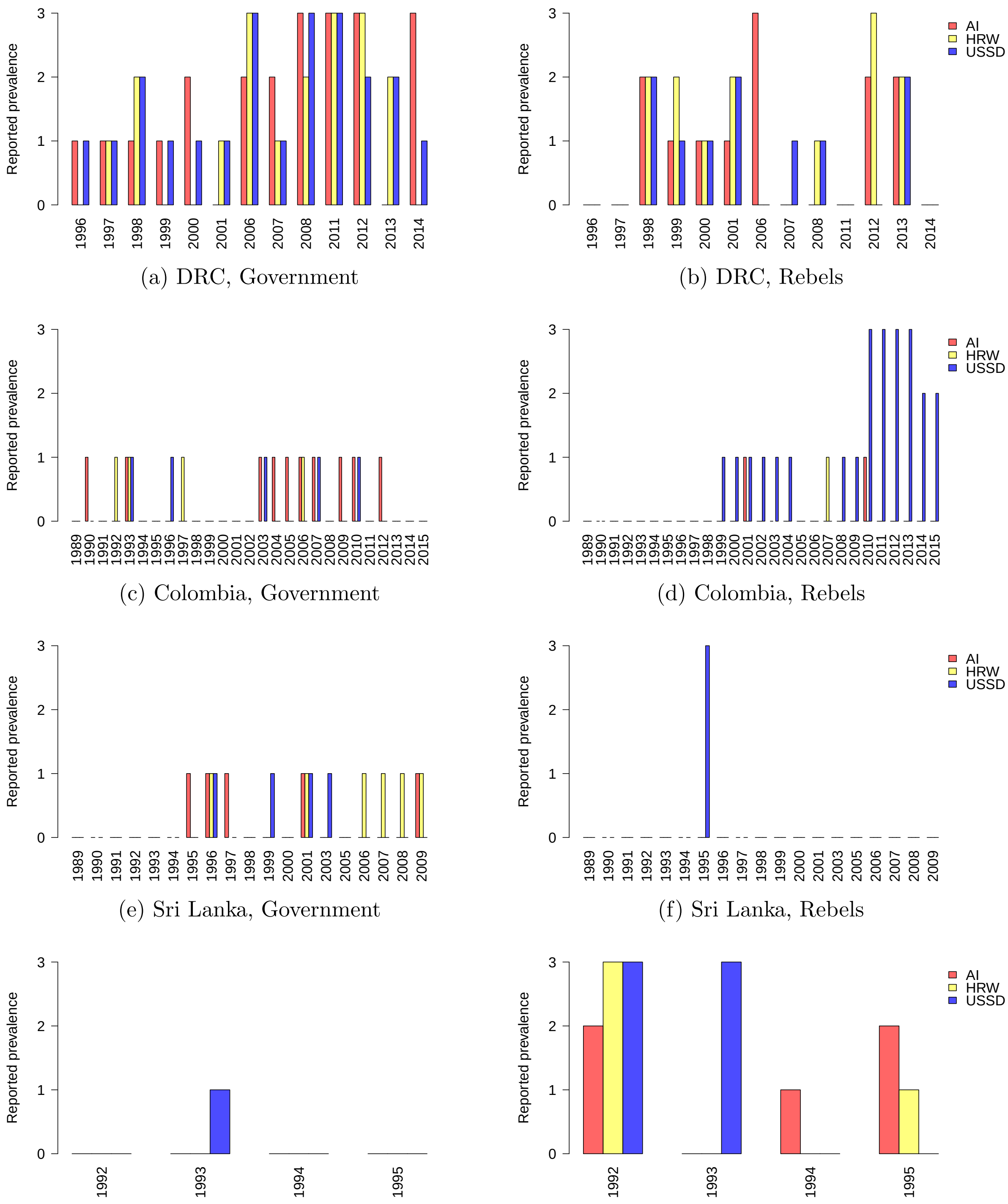
(h) Non-aggregated, maximum observed value

Figure 1. Comparison of the distribution of zeros in rebel-observation aggregated vs. non-aggregated data.

B Reported SVAC prevalence by type of conflict actor

In the main article, we used the government in the Democratic Republic of Congo and Sri Lanka, and rebel forces in Colombia and Bosnia-Herzegovina as illustrative examples. Here, we provide information on the reported prevalence of wartime sexual violence by both types of conflict actors to enable a more direct comparison across types and cases (Figure 2).

In comparison to the armed groups highlighted in the main article, each opposite actor group was reported to have engaged in less sexual violence practices in our four select cases of armed conflict, i.e., the DRC, Colombia, Sri Lanka and Bosnia-Herzegovina. This is why we did not deem them sufficiently interesting to be featured in the main article for illustrative purposes .



(a) DRC, Government

(b) DRC, Rebels

(c) Colombia, Government

(d) Colombia, Rebels

(e) Sri Lanka, Government

(f) Sri Lanka, Rebels

(g) Bosnia-Herzegovina, Government

(h) Bosnia-Herzegovina, Rebels

Figure 2. Reported prevalence of wartime sexual violence in four conflicts according to three human rights sources AI, HRW, and USSD, by type of armed group and conflict-year.

