FAST Models for ‘cm’

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Contents

Model Options and Choices

For the FAST analysis of the `cm` version of the VIEWS data, one faces a series of choices in constructing a forecast model. These are summarized by the following:

1. *Units*: Are the data units of analysis (forecast units) countries, grid cells or over months or quarters? In this case the choice is country-months, denoted `cm` units.
2. *Models*: There are a wide variety to consider here and they vary according to broad parameters set out prior. These include choices of
   a. *Functional form*: Does one using fixed effects, mixed marginal effect, or something else?
   b. *Distribution of the data*: do we assume a (marginal) Poisson, negative binomial, Tweedie, or some zero-inflated likelihood form?
3. *Information Sets*:
   a. *Covariates*: This is mainly a choice over the covariates of interest to the sponsor:
   - Climate
   - Food security
   - Demographics

   b. *Other conditioning variables or units*: Do only nearest neighbors in spadfe and time matter or should all global data be leveraged (recall we have the `cm` data for the globe, but are scored on data for Africa and the Middle East). Here this will be either `Globe` or `Africa+ME`.
4. *Scoring*: what criteria do we use to rank or evaluuate winners and losers? Options include root mean squared error (RMSE), bias, dispersion, continuous (discrete) rank probability scores (CRPS), etc.

5. *Forecast horizons* How many periods forward are needed in the forecasts? This is defined by the sponsor in months 3, 6, and 12.

Initial Model Selection from Training and Validation Splits

A prior set of model selection rounds were conducted. These build on the datasets and setup described here from May 2025.

Based on these data for the `cm` VIEWS dataset a series of models were fit to constrain and select from the larger set of options above. *For a RMSE criteria* using data from 2010:1–2022:6 and a validation comparison sample of data from 2022:10-2023:9 the top models are in the following table:

Table 1: Top 25 Models from Training and Validation (sorted by RMSE)

Model	Information Set	RMSE	CRPS	Brier (>25)
Neg Binom GLMM + COVAR	Africa+ME	19537955	192.79	0.064
Neg Binom GLMM	Globe	19538070	194.05	0.069
Neg Binom GLMM	Africa+ME	19538482	194.56	0.069
Tweedie GLMM	Globe	19540700	194.31	0.066
Tweedie GLMM + COVAR	Africa+ME	19540995	192.45	0.058
Tweedie GLMM	Africa+ME	19542195	194.64	0.061
Poisson GLMM	Globe	19544318	197.49	0.090
Poisson GLMM + COVAR	Africa+ME	19546057	197.11	0.103
Poisson GLMM	Africa+ME	19546568	198.41	0.108
ZIP+FE	Africa+ME	19558650	279.40	0.845
Poisson+FE	Africa+ME	19560708	280.66	0.845
ZIP+FE	Globe	19567670	254.33	0.823
ZINB+FE	Globe	19567707	202.01	0.135
Poisson+FE	Globe	19567839	254.33	0.823
Neg Bin+FE	Africa+ME	19571068	263.17	0.788
Tweedie+FE	Africa+ME	19575630	297.61	0.803
ZINB+FE	Africa+ME	19575884	204.90	0.134
exactly_zero	Africa+ME	19576285	202.35	0.155
last_historical	Africa+ME	19577040	214.20	0.303
Tweedie+FE	Globe	19586937	275.34	0.671
Neg Bin+FE	Globe	19593893	279.72	0.609
ZIP+LAGS+COVAR	Africa+ME	19774339	289.54	0.339
conflictology_country12	Africa+ME	21027264	380.43	0.297
Poisson+LAGS+COVAR	Africa+ME	23066160	399.25	0.627
ZIP+LAGS	Africa+ME	33776972	518.63	0.231

From the prior model searching documented in the scripts in the Appendix, *the chosen models on the RMSE and CRPS criteria are those with negative binomial or Tweedie distribution likelihoods and the inclusion of the specified predictor covariates* (consistent with Hegre et al. (2025) and Brandt (2023)). Note that these results also are better than the VIEWS baseline models of `exactly_zero`, `last_historical` and `conflictology_country12` (for details see Hegre et al. (2025)).

Several conclusions come from these results over the model, covariates, information set, and other choices:

- *Tweedie or Negative binomial models makes the most sense.* Zero inflation models are genreally not as performative in a RMSE, CRPS, or Brier score comparison.
- *General linear mixed model (GLMM) of unit effects are preferred over fixed effects.* All of the GLMM model rank above the fixed effects (`FE`) models.
- *Information set choice favors using the data only from `Africa+ME` in most cases.* There are a few exceptions to this that interact with the model and the covariates, but there is enough of a pattern to lean in this direction.

