The Fashionability of Flu Shots for the Medicare Population

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Abstract

Medicare is one of the largest drivers of consumption and spending in the United States healthcare system, and Influenza (flu) causes hospitalizations and deaths of thousands of people annually. As vaccine hesitancy has become a pressing issue in efforts to combat the Covid-19 pandemic, it seems worth exploring how this sizable and vulnerable population was already utilizing vaccinations for an extant dangerous illness. This leads to questions of "How has Medicare flu vaccination rates been changing over the last several years?" and "How does that rate vary across states?". To make these comparisons, a multilevel poisson model was fitted on Medicare claims data from 2013-2019 and its limitations are discussed.

Introduction

The United States Medicare program is a federal health insurance program that services predominately people ages 65 years and older. As of 2020, over 62.6 million people are enrolled with a projected increase of 50% over the next decade as all of the members of the "Baby Boomer" generation reach the qualifying age. Care for this population will put tremendous strain on the healthcare system, and it will become crucial to maximize individual participation in preventative health measures to reduce this burden.

Caring for flu patients is one of those strenuous healthcare activities that can be reduced by vaccinations. Flu illness routinely hospitalizes hundreds of thousands of people every year, seasonal flu vaccination is estimated to reduce the risk of having to seek medical treatment by 40-60%. The Medicare population is a high proportion of these cases as they are a large proportion of the broader US population. However there are differences in the enrollment rates per state, which is important to take into consideration. An additional comparison worth exploring is the means by which Medicare patients pursue vaccinations in these state groupings; if more beneficiaries are getting vaccinated through organizations such as a local CVS pharmacy or their individual healthcare provider, this creates different avenues through which public health campaigns may be more effective.

Multilevel poisson modeling is used to assess these comparisons in flu vaccinations rates among this population.

Method

Data Cleaning and Processing

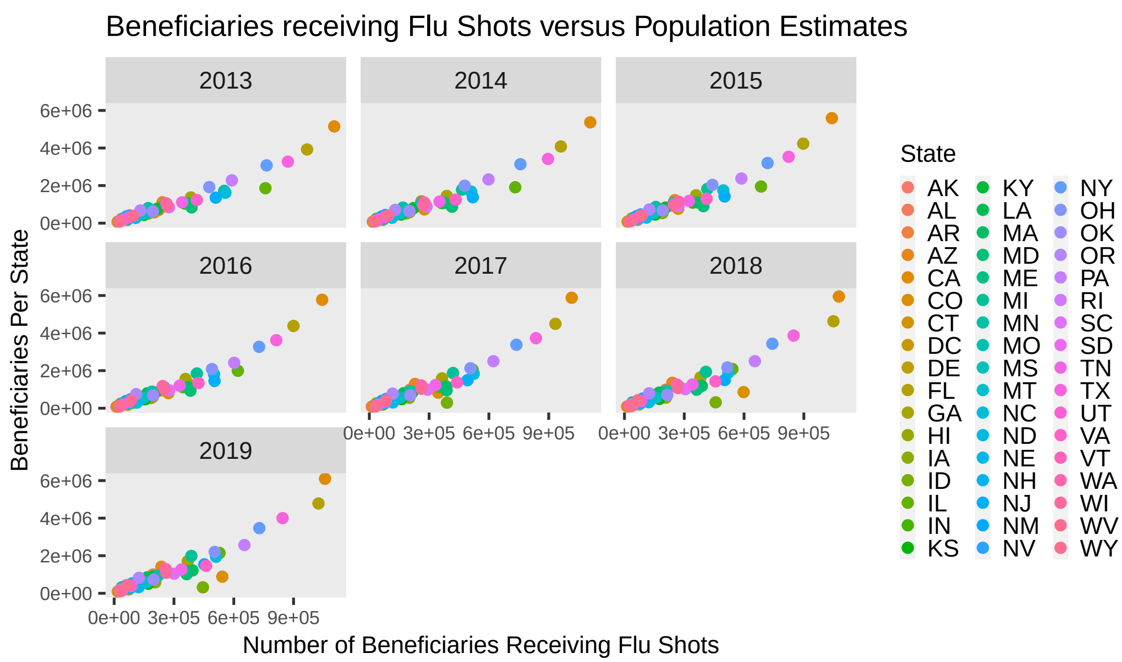
The data that is being used to answer these questions come from two sources- one from the Medicare Physician & Other Practitioners- by Provider and Service public use files provided by (CMS) website and one from the American Community Survey provided by the US Census Bureau. The CMS data set is a fairly large data set that contains all of the services that providers have submitted claims through out the year for Original Medicare Part B beneficiaries, broken out by National Provider Identifier (NPI) number and HCPCS code. To subset down to flu shot related charges for each available year, filtering was applied for selected the columns HCPCS_Desc for charges containing the words "flu" and "vaccine". Additional filtering was applied for Rndrng_Prvdr_Cntry="US". The ACS data set gives population estimates for the Medicare Part A and B populations in each of the following states through out the years which was estimated through the American Community survey for 2014-2019, the Current Population survey for 2013.

Once all the claims data sets were combined together they were then additionally subsetted down for just HCPCS code "G0008" in order to get at appropriate counts for unique beneficiaries. This is an administrative type II HCPCS code used specifically for the influenza vaccine that would be used in conjunction with other types of codes for billing, as it is the code most commonly used to bill for influenza vaccines it made sense to limit the data set to just that. Additionally territories and military bases to focus on the 50 states and the District of Columbia. Once that was complete there were 1,008,254 rows in the data set.

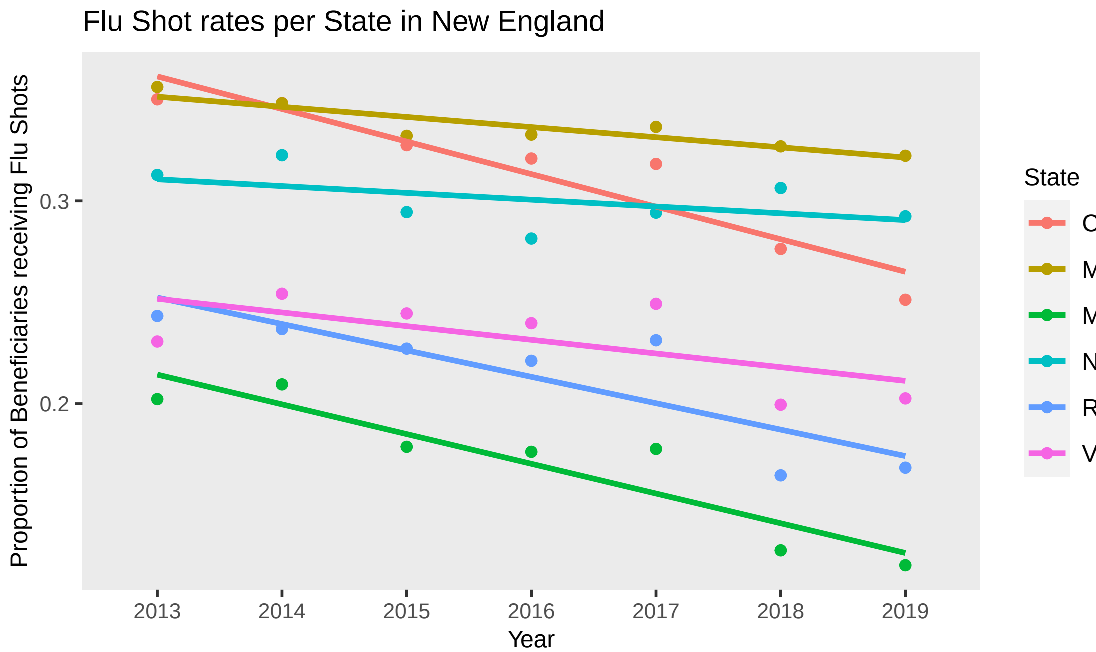
To allow for population proportion comparisons, I aggregated these rows by state, year, and entity status. I then finally paired that with the state population estimates from the ACS survey, which would be used in the regression for the offset term. The original data needed multiplied by 1000 to obtain the whole estimate number.

column names	explanation
State	The registration state of the provider
Year	The year of the claims submitted
EntityFlag	If the provider was an Individual=I or and Organization=O
Benes	The number of unique Medicare Beneficiaries serviced
estimate	Medicare population estimates for that state and year
yearnum	The indexing number for the year, 2013=1. . . 2019=7

