

Final Project - Draft Analysis

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##Potential research question: To what extent had the implementation of Fox News an effect on the US voting behavior during the presidential elections 1996 & 2000?

1 Introduction

2 Literature Review

In recent decades, there has been increasing attention on the role of media during political campaigns and its effects on the actual outcomes of elections. However, it is still debated within academia to what extent news media influence the behavior of the electorate. A potential answer to the question is that news media does not have an actual effect on people's voting behavior. It is called the sociological model of voting behavior which states that people's voting behavior is determined by long-term factors. This theory is supported by Lazarsfeld, Berelson, and Gaudet's (Lazarsfeld, Berelson, and Gaudet 1968) research analysis whose results show that the effect of media on electoral decisions is minimal but people belonging to different social groups is what determines their voting behavior. Kriesi, Grande, and Lachat (Kriesi et al. 2008) also argue people's voting behavior is determined by their belonging to different cleavages. However, instead of the old cleavages, there is a new social division within society that defines people's voting behavior which is the distinction between the winners and losers of globalization (Kriesi et al. 2008). Losers of globalization feel that their social status is protected by the nation-state and therefore they are strongly connected and identify themselves with the national community and that is what determines their voting behavior (Kriesi et al. 2008). In contrast, the winners of globalization benefit from open borders, they have more opportunities and therefore they vote differently (Kriesi et al. 2008) (I wrote this down because maybe we could test if there is any relationship between the number of Fox news subscribers in states that are doing worse economically and those that have developed in the last few decades)

However, other authors argue that issue voting explains voters' party choice which is based on voters' preferences on salient political issues. This theory argues that short-term factors like media attention,

campaigns, and current determinant issues in politics determine people's voting behavior. This theory is supported by DeMarzo, Vayanos, and Zwiebel's (DeMarzo, Vayanos, and Zwiebel 2003) research analysis that persuasion bias (like propaganda, censorship, political spin, and marketing) plays an important role in the process of social opinion formation and as a consequence, it determines people's voting behavior.

3 Hypotheses

This paper will follow Lazarsfeld et al.'s (1944) approach and main Hypotheses: The act of voting is an individual act, affected mainly by the personality of the voter and his exposure to the media. In the case of our research and our available data, we categorize the variables about socioeconomic background of the people as personality traits and the exposure to media via the existence or non-existence of Fox News.

HP1: Fox news and the socioeconomic background effects the behavior of the electorate.

Sociological model of voting Kriesi's (Kriesi et al. 2008): People's voting behavior is just shaped by long-term factors (socialization).

HP2: Just socioeconomic background effects the behavior of the electorate.

Rational expectation theories (Bray and Kreps 1987) : Voters often filter out reporting bias without being influenced. The implementation of Fox News will not effect election results.

HP3: Neither the socioeconomic background of the electorate, nor Fox News influences the electorate

Behavioral Theories (DeMarzo, Vayanos, and Zwiebel 2003): assert that media influence on voters exists.

HP4: Primarily Fox News effects the behavior of the electorate.

4 Loading Data & General Overview

```
data <- read.csv("foxnews.csv")
data$state <- factor(data$state)
```

In order to have a rough overview of the vote share among states, the *state* variable is converted into a factor variable. Afterwards the average two-party vote share for the Republicans at 2000 Presidential election in the different states is shown in this table in increasing order.

```
gop2000_by_states <- tapply(data$gopvoteshare2000, data$state, mean, na.rm = TRUE)
sort(gop2000_by_states)
```

##	Ri	Hi	Ma	Ct	Ca	Nj	Vt	Ar
##	0.3782243	0.3866320	0.3949739	0.4390149	0.4471664	0.4674222	0.4708586	0.4947215
##	Me	Tn	Ia	Wi	Nh	Mn	Sc	Ny
##	0.5017892	0.5105959	0.5268057	0.5291817	0.5294599	0.5317263	0.5318809	0.5400148
##	Mi	Al	Va	Pa	Mo	Oh	Ak	Nd
##	0.5464333	0.5633230	0.5649642	0.5663298	0.5778050	0.5817919	0.6168280	0.6742668
##	Mt	Id	Wy	Ut				
##	0.6749542	0.7337415	0.7495900	0.7981762				

From these values it is already obvious that there is quite a big variation between the two-party vote share for the Republicans in different states (highest and lowest being Utah (0.7981762) and Rhode Island (0.3782243) respectively).

