The below results were produced using the STATA code file called "Table2STATAscript.do" on June 29th, 2024. The code includes randomization, so the estimated coefficients could vary slightly from those presented here. However, the directions and the conclusions remain the same.

#How does training improve individual forecasts? Modeling Differences in Compensatory and Non-Compensatory Biases in Geopolitical Forecasts

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#This Script is used to gather numbers for the Table 2 of the manuscript.

<u> </u>
/ // 18.0
/ / // SE—Standard Edition
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Notes:
1. Unicode is supported; see help unicode_advice.
2. Maximum number of variables is set to 5,000 but can be increased; see
help set_maxvar.
3. New update available; type -update all-
. import excel "/Users/mohota/Downloads/ReCod.xlsx", sheet("ReCod") firstrow

(39 vars, 50,161 obs)

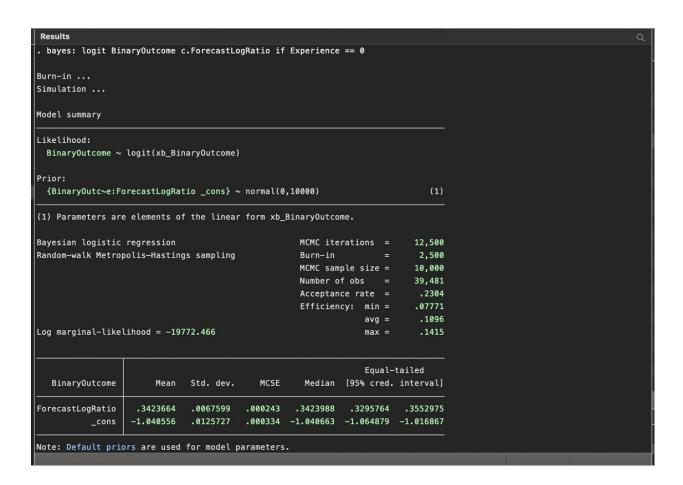
# Model 1:

. bayes: logit BinaryOutcome c.ForecastLogRatio if Experience == 0

#Time to run Model 1:

#. timer list 1

# 1: 16.54/ 1 = 16.5370



# Model 2:

Since the model has randomization, we set the seed. The coeffienents still might vary very slightly.

- . set seed 6092024
- . bayes: melogit BinaryOutcome c.ForecastLogRatio || user\_id: c.ForecastLogRatio

#Time to run Model 2:

- #. timer list 1
- # 1: 230.09/ 1 = 230.0890

Page 1 of Model 2's results:

```
Results
. set seed 6092024
. bayes: melogit BinaryOutcome c.ForecastLogRatio if Experience == 0 || user_id: c.ForecastLogRatio
Burn-in 2500 aaaaaaaaa1000aaaaaaa2000aaaaa done
Simulation 10000 .......1000......2000......3000......4000......5000.......5000......7000......8000..
 > ......9000......10000 done
Multilevel structure
user_id
    {U0}: random intercepts
    {U1}: random coefficients for ForecastLogRatio
Model summary
Likelihood:
  BinaryOutcome ~ melogit(xb_BinaryOutcome)
Priors:
  {BinaryOutc~e:ForecastLogRatio _cons} ~ normal(0,10000)
                                  {U0} ~ normal(0,{U0:sigma2})
                                  {U1} ~ normal(0,{U1:sigma2})
Hyperpriors:
  \{U0:sigma2\} \sim igamma(.01,.01)
  {U1:sigma2} ~ igamma(.01,.01)
(1) Parameters are elements of the linear form xb_BinaryOutcome.
Bayesian multilevel logistic regression
                                                    MCMC iterations =
                                                                          12,500
Random-walk Metropolis-Hastings sampling
                                                    Burn-in
                                                                          2,500
                                                    MCMC sample size =
                                                                          10,000
Group variable: user_id
                                                    Number of groups=
                                                    Obs per group:
```

