

2016 House Burglary vs Surveillance Cameras in Taipei City

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(Econ 4th)

Agenda

```
graph TD; A[Agenda] --- B[Motivation]; B --- C[Data]; C --- D[Model & Result]; D --- E[Conclusion];
```

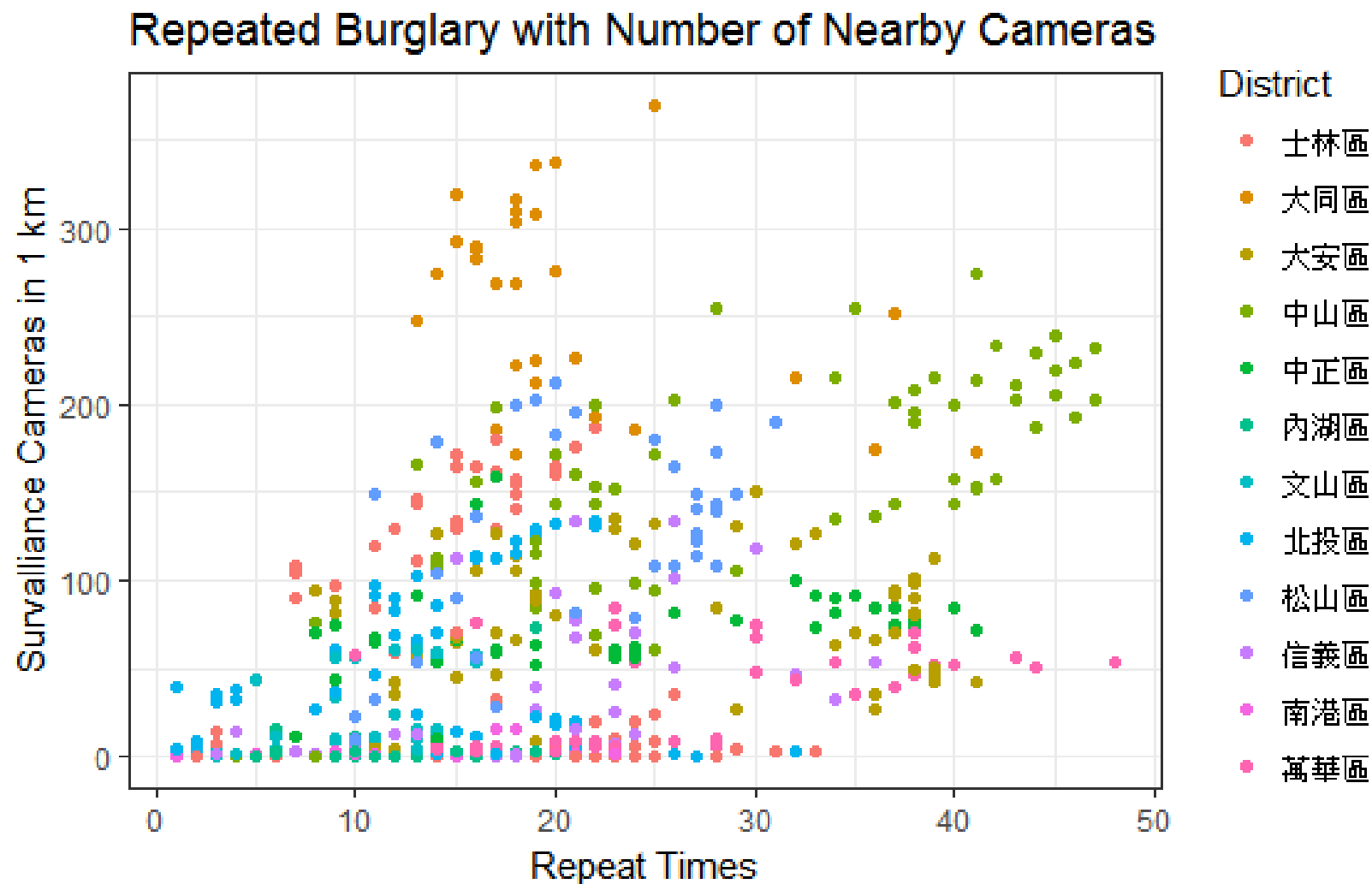
Motivation

Data

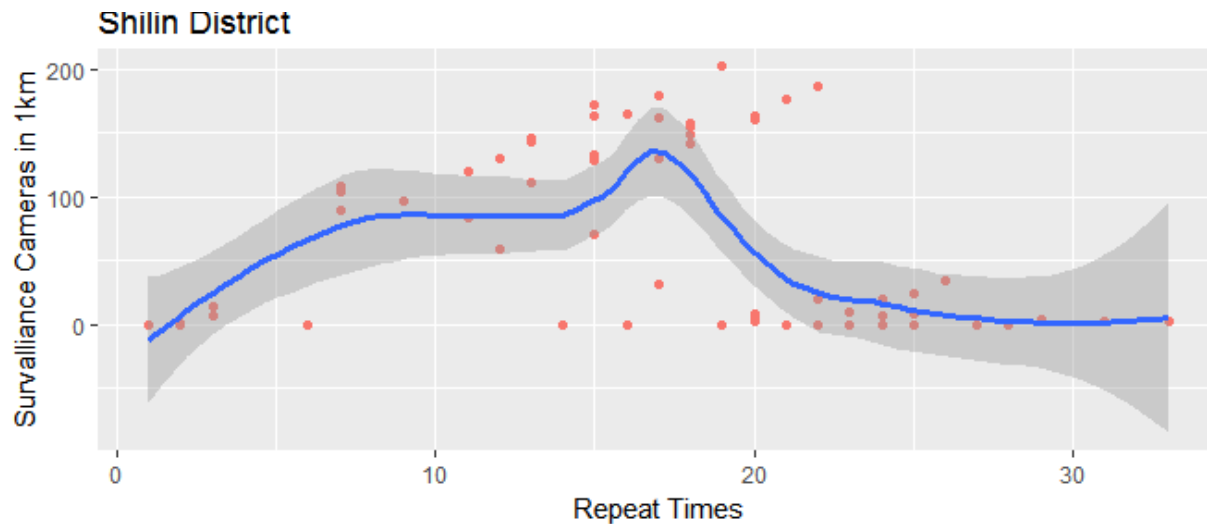
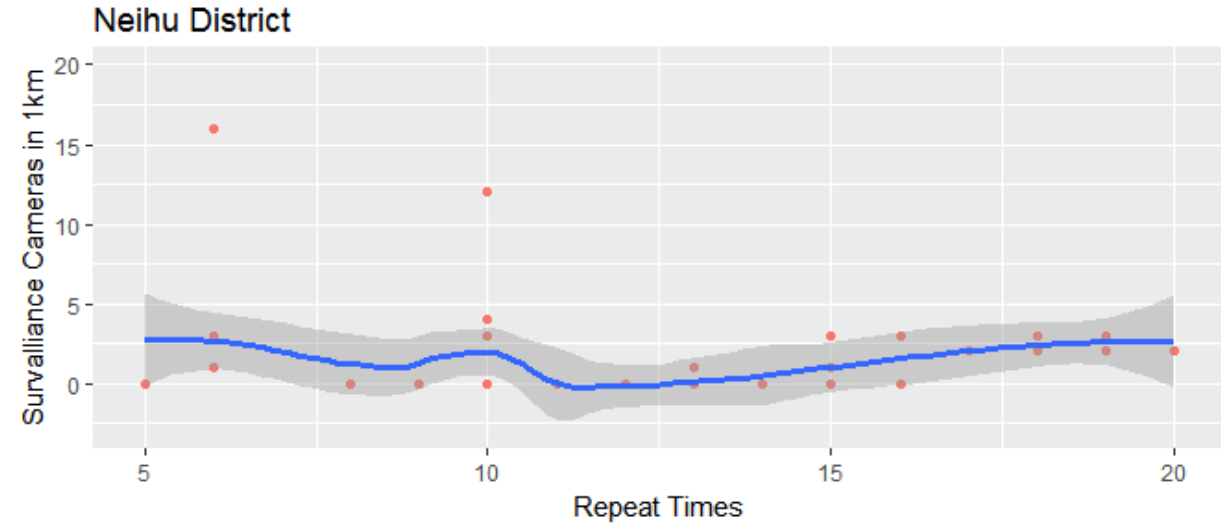
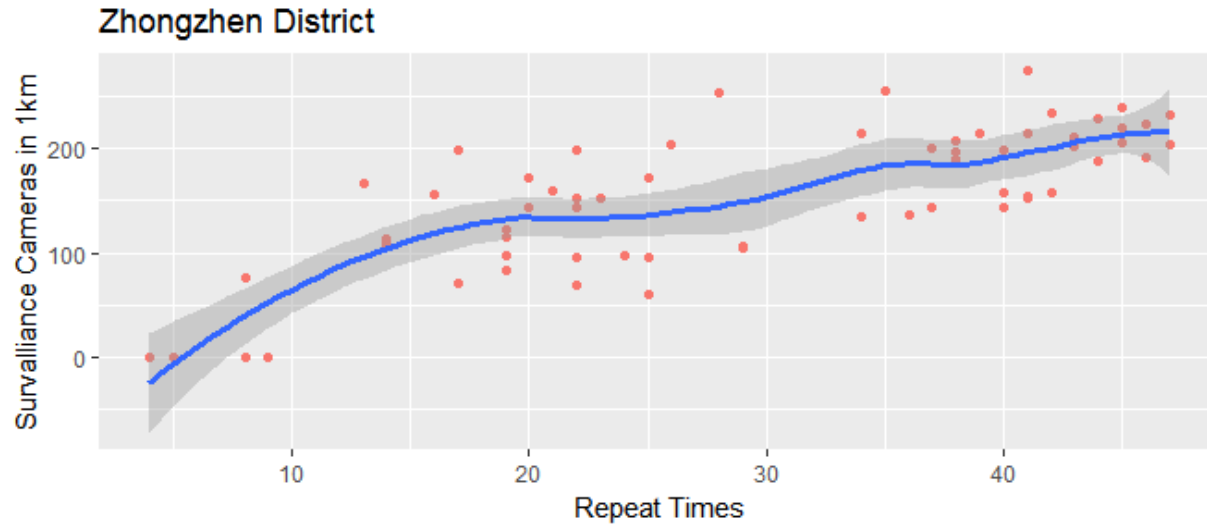
Model & Result