Final FAST Model Using Test Split

For the final selection of forecast models the evaluation is done over a training set of data from 2010:1–2023:6, evaluated over a testing data from 2023:10–2024:9. (Here we have separated out the `COVAR` portion of the earlier presentation into a separate column factor across the proposed specifications)

Table 2: Models from Final Test (sorted by RMSE)

Model	Information Set	Covariates	RMSE	CRPS	Brier (>25)
Neg Binom GLMM	Africa+ME	No	252704.4	64.21	0.085
Neg Binom GLMM	Africa+ME	Yes	252849.4	64.24	0.076
Neg Binom GLMM	Globe	No	253000.7	63.90	0.078
Tweedie GLMM	Africa+ME	No	253046.3	64.86	0.096
Neg Binom GLMM	Globe	Yes	253234.2	63.93	0.071
Tweedie GLMM	Africa+ME	Yes	253289.4	64.95	0.087
Tweedie GLMM	Globe	No	253307.0	64.95	0.094
Tweedie GLMM	Globe	Yes	253617.8	65.05	0.085
Poisson GLMM	Globe	No	254495.9	68.24	0.118
Poisson GLMM	Globe	Yes	254515.1	68.10	0.110
Poisson GLMM	Africa+ME	Yes	254946.6	68.79	0.122
Poisson GLMM	Africa+ME	No	254995.9	69.07	0.129
exactly_zero	Africa+ME	No	258082.0	74.95	0.195
exactly_zero	Globe	No	258082.0	74.95	0.195
last_historical	Africa+ME	No	264660.7	95.09	0.259
last_historical	Globe	No	330219.2	99.83	0.238
conflictology_country12	Globe	No	1764605.1	204.08	0.244
conflictology_country12	Africa+ME	No	2992357.2	289.59	0.274

Based on each of the follow criteria, the best models over the full test sample are

- *RMSE*: Negative Binomial GLMM fit to the Africa+ME data *without* covariates.
- *CRPS*: Negative Binomial GLMM fit to the Globe data *without* covariates.
- *Brier*: Negative Binomial GLMM fit to the Globe data *with* covariates.

Selected model: Negative Binomial GLMM with covariates

This shows the code and estimation of the final model, based on the initial data setup documented here and then processed with `setup.R`

```r
rm(list=ls())
load("cm_subsets.RData")

# Only keeps the global dataset
rm(list = setdiff(ls(), "globe"))

# Fit the model as in all the earlier setup code and comparisons.
# Here we just fit the final model selected in the prior section
library(glmmTMB)

# From the formulas.R script...
frm.glmm <- as.formula("ged_sb ~ ar1(month_factor + 0|country_id) +
                        wdi_sp_dyn_imrt_in +
                        wdi_ms_mil_xpnd_gd_zs +
                        wdi_ms_mil_xpnd_zs +
                        vdem_v2x_ex_military")

FAST.cm <- glmmTMB(frm.glmm,
                   family = nbinom1(),
                   data=globe)
```

Characterization of Selected Model

Below is a regression table for the fixed effects covariates. These are presented as odds ratios for the covariates in the model.

	NBGLMM
(Intercept)	**0.000 *****
	(0.000)
wdi_sp_dyn_imrt_in	**1.044 ****
	(0.017)
wdi_ms_mil_xpnd_gd_zs	1.112
	(0.075)
wdi_ms_mil_xpnd_zs	0.999
	(0.013)
vdem_v2x_ex_military	**4.090 ****
	(2.022)

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Covariate effects for the selected model

Same as above, just graphical for the odds ratios:

```
##
## Attaching package: 'ggplot2'

## The following object is masked from 'package:huxtable':
##
##     theme_grey
```

Average marginal predictions for explanations

This is overly explicit (since there are only 4 fixed effect variables across all the units). (If more covaraites are added, this should be done with vectorization or functions rather than for each variable.). Note these these are conservative effects since the estimates are the conditional predictions (given the mixed effects for the time-units). For details see here

```
library(modelbased, quietly = TRUE, warn.conflicts = FALSE)
imrt_in_effect <- estimate_means(FAST.cm, "wdi_sp_dyn_imrt_in",
                                 estimate = "average")
mil_xpnd_gd_zs_effect <- estimate_means(FAST.cm, "wdi_ms_mil_xpnd_gd_zs",
                                        estimate = "average")
mil_xpnd_zs_effect <- estimate_means(FAST.cm, "wdi_ms_mil_xpnd_zs",
                                     estimate = "average")
vdem_milex_effect <- estimate_means(FAST.cm, "vdem_v2x_ex_military",
                                    estimate = "average")
```

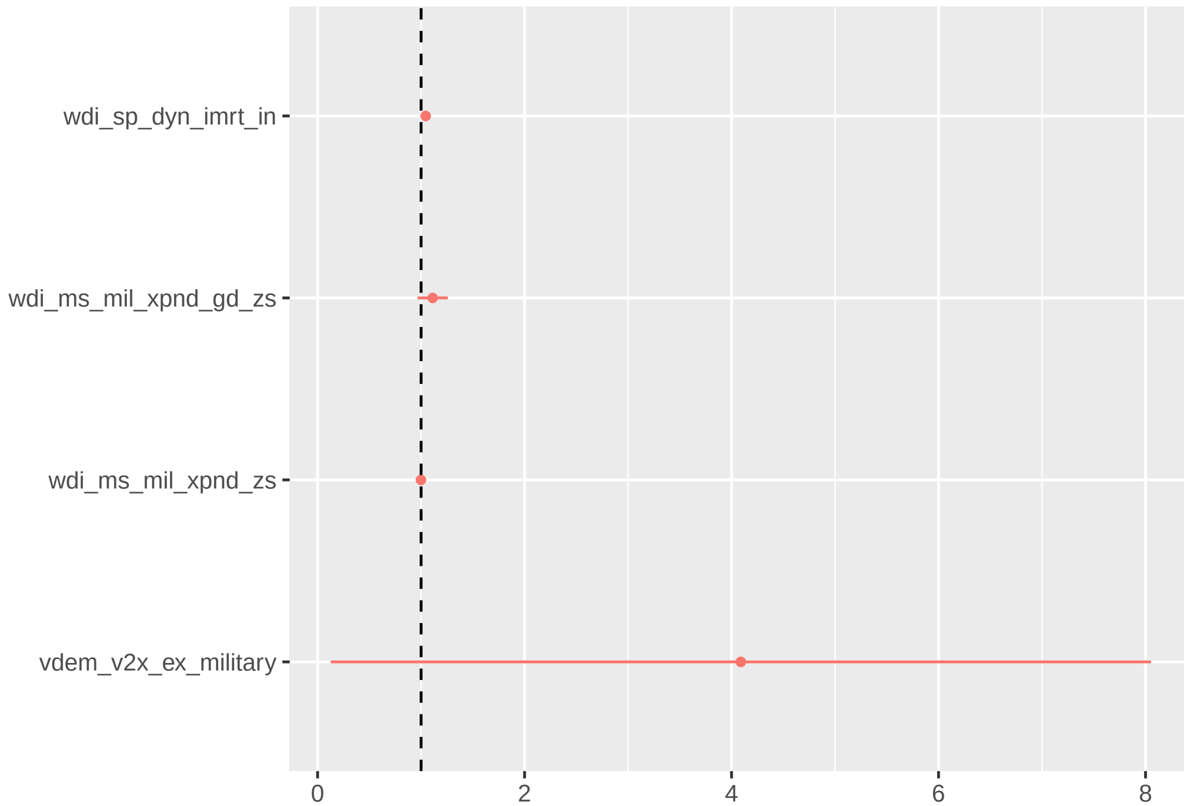


Figure 1: Odds ratios for selected covariates in the NBGLMM.

```
par(mfrow=c(1,2))
plot(imrt_in_effect)
#plot(mil_xpnd_gd_zs_effect)
#plot(mil_xpnd_zs_effect)
plot(vdem_milex_effect)
```

Average conditional predictions for explanations over time

Same as above, but with accounting for the random effects – smaller effects and possibly messier to interpret, but more realistic of the decision-maker's pattern.

```
plot(estimate_slopes(FAST.cm,
                     trend = "wdi_sp_dyn_imrt_in",
                     by = "month_factor = seq(480, 540)",
                     predict = "conditional"))
```

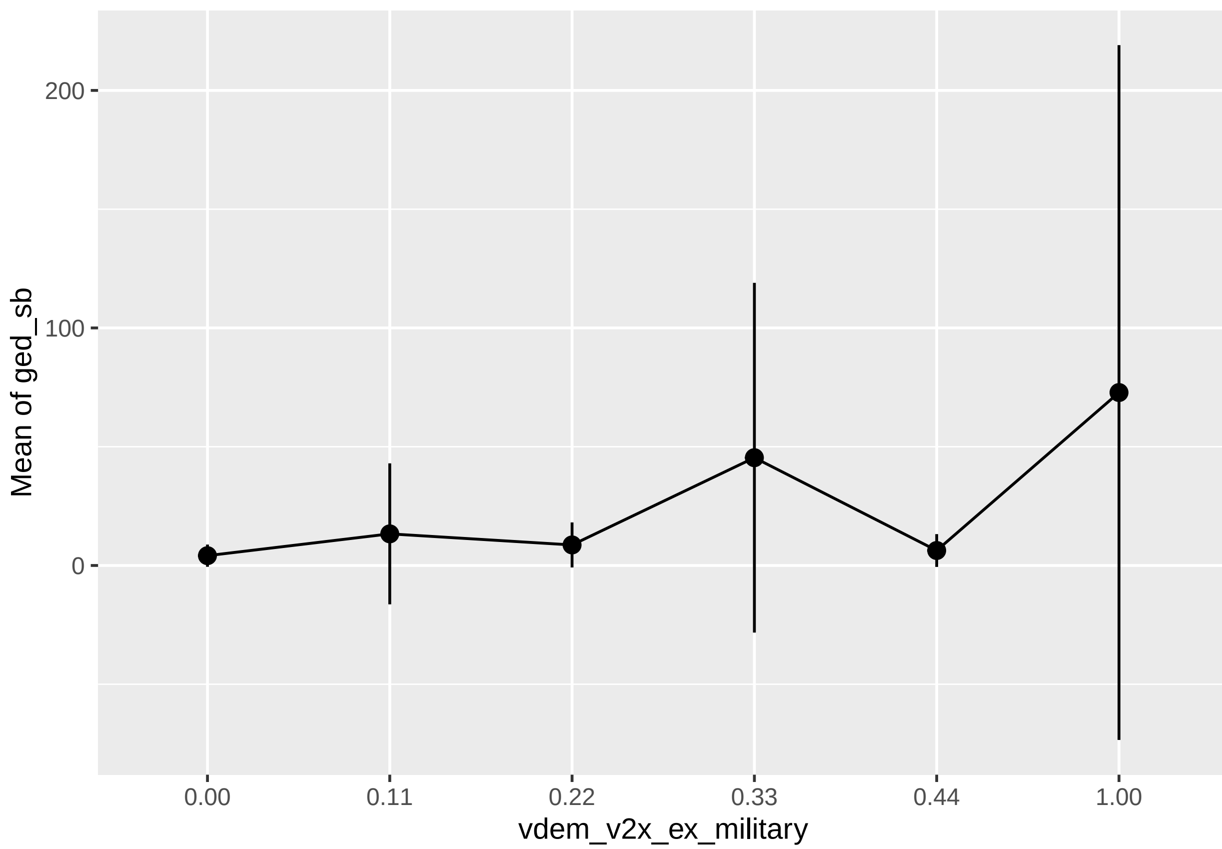
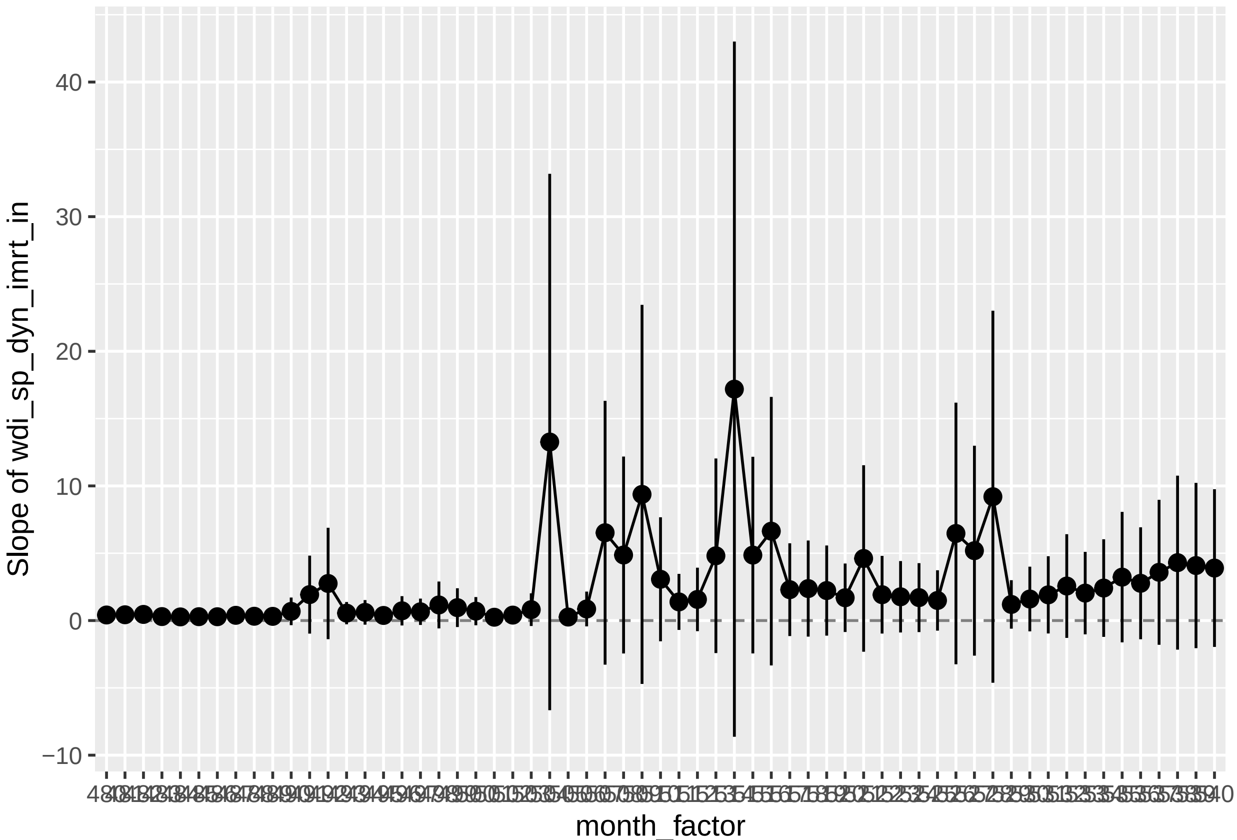