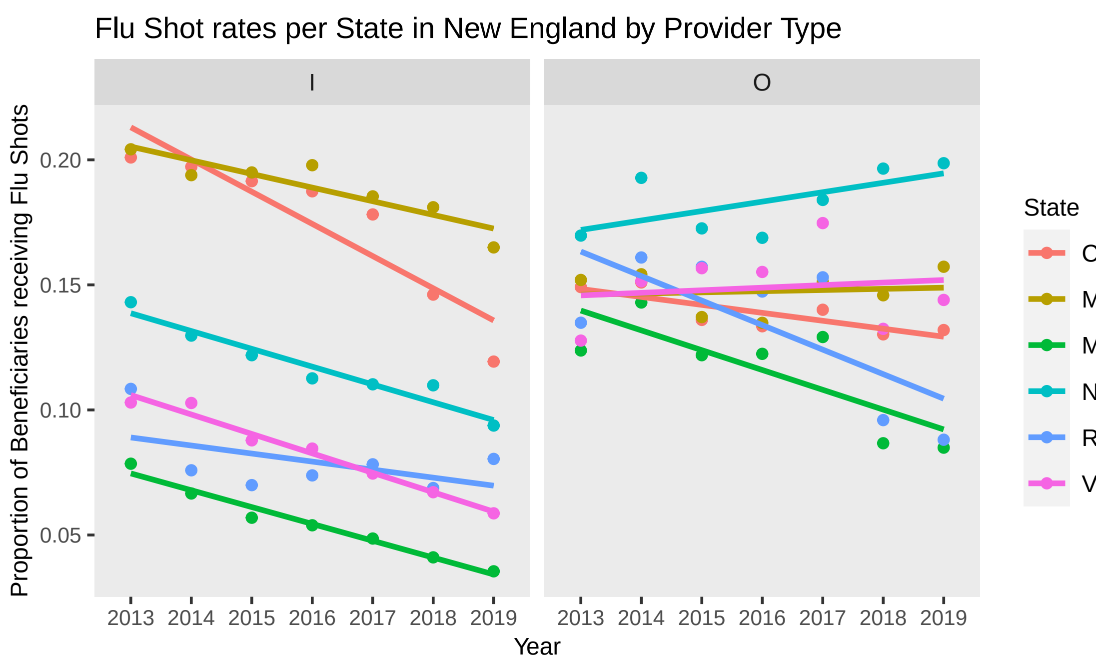
Exploratory Data Analysis



This plot justifies the requirements for a Medicare population offset term, as the number of Medicare beneficiaries receiving flu shots increases as the population with in each state increases.



To make it easier to see patterns in each of the 50 states, line graphs were restricted to different regions in the US. New England with each of the states are included here, the full state results are included in the appendix. There seems to be a declining trend in flu vaccination rates among most of these states.



This plot shows that there are differences in how rates have changed over time when broken out by provider type. Although there is a general downward trend in vaccination rates, for some states those vaccinations are increasingly taking place at organizations instead of individual providers.

Model Fitting

Considering the interest is in comparing counts across groups, a multilevel poisson model is appropriate with population estimates used for offset terms.

```
model<-glmer(Benes~EntityFlag+yearnum+(yearnum|State) +(EntityFlag|State),
offset=log(estimate),
data=flushot_s,
family=poisson(link=log))
```

The summary of the fixed effects are in the table below, year is significant at a .1 significance level:

	Estimate	Std. Error	z value	Pr(>|t|)
(Intercept)	-2.086	0.066	-31.370	<2e-16 ***
EntityFlag(O)	0.126	0.08	1.583	0.1135
yearnum	-0.017	0.009	-1.755	0.0792 .

Result

Model Coefficients

To use the state of Maine as an example, the model coefficients are as follows:

$$log(Benes/estimate) = -1.74 + 0.76 \cdot EntityFlag(O) - 0.08 \cdot yearnum$$

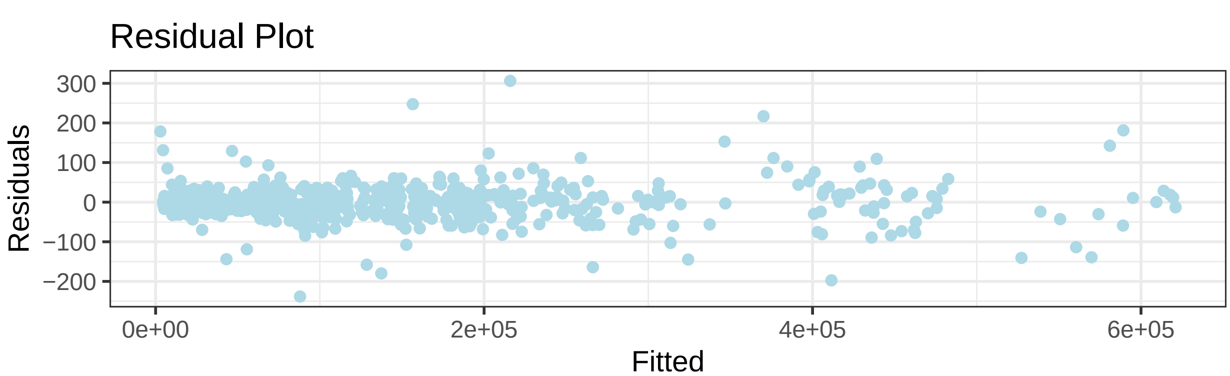
Exponentiating both sides allows the equation be interpreted as (where e=EntityFlag(O) and y=yearnum):

$$Benes/estimate = (0.175) * (1.079)^e * (0.923)^y$$

Since the outcome variable is a proportion of individuals, it makes sense for the intercept to be 0.175. While it is not possible to have a year 0 in this context, the year coefficient shows that for every year increase, the proportion of Medicare beneficiaries receiving flushots decreases by about 7%. The Entity Flag coefficient compares the proportion of Medicare beneficiaries that receive flushots from organizations to individuals, there is a 7% increase in the proportion of beneficiaries receiving flu shots from organizations than individual providers in the state of Maine.

For each state, the effects of each coefficient are different. For example in California, which has the largest state Medicare population, the baseline intercept is a little bit larger, and the entity comparison is in the opposite direction of more beneficiaries receiving flushots from individuals rather than organizations.

Model Validation



The mean of the residual plot is almost 0, however there does seem to be a heteroscedastic pattern with most of the residuals clustering towards the left hand side of the graph.

The overdispersion ratio is 2.3 which is greater than 1, which does indicate that the mean exceeds the variance which is a violation of the equal mean and equal variance assumption required for Poisson.

Discussion

This analysis has some restrictions in that there are some problems with the model- with the clustering of the residuals and the overdispersion factors. Quasipoisson and negative binomial models were also considered, however errors resulted that were not fixable. Other R formulas for running the model were also considered such as stan_glmer, but the model did not converge. Based on these challenges this was the best model that could be composed.

Another key limitation to this analysis comes from the data- it is impossible to get the true numbers of the Medicare beneficiaries that received flu shots from 2013-2019. If beneficiaries are able to obtain shots through a free clinic that didn't require insurance to pay for it, then that scenario is unrecorded here. And as it is the case that in certain states, an increasing number of patients are receiving their vaccinations from entity settings as opposed to individual providers; free clinic settings are likely getting larger shares of these patients. Another key restriction is the population estimates- the ACS survey is an estimate for patients that have both Medicare Part A and B, although it's estimated that 93% of Medicare patients do have both insurances and that an estimate for both can be a sufficient estimate for one, it is likely an overestimate for that Part B population and observed flu vaccination rates are likely higher.

Despite limitations, this analysis still produces some interesting considerations. If broader flu shot rates for this population were truly declining during this period of time, it lays somewhat of a foundation for some of the difficulties getting the broader US population vaccinated for the Covid-19 pandemic. Additionally if frequent booster shots become required to effectively control the spread of Covid-19 and its variants, understanding how this population was managing an already existing seasonal vaccination becomes relevant. Also seeing how beneficiaries are increasingly getting vaccinated in various states, whether that be most commonly through an individual physician or an organization, presents an opportunity to contemplate how to best to reach these patients to persuade them to get vaccinated.