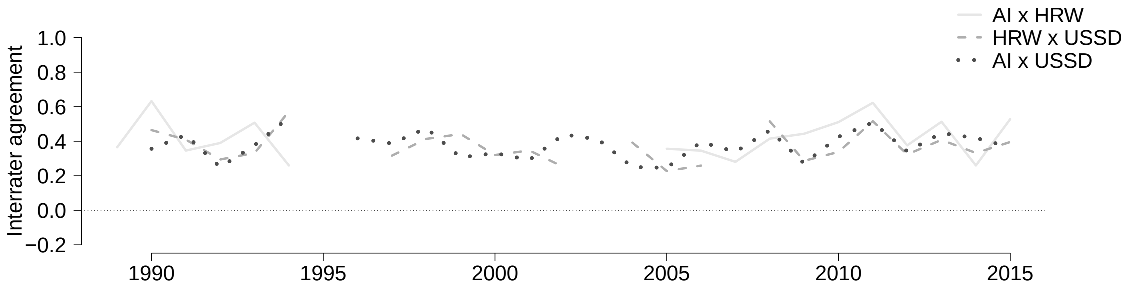
C Temporal variation in interrater agreement between human rights indicators, by conflict actor

In the main article (Figure 3), we visualized the temporal variation in interrater agreement (Cohen's weighted kappa) between the human rights indicators for all conflict-actor-year observations in the SVAC data. Here, we disaggregate these observations by conflict actor group, i.e., governments and rebels, respectively, to examine actor-group specific differences in the interrater agreement of human rights indicators over time (Figure 3).

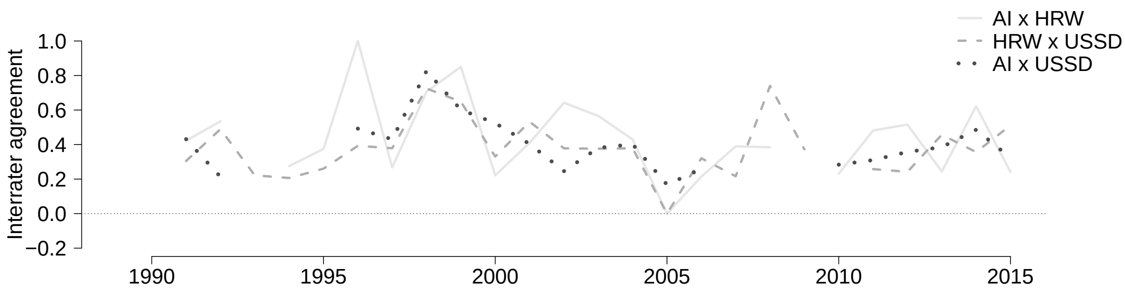
As can be seen, the temporal trends in (dis)agreement are quite diverse. For many years (1992, 1996, 1999, 2001-4, 2011, 2014), there is a considerable agreement between *Amnesty International* and *Human Rights Watch* when practices of rebel groups are concerned, which we also discussed in the main article. In a few years however (1993, 2005, 2009), there is no agreement between AI and HRW on rebel group behavior (Figure 3b). For governments, in turn, the temporal rate of agreement between these two human rights sources appears lower in general, as we also discussed in the main article. In the case of wartime sexual violence practices of governments, both AI and HRW have a tendency to agree more with the *U.S. State Department* over time (Figure 3a).

D Model convergence of latent variable estimates

The Gelman-Rubin (Rhat) statistic provides a measure of whether the latent variable models were run with a sufficient number of iterations (Gelman and Rubin 1992). To confirm the used number of iterations was sufficient, the Rhat statistic needs to be below 1.1. Based on the distribution of the Rhat statistic in the static and dynamic models, we conclude that both latent variable models converged successfully (Figures 4a and 4b).