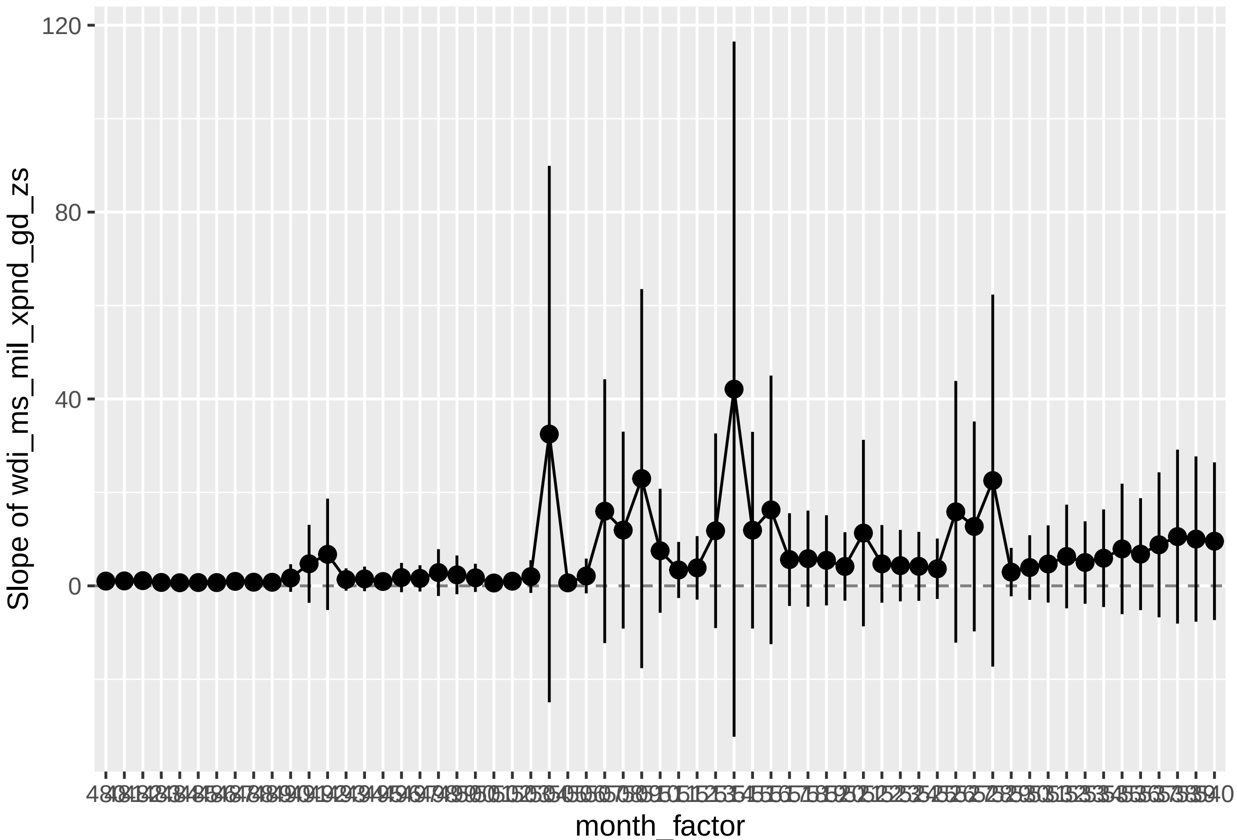