Citations

A Dozen Facts About Medicare Advantage in 2020. (2021, January 13). KFF. https://www.kff.org/medicare/issue-brief/a-dozen-facts-about-medicare-advantage-in-2020/

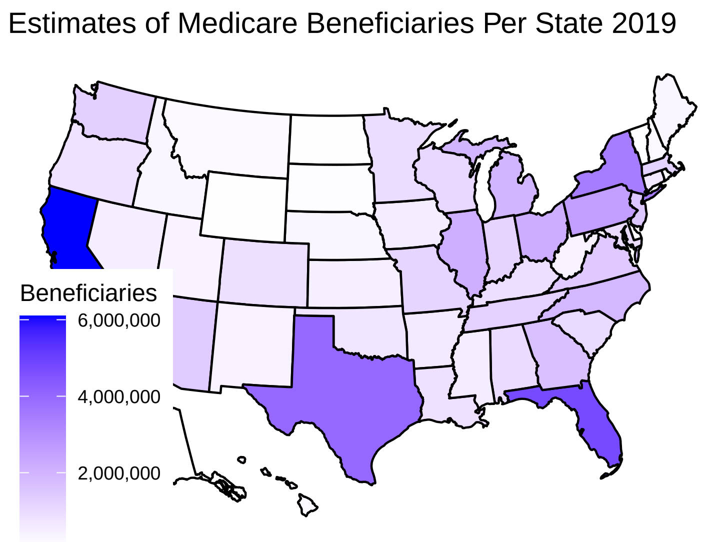
Burden of Influenza. (2021, October 4). Centers for Disease Control and Prevention. https://www.cdc.gov/flu/about/burden/index.html

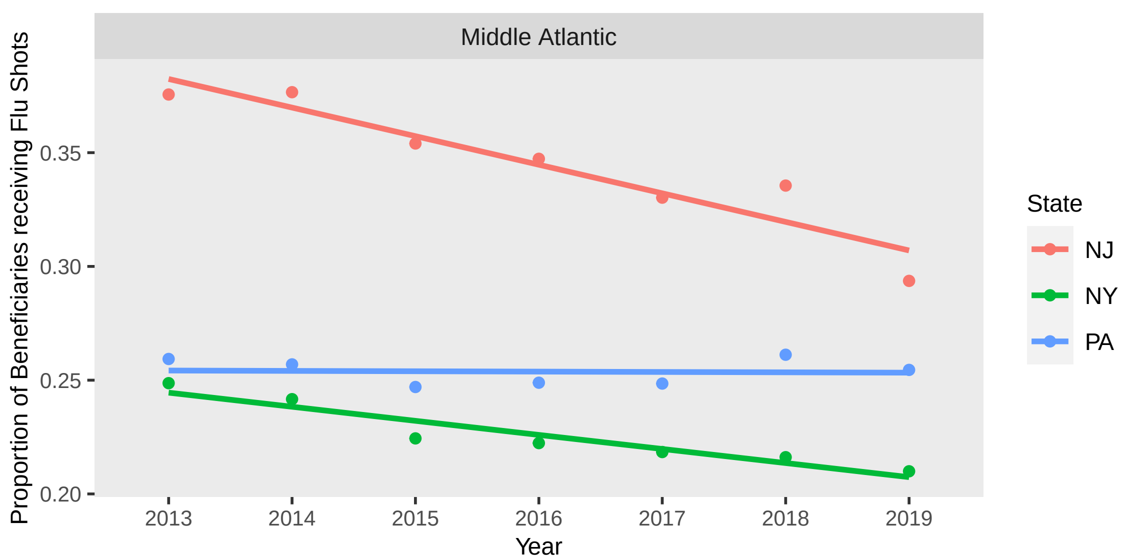
Centers for Medicare & Medicaid Services Data. (2021). Center for Medicare & Medicaid Services. https://data.cms.gov/provider-summary-by-type-of-service/medicare-physician-other-practitioners/medicare-physician-other-practitioners-by-provider-and-service

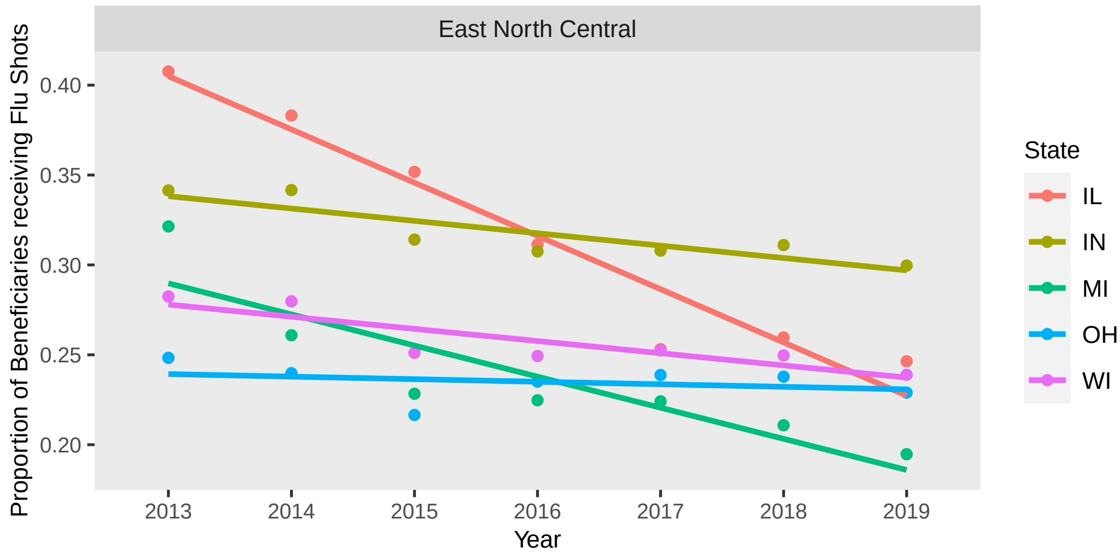
US Census Bureau. (2021, October 8). American Community Survey Tables for Health Insurance Coverage. Census.Gov. https://www.census.gov/data/tables/time-series/demo/health-insurance/acs-hi.2013.html

