Applied Stats II – Replication

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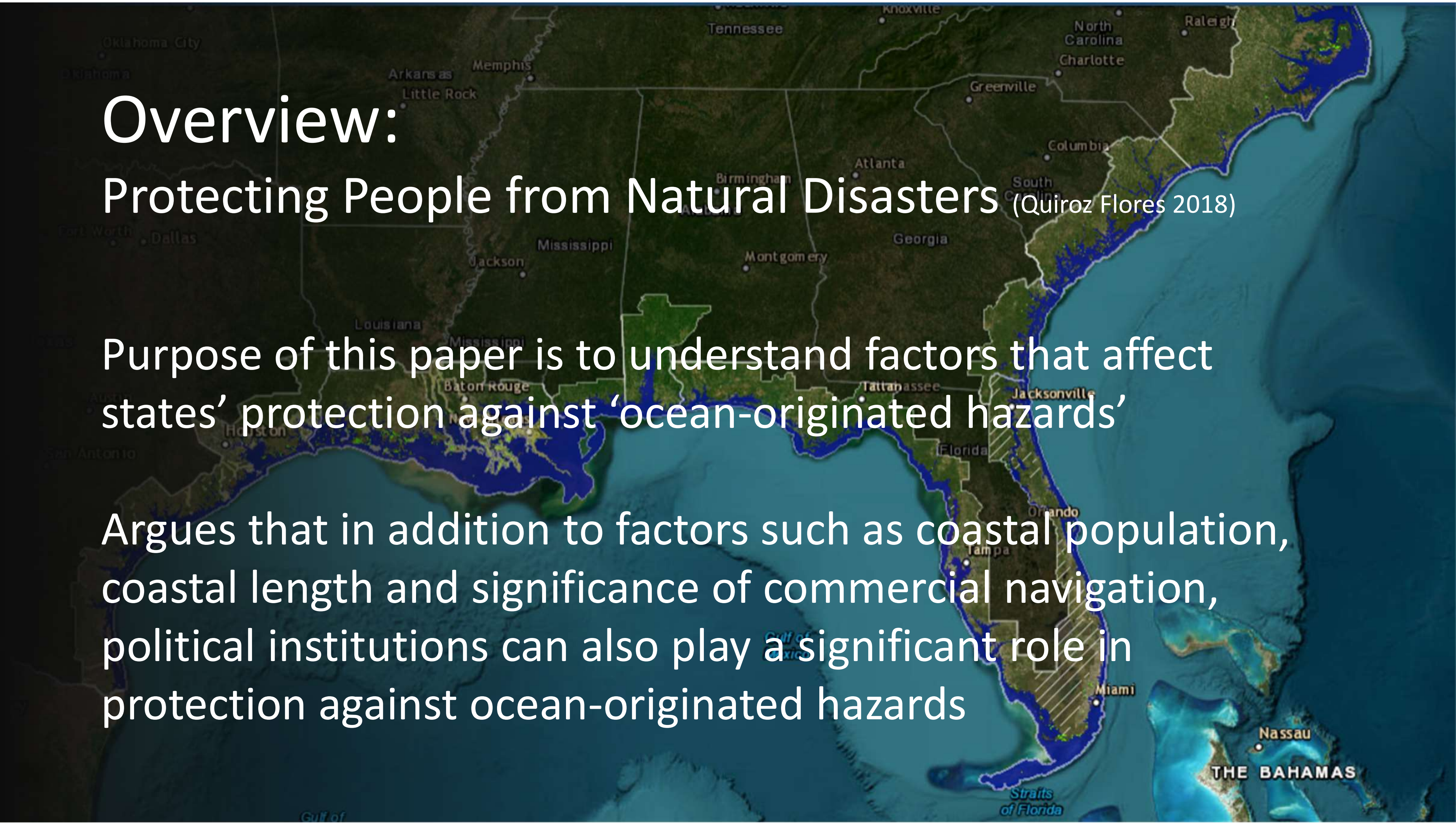
Protecting People from Natural Disasters: Political Institutions and Ocean-Originated Hazards (Quiroz Flores 2018)

Alejandro Quiroz Flores, Protecting People from Natural Disasters: Political Institutions and Ocean-Originated Hazards. *Political Science Research and Methods,* 6:1 (2018), 111-134. doi:10.1017/psrm.2015.72

Abstract

- ‘Why do some leaders protect their citizens from natural disasters while others do not? This paper argues that leaders in large coalition systems provide more protection against natural disasters than leaders in small coalition systems. Yet, autocrats also provide large-scale disaster protection if members of their winning coalition are exposed to natural hazards…Empirical evidence indicates that leaders in large coalition systems deploy more sea-level stations than their counterparts in small coalition systems. The evidence also shows that if the national capital is close to the coast, thus exposing members of the ruling coalition to ocean-originated hazards, leaders across political systems install more sea-level stations.’



