Understanding Terrorism Policy Preferences through Bayesian Model Averaging and Multiple Imputation

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Background of Survey

- This analysis comes from a two-wave panel survey on perceptions about terrorism and terrorism policy conducted 2016. The first wave was in May 2016 and had 1730 respondents (61% response), and the second wave was in November 2016 and had 1210 (71% response).
- Survey was conducted using GFK Research's Knowledge Panel which is an internet probability panel
- Some respondents had missing data items
- If a respondent had more 5 missing items per wave they were removed (1098 respondents left)
- Survey was weighted for differential nonresponse

Background of Survey

- Between the two waves multiple foreign and domestic terrorist attacks occurred including:
  - Orlando Pulse Nightclub Shooting in June 2016 (ISIS inspired)
  - Dallas Police Shooting & Baton Rouge Police Shooting in July 2016 where officers where killed (related to police killing of Alton Sterling)
  - Nice, France Truck Attack (ISIS inspired) in July 2016
  - New York City and New Jersey Bombings (Islamic extremist terrorist) in September 2016

List of questions

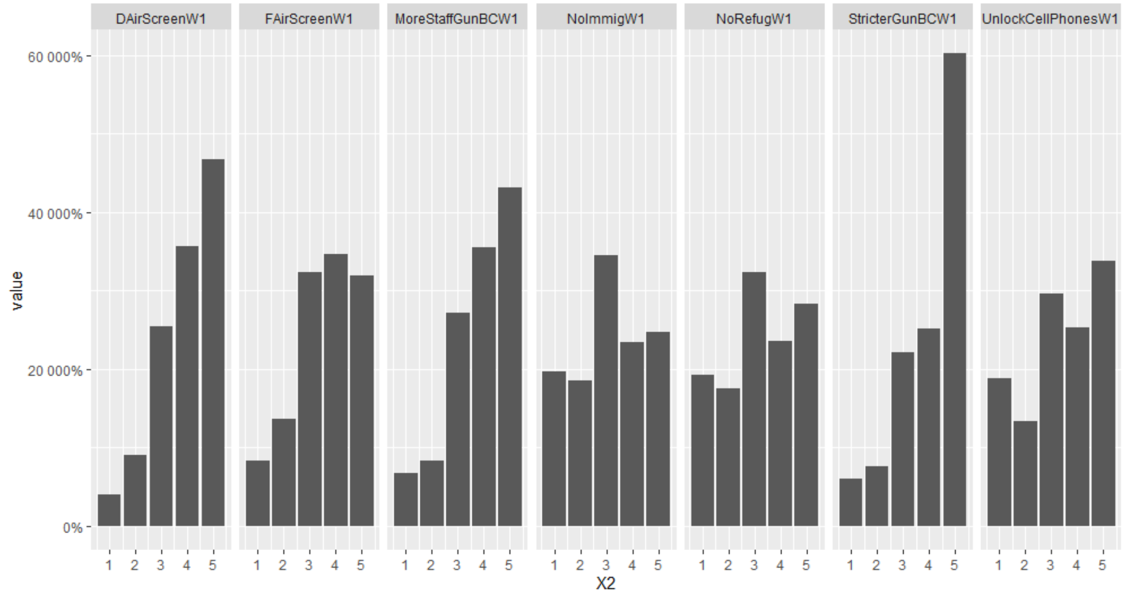
- Likelihood of attacks
- Risk of attacks
- Support for Federal funding to prevent terrorism
- Support for local funding to prevent terrorism
- List of counterterrorism policies
- How terrorist attacks made people feel
- The competence of government agencies to prevent terrorism
- Concern for certain types of attacks
- Concern about being a victim
- Concern of attacks from different kinds of terrorists
- How many people would be affected by an attack
- How severe would an attack be
- Whether the government shares your values
- If the public understands terrorism risks
- If experts understand terrorism risks

Types of Terrorist attacks

- Poisoned water supply,
- An explosion of a small nuclear device in a major U.S. city,
- airline attack similar to 9/11
- An armed attack on civilian populations
- An armed attack on military personnel or law enforcement officers
- An explosion of a bomb at a public place
- Cyber-attack on the nation’s power grid
- Attack with a biological weapon