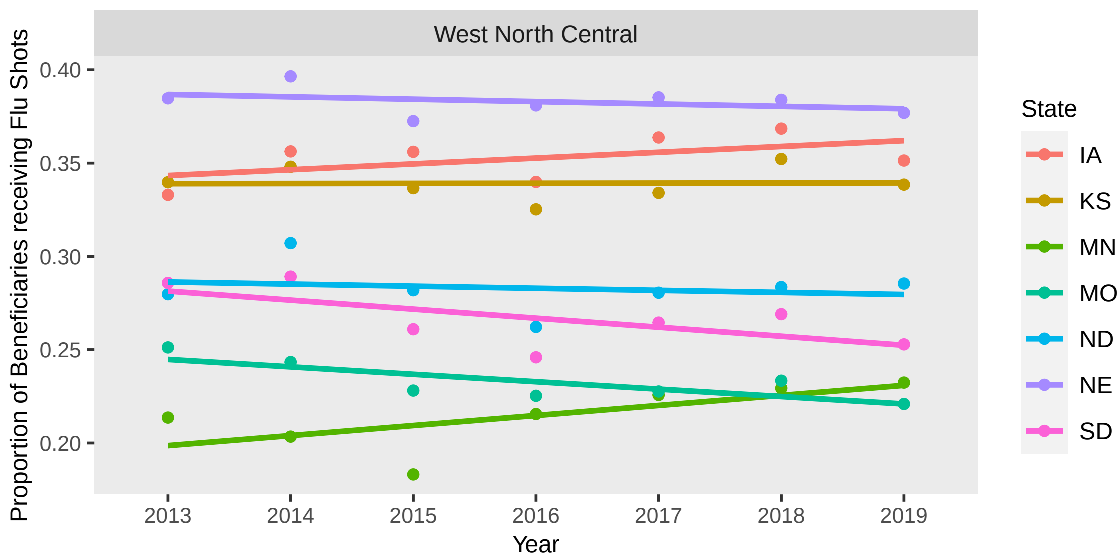
Appendix

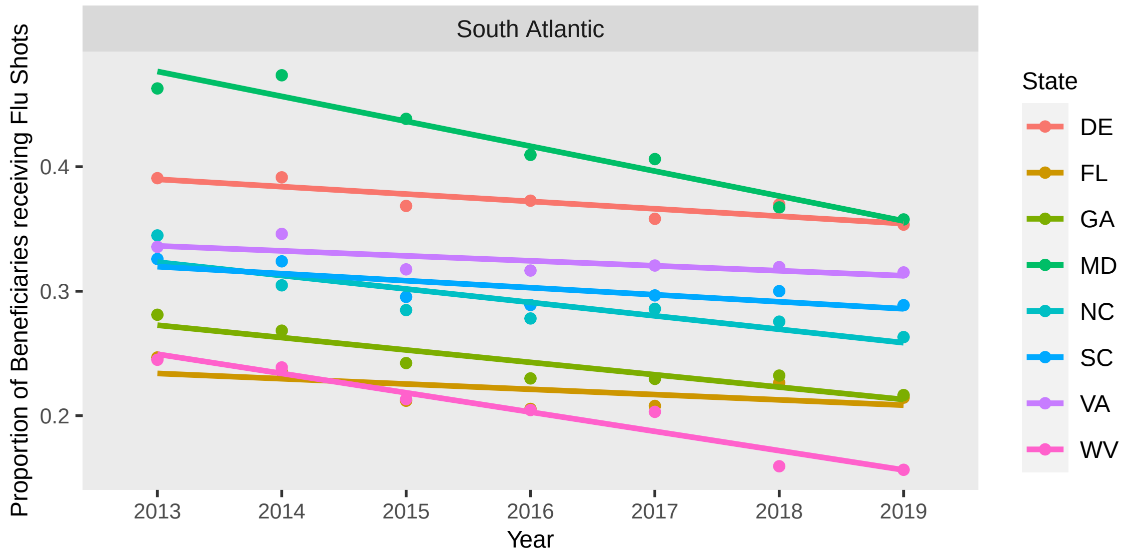
More EDA

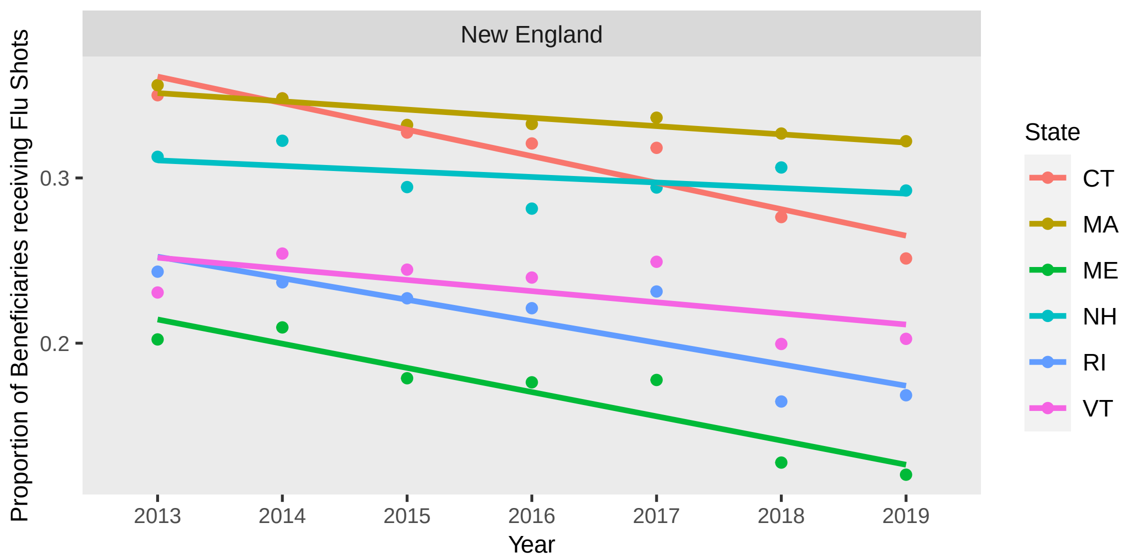


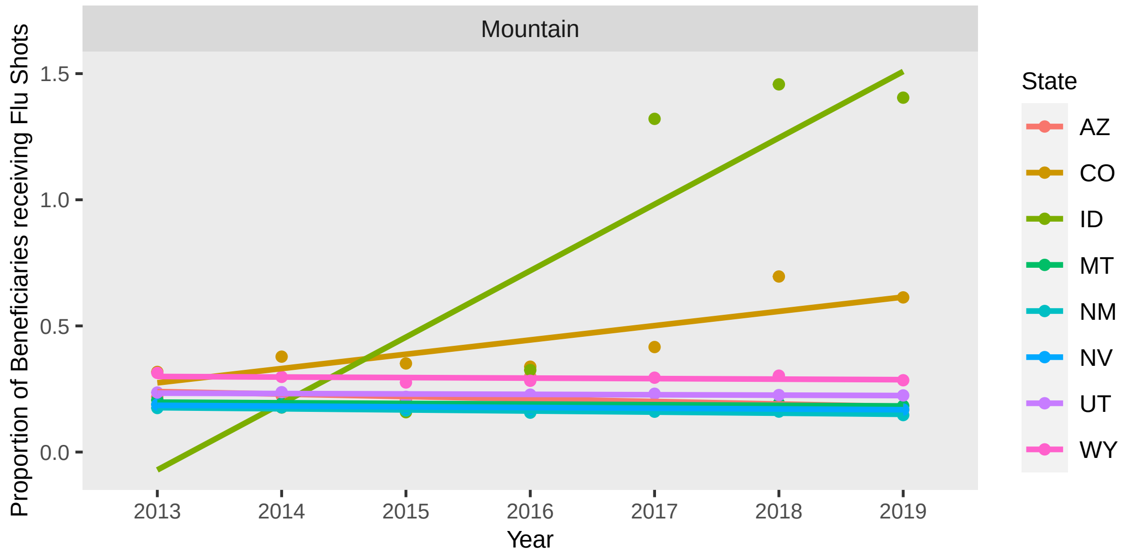


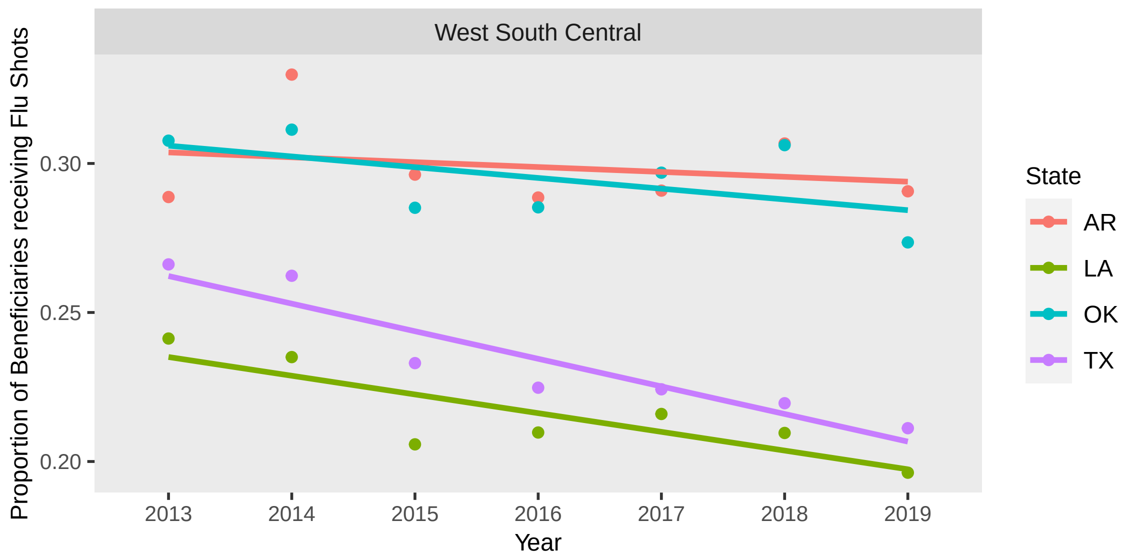

East North Central
Proportion of Beneficiaries receiving Flu Shots
0.40
0.35
0.30
0.25
0.20
2013
2014
2015
2016
2017
2018
2019
Year
State
IL
IN
MI
OH
WI