Overview:

Protecting People from Natural Disasters (Quiroz Flores 2018)

Purpose of this paper is to understand factors that affect states' protection against 'ocean-originated hazards'

Argues that in addition to factors such as coastal population, coastal length and significance of commercial navigation, political institutions can also play a significant role in protection against ocean-originated hazards

Details of original study

- Unit of analysis is country in February 2014 (all landlocked countries dropped from study)
- Dependent variable: 'Measurement of Protection' in this study is number of Sea Level Stations – (count data)
- Hypothesis 1: *'All else equal, leaders in large coalition systems provide more protection against natural disasters than their counterparts in small coalition systems'* (p 6)
- Hypothesis 2: *'All else equal, leaders across all potential systems provide ptotection against natural disasters if the country's capital is in a vulnerable location'* (p 8)

Replicating models

```r
library(pscl)
library(stargazer)
library(MAS)
library(lmtest)
library(AER)
```

Models 1-3 estimates negative binomial count models

Model 4 estimates a zero inflated negative binomial count model

```r
#####
## Models
#####

m1 <- glm.nb(stations ~ ln_distance_km + lnstm_dis + lncoast + pacific +
             ioc_mship + dipl_rep_num + pop2000_lecz_pc, data = data4)
m2 <- glm.nb(stations ~ ln_distance_km + lnstm_dis + lncoast + pacific +
             ioc_mship + dipl_rep_num + pop2000_lecz_pc + W + ship_cntc, data = data4)
m3 <- glm.nb(stations ~ capital_sea_50p + Wcapital_sea_50p + lnstm_dis +
             lncoast + pacific + ioc_mship + dipl_rep_num + pop2000_lecz_pc + W + ship_cntc, data = data4)
m4 <- zeroinfl(stations ~ capital_sea_50p + Wcapital_sea_50p + lnstm_dis + lncoast + pacific + ioc_mship +
               dipl_rep_num + pop2000_lecz_pc + ship_cntc + W | W + lnstm_dead + Wlnstm_dead,
             dist = 'negbin', data = data4)
```

Original Regression Models

	Model 1	Model 2	Model 3	Model 4
W		1.663***	3.627***	3.575***
		(0.53)	(0.87)	(0.88)
ln(Capital Distance)	-0.109	-0.062		
	(0.07)	(0.08)		
Sea Capital			2.256***	2.396***
			(0.82)	(0.85)
(W)(Sea Capital)			-2.897***	-3.023***
			(1.04)	(1.06)
ln(Number Storms)	0.364***	0.376***	0.371***	0.302**
	(0.12)	(0.12)	(0.11)	(0.13)
ln(Length Coast)	0.379***	0.455***	0.448***	0.448***
	(0.11)	(0.11)	(0.11)	(0.11)
LECZ Population Pc	-0.432	-3.222**	-2.380*	-2.323*
	(0.69)	(1.32)	(1.25)	(1.27)
Pacific	0.546*	0.443	0.409	0.375
	(0.29)	(0.3)	(0.29)	(0.29)
IOC Membership	0.72	0.686	0.695	0.719
	(0.62)	(0.88)	(0.84)	(0.87)
Diplomatic Representation	0.012***	-0.003	-0.004	-0.003
	(0.0)	(0.01)	(0.01)	(0.01)
Shipping		0.024***	0.021**	0.019**
		(0.01)	(0.01)	(0.01)
Intercept	-3.669***	-5.192***	-6.796***	-6.635***
	(0.84)	(1.14)	(1.22)	(1.24)
lnalpha	0.158	-0.123	-0.264	-0.336
	(0.18)	(0.21)	(0.22)	(0.23)
Inflation Equation				
W				-2.133
				(4.05)
ln(Storm Deaths)				-0.77
				(1.55)
(W)ln(Storm Deaths)				0.046
				(1.97)
Intercept				0.407
				(2.4)
N	137	116	116	116
LogLikelihood	-279.487	-228.603	-225.11	-224.545
DV: Number of Sea-Level Stations. Unit: Country.				
* p < 0.10, ** p < 0.05, *** p < 0.01				

My Regression Models

Table 1: results

	Dependent variable:			
	stations			
		negative binomial		*zero-inflated count data*
	(1)	(2)	(3)	(4)
ln_distance_km	−0.109	−0.062		
	(0.068)	(0.071)		
capital_sea_50p			2.256***	2.396***
			(0.820)	(0.853)
Wcapital_sea_50p			−2.897***	−3.023***
			(1.042)	(1.061)
lnstm_dis	0.364***	0.376***	0.371***	0.302**
	(0.101)	(0.108)	(0.104)	(0.129)
lncoast	0.379***	0.455***	0.448***	0.448***
	(0.094)	(0.101)	(0.100)	(0.108)
pacific	0.546*	0.443	0.409	0.375
	(0.286)	(0.293)	(0.285)	(0.287)
ioc_mship	0.720	0.686	0.695	0.719
	(0.599)	(0.920)	(0.869)	(0.871)
dipl_rep_num	0.012***	−0.003	−0.004	−0.003
	(0.004)	(0.006)	(0.006)	(0.006)
pop2000_lecz_pc	−0.432	−3.222***	−2.380**	−2.323*
	(0.693)	(1.199)	(1.083)	(1.275)
W		1.663***	3.627***	3.575***
		(0.541)	(0.805)	(0.883)
ship_cntc		0.024***	0.021***	0.019**
		(0.007)	(0.007)	(0.008)
Constant	−3.669***	−5.192***	−6.796***	−6.635***
	(0.794)	(1.139)	(1.181)	(1.239)
Observations	137	116	116	116
Log Likelihood	−280.487	−229.603	−226.111	−224.545
θ	0.854*** (0.152)	1.131*** (0.233)	1.302*** (0.281)	
Akaike Inf. Crit.	576.974	479.206	474.221	