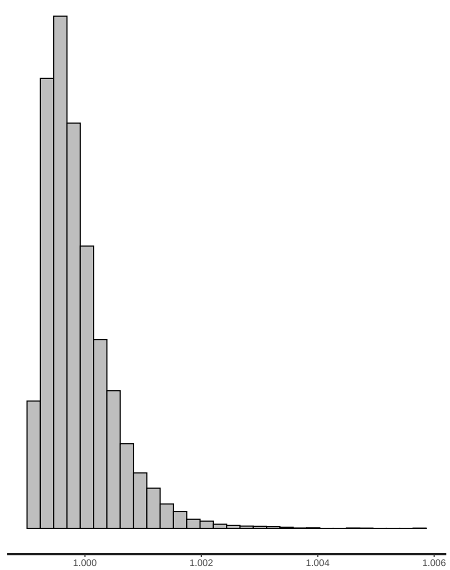


(a) Governments

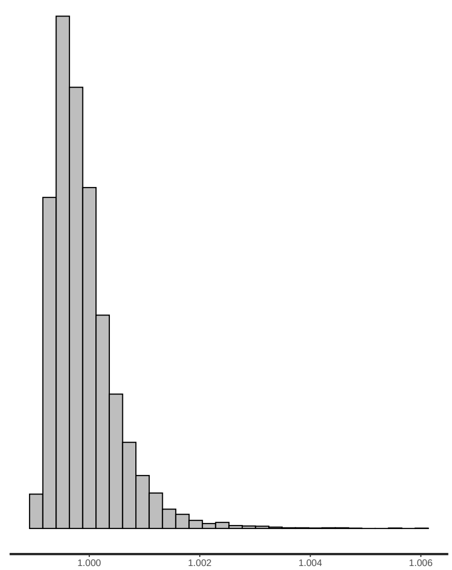


(b) Rebel groups

Figure 3. Temporal variation of interrater agreement (Cohen's weighted kappa) between human rights indicators, by year and conflict actor group. For each year, in which Cohen's weighted kappa value is not significant (p-value>0.05) or missing, it is not plotted.



(a) Static model



(b) Dynamic model

Figure 4. Rhat statistic for model convergence, by model specification.

E Estimates of α and β parameters

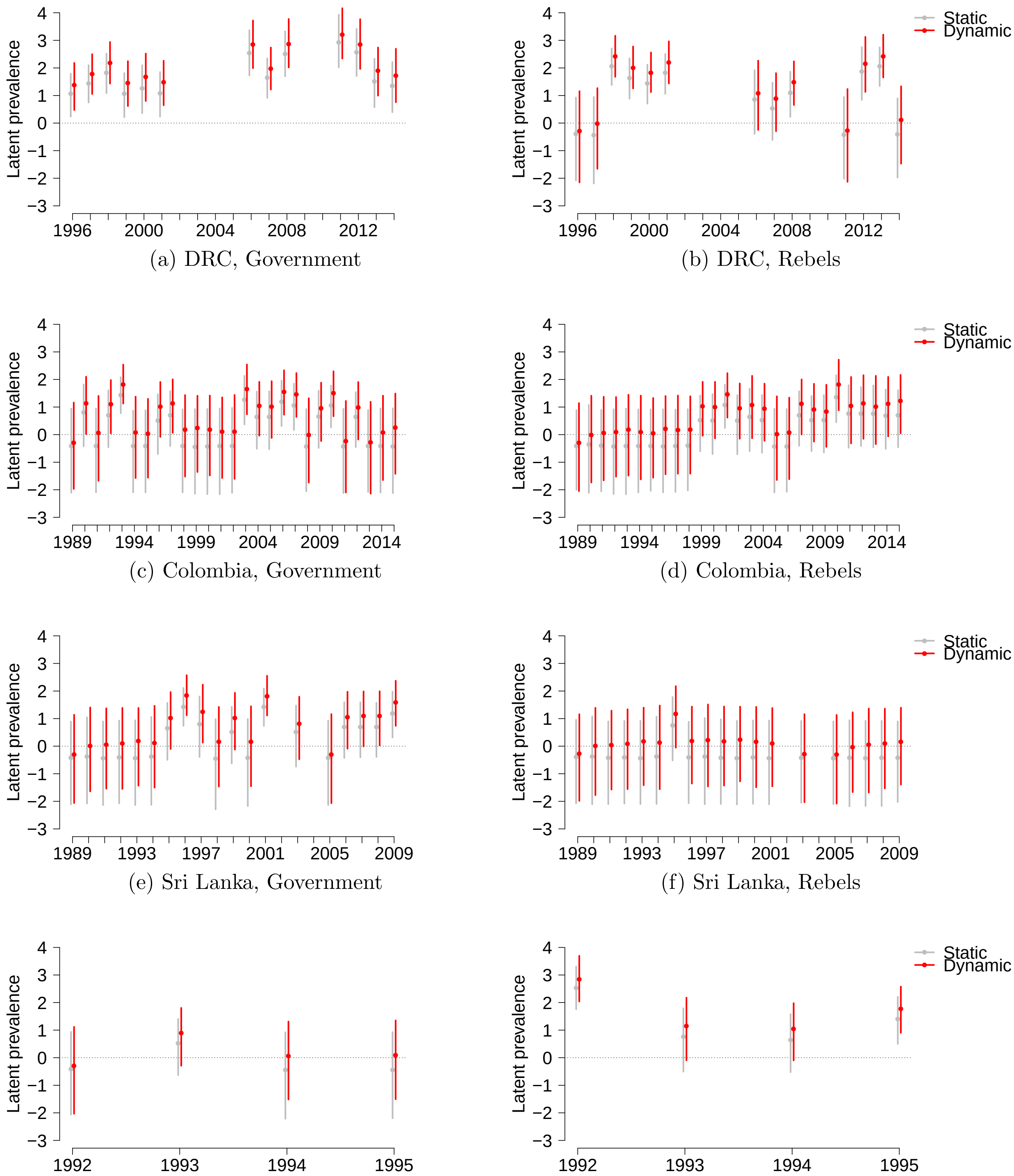
Item	Static		Dynamic	
AI				
β	2.715252	[2.244086, 3.314763]	2.712655	[2.11464, 3.455542]
α_1	3.410998	[2.957122, 4.015216]	4.416665	[3.663456, 5.361299]
α_2	5.666859	[4.971362, 6.54289]	6.632139	[5.690702, 7.808623]
α_3	7.690206	[6.739286, 8.860602]	8.62686	[7.478718, 10.03094]
α_1 (scaled)	1.259918	[1.156434, 1.370368]	1.63608	[1.451843, 1.840917]
α_2 (scaled)	2.094413	[1.918821, 2.29275]	2.46185	[2.161676, 2.81799]
α_3 (scaled)	2.843253	[2.573425, 3.151963]	3.205763	[2.765097, 3.710222]
HRW				
β	2.853393	[2.324597, 3.480303]	2.917279	[2.233921, 3.82054]
α_1	3.855604	[3.289415, 4.544296]	5.010114	[4.101555, 6.214037]
α_2	5.955573	[5.141821, 6.958776]	7.096177	[5.994321, 8.556165]
α_3	7.712477	[6.685288, 9.014325]	8.846089	[7.536857, 10.58318]
α_1 (scaled)	1.355104	[1.245396, 1.47738]	1.727127	[1.528074, 1.946541]
α_2 (scaled)	2.094335	[1.918783, 2.29061]	2.45104	[2.136379, 2.801693]
α_3 (scaled)	2.713102	[2.458944, 3.008954]	3.058707	[2.624089, 3.550339]
USSD				
β	2.295413	[1.958784, 2.737668]	2.402028	[1.915527, 2.981726]
α_1	2.356567	[2.069221, 2.706169]	3.332436	[2.757288, 4.037647]
α_2	4.241517	[3.810775, 4.785764]	5.245353	[4.542194, 6.089364]
α_3	5.554724	[5.010672, 6.232498]	6.570744	[5.755958, 7.528048]
α_1 (scaled)	1.029063	[0.9395992, 1.127873]	1.392274	[1.236202, 1.561079]
α_2 (scaled)	1.85316	[1.696291, 2.020896]	2.196224	[1.936807, 2.48207]
α_3 (scaled)	2.427627	[2.209705, 2.667683]	2.753607	[2.39722, 3.156814]