# Page 2 of Model 2's results:

```
{U0:sigma2} ~ igamma(.01,.01)
  {U1:sigma2} \sim igamma(.01,.01)
(1) Parameters are elements of the linear form xb_BinaryOutcome.
Bayesian multilevel logistic regression
                                                   MCMC iterations =
                                                                         12,500
Random-walk Metropolis-Hastings sampling
                                                                          2,500
                                                   MCMC sample size =
                                                                         10,000
Group variable: user_id
                                                   Number of groups=
                                                                          851
                                                   Obs per group:
                                                           min =
                                                            avg =
                                                                       46.4
                                                   Number of obs =
Family: Bernoulli
                                                                         39,481
Link: logit
                                                   Acceptance rate =
                                                                         .3288
                                                   Efficiency: min =
                                                                        .001905
                                                               avg =
                                                                        .03103
Log marginal-likelihood
                                                               max =
                                                                          .1094
                                                                Equal-tailed
                                           MCSE
                                                    Median [95% cred. interval]
                       Mean Std. dev.
BinaryOutcome
                                                 .5845949 .5539536 .6193767
                             .0173772
                                         .00273
{\tt ForecastLogRatio}
                   .5849568
          _cons
                  -1.009224
                             .0129421
                                        .000391
                                                 -1.00856 -1.034599 -.9837726
user_id
                   .0034942 .0015529
                                        .000356
                                                 .0030942
                                                            .0015884
                                                                       .0074536
      U0:sigma2
      U1:sigma2
                   .0941136
                             .0094083
                                        .001008
                                                 .0935117
                                                            .0771833
                                                                       .1134356
Note: Default priors are used for model parameters.
Note: There is a high autocorrelation after 500 lags.
Note: Adaptation tolerance is not met in at least one of the blocks.
```

# Model 3:

. bayes: melogit BinaryOutcome c.ForecastLogRatio##i.TrainingBinary || user\_id: c.ForecastLogR > atio

#Time to run Model 3:

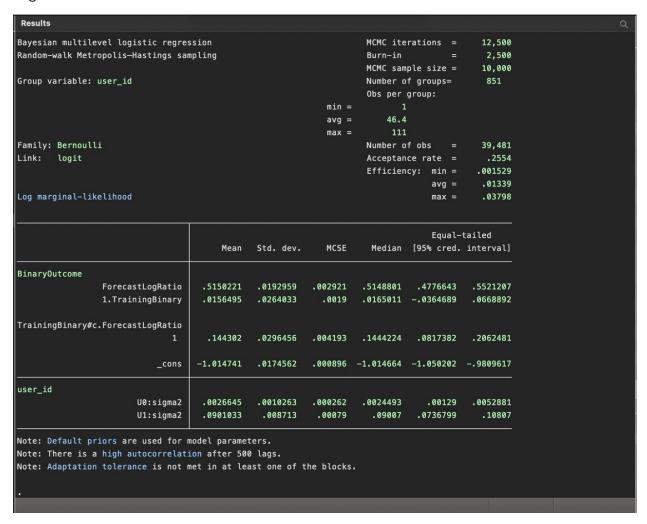
#. timer list 1

# 1: 301.42/ 1 = 301.4210

Page 1 of Model 3's results:

```
Results
. bayes: melogit BinaryOutcome c.ForecastLogRatio##i.TrainingBinary if Experience == 0 || user_id: c.ForecastLogRatio
Burn-in 2500 aaaaaaaaa1000aaaaaaa2000aaaaa done
Simulation 10000 .......1000 ......2000 .....3000 ......4000 ......5000 ......6000 .....7000 ......8000 ..
> ......9000......10000 done
Multilevel structure
user id
    {U0}: random intercepts
    {U1}: random coefficients for ForecastLogRatio
Model summary
 BinaryOutcome ~ melogit(xb_BinaryOutcome)
                    {BinaryOutc~e:ForecastLogRatio} ~ normal(0,10000)
                    {BinaryOutc~e:1.TrainingBinary} ~ normal(0,10000)
  {BinaryOutc~e:1.TrainingBinary#c.ForecastLogRatio} ~ normal(0,10000)
                               {BinaryOutc~e:_cons} ~ normal(0,10000)
                                              {U0} ~ normal(0,{U0:sigma2})
                                               {U1} \sim normal(0, {U1:sigma2})
Hyperpriors:
  {U0:sigma2} \sim igamma(.01,.01)
  {U1:sigma2} ~ igamma(.01,.01)
Parameters are elements of the linear form xb_BinaryOutcome.
Bayesian multilevel logistic regression
                                                                    MCMC iterations =
                                                                                           12,500
Random-walk Metropolis-Hastings sampling
                                                                    Burn-in
                                                                                            2,500
                                                                                           10,000
                                                                    MCMC sample size =
Group variable: user_id
                                                                    Number of groups=
```