My Analysis: Negative binomial count model vs Poisson

Estimating a Poisson count model using glm function with the same variables as Model 1

```
poisson_model <- glm(stations ~ ln_distance_km + lnstm_dis + lncoast + pacific +
            ioc_mship + dipl_rep_num + pop2000_lecz_pc, family='poisson', data = data4)
summary(poisson_model)
```

Running a likelihood ratio test

```
> lrtest(poisson_model, m1)
Likelihood ratio test

Model 1: stations ~ ln_distance_km + lnstm_dis + lncoast + pacific + ioc_mship +
    dipl_rep_num + pop2000_lecz_pc
Model 2: stations ~ ln_distance_km + lnstm_dis + lncoast + pacific + ioc_mship +
    dipl_rep_num + pop2000_lecz_pc
  #Df  LogLik Df  Chisq Pr(>Chisq)
1   8 -608.36
2   9 -279.49  1 657.75  < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The likelihood ratio test indicates the two models **do not** fit the data equally well.

My Analysis: Negative binomial count model vs Poisson

- Conducting a dispersion test on the Poisson Model (using AER package)
- Overdispersion (variance is greater than the mean value) and therefore unsuitable for the Poisson model

```
        Overdispersion test

data:  poisson_model
z = 2.1243, p-value = 0.01682
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  11.04586
```

My Analysis: Negative binomial count model vs Poisson

Poisson Model AIC : 1232.7

```
> summary(poisson_model)

Call:
glm(formula = stations ~ ln_distance_km + lnstm_dis + lncoast +
    pacific + ioc_mship + dipl_rep_num + pop2000_lecz_pc, family = "poisson",
    data = data4)

Deviance Residuals:
     Min       1Q    Median       3Q      Max
-10.5319  -1.6615   -0.7477   0.3622  14.6891

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)     -2.16005    0.48321  -4.470 7.81e-06 ***
ln_distance_km  -0.14787    0.02704  -5.468 4.54e-08 ***
lnstm_dis        0.26171    0.03515   7.446 9.61e-14 ***
lncoast          0.20116    0.02963   6.790 1.13e-11 ***
pacific          0.30898    0.10224   3.022  0.00251 **
ioc_mship        0.95252    0.45425   2.097  0.03600 *
dipl_rep_num     0.01953    0.00118  16.550  < 2e-16 ***
pop2000_lecz_pc -3.33641    0.52371  -6.371 1.88e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 3133.43  on 136  degrees of freedom
Residual deviance:  948.69  on 129  degrees of freedom
  (6 observations deleted due to missingness)
AIC: 1232.7

Number of Fisher Scoring iterations: 6
```

Negative binomial AIC: 576.97

```
> summary(m1)

Call:
glm.nb(formula = stations ~ ln_distance_km + lnstm_dis + lncoast +
    pacific + ioc_mship + dipl_rep_num + pop2000_lecz_pc, data = data4,
    init.theta = 0.8535118284, link = log)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-2.2727  -1.0413  -0.5365   0.1296   3.0375

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)     -3.668609   0.794282  -4.619 3.86e-06 ***
ln_distance_km  -0.108681   0.067912  -1.600 0.109526
lnstm_dis        0.364464   0.100727   3.618 0.000296 ***
lncoast          0.379118   0.094406   4.016 5.92e-05 ***
pacific          0.546359   0.286371   1.908 0.056408 .
ioc_mship        0.720199   0.599474   1.201 0.229602
dipl_rep_num     0.012384   0.003865   3.204 0.001356 **
pop2000_lecz_pc -0.432309   0.693228  -0.624 0.532879
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(0.8535) family taken to be 1)

    Null deviance: 349.4  on 136  degrees of freedom
Residual deviance: 134.3  on 129  degrees of freedom
  (6 observations deleted due to missingness)
AIC: 576.97
```

In conclusion…

Both Negative Binomial models and Poisson model can be implemented for count outcomes

In this instance, a likelihood ratio test was conducted and indicated Negative binomial model is better fit to the data.

References:

Quiroz Flores, Alejandro. "Protecting People from Natural Disasters: Political Institutions and Ocean-Originated Hazards." *Political Science Research and Methods* 6, no. 1 (2018): 111–34. doi:10.1017/psrm.2015.72.

NOAA Sea Level Rise View (https://coast.noaa.gov/slr/)