Table I. Estimates of α and β parameters for static and dynamic models, respectively, with 95% posterior intervals in square brackets. We report the difficulty cut-point parameters α in raw and scaled form. Dividing the item difficulty parameter α by its corresponding item discrimination parameter β, the α parameters are transformed to the same scale of the latent variable θ.

F Estimates of latent SVAC prevalence by type of conflict actor

In the main article, we focussed on the government in the Democratic Republic of Congo and Sri Lanka, and rebel forces in Colombia and Bosnia-Herzegovina. Here, we provide information on the reported prevalence of wartime sexual violence by both types of conflict actors to enable a more direct comparison across types and cases (Figure 5).

Once we empirically account for the uncertainty in the observed indicators by computing latent estimates, comparisons between conflict actor groups can sometimes reveal interesting insights. Looking at our four illustrative cases and specifically the case of Colombia, purely *observational measures* of SVAC prevalence indicated that Colombian rebels engaged more often in conflict-related sexual violence than the Colombian government (cf. Figures 2d and 2c above). However, the credible intervals of the *latent estimates* for Colombian rebel groups contain the value zero more often (cf. Figure 5d) than it is the case for the Colombian government (Figure 5c). This is a consequence of there being more government-years (5) in which two sources report on SVAC prevalence than rebel-years (2). In other words, there is more credible information for government forces to have engaged in conflict-related sexual violence in Colombia than is the case for rebel groups. The latent estimates therefore challenge our understanding of the temporal dynamics of SVAC in Colombia in a significant way compared to purely observational human rights reports.



(a) DRC, Government

(b) DRC, Rebels

(c) Colombia, Government

(d) Colombia, Rebels

(e) Sri Lanka, Government

(f) Sri Lanka, Rebels

(g) Bosnia-Herzegovina, Government

(h) Bosnia-Herzegovina, Rebels

Figure 5. Latent variable estimates of sexual violence in four cases of armed conflict, by armed group and conflict-year. Dots indicate point estimates (posterior means), lines are 95 percent credible intervals. Years with missing estimates are non-conflict years that were not estimated. The static latent variable model (gray/light) uses an indepedent standard normal prior on each θ_{it}, i.e., we assume that there is local independence of human rights indicators across years within conflicts. The dynamic latent variable model (red/dark) places hierarchical priors on each θ_{it} to allow the estimated latent level of wartime sexual violence to vary with the previous conflict-actor-year's value.