# Page 2 of Model 3's results:



# Model 4:

. bayes: melogit BinaryOutcome c.ForecastLogRatio##i.TrainingBinary c.ForecastLogRatio##i.year2binary || user\_id: c.ForecastLogRatio

#Time to run Model 4:

#. timer list 1

# 1: 388.62/ 1 = 388.6210

#### Page 1 of Model 4's results:

```
Results
. bayes: melogit BinaryOutcome c.ForecastLogRatio##i.TrainingBinary c.ForecastLogRatio##i.year2binary if Experience == 0 ||
> user_id: c.ForecastLogRatio
Burn-in 2500 aaaaaaaaa1000aaaaaaaa2000aaaaa done
Simulation 10000 .......1000 ......2000 ......3000 ......4000 .....5000 ......6000 .....7000 ......8000 ..
> .....9000......10000 done
Multilevel structure
user_id
    {U0}: random intercepts
    {U1}: random coefficients for ForecastLogRatio
Model summary
Likelihood:
  BinaryOutcome ~ melogit(xb_BinaryOutcome)
Priors:
                     {BinaryOutc~e:ForecastLogRatio} ~ normal(0,10000)
                     {BinaryOutc~e:1.TrainingBinary} ~ normal(0,10000)
  {BinaryOutc~e:1.TrainingBinary#c.ForecastLogRatio} ~ normal(0,10000)
                       {BinaryOutc~e:1.year2binary} ~ normal(0,10000)
     {BinaryOutc~e:1.year2binary#c.ForecastLogRatio} ~ normal(0,10000)
                               {BinaryOutc~e:_cons} ~ normal(0,10000)
                                               \{U0\} \sim normal(0,\{U0:sigma2\})
                                               {U1} ~ normal(0,{U1:sigma2})
Hyperpriors:
  {U0:sigma2} ~ igamma(.01,.01)
  {U1:sigma2} \sim igamma(.01,.01)
(1) Parameters are elements of the linear form xb_BinaryOutcome.
Bayesian multilevel logistic regression
                                                                     MCMC iterations =
                                                                                            12,500
```

# Page 2 of Model 4's results:

manata.							
Results						-	
Bayesian multilevel logistic regre					rations =	12,500	
Random-walk Metropolis-Hastings sa	mpling			Burn-in		2,500	
					ple size =	10,000	
Group variable: user_id					f groups=	851	
				Obs per	group:		
			min =	1			
			avg =	46.4			
			max =	111			
Family: Bernoulli				Number o	f obs =	39,481	
Link: logit				Acceptan	ce rate =	.3311	
					cy: min =	.001785	
					avg =	.005509	
Log marginal-likelihood					max =	.0179	
Log marginat tiretinood					max =	101/3	
					Equal-		
	Mean	Std. dev.	MCSE	Median	[95% cred.	interval]	
BinaryOutcome			10-10-10-10-1				
ForecastLogRatio	.5615235	.0247621	.005555	.5621972	.5141854	.6057944	
1.TrainingBinary	.0096352	.0273484	.002044		0427694	.0630151	
111141111111111111111111111111111111111	.0030332			.0103.3.		.0050151	
TrainingBinary#c.ForecastLogRatio							
1	.1431432	.0296502	.007018	.1419348	.089987	.1990223	
±.	.1431432	.0290302	.00/010	.1419346	.003307	. 1990223	
1 voo 25 in an	1402667	0202074	005644	1207164	0055494	1004227	
1.year2binary	.1402667	.0293871	.005644	.1387164	.0866484	.1994227	
year2binary#c.ForecastLogRatio							
1	0859033	.0299278	.005926	08605	1422018	0249659	
_cons	-1.08245	.0243968	.004234	-1.081174	-1.131714	-1.036687	
user_id							
U0:sigma2	.0030063	.000931	.000186	.0029052	.0015502	.0052903	
U1:sigma2	.0896008	.0085865	.000807	.0893385	.0739416	.107156	
01.Sigmaz	.0030008	.0005005	1000007	10055505	10/33410	. 107130	
Command							
Control of the Contro							