Conclusion

Different Trend on Repeated Times and Nearby Cameras



Different Trend on Repeated Times and Nearby Cameras



- ➔
- Nearby Surveillance Camera VS Repeated Burglaries
 - Burglary Rate Prediction

1. Nearby Surveillance Cameras VS Repeated Burglaries

- Burglary record from Taipei City government
(includes date, time and address)
- Date Processing:
 - get longitude and latitude
 - count how many cameras and burglaries with 1 km (dism, for-loop)

```
theft105_dis <- distm(theft_105loc)
dim(theft105_dis)[1]

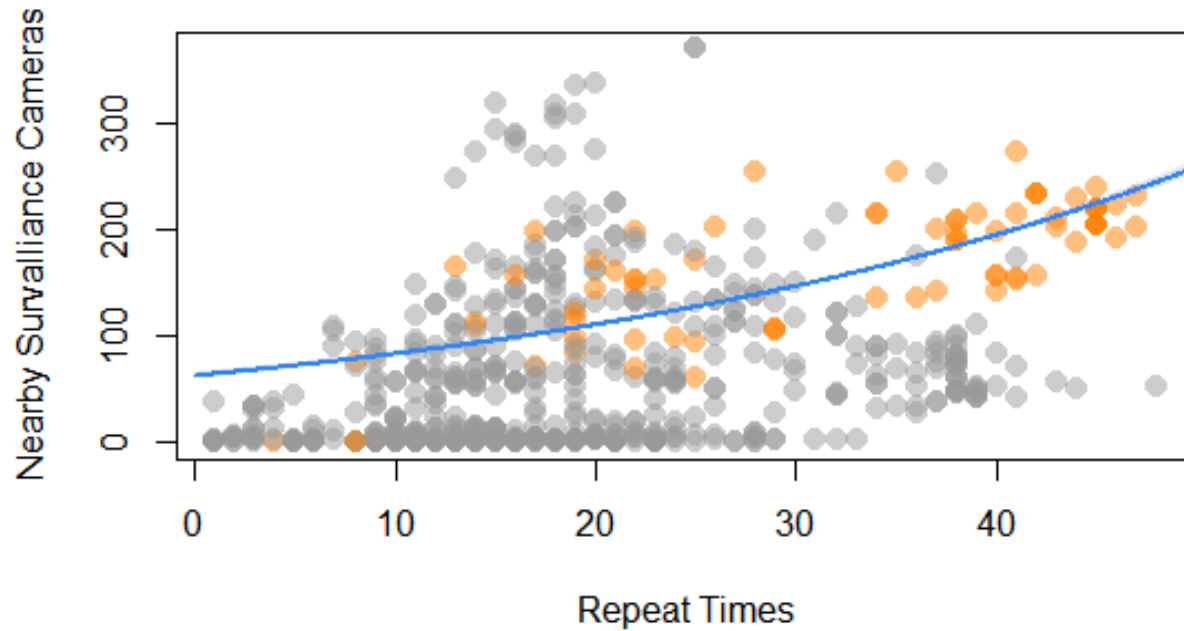
for(i in 1:dim(theft105_dis)[1]){
  under1000 = 0
  for(j in 1:dim(theft105_dis)[1]){
    if (theft105_dis[i,j]<1000){ under1000 = under1000+1}
  }
  theft_105$times[i] = under1000
}
```

2. Burglary Rate Prediction

- includes surveillance cameras density, police stations, disposable income , people with mid and low income and average cameras within 1 km of burglary location of each district

Nearby Surveillance Camera VS Repeated Burglaries

```
m.surv.dist5 <- map2stan(  
  alist(  
    totalSurv ~ dpois(lambda) ,  
    log(lambda) <- a[dist] + bT[dist]*times,  
    a[dist] ~ dnorm(0,100),  
    bT[dist] ~ dnorm(0,10)  
  ),  
  data=theft_105, iter = 1200, warmup = 600, chains = 2)
```



```
> precis(m.surv.dist5, depth = 2)
```

	Mean	StdDev	lower 0.89	upper 0.89	n_eff	Rhat
a[1]	4.37	0.03	4.32	4.43	1200	1
a[2]	5.78	0.04	5.73	5.84	1200	1
a[3]	4.34	0.04	4.28	4.40	1200	1
a[4]	4.14	0.03	4.10	4.20	1200	1
a[5]	4.22	0.04	4.16	4.29	1200	1
a[6]	-1.80	0.34	-2.36	-1.28	897	1
a[7]	1.48	0.14	1.27	1.71	787	1
a[8]	3.44	0.04	3.38	3.51	1200	1
a[9]	3.78	0.06	3.70	3.88	1200	1
a[10]	2.29	0.09	2.16	2.45	1200	1
a[11]	0.10	0.31	-0.36	0.61	671	1
a[12]	2.50	0.08	2.37	2.61	1200	1
bT[1]	-0.02	0.00	-0.02	-0.02	1200	1
bT[2]	-0.01	0.00	-0.01	-0.01	1200	1
bT[3]	0.00	0.00	0.00	0.00	1200	1
bT[4]	0.03	0.00	0.03	0.03	1200	1
bT[5]	0.01	0.00	0.00	0.01	1200	1
bT[6]	0.19	0.02	0.15	0.22	868	1
bT[7]	0.14	0.01	0.13	0.16	784	1
bT[8]	0.02	0.00	0.02	0.03	1200	1
bT[9]	0.05	0.00	0.04	0.05	1200	1
bT[10]	0.06	0.00	0.06	0.07	1200	1
bT[11]	0.05	0.02	0.01	0.08	667	1
bT[12]	0.04	0.00	0.03	0.04	1200	1

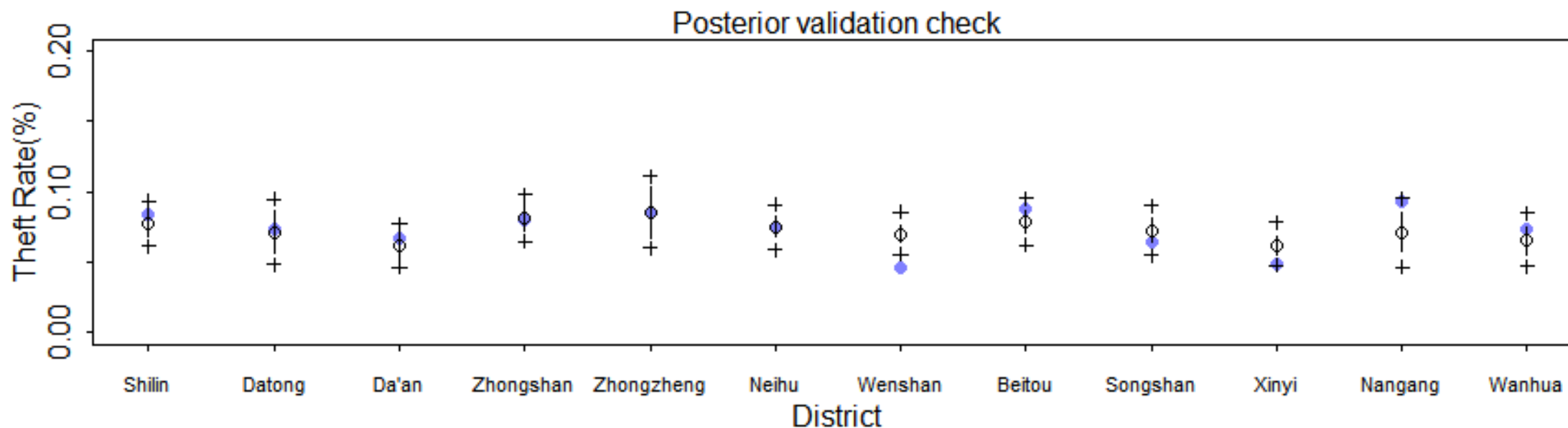
Shilin

Datong

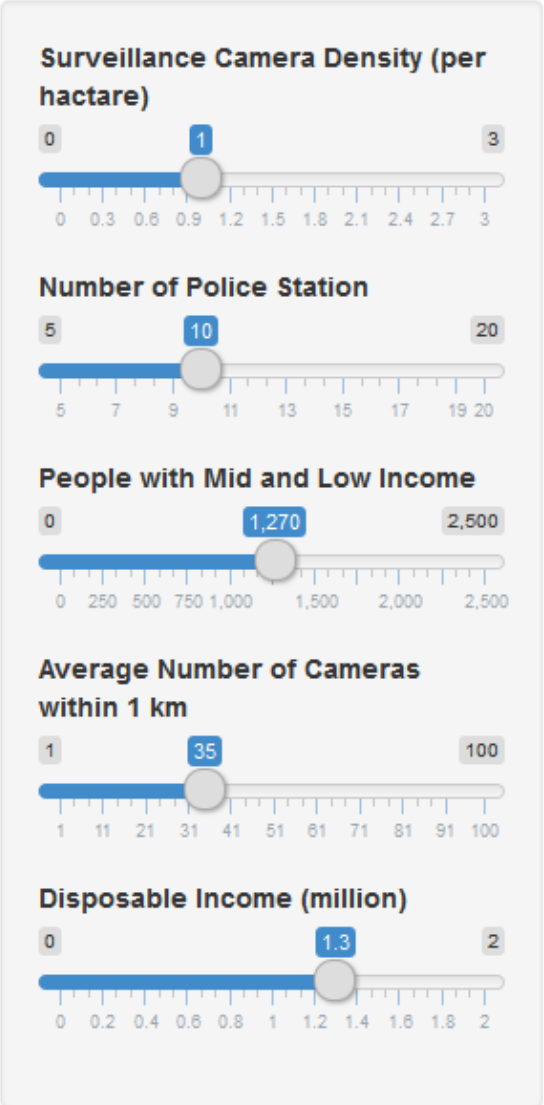
Da'an

Burglary Rate Prediction

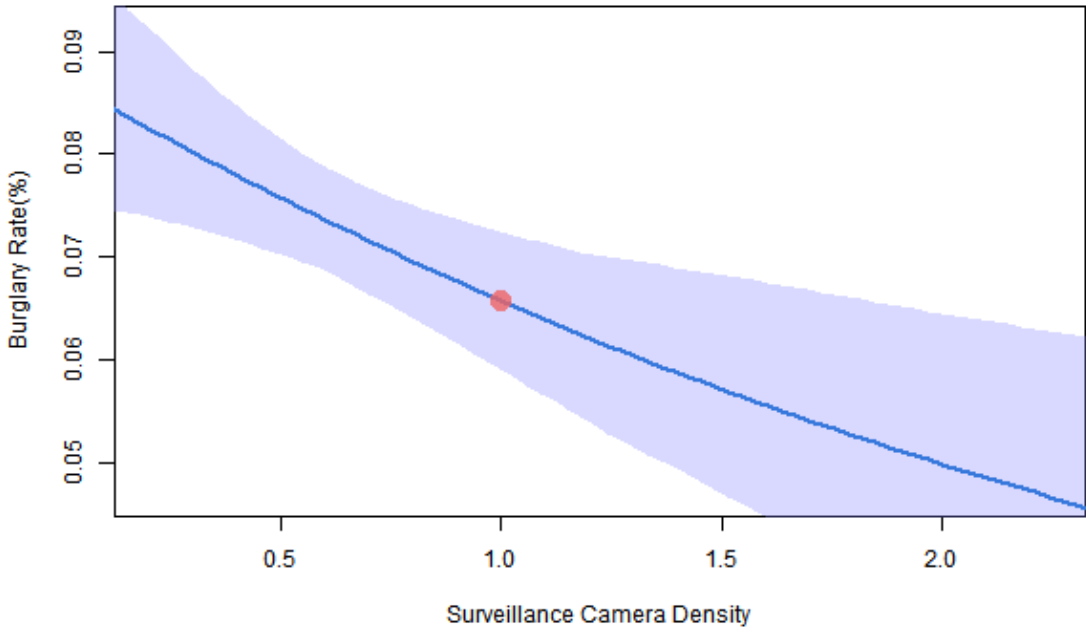
```
m7.2 <- map2stan(  
  alist(  
    theft105 ~ dbinom(househundred, p) ,  
    logit(p) <- a + bC*camDen + bP*policeStation + bM*log(mid.low.income105)  
    + bS*surv.avg + bD*DisposableInc,  
    a ~ dnorm(0,1),  
    c(bC, bP, bM, bS, bD) ~ dnorm(0,0.5)  
  ),  
  data=d, iter = 5000, warmup = 2500, chains = 2)
```