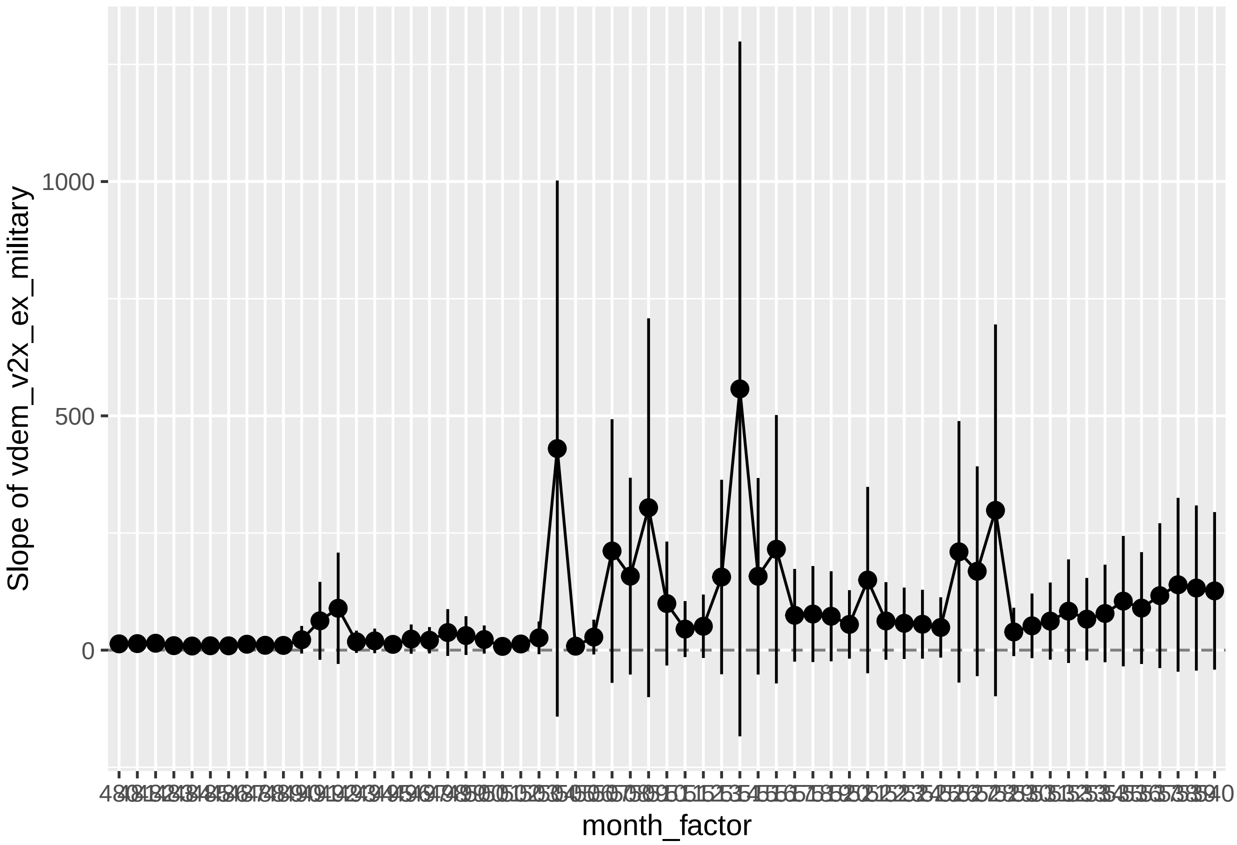
Figure 2: Average marginal effects for NBGLMM




```r
plot(estimate_slopes(FAST.cm,
                     trend = "wdi_ms_mil_xpnd_gd_zs",
                     by = "month_factor = seq(480, 540)",
                     predict = "conditional"))
```




```r
plot(estimate_slopes(FAST.cm,
                     trend = "vdem_v2x_ex_military",
                     by = "month_factor = seq(480, 540)",
                     predict = "conditional"))
```



Predictions

```r
source("predictglmm.R")

ds <- FAST.cm$frame

# Get last 12 months of data
dim(ds[as.numeric(ds$month_factor)>(max(as.numeric(ds$month_factor))-12),])
```

```
## [1] 2292    7
```

```r
xforcs <- ds[as.numeric(ds$month_factor)>(max(as.numeric(ds$month_factor))-12),]

# Set the month_factor variable and then the covariates by country to match
# the grouping in the GLMM

xnew <- aggregate(xforcs[,4:7], by=list(xforcs$country_id), mean)
names(xnew)[1] <- "country_id"

# Make new country-month ids
idxs <- expand.grid(xnew$country_id, 550:561)
colnames(idxs) <- c("country_id", "month_id")

xout <- merge(idxs, xnew, by="country_id")
xout$month_factor <- as.factor(xout$month_id)
xout$ged_sb <- NA
```

```r
set.seed(324)
forcs <- predictglmm(FAST.cm, newdata = xout, N=1000)
```

Forecast Summaries

This shows how to generate and label the forecast summaries from the forecast sample (`N=1000`).

```r
# Get country labels for any formatting below -- use latest
countrylabels <- globe[globe$month_id==max(globe$month_id),
                       c("country_id", "name", "isoname", "isoab", "isonum", "gwcode")]

# Mean Forecast for each country-month
mean.forcs <- forcs %>% group_by(country_id, month_id) %>%
  summarise(total = mean(predicted))
```

```
## `summarise()` has grouped output by 'country_id'. You can override using the
## `.groups` argument.
```

```r
# Add labels to mean forecasts
mean.forcs <- merge(mean.forcs, countrylabels[,c(1,2,4)], by="country_id")
names(mean.forcs)[3] <- "predicted"

# Add dates to mean forecasts
forc.idx <- data.frame(month_id = 550:561,
                       dates=seq(as.Date("2025-10-01"), by="month", length=12))

mean.forcs <- merge(mean.forcs, forc.idx, by="month_id")

# Generate cumulative mean forecasts for each country
# over the 12 months of performance

cum.mean.forcs <-  mean.forcs %>% group_by(country_id) %>%
  mutate(cumulative_predicted = cumsum(predicted)) %>% arrange(country_id, month_id)

# Write the results out into a spreadsheet
library(writexl)
write_xlsx(x = list("Forecasts" = cum.mean.forcs),
           path = "FAST-cm-Forecasts.xlsx")
```

Characterization of cumulative forecasts

Where are the highest cumulative forecasts in month 3 (December 2025)?

Table 3: Highest predicted forecasts, December 2025

month_id	country_id	predicted	name	isoab	dates	cumulative_predicted
552	60	23.976	Iraq	IRQ	2025-12-01	76.288
552	28	27.046	Colombia	COL	2025-12-01	86.761
552	223	31.381	India	IND	2025-12-01	99.274
552	50	42.118	Mali	MLI	2025-12-01	130.975
552	47	44.760	Burkina Faso	BFA	2025-12-01	139.144
552	167	50.134	Congo, DRC	COD	2025-12-01	156.375
552	133	51.644	Afghanistan	AFG	2025-12-01	162.024
552	124	55.306	Yemen	YEM	2025-12-01	177.412

month_id	country_id	predicted	name	isoab	dates	cumulative_predicted
552	57	97.453	Ethiopia	ETH	2025-12-01	311.661
552	94	108.962	Lebanon	LBN	2025-12-01	346.904
552	79	113.313	Nigeria	NGA	2025-12-01	355.057
552	120	124.280	Somalia	SOM	2025-12-01	394.969
552	149	135.042	Myanmar	MMR	2025-12-01	433.907
552	78	140.505	Niger	NER	2025-12-01	442.857
552	136	201.261	Pakistan	PAK	2025-12-01	649.905
552	220	404.222	Syria	SYR	2025-12-01	1310.042
552	245	419.866	Sudan	SDN	2025-12-01	1346.092
552	65	1134.935	Russia	RUS	2025-12-01	3645.834
552	218	1430.816	Israel	ISR	2025-12-01	4621.767
552	117	4221.503	Ukraine	UKR	2025-12-01	13989.559

Where are the highest cumulative forecasts in month 6 (March 2026)?