G Correlating observed values with latent estimates

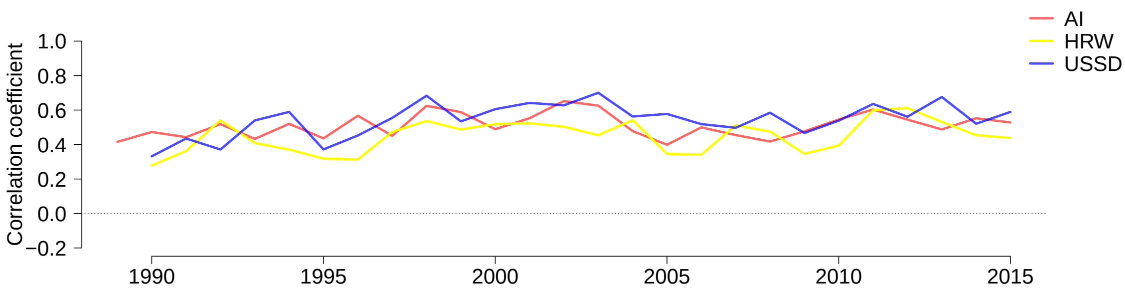
We compute Spearman rank correlations between the three human rights indicators and the static and dynamic latent estimates of SVAC prevalence, respectively. To incorporate the uncertainty associated with our latent measures, we adopt the multiple imputation procedure suggested by Schnakenberg and Fariss (2014, 22). For each examined relationship, i.e., AI * static estimates (All SVAC), AI * dynamic estimates (All SVAC), etc., we take 1,000 draws from the posterior distribution of the static and dynamic estimates to calculate the values of the respective latent estimate variable in each correlation analysis. We then compute 1,000 correlations for each examined relationship, and average the correlation coefficients and p-values across the 1,000 samples to report in Table II. In addition, in Figures 6 through 8, we report the Spearman rank correlation coefficients between each human rights indicator and the static/dynamic estimates of latent SVAC prevalence over time to allow for temporal comparison.

Generally, the USSD indicator correlates positively and most strongly with the dynamic and static latent estimates, followed by AI. The weakest positive correlation is between the latent estimates and the HRW indicator. Our findings suggest that values in the USSD indicator, which as we show in the main article rate higher on average than the other two human rights indicators, had a significant statistical impact on the values of the latent estimates.

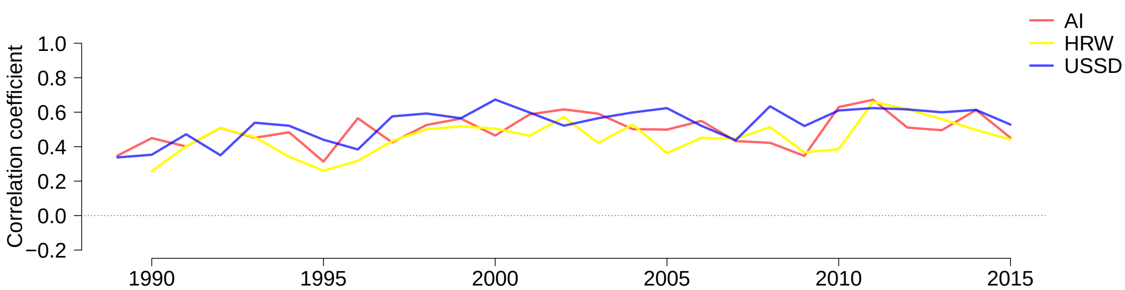
When disaggregating the SVAC data into government and rebel group conflict-actor years, an interesting pattern emerges. For all three human rights indicators, the positive correlation between observed values and latent estimates is stronger for government conflict-year observations than for rebel conflict-year observations. This suggests that the human rights indicators were in relatively more agreement about the level of SVAC prevalence for government observations than for rebel observations. This can be seen in the relationship between USSD and AI in Table I in the main article, which are the two indicators that also correlate the strongest with the latent estimates (Table II here).

Table II. Spearman rank correlation coefficients (with p-values) for all combinations of SVAC prevalence indicators with the static and dynamic latent variable estimates, respectively, and by dataset. We compute correlations for the entire SVAC dataset, and then separately for government and rebel group observations. The Spearman rank correlations account for the uncertainty in the estimates of latent prevalence. To this aim, we take 1,000 draws from the posterior distributions of the static and dynamic estimates to obtain the empirical values for computing 1,000 correlations for each examined relationship. Here, we report the average correlation coefficients and p-values across each set of 1,000 samples.

Correlation between	All SVAC	p-value	Governments	p-value	Rebels	p-value
AI x static	0.499	0.000	0.553	0.000	0.419	0.000
HRW x static	0.454	0.000	0.480	0.000	0.385	0.000
USSD x static	0.558	0.000	0.597	0.000	0.438	0.000
AI x dynamic	0.503	0.000	0.565	0.000	0.409	0.000
HRW x dynamic	0.439	0.000	0.506	0.000	0.381	0.000
USSD x dynamic	0.556	0.000	0.611	0.000	0.454	0.000