Afterwards the two-party vote share is calculated for the other two measurement time points as well and the trends are illustrated on a plot below.

```
gop1996_by_states <- tapply(data$gopvoteshare1996, data$state, mean, na.rm = TRUE)
gop1992_by_states <- tapply(data$gopvoteshare1992, data$state, mean, na.rm = TRUE)

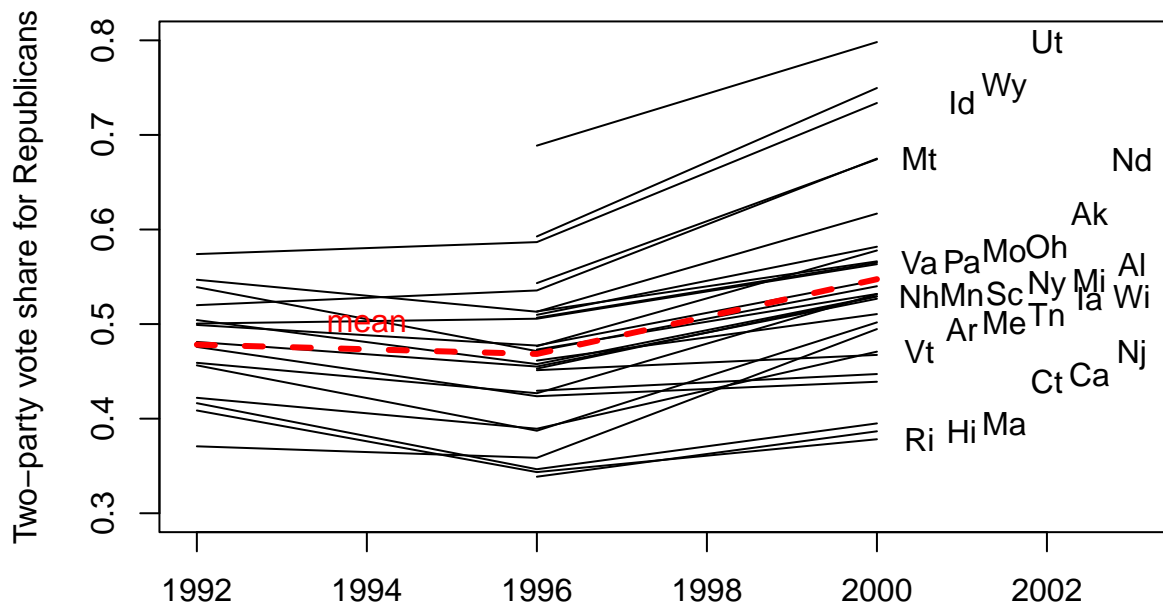
# this dataframe contains the mean gop for the three years (1992, 1996, 2000) by state
gop_by_states <- data.frame(gop1992_by_states, gop1996_by_states, gop2000_by_states)

# sort it for easier use
gop_by_states <- gop_by_states[order(gop_by_states$gop2000_by_states), ]

# plot the results
plot(1, type = "n", xlab = "",
     ylab = "Two-party vote share for Republicans",
     main = "Change of two-party vote share for Republicans over time",
     xlim = c(1992, 2003),
     ylim = c(0.3, 0.8))
for(x in 1:nrow(gop_by_states)){
  lines(as.numeric(gop_by_states[x, ]) ~ c(1992, 1996, 2000))
  text(2000.5+((x-1)%6)/2, gop_by_states$gop2000_by_states[x], row.names(gop_by_states)[x])
}

lines(c(mean(gop1992_by_states, na.rm=T), mean(gop1996_by_states), mean(gop2000_by_states)) ~ c(1992, 1996, 2000),
      lty=2,
      col="red",
      lwd=3)
text(1994, 0.5, "mean", col="red")
```

Change of two-party vote share for Republicans over time



Obviously this graph is not intended to clearly show the variance of each state, rather the general trends in the different states over time. From this plot it is clear that on average there has been a slight decrease in republican vote share in the period of 1992 and 1996, however there has been differences in different region. For example Main experienced a huge drop while in Idaho a slight increase is visible.

On the other hand in the time period of 1996 and 2000 there has been a strong increase (on average from 0.468436 to 0.5474526). An important note is that there has been no single state where the republican vote share has decreased in this time period.

```
cor(data[,c(3, 4, 5, 6, 7, 12)])
```

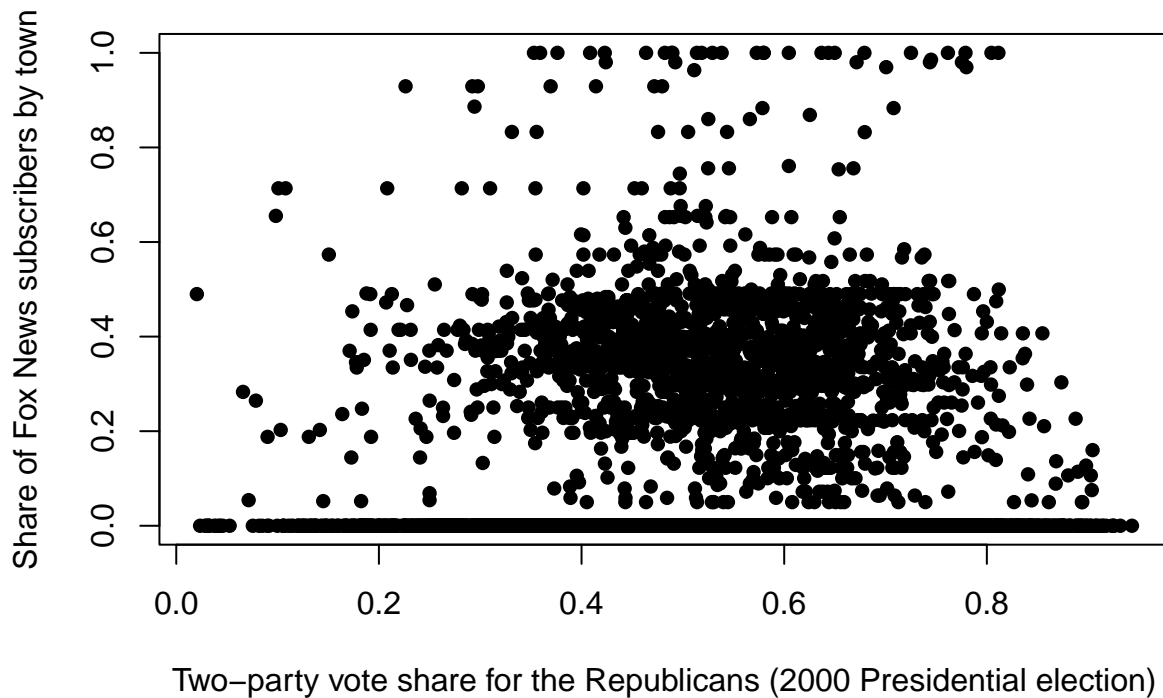
```
##          college1990    male1990    black1990    hisp1990    income1990
## college1990          1.00000000 -0.02564961 -0.04951600  0.01102930  0.67344439
## male1990             -0.02564961  1.00000000 -0.08323473  0.10585356  0.15350228
## black1990            -0.04951600 -0.08323473  1.00000000  0.06078667 -0.13253234
## hisp1990              0.01102930  0.10585356  0.06078667  1.00000000  0.01149702
## income1990            0.67344439  0.15350228 -0.13253234  0.01149702  1.00000000
## gopvoteshare2000     -0.09908543  0.18130369 -0.33131949 -0.22898806  0.01933208
##
##          gopvoteshare2000
## college1990          -0.09908543
## male1990              0.18130369
## black1990            -0.33131949
## hisp1990             -0.22898806
## income1990           0.01933208
## gopvoteshare2000      1.00000000
```

```

gop1992_df<- data[ , c("state","town","college1990", "male1990", "black1990", "hisp1990", "income1990",
gop1996_df<- data[ , c("state","town","college1990", "male1990", "black1990", "hisp1990", "income1990",
gop2000_df<- data[ , c("state","town","college1990", "male1990", "black1990", "hisp1990", "income1990",

plot(gop2000_df$gopvoteshare2000, gop2000_df$subrf2000,
     pch = 16, col = "black",
     xlab = "Two-party vote share for the Republicans (2000 Presidential election)",
     ylab = "Share of Fox News subscribers by town")