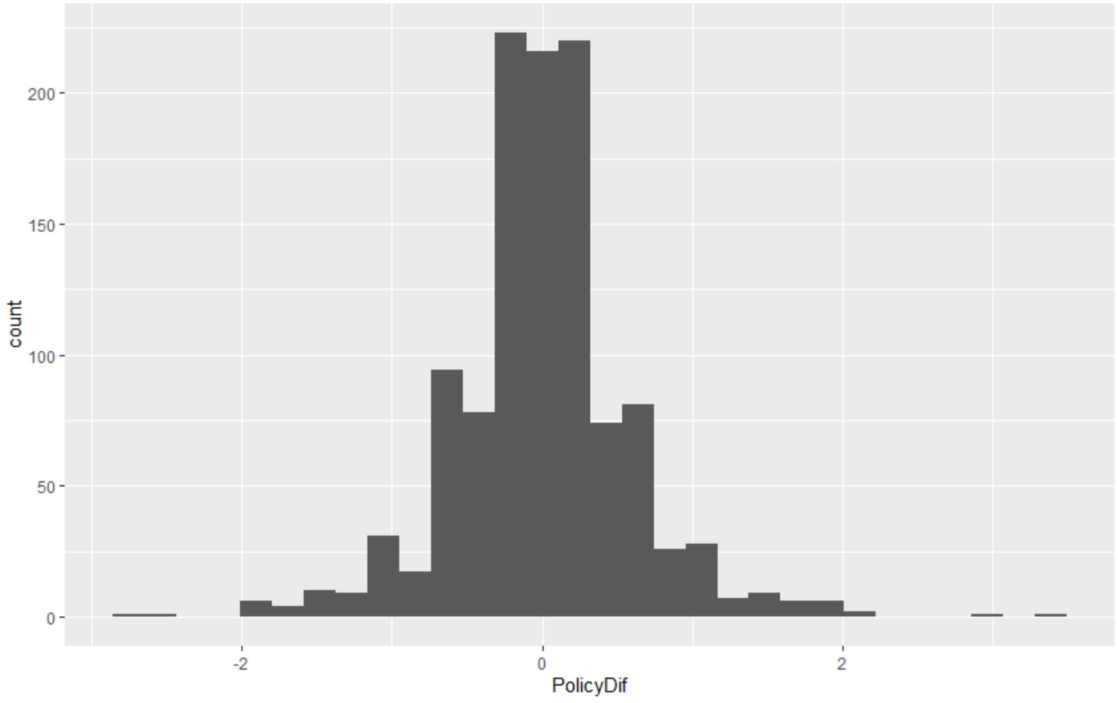
Support for Policies in Wave 1

- Scale: 1 = Strongly Oppose, 2=Somewhat Oppose, 3 = Neutral, 4 = Somewhat Support, 5 = Strongly Support
- FAirScreen: extra screening at airports for international flights
- DAirScreen: extra screening at airports for domestic flights
- StricterGunBC: Stricter gun background checks
- NoImmig: Halt all immigration
- NoRefug: no Refugees from Syria and Iraq
- MoreStaffGunBC: Increase staffing for gun background checks
- UnlockCellPhones: Require cell phone manufacturers to unlock the data in cell phones of terrorists



Change in Policy Support

- This is a histogram in the change in average support for a policy.
- Wave 2 – Wave 1
- Theoretical scale is -4 to 4



The original analysis

- Liu et al. 2018 studied this survey originally using Ordinary Least Squares without imputation of missing responses or a data-driven variable selection strategy
- This analysis was helpful but had left some questions unanswered
- Modeling support at individual time points was good but the difference was more difficult
- Only a small subset of the available items were used
- It wasn’t clear if the variables chosen were the best
- Models focused more on spending than policy support

New Model

- We wanted a model that dealt with missing data and would let the data decide what variables were important
- Bayesian model averaging (R package BMA, Hoeting et. al. (1999)) efficiently searches all possible combinations of variables for models
- Multiple imputation (R package MI, Su et. al (2011), Rubin (1996)), uses regressions to create multiple datasets with the missing data filled in by samples and then the samples are combined to preform inference
- Both methods have been applied to a variety of problems, but a literature search did not find a case where BMA and MI were applied together to public opinion survey data
- Party and Ideology were included as predictors but they were completely ignored by the model

Fitting the Model

- Rubin (1999) provides rules to combine the multiple sample for statistical inference
- We use 4 imputed data sets
- The final means for the regression parameters are an average across the datasets and the variance is the average variance plus the covariance between the samples
- The R packages mi and BMA which contain the code for multiple imputation and Bayesian Model Averaging were used to fit the model