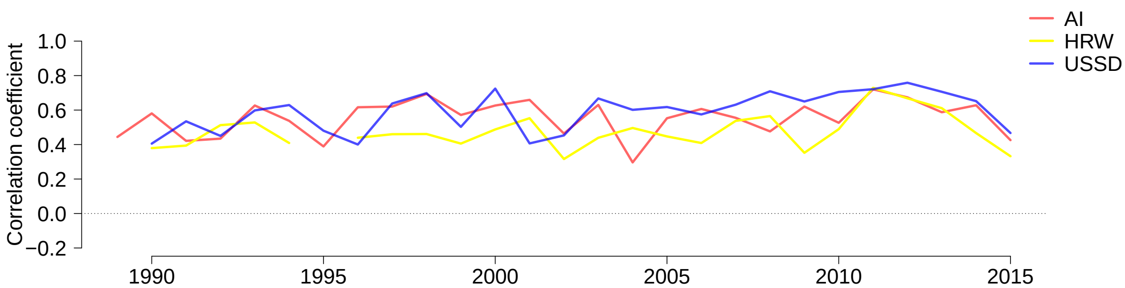


(a) Static estimates

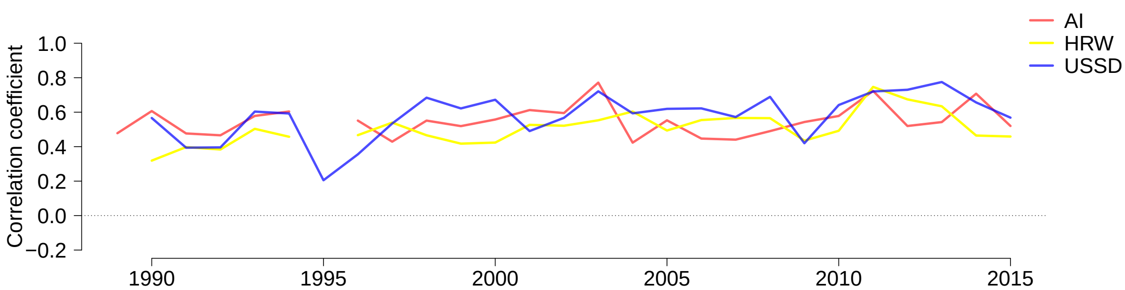


(b) Dynamic estimates

Figure 6. Spearman rank correlation coefficients between observed human rights indicators and estimates of latent SVAC prevalence for *all* conflict-actor-year observations, by type of latent estimate. The Spearman rank correlations account for the uncertainty in the estimates of latent prevalence by using our multiple imputation procedure of 1,000 draws from the posterior distributions of the latent estimates. For each year, in which the correlation coefficient is not significant (p-value>0.05) or missing, it is not plotted.

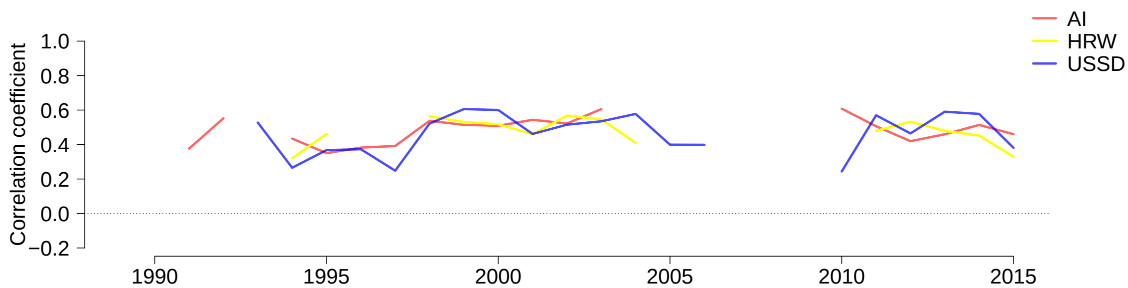


(a) Static estimates

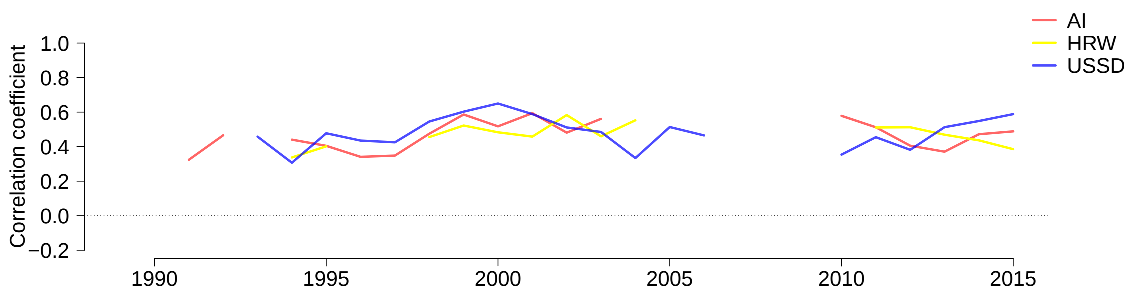


(b) Dynamic estimates

Figure 7. Spearman rank correlation coefficients between observed human rights indicators and estimates of latent SVAC prevalence for *government* actor-year observations, by type of latent estimate. The Spearman rank correlations account for the uncertainty in the estimates of latent prevalence by using our multiple imputation procedure of 1,000 draws from the posterior distributions of the latent estimates. For each year, in which the correlation coefficient is not significant (p-value>0.05) or missing, it is not plotted.