```



```

tapply(gop2000_df$gopvoteshare2000, gop2000_df$subrf2000, mean, na.rm=T)

```

```

##          0 0.0500000007450581 0.0520643517374992 0.0536635704338551
##      0.5392109      0.6366205      0.1637436      0.8441558
## 0.0541385859251022 0.0589936375617981 0.0590207874774933 0.0638030841946602
##      0.1607113      0.3890845      0.5081695      0.7060595
## 0.0688695684075356 0.0720589607954025 0.0740825161337852 0.0753911808133125
##      0.2500000      0.6399730      0.6633561      0.9035785
## 0.0788345783948898 0.0829605311155319 0.0862447917461395 0.0890014469623566
##      0.5072569      0.4284538      0.5341276      0.8679707
## 0.0895130336284637 0.091968908905983 0.100323617458344 0.100549928843975
##      0.5591316      0.3974592      0.6217725      0.5904004
## 0.102046422660351 0.105475880205631 0.105713538825512 0.106446780264378
##      0.4256259      0.5624005      0.3952321      0.8914241
## 0.108771935105324 0.113510467112064 0.114180482923985 0.116289548575878
##      0.8406285      0.5697758      0.8898305      0.6329502

```

##	0.121189139783382	0.1224694699049	0.122588261961937	0.122627317905426
##	0.6895806	0.4460154	0.6440519	0.6211788
##	0.127177700400352	0.128672987222672	0.130654335021973	0.131381511688232
##	0.8978979	0.6212318	0.6223822	0.5312972
##	0.132803708314896	0.136380881071091	0.139265760779381	0.141539826989174
##	0.4708939	0.8684211	0.8088608	0.5555657
##	0.142235711216927	0.14431557059288	0.144477188587189	0.144631519913673
##	0.5394314	0.2066917	0.4852768	0.7402808
##	0.146110191941261	0.146953403949738	0.147063747048378	0.148989886045456
##	0.7182131	0.5862928	0.5179407	0.8015398
##	0.149467602372169	0.155888840556145	0.156111925840378	0.158471927046776
##	0.6102979	0.6895102	0.7401245	0.7020530
##	0.159956902265549	0.159959927201271	0.163186192512512	0.163383826613426
##	0.9043543	0.5635119	0.4994638	0.5657742
##	0.163719698786736	0.167161017656326	0.17249721288681	0.174626871943474
##	0.5516812	0.5336027	0.4970568	0.5044845
##	0.1749437302351	0.176656141877174	0.17965367436409	0.184311330318451
##	0.6515175	0.6463116	0.5572289	0.5229443
##	0.187394946813583	0.188007637858391	0.188418865203857	0.189808577299118
##	0.7951613	0.1948264	0.4745814	0.4928910
##	0.192889556288719	0.193782031536102	0.193796068429947	0.196537375450134
##	0.7554348	0.4380937	0.6440717	0.3910624
##	0.196705892682076	0.198570907115936	0.19989287853241	0.200479224324226
##	0.4419961	0.8218475	0.5684981	0.7726052
##	0.202627271413803	0.203210890293121	0.204534247517586	0.205380246043205
##	0.1981703	0.4331984	0.6826265	0.6392857
##	0.205773323774338	0.207019627094269	0.207442104816437	0.207811087369919
##	0.2411566	0.5692324	0.5426327	0.4101761
##	0.210565343499184	0.210835501551628	0.212110474705696	0.213036566972733
##	0.8564650	0.6067416	0.8154808	0.4341463
##	0.213308453559875	0.214132100343704	0.215816274285316	0.216241747140884
##	0.4599212	0.8091483	0.6257116	0.5560976
##	0.216911762952805	0.217025265097618	0.218978106975555	0.220140725374222
##	0.5848485	0.4519851	0.5988506	0.6876679
##	0.220338985323906	0.220519289374352	0.222096189856529	0.222449839115143
##	0.5785340	0.5556979	0.5385834	0.6877645
##	0.222672820091248	0.223060861229897	0.223320096731186	0.224394783377647
##	0.6217079	0.6247333	0.6845554	0.5494943
##	0.225008994340897	0.225741773843765	0.226240143179893	0.22634445130825
##	0.5635982	0.7606925	0.2362637	0.8445392
##	0.227969020605087	0.229936257004738	0.230514511466026	0.230816766619682
##	0.5018218	0.5275665	0.5740971	0.5394770
##	0.231235027313232	0.232144445180893	0.232267916202545	0.233162924647331
##	0.5093796	0.4353816	0.5849129	0.5831967
##	0.233473598957062	0.234679669141769	0.235462710261345	0.236203372478485
##	0.5566823	0.4690990	0.5628679	0.1638405
##	0.236365213990211	0.238625511527061	0.240955576300621	0.247474074363708
##	0.6347324	0.4034355	0.3504591	0.1832814
##	0.24762162566185	0.248205080628395	0.249626308679581	0.249738439917564
##	0.4856232	0.5581918	0.4902439	0.2632688
##	0.25	0.250067919492722	0.252699792385101	0.253139644861221
##	0.7475248	0.4889276	0.5298037	0.5135630
##	0.254216402769089	0.256126254796982	0.257487148046494	0.257828652858734
##	0.6323848	0.6249256	0.5832797	0.5592674