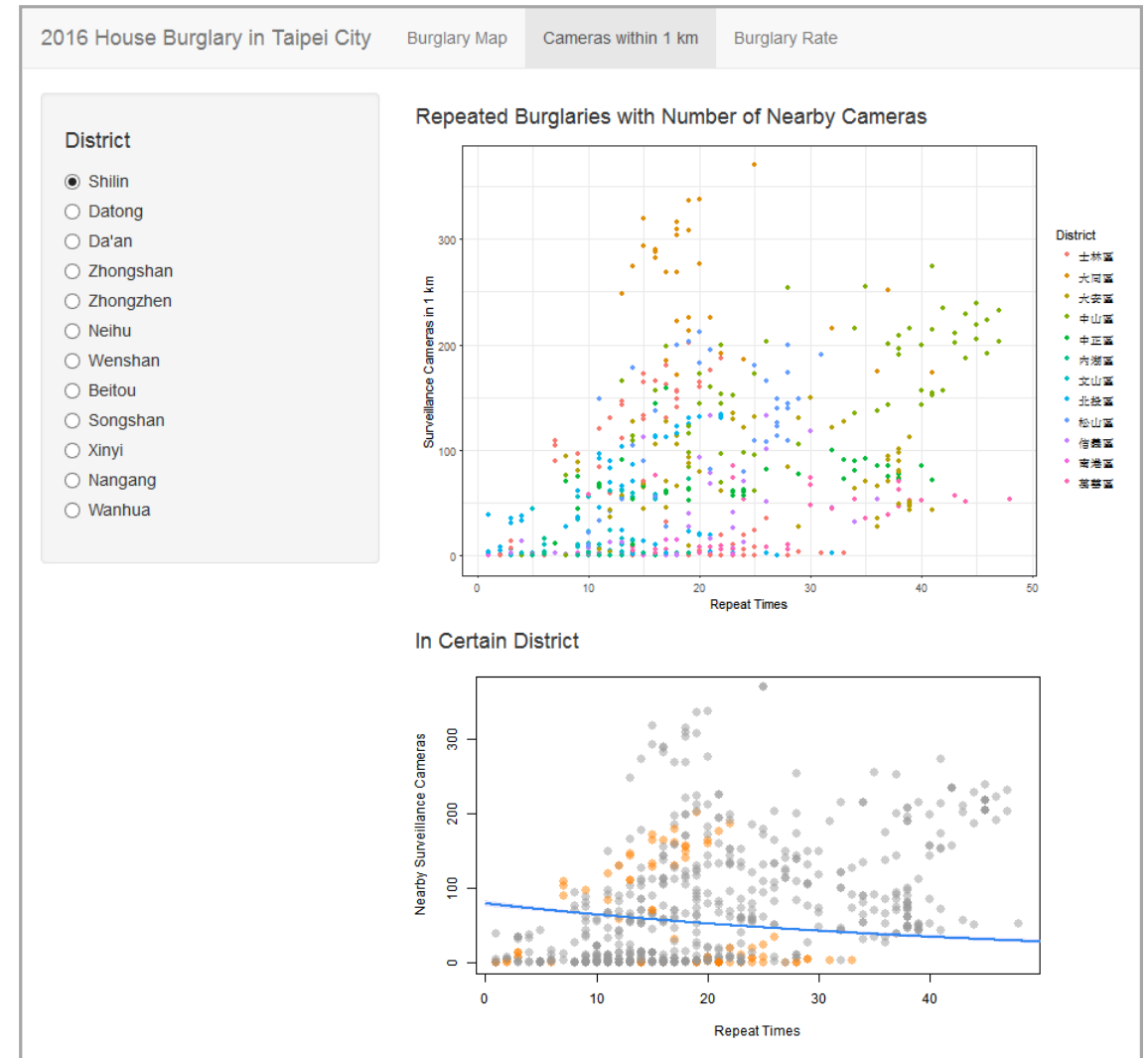
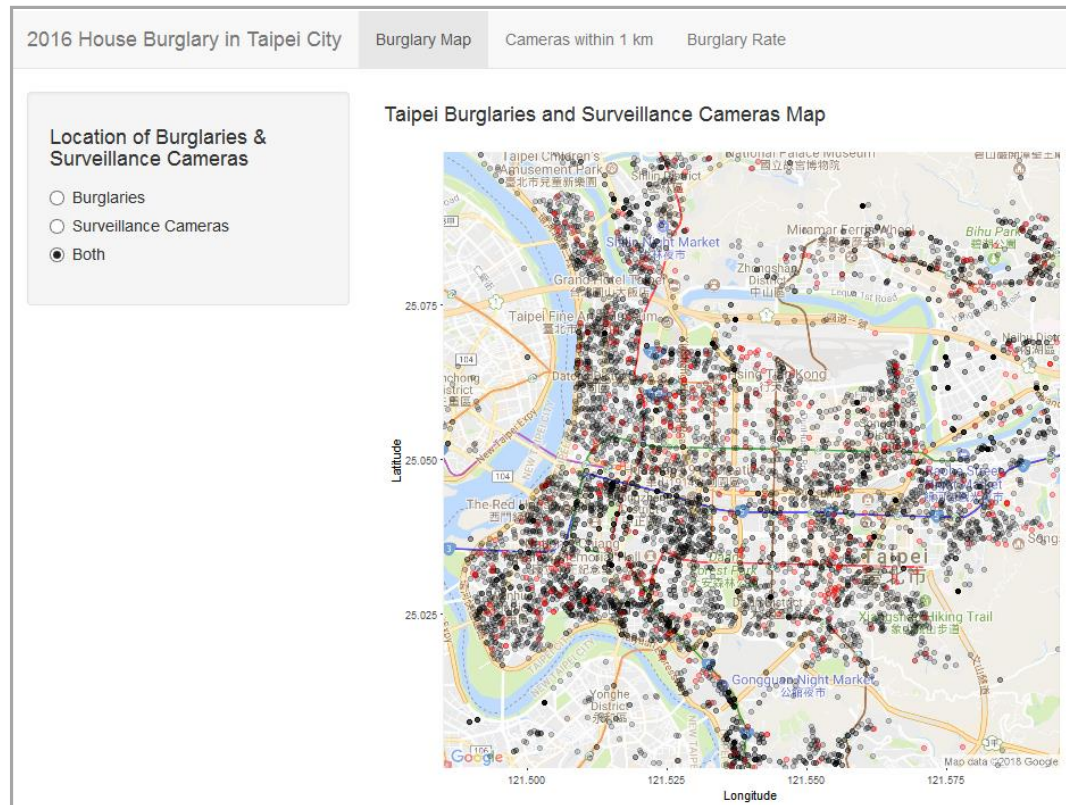
Burglary Rate Prediction