(a) Static estimates



(b) Dynamic estimates

Figure 8. Spearman rank correlation coefficients between observed human rights indicators and estimates of latent SVAC prevalence for *rebel* actor-year observations, by type of latent estimate. The Spearman rank correlations account for the uncertainty in the estimates of latent prevalence by using our multiple imputation procedure of 1,000 draws from the posterior distributions of the latent estimates. For each year, in which the correlation coefficient is not significant (p-value>0.05) or missing, it is not plotted.

H Predictive validity of latent variable estimates

In this section, we provide the details and empirical results of our analysis of the predictive validity of the static and dynamic estimates of latent prevalence of wartime sexual violence we refer to in the main article in Section "*Latent estimates express observational uncertainty*".

For the latent estimates of SVAC prevalence to be a valid measure of the latent trait, they have to perform well at predicting future levels of wartime sexual violence (cf. Schnakenberg and Fariss 2014, 20). To examine predictive performance, we compute four versions of ordinal logistic regression, using each human rights indicator as the dependent variable and a 1-year lagged version of itself, the static, or dynamic estimates, as right-hand side predictors (Tables III to V). We compute a fourth version of regression models in which the maximum reported value for each conflict-actor-year across the three human rights measures AI, HRW, and USSD, is the dependent variable (Table VI).

To account for the uncertainty in the latent static and dynamic estimates, we again rely on multiple imputation.[1] This means, when refitting models with the static or dynamic estimates as the lagged predictor variable, we take 1,000 draws from an estimate's posterior distribution to calculate 1,000 versions of itself, each of which we lag. We then compute 1,000 regressions for each examined relationship, and average the coefficients and goodness-of-fit statistics across the 1,000 samples.

The log-Likelihood of each model is a statistic of overall model fit. The higher the log-Likelihood (i.e., the closer to zero), the better a model fits the data. In addition to the log-Likelihood, we also compute 1,000 Spearman rank correlations between the predicted values of each model and the respective human rights indicator (dependent variable), reporting the average Spearman rank correlation coefficients and p-values in each regression table. The higher the correlation coefficient, the better the lagged variable is at predicting future levels

[1] There is only one regression each when the predictor variable is a lagged version of the *observed dependent variable*.

of wartime sexual violence as reported in the relevant human rights indicator.

	Observed Lag	Static Latent Lag	Dynamic Latent Lag
y>=1	2.158***	1.953***	2.283***
	(0.082)	(0.087)	(0.111)
y>=2	3.814***	3.485***	3.811***
	(0.144)	(0.139)	(0.159)
y>=3	5.308***	4.832***	5.156***
	(0.250)	(0.235)	(0.248)
Observed AI, lag	1.552***		
	(0.105)		
Static latent, lag		0.909***	
		(0.094)	
Dynamic latent, lag			0.897***
			(0.094)
log-Likelihood	-844.690	-873.991	-876.624
Num. obs.	1738	1738	1738
Corr. obs x predicted	0.279	0.188	0.169
Corr. p-value	0.000	0.027	0.046

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table III. *Amnesty International*: Ordinal logistic regression using the AI human rights indicator as dependent variable. In the first model ("Observed Lag"), the predictor is a 1-year lag of the observed AI response variable. In the second model ("Static Latent Lag"), the predictor is a 1-year lag of the static estimates of SVAC prevalence, using a multiple imputation procedure that averages across 1,000 draws from the posterior distribution to account for the statistical uncertainty in the LVM estimates. In the third model ("Dynamic Latent Lag"), the predictor is a 1-yar lag of the dynamic latent estimates of SVAC prevalence, also using a multiple imputation procedure that averages across 1,000 draws. To assess model performance, we compare the log-Likelihood across models, as well as, the Spearman rank correlation coefficients between the dependent variable and the predicted values of each regression model.

We obtain comparable empirical results across the four sets of regression models. The log-Likelihood is highest (i.e., closest to zero) in each regression model that uses the lag of the *observed* human rights indicator as the main predictor, indicating best model fit. The log-Likelihoods for the multiply-imputed regressions with a lagged (draw) version of the static and dynamic estimates are consistently close to each other, with the static version slighlty outperforming its dynamic counterpart each time. The correlation between the dependent variable and its predicted values from the model is strongest for regressions with the lagged

	Observed Lag	Static Latent Lag	Dynamic Latent Lag
y>=1	2.477***	2.395***	2.786***
	(0.093)	(0.108)	(0.139)
y>=2	4.020***	3.778***	4.168***
	(0.161)	(0.161)	(0.186)
y>=3	5.299***	4.939***	5.326***
	(0.254)	(0.244)	(0.263)
Observed HRW, lag	1.662***		
	(0.114)		
Static latent, lag		1.037***	
		(0.105)	
Dynamic latent, lag			1.036***
			(0.106)
log-Likelihood	-676.390	-700.925	-702.212
Num. obs.	1695	1695	1695
Corr. obs x predicted	0.305	0.154	0.145
Corr. p-value	0.000	0.096	0.115