##	0.257997959852219	0.258340716362	0.260451465845108	0.260510265827179
##	0.6006288	0.4917659	0.3862292	0.7452210
##	0.261956512928009	0.263494610786438	0.263996720314026	0.264577269554138
##	0.5036546	0.5315963	0.7150259	0.3101019
##	0.267191916704178	0.272181868553162	0.272601306438446	0.27475443482399
##	0.5061973	0.5331828	0.6647059	0.8118196
##	0.274912357330322	0.275548428297043	0.276611238718033	0.277875334024429
##	0.5464632	0.7006303	0.5878713	0.7144670
##	0.281903624534607	0.282375872135162	0.282479703426361	0.282485872507095
##	0.6272307	0.5079128	0.5306566	0.5899149
##	0.283079653978348	0.286630660295486	0.288192003965378	0.288231283426285
##	0.5038594	0.7126623	0.6168155	0.4580382
##	0.288282126188278	0.288300067186356	0.289313644170761	0.291665703058243
##	0.7760779	0.4330177	0.5228536	0.5837929
##	0.292167007923126	0.293145418167114	0.293710827827454	0.295802533626556
##	0.4473033	0.5892756	0.6593592	0.5611365
##	0.295850515365601	0.297012388706207	0.297536015510559	0.298522800207138
##	0.3824860	0.5484048	0.7118156	0.7472044
##	0.298714160919189	0.299594670534134	0.299787372350693	0.299832075834274
##	0.5716259	0.3692519	0.6335188	0.5718941
##	0.299908012151718	0.300581693649292	0.300810903310776	0.301852643489838
##	0.4915014	0.5885913	0.5028868	0.5830890
##	0.303223878145218	0.303375035524368	0.304845333099365	0.306082516908646
##	0.7013650	0.5531865	0.3871967	0.4812287
##	0.307096064090729	0.308187067508698	0.30893537402153	0.309337854385376
##	0.4277361	0.3954434	0.4794165	0.5688804
##	0.310367494821548	0.311765998601913	0.311787992715836	0.312031656503677
##	0.6119887	0.7013415	0.4743419	0.5559457
##	0.312965720891953	0.313309252262115	0.31622177362442	0.31632524728775
##	0.4457928	0.6010733	0.5923358	0.5785958
##	0.316943854093552	0.322613686323166	0.322872251272202	0.324510812759399
##	0.6633684	0.3765003	0.6446019	0.4663623
##	0.325453788042068	0.326466292142868	0.326767653226852	0.328846722841263
##	0.7971347	0.6075650	0.4382020	0.7530973
##	0.329017996788025	0.330564677715302	0.333464622497559	0.334591001272202
##	0.7192817	0.3641074	0.5967061	0.4866473
##	0.334957391023636	0.335085779428482	0.335137575864792	0.335634022951126
##	0.7360441	0.7186398	0.4976435	0.6285394
##	0.335897445678711	0.336291134357452	0.337344169616699	0.338808476924896
##	0.6569310	0.4625435	0.6869436	0.5042159
##	0.341147631406784	0.341296941041946	0.342777848243713	0.343810141086578
##	0.6229607	0.4920925	0.6104162	0.4710841
##	0.345329344272614	0.345754861831665	0.346248835325241	0.346486210823059
##	0.5282922	0.4343596	0.5814060	0.6598463
##	0.347454220056534	0.347818911075592	0.347976624965668	0.349253743886948
##	0.6692863	0.7290503	0.7465681	0.5495772
##	0.349272549152374	0.349436402320862	0.3498874604702	0.349890828132629
##	0.5545296	0.4985299	0.5742643	0.4558200
##	0.350805521011353	0.354196101427078	0.355425268411636	0.35549333691597
##	0.3912821	0.8353870	0.3837783	0.4823529
##	0.358507752418518	0.360465109348297	0.361147314310074	0.36162006855011
##	0.4973253	0.4735632	0.4671533	0.4972564
##	0.363522559404373	0.368566155433655	0.368734270334244	0.369409769773483
##	0.6815402	0.5330454	0.3673757	0.4509809

##	0.369963318109512	0.370234042406082	0.370754957199097	0.371489465236664
##	0.3607318	0.4501135	0.4828872	0.6216082
##	0.372654736042023	0.374305576086044	0.374587267637253	0.375238448381424
##	0.5595064	0.5188602	0.5684460	0.3950814
##	0.375972867012024	0.37806710600853	0.378663539886475	0.378905028104782
##	0.5845152	0.5392670	0.6598131	0.5683891
##	0.379260301589966	0.379491478204727	0.38083353638649	0.381188362836838
##	0.5318269	0.4221772	0.3728740	0.4839138
##	0.381966292858124	0.383066713809967	0.383630514144897	0.384447574615479
##	0.5431709	0.3800000	0.6603670	0.3740014
##	0.384960889816284	0.38517102599144	0.385570526123047	0.386660218238831
##	0.5825547	0.5069615	0.4820493	0.6081594
##	0.387563496828079	0.387564063072205	0.388699501752853	0.38873365521431
##	0.6369760	0.4421488	0.4976464	0.5479577
##	0.38955095410347	0.390175551176071	0.3910031914711	0.392087131738663
##	0.6741793	0.4544973	0.4998621	0.3029801
##	0.393029451370239	0.398379534482956	0.399632215499878	0.401474982500076
##	0.4903851	0.5641542	0.4803722	0.5397843
##	0.402131319046021	0.40234711766243	0.402763903141022	0.405161798000336
##	0.4795994	0.6188184	0.5436877	0.7176625
##	0.405674189329147	0.406886070966721	0.407826513051987	0.408293873071671
##	0.4863100	0.7111671	0.4089069	0.5105345
##	0.412557423114777	0.413030385971069	0.413380146026611	0.413719326257706
##	0.6068054	0.4662572	0.4631148	0.7681197
##	0.41434720158577	0.414364635944366	0.41679722070694	0.419378936290741
##	0.3657540	0.6082687	0.4685614	0.6415501
##	0.419463753700256	0.421019464731216	0.421209931373596	0.421801567077637
##	0.5361842	0.5809699	0.4235102	0.5362162
##	0.423163443803787	0.423816919326782	0.425180107355118	0.426724135875702
##	0.4221036	0.6788441	0.4347393	0.4720630
##	0.427931904792786	0.429210871458054	0.429246932268143	0.430346965789795
##	0.3864307	0.5462125	0.7220157	0.4790230
##	0.430856823921204	0.430919051170349	0.431238681077957	0.431481689214706
##	0.4908061	0.3591629	0.7276132	0.6477302
##	0.43424317240715	0.436845511198044	0.437311172485352	0.43936887383461
##	0.4750958	0.6681922	0.5559105	0.4634993
##	0.440043210983276	0.440081119537354	0.441027045249939	0.44239130616188
##	0.6479401	0.5546933	0.6120444	0.4864603
##	0.447855323553085	0.448143392801285	0.450825959444046	0.451651513576508
##	0.7346383	0.5389791	0.6444316	0.4756359
##	0.453429371118546	0.4569051861763	0.457402914762497	0.458289355039597
##	0.6123891	0.4459565	0.6211456	0.7063310
##	0.459141194820404	0.462137699127197	0.462505221366882	0.463054180145264
##	0.6141764	0.6597414	0.7394508	0.5114878
##	0.463700473308563	0.463966071605682	0.464091002941132	0.464345842599869
##	0.5873337	0.5340314	0.5702813	0.6102834
##	0.465924799442291	0.466560035943985	0.472219556570053	0.474683523178101
##	0.7325383	0.4013797	0.4656170	0.8092399
##	0.475969344377518	0.476609438657761	0.478062212467194	0.480129271745682
##	0.4816815	0.4327071	0.5096221	0.4110846
##	0.482440680265427	0.483656018972397	0.485136747360229	0.487891435623169
##	0.4976509	0.4301382	0.6666667	0.4689962
##	0.489403188228607	0.489851415157318	0.490078806877136	0.490954160690308
##	0.6243221	0.5881696	0.6306306	0.5598358

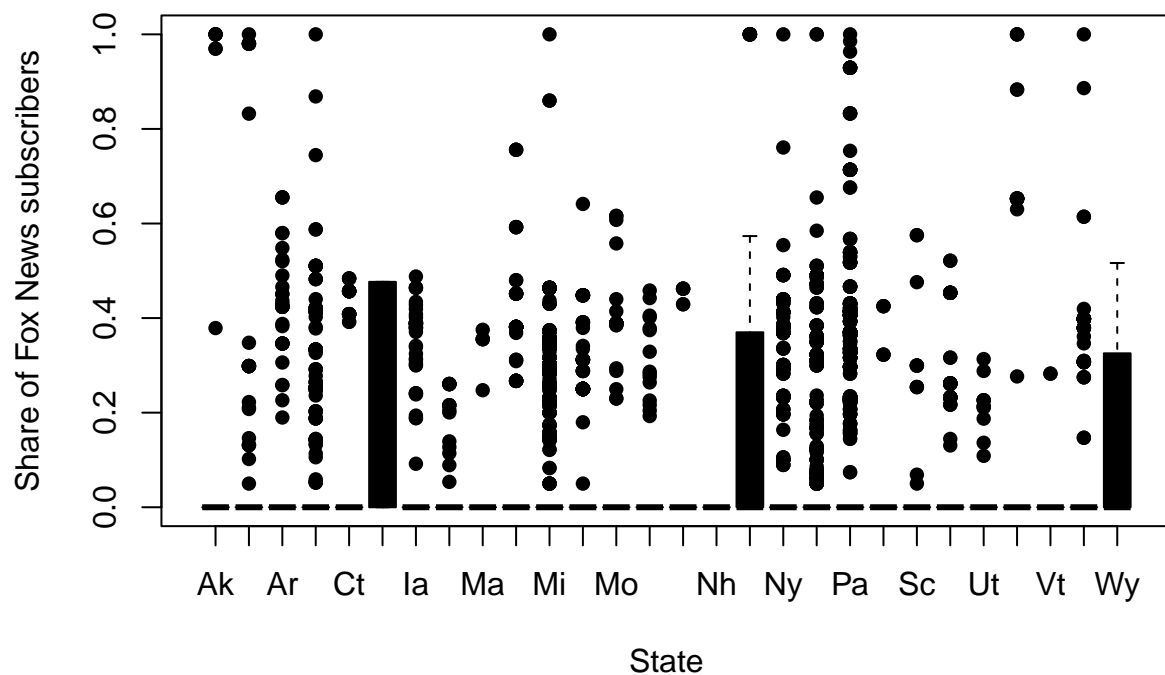
##	0.491258770227432	0.499464333057404	0.510346949100494	0.510463058948517
##	0.5213177	0.6292902	0.4953866	0.5063417
##	0.516448199748993	0.517558157444	0.520266175270081	0.521328091621399
##	0.5479082	0.6906844	0.3714689	0.5546531
##	0.523506999015808	0.530230581760406	0.53913289308548	0.548274040222168
##	0.3413174	0.5510016	0.4440201	0.4545455
##	0.554283320903778	0.557857155799866	0.567338287830353	0.573411881923676
##	0.4668753	0.6464789	0.6921880	0.5210236
##	0.575334668159485	0.579721450805664	0.584762692451477	0.587519884109497
##	0.4715058	0.4791269	0.7183771	0.5233741
##	0.592390179634094	0.607692956924438	0.614366710186005	0.616058051586151
##	0.4987767	0.6496958	0.4343581	0.4805707
##	0.630079030990601	0.641348659992218	0.652668833732605	0.654961287975311
##	0.4432231	0.5233645	0.5331821	0.5426908
##	0.655275642871857	0.676033437252045	0.713625907897949	0.744621276855469
##	0.3703068	0.5102186	0.3328478	0.4969660
##	0.753681421279907	0.755886971950531	0.760725617408752	0.832339286804199
##	0.6537530	0.5795711	0.6045802	0.6794731
##	0.832746267318726	0.85995626449585	0.868728697299957	0.883227825164795
##	0.4422358	0.5456175	0.6253061	0.6432451
##	0.886317133903503	0.929291486740112	0.96340548992157	0.969715058803558
##	0.2943457	0.3644520	0.5111826	0.7402226
##	0.980178356170654	0.985493779182434	1	
##	0.6214041	0.7449275	0.5681401	

```

gop_by_s92<- data.frame(gop1992_by_states)
gop_by_s96<- data.frame(gop1996_by_states)
gop_by_s20<- data.frame(gop2000_by_states)

plot(gop2000_df$state, gop2000_df$subrf2000,
     pch = 16, col="black",
     xlab = "State",
     ylab = "Share of Fox News subscribers")

```



```
towns_w_foxnews<- subset(data, (subset = subrf2000 >0))
towns_no_foxnews<-subset(data, (subset = subrf2000 ==0))

means.all.elections.wFN<-colMeans(towns_w_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])
means.all.elections.wFN
```

```
## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##           0.5026492           0.4790478           0.5373097
```

```
means.all.elections.noFN<-colMeans(towns_no_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])
means.all.elections.noFN
```

```
## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##           0.4797481           0.4679651           0.5392109
```

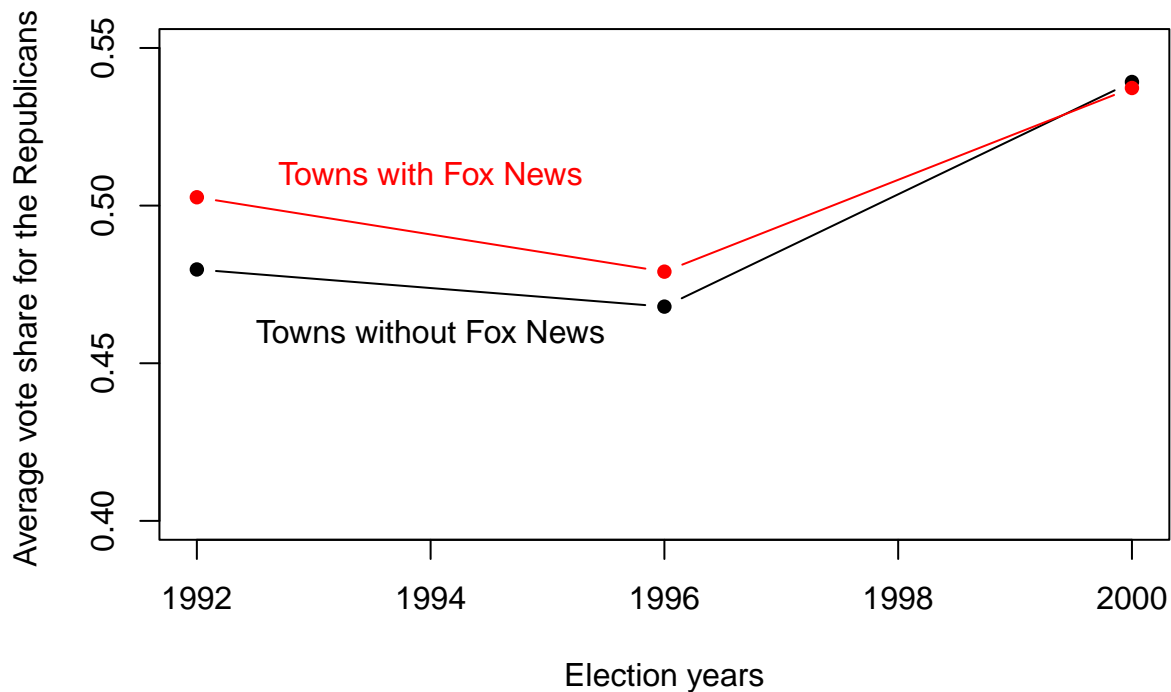
```
years<- c(1992, 1996, 2000)
```

```
plot(years, means.all.elections.noFN, pch = 16, col = "black",
      xlim = c(1992, 2000), ylim = c(0.4, 0.55), xlab = "Election years",
      ylab = "Average vote share for the Republicans ",
      main = "Difference in Average vote share across towns with/without fox news")
```

```
points(years, means.all.elections.wFN,pch = 16, col = "red")
```

```
lines(years, means.all.elections.noFN, type = "c")
lines(years, means.all.elections.wFN, type = "c", col="red")
text(1994,0.51, "Towns with Fox News", col="red")
text(1994,0.46, "Towns without Fox News")
```

Difference in Average vote share across towns with/without fox new



##A Question I (Thea) would like to do for final assignment

Our hypotheses stating, that it might be possible that education, gender, and people with different race reacting differently to the implementation of Fox News. It could be also possible that voters with different incomes get effected differently by the input of Fox News.

We will evaluate whether these hypotheses are supported by finding the differences in sample average treatment effects by education, gender, race and income in towns with access to Fox News and towns without access to Fox News.

Furthermore, Computing the average change of votes for republican (during presidential elections) among towns before and after the availability of Fox News could be an crucial indicator to understand the effect.

```
##SATE town with high proportion of a black population
summary(data$black1990)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.000000 0.000000 0.002165 0.031380 0.013411 0.990427
```

```

high_black_pop.t_w_foxnews<- subset(towns_w_foxnews, subset = black1990 >= 0.031380)
high_black_pop.t_no_foxnews<- subset(towns_no_foxnews, subset = black1990 >= 0.031380)

means_high_black_pop.t_w_foxnews<-colMeans(high_black_pop.t_w_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])
means_high_black_pop.t_no_foxnews<-colMeans(high_black_pop.t_no_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])

sate_high_black_pop<- means_high_black_pop.t_w_foxnews - means_high_black_pop.t_no_foxnews
sate_high_black_pop

```

```

## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##      0.05143725      -0.01580532      -0.02403391

```

####SATE town with low proportion of a black population

```

low_black_pop.t_w_foxnews<- subset(towns_w_foxnews, subset = black1990 > 0 & black1990 < 0.013411)
low_black_pop.t_no_foxnews<- subset(towns_no_foxnews, subset = black1990 > 0 & black1990 < 0.013411)

means_low_black_pop.t_w_foxnews<-colMeans(low_black_pop.t_w_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])
means_low_black_pop.t_no_foxnews<-colMeans(low_black_pop.t_no_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])

sate_low_black_pop<- means_low_black_pop.t_w_foxnews - means_low_black_pop.t_no_foxnews
sate_low_black_pop

```

```

## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##      0.029511110      0.017182925      0.008770301

```

####SATE town with no proportion of a black population

```

no_black_pop.t_w_foxnews<- subset(towns_w_foxnews, subset = black1990 == 0)
no_black_pop.t_no_foxnews<- subset(towns_no_foxnews, subset = black1990 == 0)

means_no_black_pop.t_w_foxnews<-colMeans(no_black_pop.t_w_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])
means_no_black_pop.t_no_foxnews<-colMeans(no_black_pop.t_no_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])

sate_no_black_pop<- means_no_black_pop.t_w_foxnews - means_no_black_pop.t_no_foxnews
sate_no_black_pop

```

```

## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##      0.01537377      0.02805453      0.01320826

```

```

plot(years,sate_high_black_pop, pch = 16, col = "aquamarine3",
xlim = c(1992, 2000), ylim = c(-0.1, 0.1), xlab = "Days of presidential election",
ylab = "Estimated sample average fox news effect",
main = "Trends in Fox News Effects among black population")

points(years, sate_low_black_pop,pch = 16, col = "darkseagreen4")

```

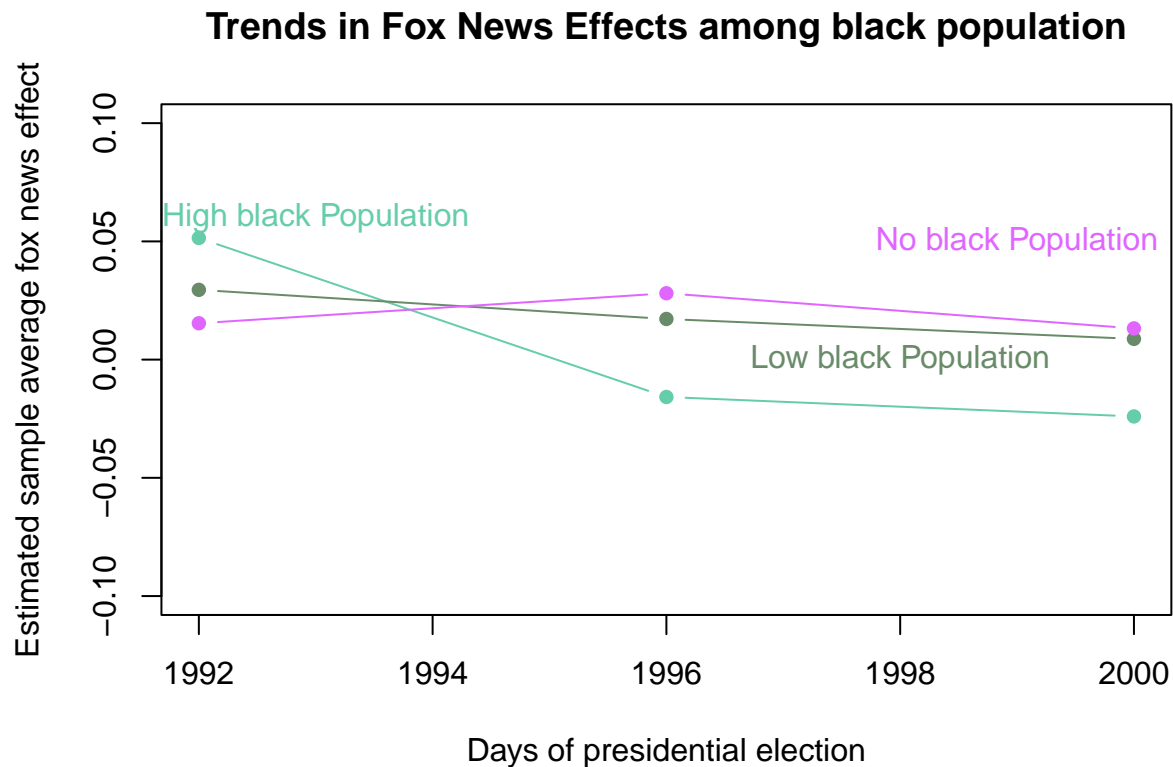
```

points(years, sate_no_black_pop, pch = 16, col = "mediumorchid1")

lines(years, sate_high_black_pop, type="c", col="aquamarine3")
lines(years, sate_low_black_pop, type="c", col = "darkseagreen4")
lines(years, sate_no_black_pop, type="c", col = "mediumorchid1")

text(1993, 0.06, "High black Population", col="aquamarine3")
text(1998, 0, "Low black Population", col="darkseagreen4")
text(1999, 0.05, "No black Population", col="mediumorchid1")

```



```
summary(data$income1990)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.420   1.946   2.586   2.808   3.420  15.000
```

```
##SATE town with high proportion of rich people
```

```

high_income.t_w_foxnews<- subset(towns_w_foxnews, subset = income1990 >= 3.420)
high_income.t_no_foxnews<- subset(towns_no_foxnews, subset = income1990 >= 3.420)

```

```
means_high_income.t_w_foxnews<-colMeans(high_income.t_w_foxnews[c('gopvoteshare1992','gopvoteshare1996')
```

```
means_high_income.t_no_foxnews<-colMeans(high_income.t_no_foxnews[c('gopvoteshare1992','gopvoteshare1996')
```

```
sate_high_income<- means_high_income.t_w_foxnews - means_high_income.t_no_foxnews
sate_high_income
```

```
## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##      0.03359662      0.02498114      0.01709393
```

```
##SATE town with medium income
```

```
medium_income.t_w_foxnews<- subset(towns_w_foxnews, subset = income1990 >1.946 & income1990 <3.420 )
medium_income.t_no_foxnews<- subset(towns_no_foxnews, subset =income1990 >1.946 & income1990 <3.420 )

means_medium_income.t_w_foxnews<-colMeans(medium_income.t_w_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])
means_medium_income.t_no_foxnews<-colMeans(medium_income.t_no_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])

sate_medium_income<- means_medium_income.t_w_foxnews - means_medium_income.t_no_foxnews
sate_medium_income
```

```
## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##      0.0130079946      0.0006340113      -0.0081789829
```

```
##SATE town with high proportion of poor people
```

```
low_income.t_w_foxnews<- subset(towns_w_foxnews, subset = income1990 <= 1.946)
low_income.t_no_foxnews<- subset(towns_no_foxnews, subset = income1990 <= 1.946)

means_low_income.t_w_foxnews<-colMeans(low_income.t_w_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])
means_low_income.t_no_foxnews<-colMeans(low_income.t_no_foxnews[c('gopvoteshare1992','gopvoteshare1996','gopvoteshare2000')])

sate_low_income<- means_low_income.t_w_foxnews - means_low_income.t_no_foxnews
sate_high_income
```

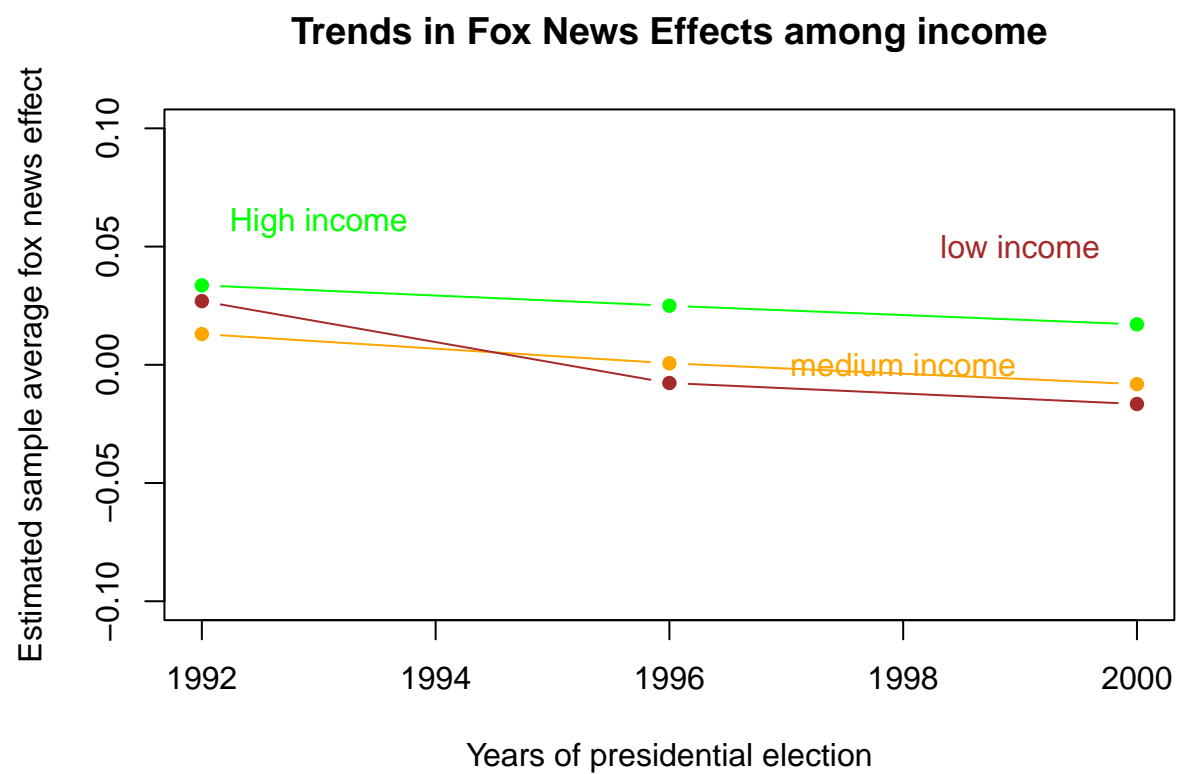
```
## gopvoteshare1992 gopvoteshare1996 gopvoteshare2000
##      0.03359662      0.02498114      0.01709393
```

```
plot(years,sate_high_income, pch = 16, col = "green",
xlim = c(1992, 2000), ylim = c(-0.1, 0.1), xlab = "Years of presidential election",
ylab = "Estimated sample average fox news effect",
main = "Trends in Fox News Effects among income")

points(years, sate_medium_income,pch = 16, col = "orange")
points(years, sate_low_income,pch = 16, col = "brown")

lines(years,sate_high_income, type="c", col="green")
lines(years, sate_medium_income,type="c", col = "orange")
lines(years, sate_low_income,type="c", col = "brown")

text(1993,0.06,"High income", col="green")
text(1998,0,"medium income", col="orange")
text(1999, 0.05, "low income", col="brown")
```



5 Conclusion

References

- Bray, Margaret, and David M. Kreps. 1987. "Rational Learning and Rational Expectations." In *Arrow and the Ascent of Modern Economic Theory*, 597–625. Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-07239-2_19.
- DeMarzo, P. M., D. Vayanos, and J. Zwiebel. 2003. "Persuasion Bias, Social Influence, and Unidimensional Opinions." *The Quarterly Journal of Economics* 118 (3): 909–68. <https://doi.org/10.1162/00335530360698469>.
- Kriesi, Hanspeter, Edgar Grande, Romain Lachat, Martin Dolezal, Simon Bornschie, and Timotheos Frey. 2008. *West European Politics in the Age of Globalization*. Cambridge University Press. <https://doi.org/10.1017/cbo9780511790720>.
- Lazarsfeld, Paul F., Bernard Berelson, and Hazel Gaudet. 1968. *The People's Choice*. Columbia University Press. <https://doi.org/10.7312/laza93930>.