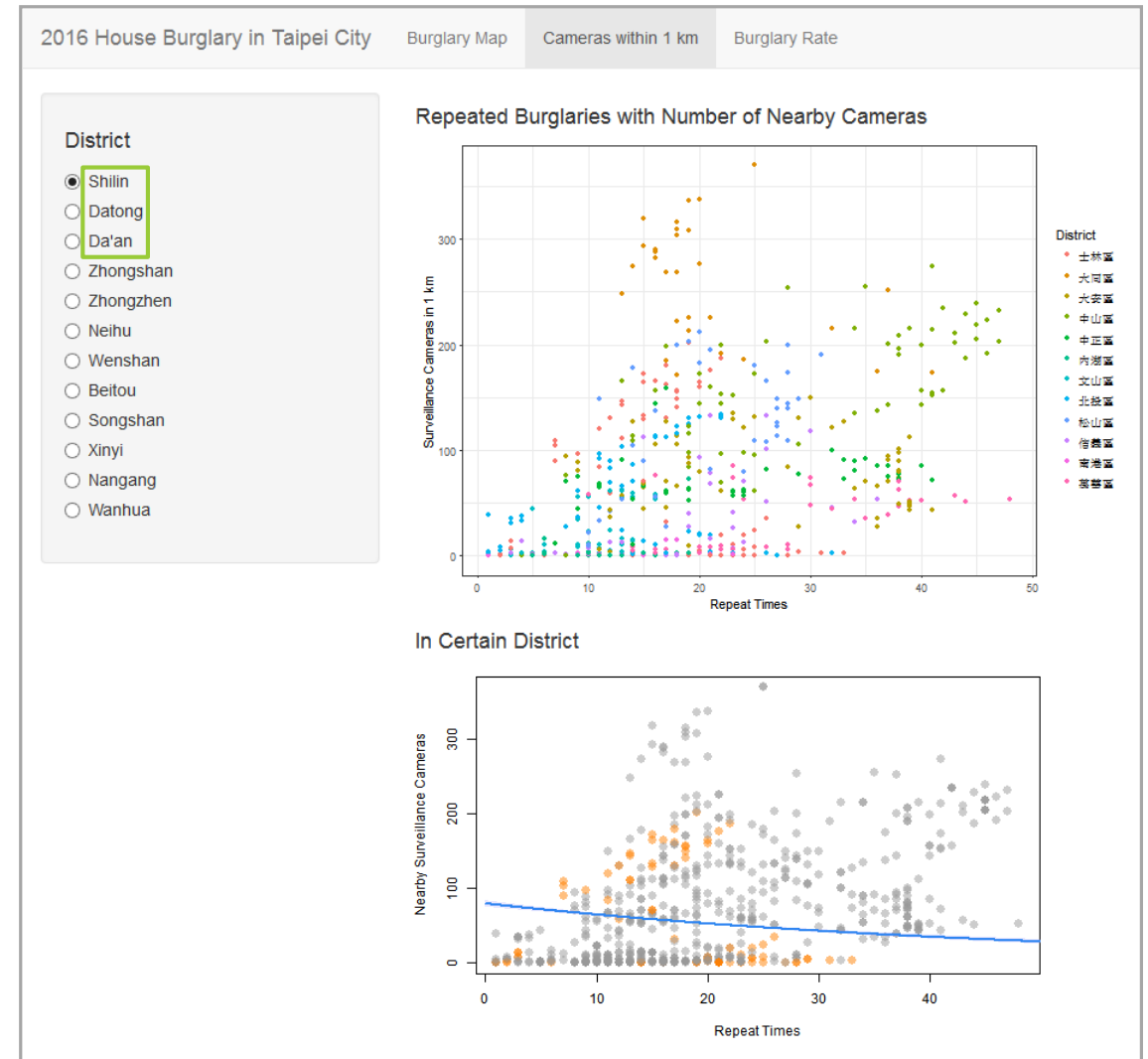
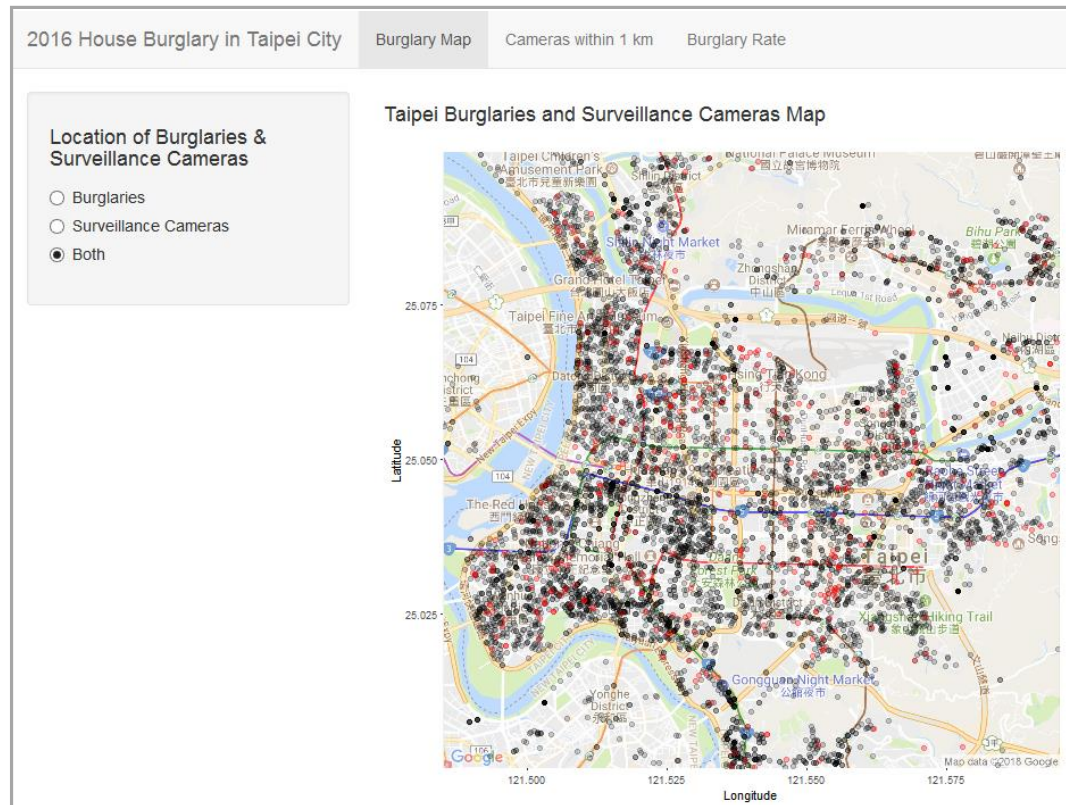