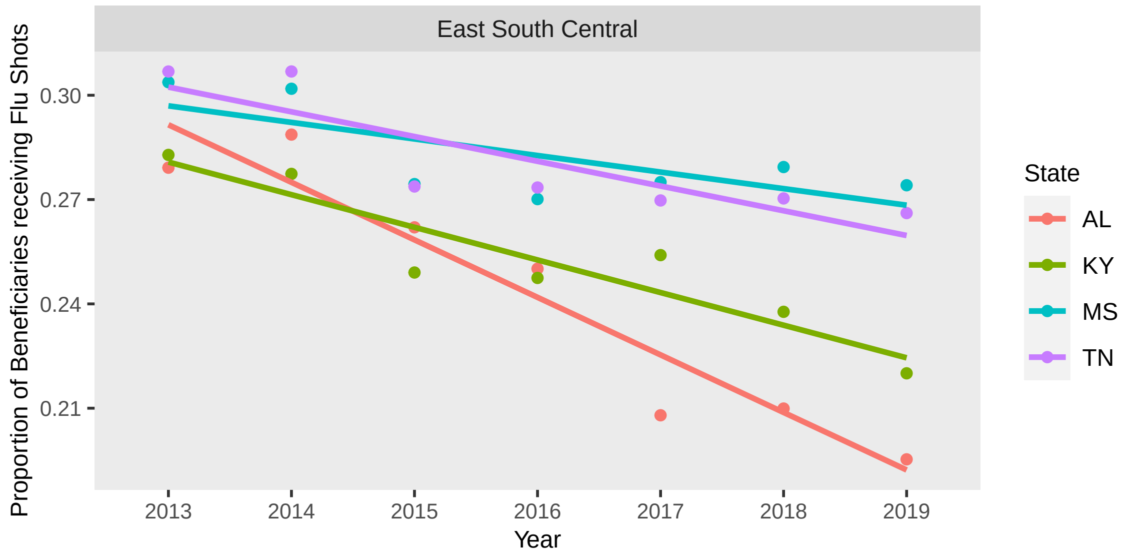

West North Central
Proportion of Beneficiaries receiving Flu Shots
0.40
0.35
0.30
0.25
0.20
2013
2014
2015
2016
2017
2018
2019
Year
State
IA
KS
MN
MO
ND
NE
SD

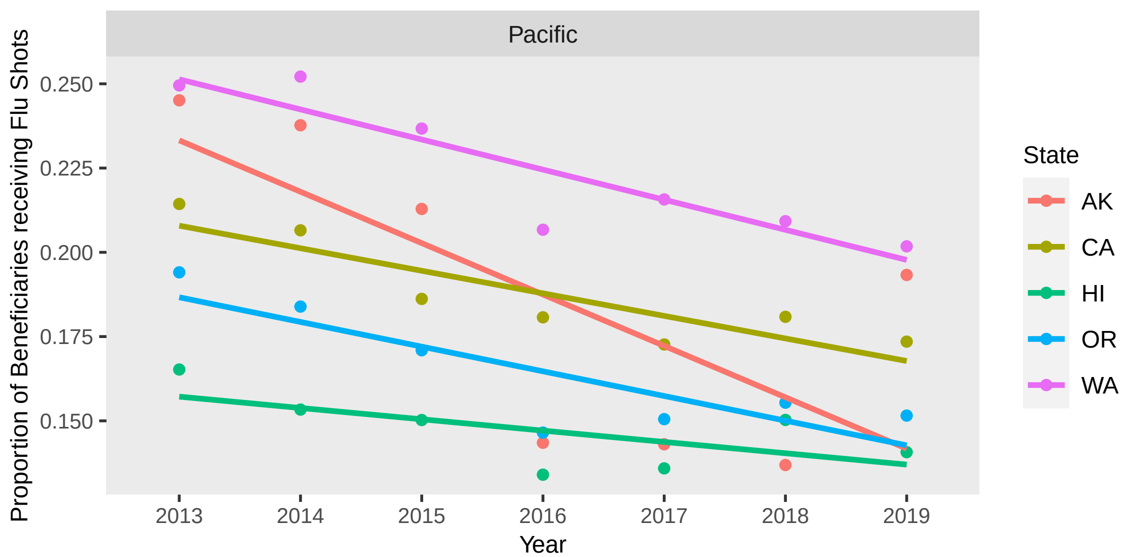

South Atlantic
Proportion of Beneficiaries receiving Flu Shots
0.4
0.3
0.2
2013
2014
2015
2016
2017
2018
2019
Year
State
DE
FL
GA
MD
NC
SC
VA
WV

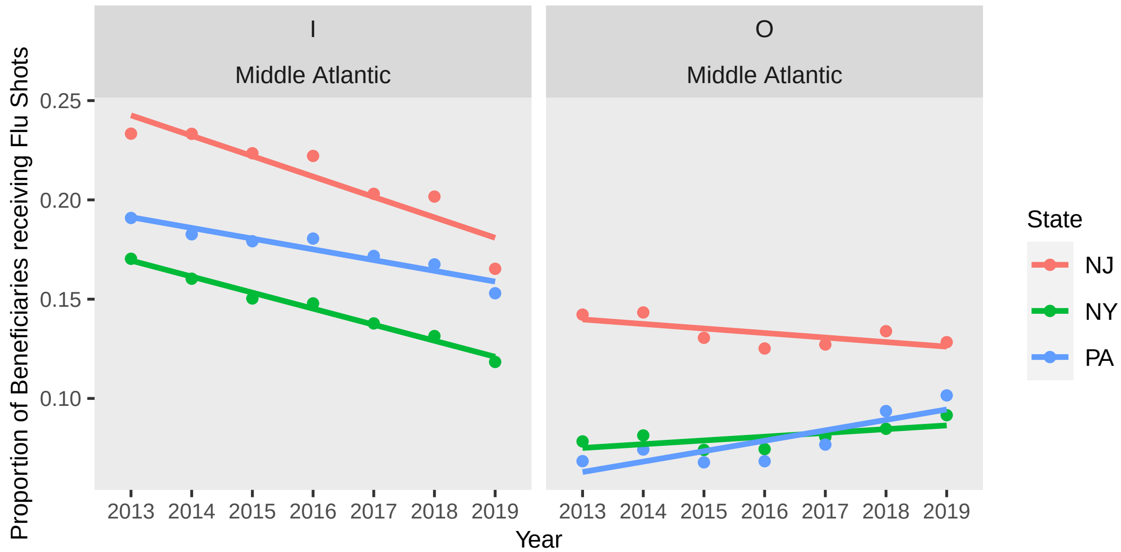

New England
Proportion of Beneficiaries receiving Flu Shots
0.3
0.2
2013
2014
2015
2016
2017
2018
2019
Year
State
CT
MA
ME
NH
RI
VT

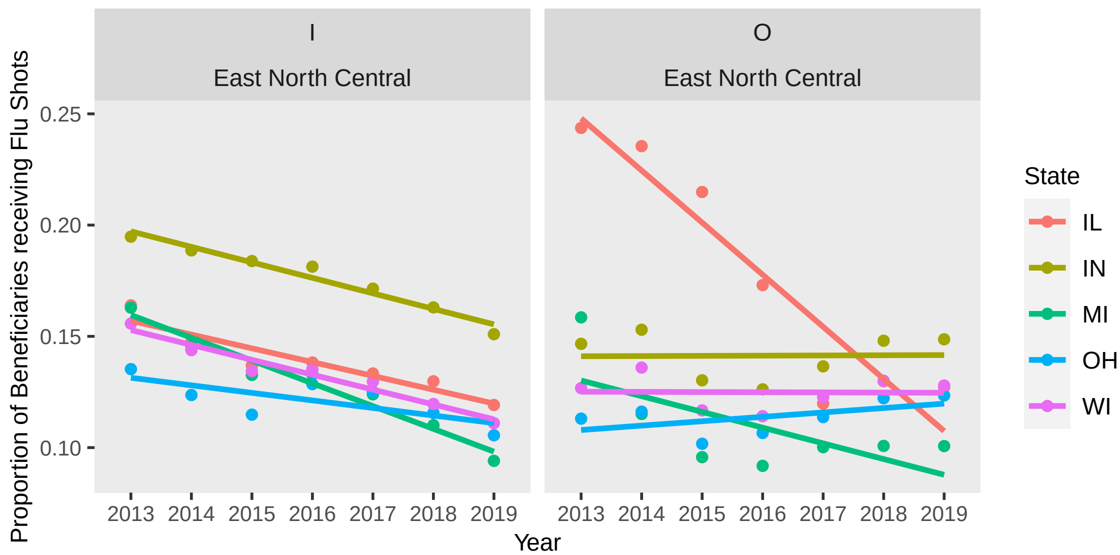

Mountain
Proportion of Beneficiaries receiving Flu Shots
1.5
1.0
0.5
0.0
2013
2014
2015
2016
2017
2018
2019
Year
State
AZ
CO
ID
MT
NM
NV
UT
WY