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table IV. *Human Rights Watch*: Ordinal logistic regression using the HRW human rights indicator as dependent variable. In the first model ("Observed Lag"), the predictor is a 1-year lag of the observed HRW response variable. In the second model ("Static Latent Lag"), the predictor is a 1-year lag of the static estimates of SVAC prevalence, using a multiple imputation procedure that averages across 1,000 draws from the posterior distribution to account for the statistical uncertainty in the LVM estimates. In the third model ("Dynamic Latent Lag"), the predictor is a 1-yar lag of the dynamic latent estimates of SVAC prevalence, also using a multiple imputation procedure that averages across 1,000 draws. To assess model performance, we compare the log-Likelihood across models, as well as, the Spearman rank correlation coefficients between the dependent variable and the predicted values of each regression model.

emphobserved human rights indicator as predictor, indicating that the observed measures perform best at predicting future levels of reported SVAC prevalence.

While it may seem (somewhat) unexpected, we attribute these empirical results to very important features of the research context of wartime sexual violence. In particular, we believe that significantly low levels of agreement across the observed human rights measures are caused by the restricted capabilities of human rights monitors to register and document sexual violence events, given that sexual violence is particularly hard to measure. Because LVM methodology expresses inherent observational uncertainty in the form of a credible

	Observed Lag	Static Latent Lag	Dynamic Latent Lag
y>=1	2.109***	1.590***	2.074***
	(0.082)	(0.082)	(0.106)
y>=2	4.106***	3.056***	3.542***
	(0.148)	(0.121)	(0.146)
y>=3	5.696***	4.156***	4.642***
	(0.222)	(0.168)	(0.189)
Observed USSD, lag	2.234***		
	(0.098)		
Static latent, lag		1.265***	
		(0.091)	
Dynamic latent, lag			1.276***
			(0.092)
log-Likelihood	-954.230	-1109.235	-1109.376
Num. obs.	1746	1746	1746
Corr. obs x predicted	0.467	0.284	0.281
Corr. p-value	0.000	0.000	0.000

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table V. *U.S. State Department*: Ordinal logistic regression using the USSD human rights indicator as dependent variable. In the first model ("Observed Lag"), the predictor is a 1-year lag of the observed USSD response variable. In the second model ("Static Latent Lag"), the predictor is a 1-year lag of the static estimates of SVAC prevalence, using a multiple imputation procedure that averages across 1,000 draws from the posterior distribution to account for the statistical uncertainty in the LVM estimates. In the third model ("Dynamic Latent Lag"), the predictor is a 1-yar lag of the dynamic latent estimates of SVAC prevalence, also using a multiple imputation procedure that averages across 1,000 draws. To assess model performance, we compare the log-Likelihood across models, as well as, the Spearman rank correlation coefficients between the dependent variable and the predicted values of each regression model.

interval, the resulting estimates of latent SVAC prevalence express our uncertainty in this research context. Empirical analysis using observational data of wartime sexual violence that, probabilistically speaking, report conflict-related sexual abuse with a probability of 1, risk to overestimate substantive effects if inherent data uncertainty remains unaccounted for. Latent variable estimates enable the analyst to direclty incorporate this observational uncertainty in substantive empirical analysis of wartime sexual violence by using a multiple imputation approach that averages across draws from the estimates' posterior distribution.

	Observed Lag	Static Latent Lag	Dynamic Latent Lag
y>=1	1.700***	0.988***	1.394***
	(0.074)	(0.065)	(0.081)
y>=2	3.610***	2.460***	2.865***
	(0.124)	(0.095)	(0.114)
y>=3	5.206***	3.674***	4.077***
	(0.184)	(0.140)	(0.156)
Observed max value, lag	1.891***		
	(0.080)		
Static latent, lag		1.076***	
		(0.078)	
Dynamic latent, lag			1.078***
			(0.078)
log-Likelihood	-1221.260	-1399.122	-1400.588
Num. obs.	1748	1748	1748
Corr. obs x predicted	0.488	0.291	0.291
Corr. p-value	0.000	0.000	0.000

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table VI. *Maximum observed value*: Ordinal logistic regression using the maximum observed value across the three human rights indicators as dependent variable. In the first model ("Observed Lag"), the predictor is a 1-year lag of the observed maximum value response variable. In the second model ("Static Latent Lag"), the predictor is a 1-year lag of the static estimates of SVAC prevalence, using a multiple imputation procedure that averages across 1,000 draws from the posterior distribution to account for the statistical uncertainty in the LVM estimates. In the third model ("Dynamic Latent Lag"), the predictor is a 1-yar lag of the dynamic latent estimates of SVAC prevalence, also using a multiple imputation procedure that averages across 1,000 draws. To assess model performance, we compare the log-Likelihood across models, as well as, the Spearman rank correlation coefficients between the dependent variable and the predicted values of each regression model.

References

Gelman, Andrew and Donald B Rubin (1992). Inference from iterative simulation using multiple sequences. *Statistical Science* 7(4): 457–472.

Schnakenberg, Keith E and Christopher J Fariss (2014). Dynamic patterns of human rights practices. *Political Science Research and Methods* 2(1): 1–31.