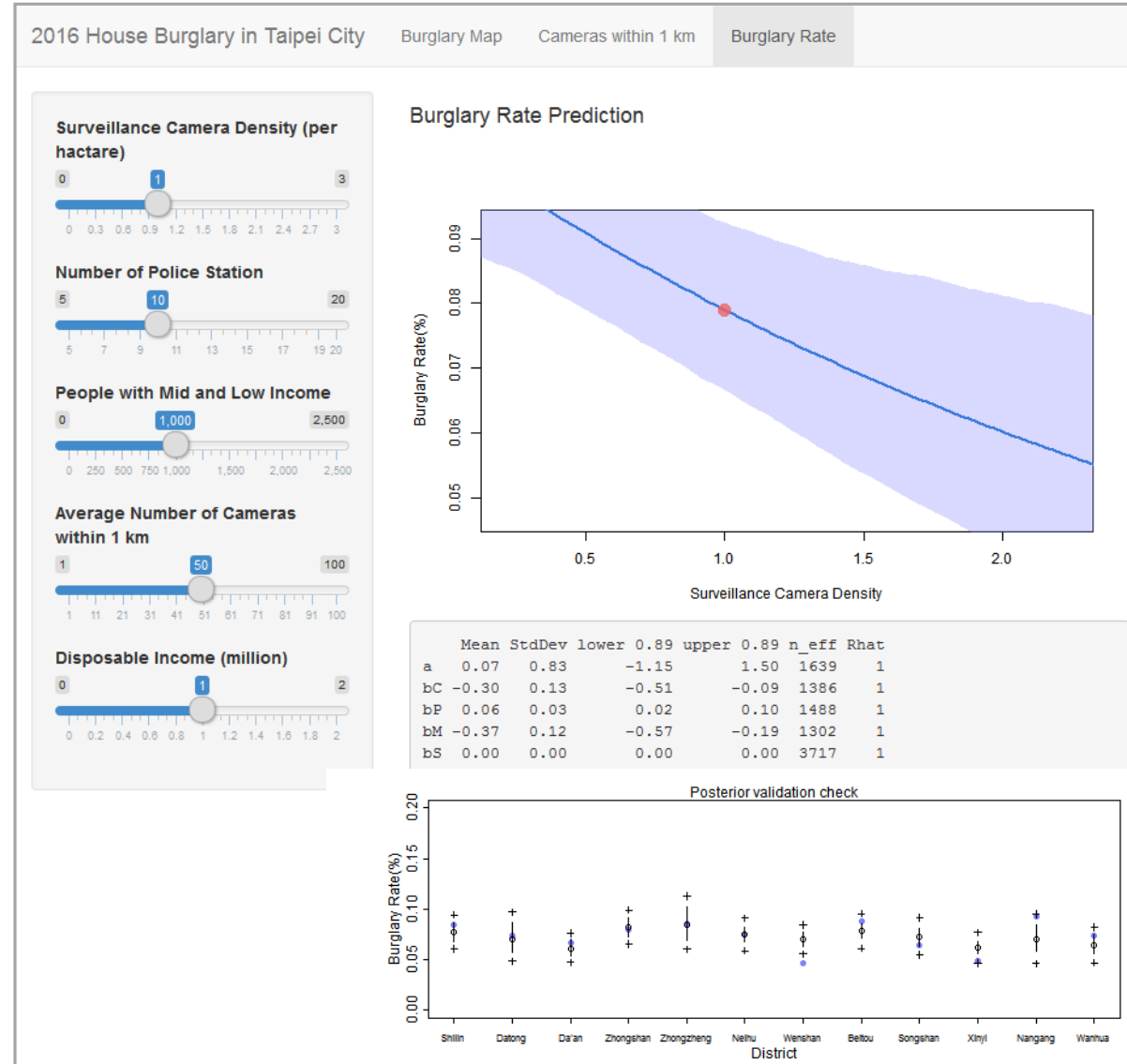
Burglary Rate Prediction



	Mean	StdDev	lower 0.89	upper 0.89	n_eff	Rhat	
a	0.09	0.82	-1.20	1.43	1509	1	
bC	-0.31	0.14	-0.52	-0.09	1674	1	[Camera density]
bP	0.06	0.03	0.02	0.10	1791	1	[Police station]
bM	-0.37	0.12	-0.56	-0.18	1460	1	[People with mid and low income]
bS	0.00	0.00	0.00	0.00	3237	1	[Nearby cameras (within 1km)]
bD	-0.32	0.30	-0.80	0.13	1991	1	[Disposable income]







Thanks for your listening!