Regression Results Wave 1 & Wave 2

Wave 1		Wave 2	
(Intercept)	1.943 (0.199) [-]	(Intercept)	0.153 (0.165) [-]
Very Concerned about Terrorism	0.271 (0.053) [1]	**Very Concerned about Terrorism**	0.288 (0.051) [1]
Extremely Concern about Terrorism	0.478 (0.061) [1]	**Extremely Concern about Terrorism**	0.498 (0.058) [1]
Well Informed	-0.196 (0.052) [0.99]	Well Informed	-0.003 (0.02) [0.034]
LocalSpend	0.001 (0.009) [0.03]	**FedSpend**	0.178 (0.038) [1]
FedSpend	0.204 (0.039) [1]	Likelihood	0.001 (0.009) [0.029]
Remember	-0.041 (0.092) [0.199]	GovShareValues	0.154 (0.034) [1]
GovCompetent	0.032 (0.05) [0.335]	**PublicUnderstand**	0.092 (0.032) [0.963]
GovShareValues	0.027 (0.044) [0.323]	**ExpertsUnderstand**	-0.09 (0.035) [0.944]
Feelings	0.001 (0.009) [0.042]	Actions	0.065 (0.12) [0.265]
ExpertsUnderstand	-0.003 (0.013) [0.055]	ConcernActor	0.012 (0.031) [0.157]
ConcernActor	0.002 (0.011) [0.032]	ConcernType	0.003 (0.014) [0.051]
ConcernType	0.017 (0.038) [0.207]	HowBad	0.003 (0.016) [0.047]
NumAffected	0.127 (0.033) [1]	**NumAffected**	0.175 (0.035) [1]
Risk	0.104 (0.037) [0.953]	Psuedo-R-square	0.282
Psuedo-R-square	0.293		

Regression results: Wave 2 – Wave 1

Wave 1 Terms		Wave 2 Terms	
(Intercept)	0.153 (0.165) [-]	LocalSpendW2	0.005 (0.02) [0.061]
LocalSpendW1	-0.022 (0.041) [0.251]	**FedSpendW2**	0.105 (0.047) [0.903]
FedSpendW1	-0.101 (0.063) [0.777]	RememberW2	-0.035 (0.083) [0.175]
GovCompetentW1	-0.075 (0.064) [0.639]	GovCompetentW2	0.083 (0.066) [0.674]
ConcernActorW1	-0.006 (0.022) [0.073]	PublicUnderstandW2	0.002 (0.009) [0.038]
ConcernTypeW1	-0.031 (0.045) [0.356]	ConcernActorW2	0.01 (0.027) [0.134]
HowBadW1	-0.001 (0.012) [0.02]	ConcernVicW2	0.018 (0.031) [0.279]
LocalSpendW1	-0.022 (0.041) [0.251]	HowBadW2	0.009 (0.028) [0.122]
FedSpendW1	-0.101 (0.063) [0.777]	Psuedo-R-square	0.037
RiskW1	-0.041 (0.039) [0.576]		

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References

- Brogan, M., Rusciano, F. L., Thompson, V., & Walden, K. (2019). Perceptions of terrorism and counterterrorism: fear, risk and the 2016 Trump effect. *Journal of homeland security and emergency management*, *17*(1).
- Gelman, A., Goodrich, B., Gabry, J., & Vehtari, A. (2019). R-squared for Bayesian regression models. The American Statistician, 73(3), 307-309.
- Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian model averaging: a tutorial. Statistical Science, 382-401.
- Kass, Robert & Raftery, Adrian (1995) Bayes Factors, Journal of the American Statistical Association, 90:430, 773-795
- Leite, Walter and Beretvas, S. Natasha (2010) "The Performance of Multiple Imputation for Likert-type Items with Missing Data," Journal of Modern Applied Statistical Methods: Vol. 9: Iss. 1, Article 8. DOI: 10.22237/jmasm/1272686820
- Rubin, D. B. (1996). Multiple imputation after 18+ years. Journal of the American Statistical Association, 91(434), 473-489.
- Su Y.S., Gelman A., Hill J., Yajima M. (2011). “Multiple Imputation with Diagnostics (mi) in
- R: Opening Windows into the Black Box.” Journal of Statistical Software, 45(2), 1–31.
- doi:10.18637/jss.v045.i02.
- Wang, R. “Understanding multicollinearity in Bayesian model averaging with BIC approximation” (2018) Available at: http://summit.sfu.ca/item/17968