Table 4: Highest predicted forecasts, March 2026

month_id	country_id	predicted	name	isoab	dates	cumulative_predicted
555	60	20.855	Iraq	IRQ	2026-03-01	141.876
555	28	22.990	Colombia	COL	2026-03-01	159.972
555	223	26.421	India	IND	2026-03-01	183.883
555	50	36.796	Mali	MLI	2026-03-01	246.151
555	47	38.910	Burkina Faso	BFA	2026-03-01	261.926
555	167	41.619	Congo, DRC	COD	2026-03-01	290.458
555	133	43.822	Afghanistan	AFG	2026-03-01	299.896
555	124	47.978	Yemen	YEM	2026-03-01	330.458
555	57	82.864	Ethiopia	ETH	2026-03-01	573.976
555	94	88.274	Lebanon	LBN	2026-03-01	629.624
555	79	95.708	Nigeria	NGA	2026-03-01	657.576
555	120	106.397	Somalia	SOM	2026-03-01	731.356
555	149	114.197	Myanmar	MMR	2026-03-01	799.304
555	78	121.191	Niger	NER	2026-03-01	824.930
555	136	172.344	Pakistan	PAK	2026-03-01	1200.532
555	220	325.003	Syria	SYR	2026-03-01	2361.893
555	245	347.300	Sudan	SDN	2026-03-01	2465.633
555	65	886.321	Russia	RUS	2026-03-01	6543.786
555	218	1110.128	Israel	ISR	2026-03-01	8252.646
555	117	3270.033	Ukraine	UKR	2026-03-01	24787.770

Where are the highest cumulative forecasts in month 12 (September 2026)?

Table 5: Highest predicted forecasts, September 2026

month_id	country_id	predicted	name	isoab	dates	cumulative_predicted
561	60	14.498	Iraq	IRQ	2026-09-01	242.840
561	28	16.024	Colombia	COL	2026-09-01	272.278
561	223	19.325	India	IND	2026-09-01	315.778
561	50	28.113	Mali	MLI	2026-09-01	435.411
561	47	29.835	Burkina Faso	BFA	2026-09-01	460.277

month_id	country_id	predicted	name	isoab	dates	cumulative_predicted
561	167	31.664	Congo, DRC	COD	2026-09-01	506.547
561	133	32.250	Afghanistan	AFG	2026-09-01	518.771
561	124	35.119	Yemen	YEM	2026-09-01	571.852
561	57	57.613	Ethiopia	ETH	2026-09-01	974.440
561	94	59.697	Lebanon	LBN	2026-09-01	1054.750
561	79	69.790	Nigeria	NGA	2026-09-01	1133.800
561	120	77.027	Somalia	SOM	2026-09-01	1262.953
561	149	80.004	Myanmar	MMR	2026-09-01	1359.696
561	78	90.383	Niger	NER	2026-09-01	1435.959
561	136	123.335	Pakistan	PAK	2026-09-01	2060.828
561	220	217.047	Syria	SYR	2026-09-01	3922.442
561	245	241.879	Sudan	SDN	2026-09-01	4159.521
561	65	557.141	Russia	RUS	2026-09-01	10670.510
561	218	705.735	Israel	ISR	2026-09-01	13398.871
561	117	2006.682	Ukraine	UKR	2026-09-01	39761.365

Appendix

The initial model runs to do preliminary model selection and specification searches are all run via a set of batch scripts included with this repo. These are run in the following sequence via the `batch.sh` bash shell script to invoke `R` and the code files designated.

```
#! bash

# Training models
R CMD BATCH setup.R
R CMD BATCH modelselect.R &
R CMD BATCH modelselect-globe.R

# Validation models
R CMD BATCH modelselect-valid.R &
R CMD BATCH modelselect-globe-valid.R

R CMD BATCH modelselect-glmm-covar.R

# Scoring across the sets
R CMD BATCH scoring-cm.R
R CMD BATCH scoring-cm-valid.R
```

References

Brandt, Patrick T. 2023. "VIEWS 2.0 Bayesian Density Forecasts Replication Code: Setup and Estimation." https://github.com/PTB-OEDA/VIEWS2-DensityForecasts.

Hegre, Håvard, Paola Vesco, Michael Colaresi, Jonas Vestby, Alexa Timlick, Noorain Syed Kazmi, Angelica Lindqvist-McGowan, et al. 2025. "The 2023/24 VIEWS Prediction Challenge: Predicting the Number of Fatalities in Armed Conflict, with Uncertainty." *Journal of Peace Research* 0 (0): 00223433241300862. https://doi.org/10.1177/00223433241300862.