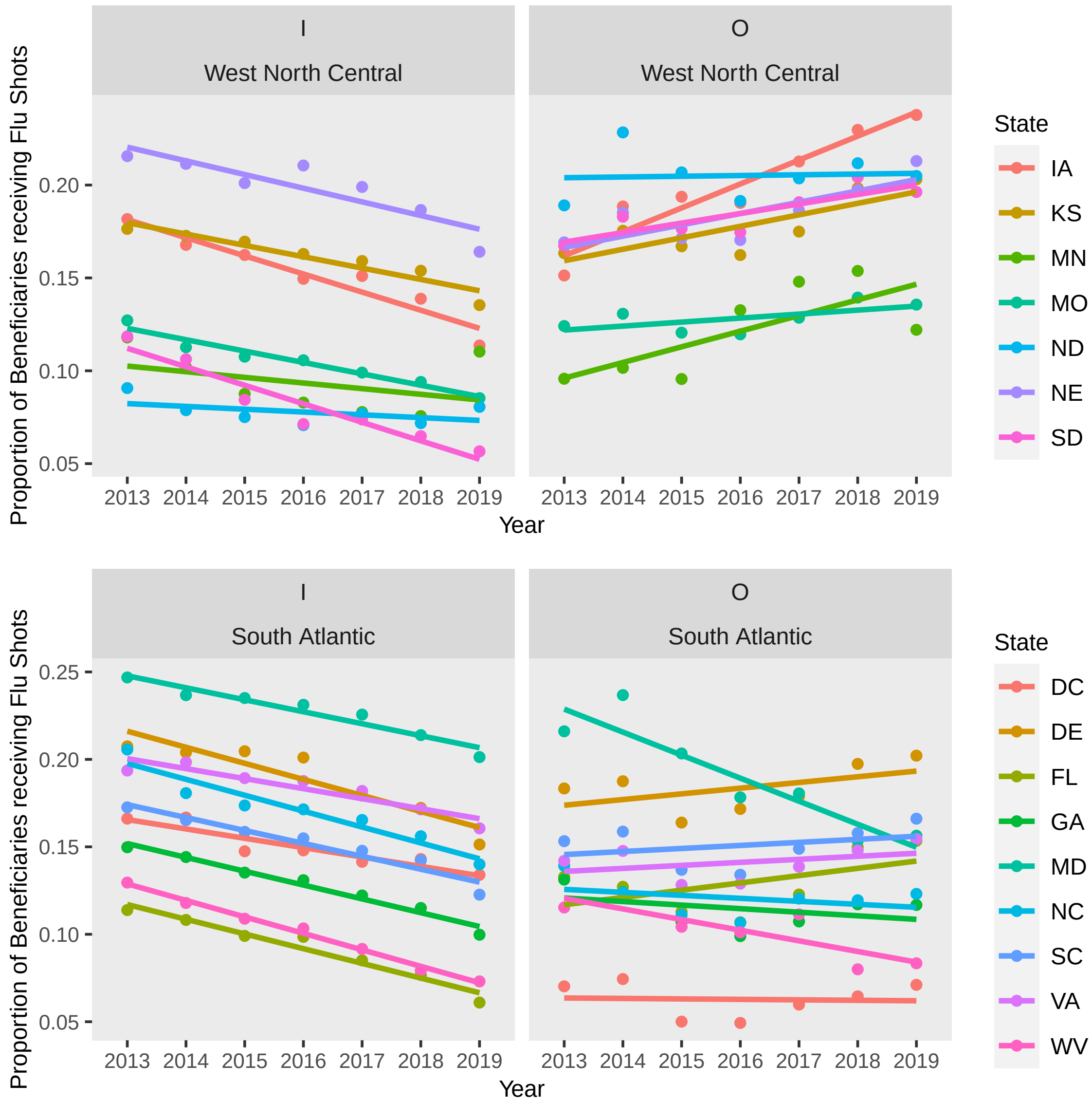

West South Central
Proportion of Beneficiaries receiving Flu Shots
0.30
0.25
0.20
2013
2014
2015
2016
2017
2018
2019
Year
State
AR
LA
OK
TX


East South Central
Proportion of Beneficiaries receiving Flu Shots
0.30
0.27
0.24
0.21
2013
2014
2015
2016
2017
2018
2019
Year
State
AL
KY
MS
TN

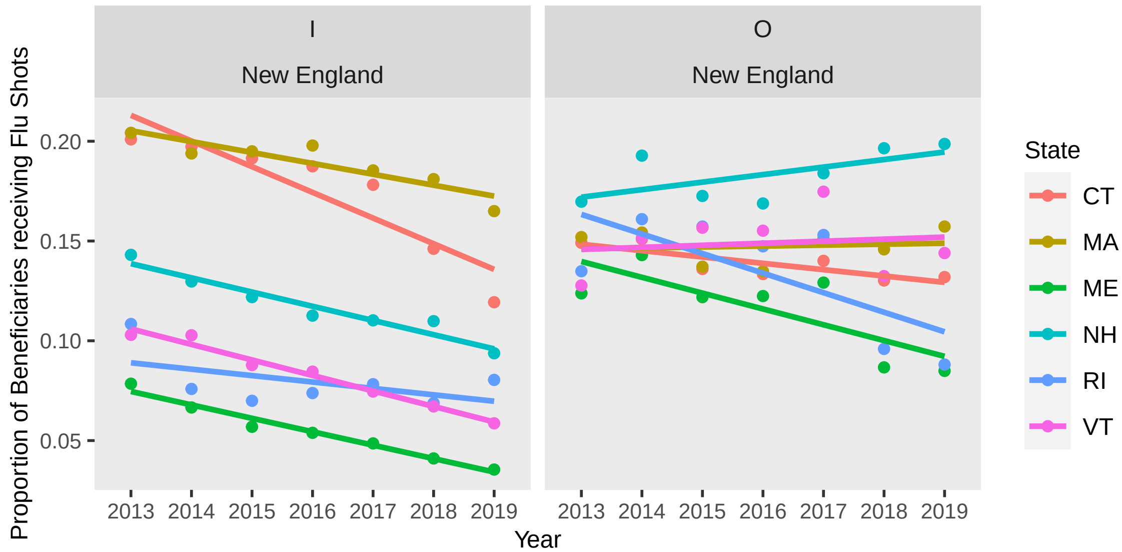

Pacific
Proportion of Beneficiaries receiving Flu Shots
0.250
0.225
0.200
0.175
0.150
2013
2014
2015
2016
2017
2018
2019
Year
State
AK
CA
HI
OR
WA

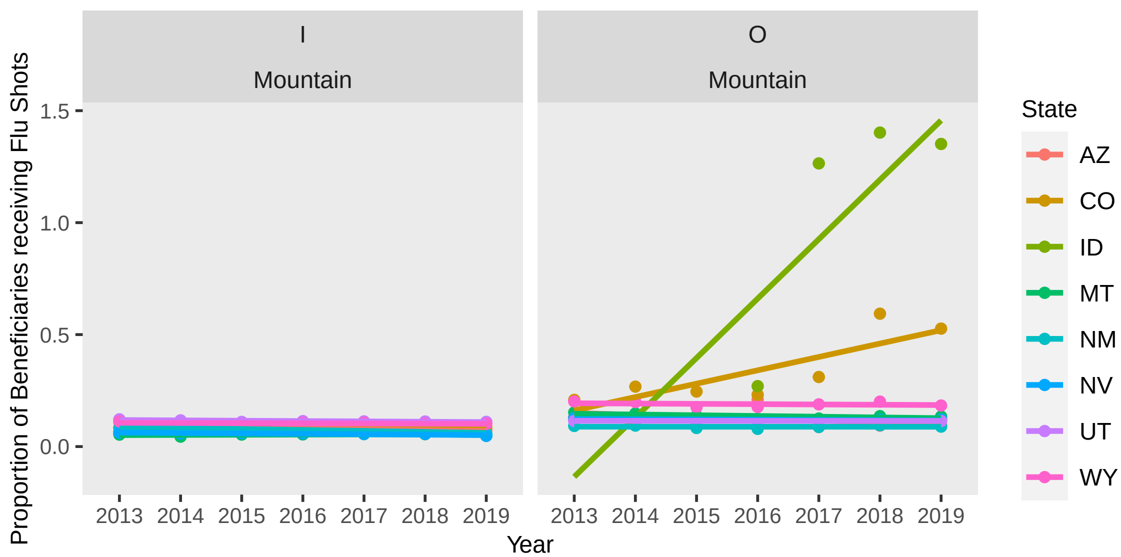

I
Middle Atlantic
O
Middle Atlantic
Proportion of Beneficiaries receiving Flu Shots
0.25
0.20
0.15
0.10
2013 2014 2015 2016 2017 2018 2019
Year
State
NJ
NY
PA


I
East North Central
O
East North Central
Proportion of Beneficiaries receiving Flu Shots
0.25
0.20
0.15
0.10
2013 2014 2015 2016 2017 2018 2019
Year
State
IL
IN
MI
OH
WI

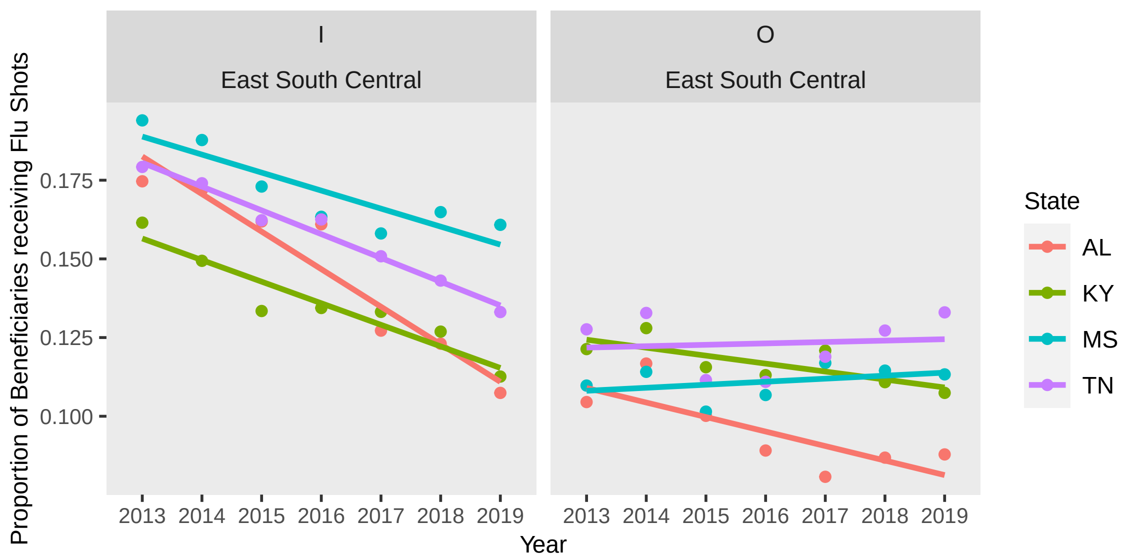


I
West North Central
O
West North Central
Proportion of Beneficiaries receiving Flu Shots
0.05
0.10
0.15
0.20
2013
2014
2015
2016
2017
2018
2019
Year
State
IA
KS
MN
MO
ND
NE
SD
I
South Atlantic
O
South Atlantic
Proportion of Beneficiaries receiving Flu Shots
0.05
0.10
0.15
0.20
0.25
2013
2014
2015
2016
2017
2018
2019
Year
State
DC
DE
FL
GA
MD
NC
SC
VA
WV


I
New England
O
New England
Proportion of Beneficiaries receiving Flu Shots
0.20
0.15
0.10
0.05
2013 2014 2015 2016 2017 2018 2019
Year
State
CT
MA
ME
NH
RI
VT


I
Mountain
O
Mountain
Proportion of Beneficiaries receiving Flu Shots
1.5
1.0
0.5
0.0
2013 2014 2015 2016 2017 2018 2019
Year
State
AZ
CO
ID
MT
NM
NV
UT
WY


I
West South Central
O
West South Central
Proportion of Beneficiaries receiving Flu Shots
0.20
0.15
0.10
2013 2014 2015 2016 2017 2018 2019
2013 2014 2015 2016 2017 2018 2019
Year
State
AR
LA
OK
TX


I
East South Central
O
East South Central
Proportion of Beneficiaries receiving Flu Shots
0.175
0.150
0.125
0.100
2013 2014 2015 2016 2017 2018 2019
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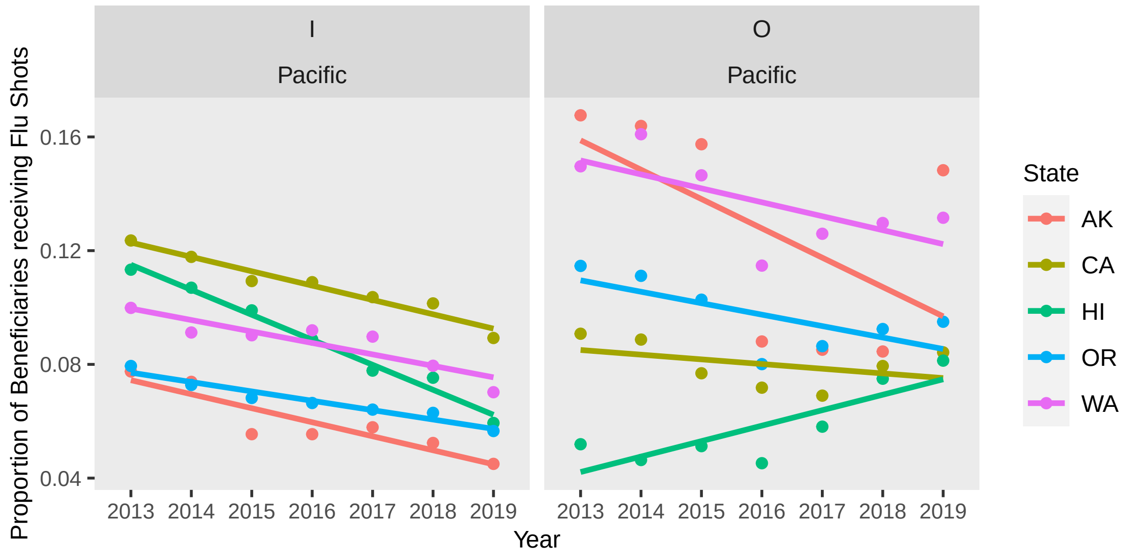
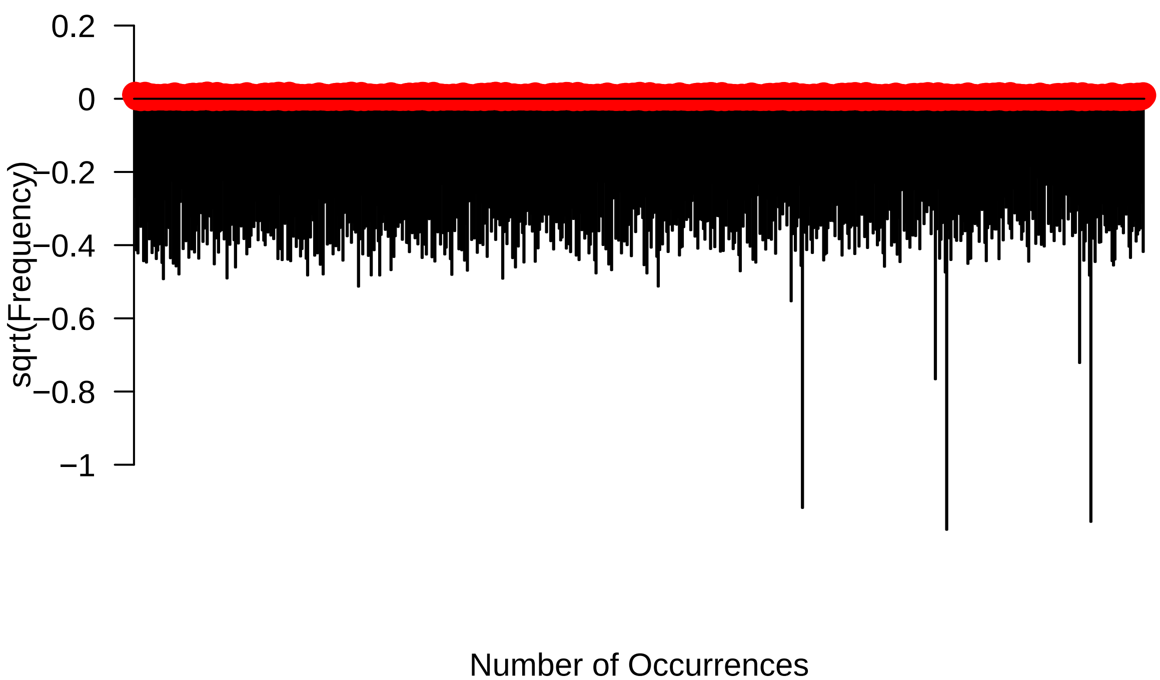
Year
State
AL
KY
MS
TN





Rootogram plot showing model prediction issues

###Full Results

```
## $State
##      (Intercept)       yearnum  (Intercept) EntityFlag0
## AK  0.1435245052 -0.0591534676 -0.585025833  0.63733761
## AL  0.1260939295 -0.0519694147  0.305518098 -0.55716551
## AR -0.0280541974  0.0115625399  0.396190930 -0.48283974
## AZ  0.0796413822 -0.0328241095 -0.258388747  0.25102684
## CA  0.0437746666 -0.0180418837 -0.050227378 -0.42025694
## CO -0.3606046915  0.1486227578 -0.404589886  1.09250820
## CT  0.0847925116 -0.0349469062  0.454561610 -0.34990361
## DC  0.0206637125 -0.0085167942  0.263912081 -0.99067510
## DE -0.0028859889  0.0011897349  0.477838394 -0.14349510
## FL  0.0026539759 -0.0010938967 -0.243325457  0.23268230
## GA  0.0567169800 -0.0233758108  0.129505389 -0.23179146
## HI  0.0119832482 -0.0049393220 -0.272566918 -0.51822604
## IA -0.0619635000  0.0255383780  0.223808265  0.16078412
## ID -1.0368325810  0.4273284148 -1.745289234  2.37737735
## IL  0.1872012960 -0.0771543887  0.284278458  0.11526743
## IN  0.0108418725 -0.0044683140  0.422270929 -0.34392010
## KS -0.0420547610  0.0173329959  0.298837908 -0.02305515
## KY  0.0491433055 -0.0202543159  0.185315565 -0.27566482
## LA  0.0284321028 -0.0117184044  0.137858322 -0.55748425
## MA -0.0054022784  0.0022267118  0.481454133 -0.37062003
## MD  0.0764914164 -0.0315254153  0.718865540 -0.31411637
## ME  0.1715785297 -0.0707159390 -0.665225489  0.63569352
## MI  0.1335722905 -0.0550515710  0.180078347 -0.29297738
## MN -0.1037072032  0.0427425801 -0.292873104  0.14704255
## MO -0.0004254395  0.0001753053 -0.109809982  0.08609246
## MS -0.0011637543  0.0004796533  0.388774080 -0.55968424
## MT -0.0105192334  0.0043353018 -0.777304869  0.80511568
## NC  0.0471761560 -0.0194434877  0.409814251 -0.46811912
## ND -0.0321643081  0.0132565561 -0.423045664  0.84558678
## NE -0.0331052288  0.0136445375  0.510428876 -0.19031901
## NH -0.0155122117  0.0063934828 -0.006672515  0.33069720
## NJ  0.0480453941 -0.0198016410  0.628524857 -0.58934155
## NM  0.0238928248 -0.0098476733 -0.437368776  0.05826728
## NV -0.0026149814  0.0010775339 -0.718566740  0.62124284
## NY  0.0248218952 -0.0102304645  0.236084768 -0.70669342
## OH -0.0272603453  0.0112352263  0.023507004 -0.18533684
## OK -0.0115719996  0.0047694808  0.252779968 -0.16858283
## OR  0.0641636172 -0.0264451644 -0.509534611  0.24656317
## PA -0.0401614437  0.0165522978  0.382418871 -0.91853763
## RI  0.1100156691 -0.0453427860 -0.315185119  0.39334522
## SC  0.0027194819 -0.0011206952  0.266349129 -0.12601234
## SD  0.0015749191 -0.0006490229 -0.357394919  0.70100300
## TN  0.0194155419 -0.0080020252  0.316768986 -0.37049799
## TX  0.0535932802 -0.0220883907  0.010144707 -0.06472709
## UT -0.0247264377  0.0101908709 -0.035791950 -0.11699216
## VA -0.0118648747  0.0048902271  0.446241001 -0.38224341
## VT  0.0325017033 -0.0133955255 -0.327280560  0.47245753
## WA  0.0548186256 -0.0225934181 -0.250654793  0.32283491
## WI  0.0218823507 -0.0090187508  0.144643042 -0.18236682
## WV  0.1461767302 -0.0602465536 -0.061890511 -0.10683319
```

```
## WY -0.0252955490  0.0104256471 -0.128655083  0.47558595
##
## with conditional variances for "State"
```

Fixed effects of model

```
## (Intercept) EntityFlag0     yearnum
## -2.08565958  0.12643928 -0.01694643
```

Coefficients of model

```
## $State
##    (Intercept)   EntityFlag0       yearnum
## AK   -1.798611  0.7637768928 -0.0760999003
## AL   -1.833472 -0.4307262254 -0.0689158474
## AR   -2.141768 -0.3564004582 -0.0053838928
## AZ   -1.926377  0.3774661222 -0.0497705422
## CA   -1.998110 -0.2938176590 -0.0349883164
## CO   -2.806869  1.2189474786  0.1316763251
## CT   -1.916075 -0.2234643271 -0.0518933389
## DC   -2.044332 -0.8642358165 -0.0254632269
## DE   -2.091432 -0.0170558199 -0.0157566978
## FL   -2.080352  0.3591215797 -0.0180403294
## GA   -1.972226 -0.1053521756 -0.0403222435
## HI   -2.061693 -0.3917867562 -0.0218857547
## IA   -2.209587  0.2872234026  0.0085919453
## ID   -4.159325  2.5038166251  0.4103819821
## IL   -1.711257  0.2417067085 -0.0941008214
## IN   -2.063976 -0.2174808214 -0.0214147467
## KS   -2.169769  0.1033841290  0.0003865632
## KY   -1.987373 -0.1492255451 -0.0372007486
## LA   -2.028795 -0.4310449729 -0.0286648371
## MA   -2.096464 -0.2441807515 -0.0147197209
## MD   -1.932677 -0.1876770861 -0.0484718480
## ME   -1.742503  0.7621328002 -0.0876623717
## MI   -1.818515 -0.1665380964 -0.0719980037
## MN   -2.293074  0.2734818323  0.0257961474
## MO   -2.086510  0.2125317412 -0.0167711274
## MS   -2.087987 -0.4332449646 -0.0164667794
## MT   -2.106698  0.9315549647 -0.0126111309
## NC   -1.991307 -0.3416798442 -0.0363899204
## ND   -2.149988  0.9720260626 -0.0036898766
## NE   -2.151870 -0.0638797343 -0.0033018952
## NH   -2.116684  0.4571364795 -0.0105529499
## NJ   -1.989569 -0.4629022725 -0.0367480737
## NM   -2.037874  0.1847065611 -0.0267941060
## NV   -2.090890  0.7476821161 -0.0158688988
## NY   -2.036016 -0.5802541441 -0.0271768972
## OH   -2.140180 -0.0588975626 -0.0057112064
## OK   -2.108804 -0.0421435490 -0.0121769519
## OR   -1.957332  0.3730024499 -0.0433915971
## PA   -2.165982 -0.7920983542 -0.0003941350
## RI   -1.865628  0.5197845030 -0.0622892187
## SC   -2.080221  0.0004269373 -0.0180671279
## SD   -2.082510  0.8274422815 -0.0175954556
## TN   -2.046829 -0.2440587116 -0.0249484579
```

```
## TX   -1.978473  0.0617121937 -0.0390348234
## UT   -2.135112  0.0094471168 -0.0067555618
## VA   -2.109389 -0.2558041297 -0.0120562056
## VT   -2.020656  0.5988968055 -0.0303419582
## WA   -1.976022  0.4492741926 -0.0395398508
## WI   -2.041895 -0.0559275409 -0.0259651835
## WV   -1.793306  0.0196060853 -0.0771929863
## WY   -2.136251  0.6020252301 -0.0065207856
##
## attr(,"class")
## [1] "coef.mer"
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