's results:

# Model 5:

- . bayes: melogit BinaryOutcome c.ForecastLogRatio##i.TrainingBinary##i.year2binary if Experience == 0 || user\_id
- >: c.ForecastLogRatio

#Time to run Model 5:

#. timer list 1

# 1: 649.75/ 1 = 649.7470

#### Page 1 of Model 5

```
. bayes: melogit BinaryOutcome c.ForecastLogRatio##i.TrainingBinary##i.year2binary if Experience == 0 || user_id: c.Forecas
> tLogRatio
Burn-in 2500 aaaaaaaaa1000aaaaaaaa2000aaaaa done
Simulation 10000 .......1000.......2000......3000.......4000......5000......6000......7000.......8000..
> ......9000......10000 done
Multilevel structure
user_id
   {U0}: random intercepts
   {U1}: random coefficients for ForecastLogRatio
Model summary
Likelihood:
 BinaryOutcome ~ melogit(xb_BinaryOutcome)
Priors:
                                  {BinaryOutc~e:ForecastLogRatio} ~ normal(0,10000)
                                  {BinaryOutc~e:1.TrainingBinary} ~ normal(0,10000)
               {BinaryOutc~e:1.TrainingBinary#c.ForecastLogRatio} ~ normal(0,10000)
                                    {BinaryOutc~e:1.year2binary} ~ normal(0,10000)
                  {BinaryOutc~e:1.year2binary#c.ForecastLogRatio} ~ normal(0,10000)
                    {BinaryOutc~e:1.TrainingBinary#1.year2binary} ~ normal(0,10000)
  {BinaryOutc∼e:1.TrainingBinary#1.year2binary#c.ForecastLogRatio} ~ normal(0,10000)
                                            {BinaryOutc~e:_cons} ~ normal(0,10000)
                                                            {U0} ~ normal(0,{U0:sigma2})
                                                            {U1} ~ normal(0,{U1:sigma2})
Hyperpriors:
 {U0:sigma2} ~ igamma(.01,.01)
 {U1:sigma2} ~ igamma(.01,.01)
(1) Parameters are elements of the linear form xb_BinaryOutcome.
Command
```

's results:

# Page 2 of Model 5's results:

Results							Q
(1) Parameters are elements of the linear form	xb_Binary0u	tcome.					
Bayesian multilevel logistic regression				MCMC ite	rations =	12,500	
Random-walk Metropolis—Hastings sampling					Burn-in = 2,5		
				MCMC sam	ple size =	10,000	
Group variable: user_id			of groups=	851			
				Obs per	group:		
		min =	1				
		avg =	46.4				
		max =	111				
Family: Bernoulli		Number o		39,481			
Link: logit					ice rate =	.2835	
				Efficien	icy: min =	.002098	
					avg =	.00631	
Log marginal-likelihood					max =	.01741	
					Equal-	tailed	
	Mean	Std. dev.	MCSE	Median	[95% cred.		
	i i cuii		11032		1550 01041		
BinaryOutcome							
ForecastLogRatio	.5539816	.0188804	.002993	.5563495	.5094402	.5848905	
1.TrainingBinary	0473222	.0321662	.003227	0474587	1078511	.0190324	
TrainingBinary#c.ForecastLogRatio							
1	.1387734	.0303295	.005267	.135788	.0882398	.1983211	
1.year2binary	.0779092	.0265128	.004065	.0808747	.0181696	.1205499	
year2binary#c.ForecastLogRatio							
1	0921883	.0319851	.004891	092612	1512925	0271536	
TrainingBinary#year2binary							
1 1	.1393874	.0428197	.0052	.140212	.0533425	.2177178	
TrainingBinarv#vear2binarv#c.ForecastLogRatio							
Command							

Page 3 of Model 5's results:

