Replication of "Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots"

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Contents

1 Abstract

Campbell et al (2019) show that candidate's with shared local roots appeals to voters and that having local roots is an important factor in a voter's candidate selection. I was successfully able to replicate all the results presented in the orignal article "Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots." by Rosie Campbell, Philip Cowley, Nick Vivyan, Markus Wagner. To further their analysis, I modeled how local roots influence different sub-populations including male vs. female voters as well as between different age groups. I found the average marginal effect of local roots to not remain constant across subgroups, meaning local roots affect groups of voters differently. Thus, any further research regarding local roots effects should consider the gender as well as age makeup of the sample.

2 Introduction

"Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots"[1] takes a deeper look into the "friends and neighbors effect" first researched by Valdimer Orlando Key in 1949. The "friends and neighbors effect" has been well documented over the years; however, the research has been been focused on observing its existence with the reasoning for why it occurs being untested and unknown. The prevailing prior conceptual understanding has been that voters use the fact a candidate has local roots to make assumptions about how a said candidate may represent their constituents. Campbell et al are the first to test this hypothesis, measuring how varying the level of information voter's receive about those running affects the candidate with local roots chances of being elected. They performed a vignette experiment of fake elections instead of analyzing a real election to isolate the effects of local roots and control for the amount of information, not allowing prior information about any candidates influence the results. They modeled respondents' satisfaction with candidates described in the experiment using linear regression, paying attention to the interaction term between local roots and behavioral information. They found results in favor of their hypthoesis as the local roots effect diminished in the presence of more information; however, the result being positive, they took a deeper look with a second study. After performing a conjoint survey experiment, they measured the average marginal component effect, change in probability of a candidate being preferred compared to a baseline for each regressor variable, using an OLS model. The model showed candidates with local roots compared to no local roots to be substantially preferred with this difference being one of the largest out of all the attributes analyzed. Thus, the reasoning for why this "friends and neighbors" effect occurs is not solely that voters using local roots to make inferences, suggesting that local roots on their own is important in candidate selection.

I utilized R, a language and environment for statistical computing, for the replication of the author's code (R Core Team 2019). The data and code for the paper were made available on Dataverse (Campbell et al. 2018). I followed the format laid out by Gary King in "Publication, Publication" to guide my replication project (King 2006). I use many techniques from the Gov 1006 textbook "Regression and Other Stories" (Andrew Gelman 2019) as well. I was able to succesfully replicate all the results of the paper. All of the their code as well as my own can be found in my Github repository.[2]

I found the results of the original paper very intriguing; however, my immediate question was how would the results hold across subsets of the sample population. Different age groups as well as genders display different preferences in political issues and voting trends, thus, should it be expected that they react to local roots in the same way? I began by simplying the regression model utilized by the authors in study 1 by excluding the education and social grade variables.[3] I also performed my analysis within a Bayesian framework, using stan_glm instead of just lm for my modeling. In order to look at how local roots affects subsets differently, I interacted the local roots treatment variable with the gender and age group variables. The average local roots treatment effect were slightly different across genders; however, the effect varied signicantly between age groups with the effect being stronger for older voters.

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[1]Replication Paper

[2]Github Reposotory

[3]After performing leave one out cross validation, loo, I found a model without these variables to be just as predictive, meaning these were only adding noise

To continue with this theory, I also extended my analysis to the study 2 data. Being a conjoint survey experiment, the best method in which to model such data is using an OLS model. Thus, the only way to compare the local roots effects across genders and age groups was to filter and subset the data prior to running their model. I found that the change in probability of MP being preferred due to local roots for men was about 1/3 less than that for women. In between age groups, I saw similar results to those I found in my extension of study 1. The older voters showed a much stronger affinite for local roots, while younger voters change in probability was more affected by changes in the levels of behavioral information.

3   Literature Review

The local roots effects has been well studied since 1949. Valdimer Orlando Key was the first to study this for Presidential Elections in southern USA, dubbing his findings as the "friends and neighbors effect" (Key 1949). In analyzing Arkansas, he found that in their one party political system that the best explanation for support was just where you are from and who you know. Key himself was concerned by his own findings stating that candidates "can gain support, not primarily for what he stands for or because of his capacities, but because of where he lives" (Key 1949) . However, what Key found was only observational evidence that "candidates for state office tend to poll overwhelming majorities in their home counties" (Key 1949). This friends and neighbors effect was not quantitatively highlighted until 1973 in an analysis of George Wallace's support across his govenitorial elections. In this analysis, counties of Alabama were classified as friends and neighbor counties were ones he had a disprortionate level of support and they all happened to be located around his home county in southeastern Alabama (E. Black and Black 1973). They found "evidence for the persitence of a strong degree of localism in politics" due to the importance of the the friends-and-neighbors indicator variable in their regression models (E. Black and Black 1973). A year later Raymond Tatalovich confirmed many of the previous findings in his research of Mississippi as well as made extensions across different types of elections. He found that the most national elections in Mississippi (Senate Races) in fact had the most "friends and neighbors" voting (Tatalovich 1975). Furthermore, important to my replication paper, he found that "increased visbility of candidates does serve to blunt their friends and neighbors support" (Tatalovich 1975).

At this point, there was criticism as to the validity of this theory as their had not been anything larger than statewide elections tested and all the testing so far was on Southern states in the USA. The question was were these friends and neighbors results generalizable. Michael Gallagher was the first to document Key's theories outside the US in the importance of localism in candidate selection in Ireland (Gallagher 1980). Michael Lewis-Beck, Michael and Tom Rice were the first to look at localism on the national level of a presidential election, testing the true presence of the home state advantage. Not only did they find that there is such a thing, but they also most interestingly found that this has not diminished over time, even with the nationalization of elections and greater ease with which candidates were able to reach voters across the USA (Lewis-Beck and Rice 1983). The local advantage still endures. A myrad of further studies have been conducted on varying levels of elections from local to state wide to nation wide in a fair amount of different countries including Australia, Canada, Britain, Germany Estona, and Norway. The local roots/"friends and neighbors effect" appears has been proven to be far more than just a local phenomenon in one particular part of the world.

The more recent studies have focused on the causes of the friends and neighbors effect instead of just proving its existence. Shaun Bowler Todd Donovan and Joseph Snipp believed the friends and neighbors effect is indirect, coming just out of having more information about candidates due to greater local media coverage for local candidates. Thus, there conclusion were opposed to previous understanding that people use local roots to evaluate candidates. However, they find localism merely comes out of "a voter's proximity to local media sources" and how "knowledge about candidates is distributed" (Bowler, Donovan, and Snipp 1993). Similar results were also found in the UK that "the effects result more from the distribution of information than"from the hometown boy infuence" Key origonally proposed (Johnston et al. 2016). However, nothing has been definitive with studies still showing from surveys responses that voters exhibit "small differences in the ratings of candidates in response to sex, religion, age and education cues but more sizeable effects are apparent for the candidate's occupation and place of residence" (Campbell and Cowley 2013).

Thus, with conflicting evidence, at the time of the paper I am analzying, there was still much unkown about the nature of the friends and neighbors effect that Campbell et al sought to finally answer. Their explanation for the "direct effect of local roots on voter evaluations of a politician" is that "voters rationally use local roots as a low-cost cue for making inferences about a politician's "behavioral localism" (Campbell et al. 2019). This idea of behavioral localism was defined as a politician's willingness to act in the local communities interest (Shugart, Valdini, and Suominen 2005). This comes out of voters believing that candidates with local roots"are more emotionally connected to the constituency and better informed about constituents' needs (Shugart, Valdini, and Suominen 2005). Voters tend to believe local candidates share ideologies, experiences, and will have greater concern for them, thus, they receive the local support out of mere inference. This theory is finally tested in the article I analyze, directly testing whether or not local roots effect is just a filler for lack of other information. They do so by treating voters with behavioral localism information. The quantity measured is the presence as well as the change of magntitude in the friends and neigbors effect when voters are given more information.

4 Paper Review

My replication paper will be looking at Rosie Campbell, Philip Cowley, Nick Vivyan, Markus Wagner's paper, "Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots"[4] published in The Journal of Politics. Whereas the "friends and neigbors" effect has previously been found to arise when there is a lack of information in regard to policy, the only thing voters know is they are local, this article's purpose is to explain the "direct effect of local roots on voter evaluations of a politician" (Campbell et al. 2019). It is the authors belief that voters "use local roots as a low-cost cue for making inferences about a politician's "behavioral localism" (extend to which an elected official acts in the interest of their local consitutients)(Campbell et al. 2019). Their hypothesis is that the power of local roots in decision making for voters is weakened when voters are more informed about their behavioral localism. The authors use survey experiments of made up candidates running for Parliament in the UK rather than performing an observational study on real elections. Thus, they are able to isolate the effects of local roots, ensuring prior knowledege is not a factor. Everyone in the experiment will have the same level of knowledge about each candidate given to them in biographical descriptions through the survey. During real elections, a cofounding variable of the local roots effect is the disproportionate amount of local media coverage for local candidates leading to easier recognition.

Study 1 used a vignette experiment to more generally test whether the presence of information on behavioral localism impacts the effects of local roots while Study 2 gives people a more wide array of information to test whether having greater knowledge of each candidate eliminates the effects of local roots. Study 1 presented a hypothetical election between two candidates, testing how varying levels of behavioral localism information interacts with being a local candidate. The election was between Phillip (the constant), who moved to the area five years ago, and Nick whose localness was subject to change and assigned randomly. The experiment was set up in such a way that respondents were randomly given either no behavioral information or a short description for each candidate. When behavioral information was provided, Nick's behavior also varied between low (spending majority of time on national issues) and high behavioral localism (spending majority of time on local issues) while Phillip always had a constant average behavioral localism (splits time each week between dealing with local issues vs. dealing with national issues). With the information provided, respondants were asked on a scale from 0 to 10 (10 being most satisfied), how satisfied would they be with having each candidate as their elected official. The depedent variable for the model was Nick's score minus Phillip's. The authors modeled this with a least squares regression model and their focus was on the interaction term (being a local candidate and behavioral information presented). The results were that the presence of behavioral information whether positive or negative for Nick does lessen the friends and neighbors effect, agreeing with their hypothesis that local roots is a cue when no other information is provide. However, they found Nick being a local candidate still positively impacts voters as the average treatment effect was positive and significant. The authors thus took a deeper look into this with study 2.

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[4]Replication Paper

In study 2, every respondent was treated with information on behavioral localism, local roots, and other varying characteristics such as gender, political interests, and party. Thus, in contrast to study 1, this will test if the local roots effect is nullfied in the candidate selection process when a wealth of other knowledege is presented to the voters, leaving them without the need to use local roots as a cue for the unknown. Each respondent was given five hypothetical elections with randomly varying attributes, all of which were more specific than in study 1. The respondents were asked to pick wihch candidate they preferred based on information about the localness of the candidates, behavioral localism measured by on how much time is spent on local issues and where the candidates allegiance lies (national party, constituents, or personal views), and other defining characterstics like age, gender, and policy interests. Since study 2 posseses much more and much more varied information on the candidates in question, they analyze the average marginal component effect (AMCE) using an OLS model. This measures the probability of why a candidate is being chosen based on the candidate's particular attribute for each category compared to a baseline. This will present the change in probability of a candidate being preferred broken down by each possible indivual component of their profile. Even here with so much more information, they found the AMCE for being local was positive and one of the most prominent compared to other categories as well as the baseline of not being local. Thus, the authors empirically found local roots to be an important aspect for voter's in candidate selection and it is not merely a cue.

5   Replication

I was able to replicate all the results of the paper. I came across a few errors based on the updating of packages; however, these were easily fixed. I had the most difficulty trying to replicate the aesthetics of the figures and tables, particularly the stargazer table. I was able to replicate all the numerical results; however, the style and formatting were not exactly the same. My main issues were with the formatting of captions and notes after a table or figure. I turned to the bookdown package to handle adding the neccessary captions.

6   Extensions

My immediate question after reading the article was how would the results hold across subsets of the sample population. For study 1, the authors in one of the appendices performed balance and randomization checks to ensure that there is a "distributional balance of four respondent characteristics – gender, age, education and social grade, all measured pretreatment – across the six treatment groups created in the experiment" (Campbell et al. 2019). Since "none of the differences in proportions across treatment groups are bigger than 10% and only a small number are greater than 5%" (Campbell et al. 2019), this presents an excellent opportunity to dive deeper into if the "friends and neighbors" effect is stronger for one subset of the population than others. I hypothesis that there may in fact be differences, especially in regard to age and gender. For example, do the younger people in the study, who may not be as engaged in politics or care how they are represented in Parliament, more often vote for the candidate with local roots. Or even on the opposite end of the spectrum, do the elder people in the study, who have been engrained in their community and care about their representation, vote for the local candidate? Different age groups as well as genders display different preferences in political issues and voting trends, thus, should it be expected that they react to local roots in the same way?

The authors built four different linear regression models to analyze the data from study 1; however, they focused on one for the entire project. They used this particular model to analyze the average treatment effect as well as make predictions.[5] I compared the model they used which included all four of the respondent characterstics variables with the simple model that only included the interaction between local roots and behavioral information, using leave one out cross validation. To perform such an analysis, I needed to utilize

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[5]Repliction Appendix Table A. - They solely used model 4. Differed from the first two as different levels of behavioral information were interacted with the local roots effect whereas the others only interacted with the presence of additional information. Differered from model 3 as model 3 simply looked at the interaction while model 4 included respondent characteristic variables

stan_glm instead of lm as the authors did. I found the model without the extra variables to be only slighlty inferior, meaning these variables were potentially only adding noise..[6] Still wanting to subset the results, I simplified the regression model by excluding the education and social grade variables (Extension Appendix B). I only used this model to test that I would get similar results using stan_glm instead of lm. In figure 3 (Extension Appendix B), the predictions[7] using stan_glm and posterior_linepred mirrored the predictions displayed in figure 1 of the original paper (Replication Appenix B).

In order to look at how local roots affect subsets differently, I interacted the local roots treatment variable with the gender and age group variables. The average local roots treatment effect[8] were slightly different across genders; however, the effect varied signicantly between age groups with the effect being stronger for older voters (Extension Appendix C). For all subgroups, the the effects of local roots on voter evaluations of politicians are reduced when voters receive direct information. However, my findings differ in tha fact that local roots do not always have a significant positive impact. For the youngest category, 18-24, even with no behavioral information provided, the local roots effect is negligible for females. However, contrasting this, the local roots effects are even stronger than those reported in the article for the older members of the sample population. Thus, it should not be assumed that the local roots effect is homogenous with such a wide range of average treatment effects across gender and age subgroups.

To continue my analysis, I also wanted to frame my findings using the context of study 2. With study 2 being a conjoint survey experiment, the best method in which to model such data is OLS. Thus, I compare the local roots effects across genders and age groups by filtering the data prior to running the separe OLS models. Figure 4 shows the results when subsetting by gender and figure 5 shows the results when subsetting by age (Extension Appendix D) . In line with my previous findings, the changes between groups were substantial.The change in probability of a candidate being preferred due to local roots for men was about 1/3 less than that for women. In between age groups, I also saw that older voters showed a much stronger affinite for local roots, while younger voters change in probability was more affected by changes in the levels of behavioral information. From the original study, MPs with any level of local roots were 10% and 13% more likely to be chosen by respondents. From my tests, males showed a lower response of only about a 10% increase for the 20 year as well as grew up in the area levels of local roots whereas the effect on females exceeded 15 %. The results between the age groups were much more varied and there was not a distinct trend in the older a voter is the more likely they will chose a candidate based on local roots. However, all the results agreed with those of the original article in that the magnitude of the local roots effect is consistantly amongst the largest across all the attributes.

Thus, I got mixed results in comparison to those documented in the original article as well as between my two different extensions. The conclusion that the presence of behavioral information negatively impacts the magnitude of the local roots effect is consistent across all my findings. However, the conclusion that local roots have a positive and significant effect do not hold constant across subsets of the population. The treatment effect of local roots varied substantially across age subgroups from the study 1 data, ranging from being not significant for the younger groups to being even large than the average treatment effect presented in the article. However, interestingly, the results of for my extension of study 2 showed opposite findings. Here, the difference in the average marginal component effect for females was greater than for males, while the differences across age subsets were smaller. Thus, there are definitely differences in the local roots effect and it cannot be assumed to be held constant across the entire electorate. More research should be performed directly on why local roots effect males vs. females as well as older vs. younger voters.

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[6]Extension Appendix A for full results of the loo comparison

[7]Predictions for Nick minus Phill's scores analyzed at the modal value of each category (females, aged 25-49)

[8]Since I am using stan_glm and posterior_linpred, the regression models as well as predictions are based off of thousands of simulations. Thus, I chose to use the median and mad instead of mean and standard deviation as they ar emore stable with simulated results.

7 Replication Appendix

7.1 A.

Table 1: Relative Ratings of MP Nick by Local Roots and Behavioral Information Treatments in Study

	Conditioning Effect of Any Behavioral Localism Information		Separate Conditioning Effects for High and Low Behavioral Localism	
	(1)	(2)	(3)	(4)
Intercept	−0.412*** (0.057)	−0.661*** (0.128)	−0.412*** (0.057)	−0.664*** (0.125)
Local roots	0.755*** (0.080)	0.759*** (0.080)	0.755*** (0.080)	0.758*** (0.080)
Behavioral localism information	0.683*** (0.078)	0.691*** (0.079)		
Behavioral localism: High (vs. no info)			1.395*** (0.098)	1.402*** (0.098)
Behavioral localism: Low (vs. no info)			−0.007 (0.085)	−0.0002 (0.086)
Local roots X Behavioral info.	−0.253** (0.110)	−0.257** (0.110)		
Local roots X High behavioral localism			−0.311** (0.140)	−0.311** (0.139)
Local roots X Low behavioral localism			−0.233* (0.119)	−0.238** (0.119)
Controls for voter characteristics?	No	Yes	No	Yes
Observations	5,203	5,203	5,203	5,203
R^2	0.036	0.046	0.107	0.116
Adjusted R^2	0.036	0.044	0.106	0.114

All models estimated via ordinary least squares. Dependent variable is respondent relative rating of MP Nick (the 0–10 rating of Nick minus that of Philip). Robust standard errors in parentheses. N = 5,203. * p <= .1.,** p <= .05., *** p < .01.

*p<0.1; **p<0.05; ***p<0.01

7.2   B.

(a) Predicted relative rating

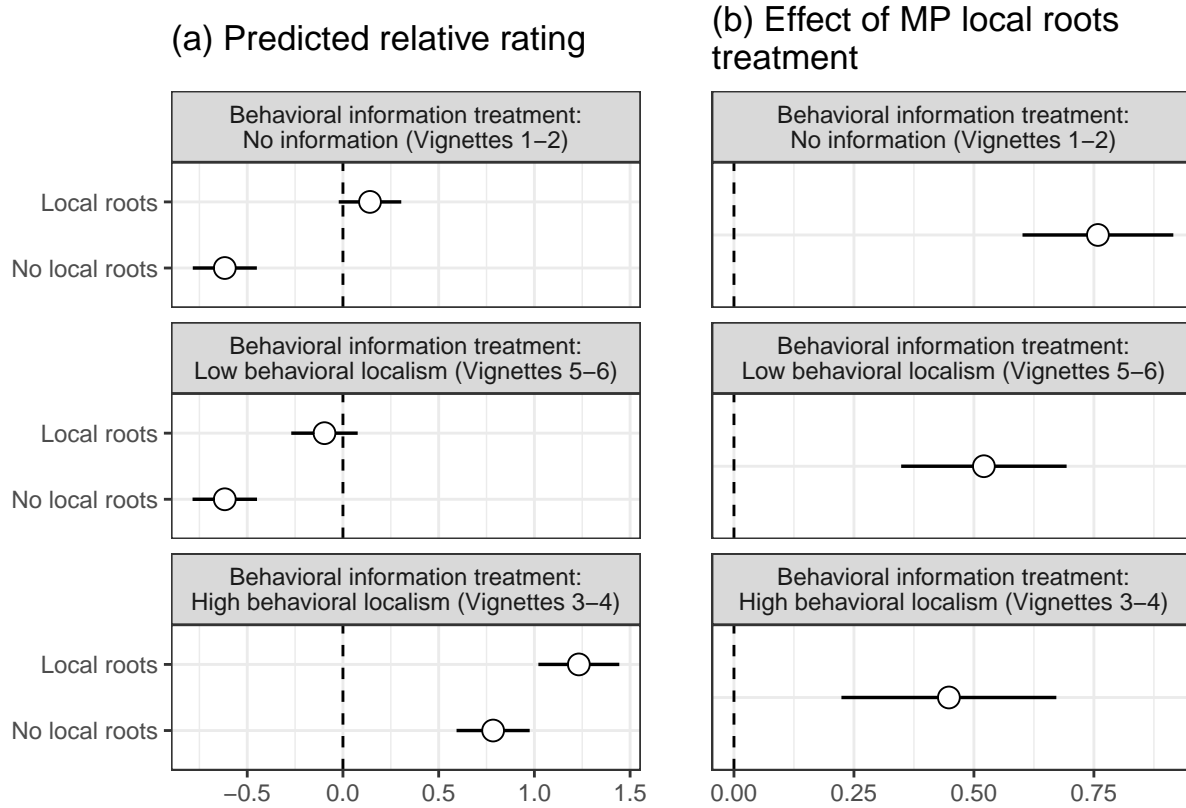### (b) Effect of MP local roots treatment

Figure 1: Effects of local roots conditional on behavioral information treatments (study 1). A, Predicted relative rating of MP Nick (MP Nick rating minus MP Philip rating) as the MP local roots treatment varies, with all control variables held constant at their modal value in the sample. Top, predicted values when respondents receive no information about MP behavioral localism. Middle, predicted values when respondents receive information about MP behavioral localism and Nick is revealed to be low in behavioral localism. Bottom, predicted values when respondents receive information about MP behavioral localism and Nick is revealed to be high in behavioral localism. For each of the same behavioral localism conditions, B show the estimated treatment effect of MP Nick having local roots. Estimates are calculated from model 4 in table 2. Open circles indicate point estimates. Lines denote 95% confidence intervals.
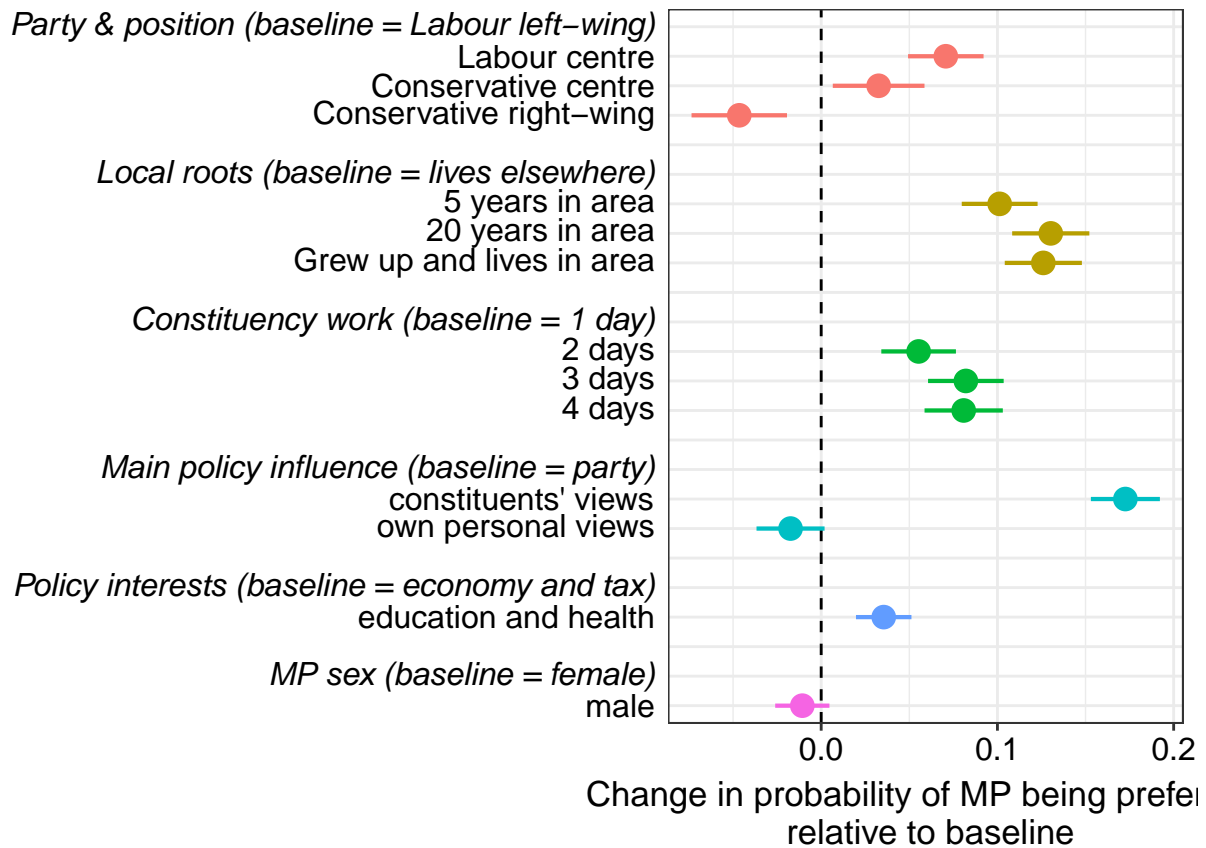
8 C.

Figure 2: Estimated average marginal component effects of each MP attribute level compared to the baseline level of the attribute, estimated via ordinary least squares regression, with standard errors clustered by respondent. Bars show 95% confidence intervals.

9 Extension Appendix

9.1 A.

```
## stan_glm
##  family:       gaussian [identity]
##  formula:      nickminusphil ~ localtreat * behtreat
##  observations: 5203
##  predictors:   6
## ------
##                                                 Median MAD_SD
## (Intercept)                                     -0.41   0.07
## localtreatLocal roots                            0.76   0.09
## behtreatConst. focus                             1.39   0.10
## behtreatWestmin. focus                           0.00   0.10
## localtreatLocal roots:behtreatConst. focus      -0.31   0.14
## localtreatLocal roots:behtreatWestmin. focus    -0.24   0.13
##
## Auxiliary parameter(s):
##       Median MAD_SD
## sigma 1.99   0.02
##
## ------
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg


## stan_glm
##  family:       gaussian [identity]
##  formula:      nickminusphil ~ localtreat * behtreat + gender + agegrp + socgrade +
##     qual
##  observations: 5203
##  predictors:   16
## ------
##                                                 Median MAD_SD
## (Intercept)                                     -0.66   0.13
## localtreatLocal roots                            0.75   0.10
## behtreatConst. focus                             1.40   0.10
## behtreatWestmin. focus                           0.00   0.09
## genderMale                                      -0.14   0.05
## agegrp25-49                                      0.16   0.10
## agegrp50-64                                      0.42   0.10
## agegrp65+                                        0.51   0.11
## socgradeC2                                       0.08   0.09
## socgradeC1                                       0.06   0.08
## socgradeAB                                       0.01   0.08
## qualLevel 1/2                                    0.04   0.08
## qualLevel 3                                      0.11   0.08
## qualLevel 4                                     -0.13   0.08
## localtreatLocal roots:behtreatConst. focus      -0.30   0.13
## localtreatLocal roots:behtreatWestmin. focus    -0.23   0.13
##
## Auxiliary parameter(s):
##       Median MAD_SD
```

```
## sigma 1.98   0.02
##
## ------
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg


## stan_glm
##  family:       gaussian [identity]
##  formula:      nickminusphil ~ localtreat * behtreat + agegrp + gender
##  observations: 5203
##  predictors:   10
## ------
##                                               Median MAD_SD
## (Intercept)                                   -0.60  0.11
## localtreatLocal roots                          0.76  0.10
## behtreatConst. focus                           1.40  0.09
## behtreatWestmin. focus                         0.00  0.10
## agegrp25-49                                    0.10  0.09
## agegrp50-64                                    0.39  0.10
## agegrp65+                                      0.47  0.10
## genderMale                                    -0.14  0.05
## localtreatLocal roots:behtreatConst. focus    -0.32  0.13
## localtreatLocal roots:behtreatWestmin. focus -0.24  0.13
##
## Auxiliary parameter(s):
##        Median MAD_SD
## sigma 1.98   0.02
##
## ------
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg
```
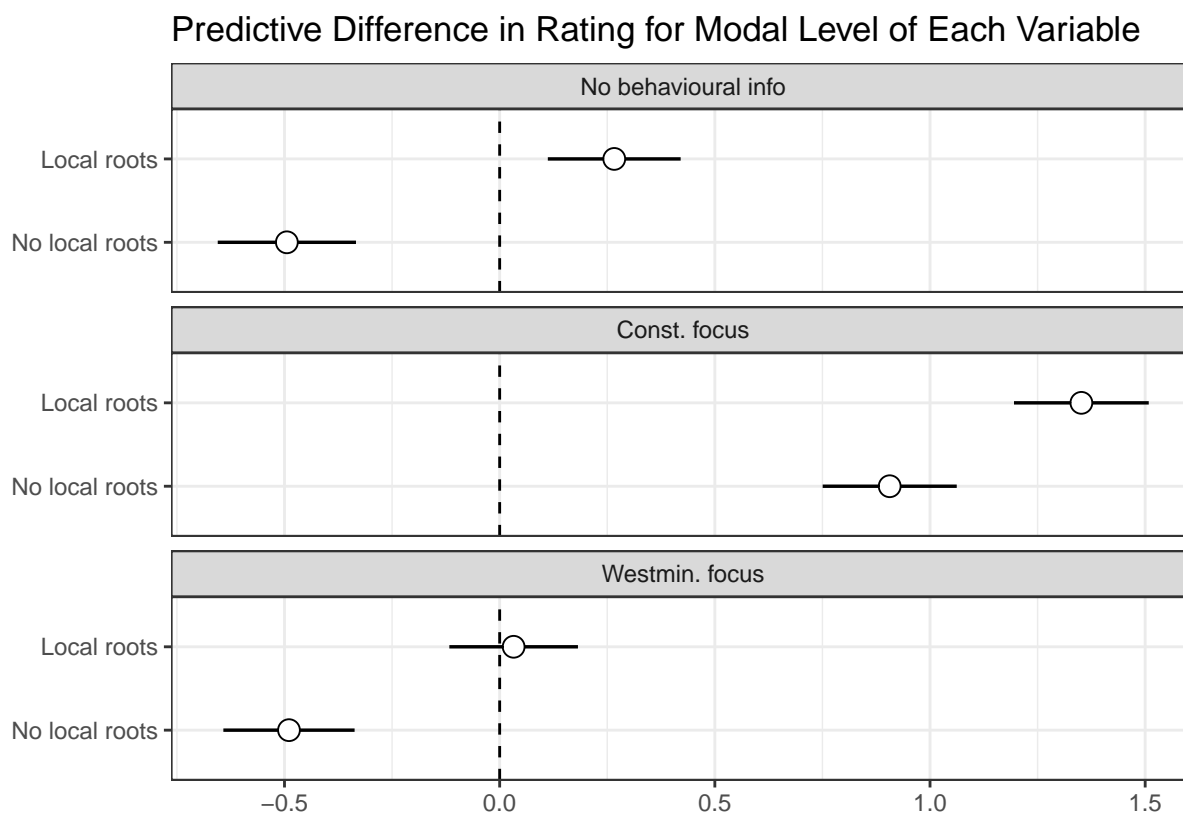
9.2 B.

Figure 3: Presented is the predictions for the nick minus phil ratings for the modal value of each category in the datset, comparing the results between local and no local roots.. This is a method that the authors use and the modal values are a women age 25-49. The purpose of the graphic is to ensure I get similar results when I use stan_glm instead of lm as well as if I get similar predictions taking out the education and socail grade variables. The predictions are concurrent with those found in the orignal paper and we are able to see the diminishing effect of local roots when behavioral information is present.

9.3   C.

```
## stan_glm
##  family:       gaussian [identity]
##  formula:      nickminusphil ~ localtreat * (behtreat + gender * agegrp)
##  observations: 5203
##  predictors:   20
## ------
##                                                    Median MAD_SD
## (Intercept)                                        -0.197  0.161
## localtreatLocal roots                               0.135  0.221
## behtreatConst. focus                                1.405  0.094
## behtreatWestmin. focus                             -0.007  0.096
## genderMale                                         -0.389  0.244
## agegrp25-49                                        -0.345  0.168
## agegrp50-64                                        -0.204  0.185
## agegrp65+                                           0.129  0.193
## genderMale:agegrp25-49                              0.487  0.270
## genderMale:agegrp50-64                              0.392  0.286
## genderMale:agegrp65+                               -0.094  0.290
## localtreatLocal roots:behtreatConst. focus         -0.321  0.137
## localtreatLocal roots:behtreatWestmin. focus       -0.226  0.136
## localtreatLocal roots:genderMale                    0.207  0.332
## localtreatLocal roots:agegrp25-49                   0.604  0.236
## localtreatLocal roots:agegrp50-64                   0.985  0.252
## localtreatLocal roots:agegrp65+                     0.705  0.263
## localtreatLocal roots:genderMale:agegrp25-49       -0.423  0.371
## localtreatLocal roots:genderMale:agegrp50-64       -0.465  0.392
## localtreatLocal roots:genderMale:agegrp65+          0.056  0.392
##
## Auxiliary parameter(s):
##       Median MAD_SD
## sigma 1.981  0.020
##
## ------
## * For help interpreting the printed output see ?print.stanreg
## * For info on the priors used see ?prior_summary.stanreg
```

Average Treatment Effect of Local Roots Across Gender and Age Subsets
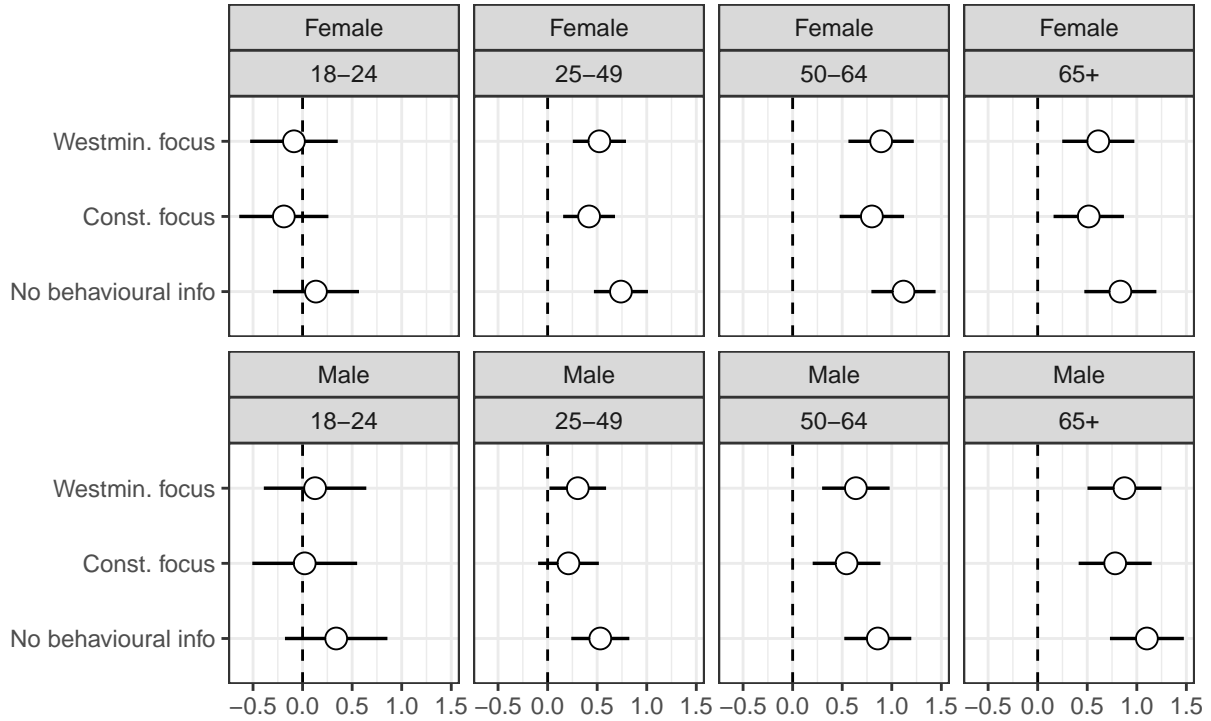

Figure 4: Shows the estimated treatment effect of MP Nick having local roots faceted by age and gender. Estimates are calculated from stan_m7. Open circles indicate point estimates. Lines denote 95% confidence intervals. There are considerable differences in the treatment effects between the various subgroups. The reported average treatment effect is 0.7 for no information. This figure shows that the average treatment effect varies in both directions for the subgroups. When no behavioral information is present, the local roots effect ranges from 0.13 (Females 18-24) to 1.16 (Female 50-64). We can also see the diminishing effect when behavioral information is included as the highest effect across subgroups for Constituent focus is 0.8 while for Westminster focus is 0.9. Between genders, there does not appear to be signficant differences; however, for both Males and Females the older age groups have much larger local roots effects.
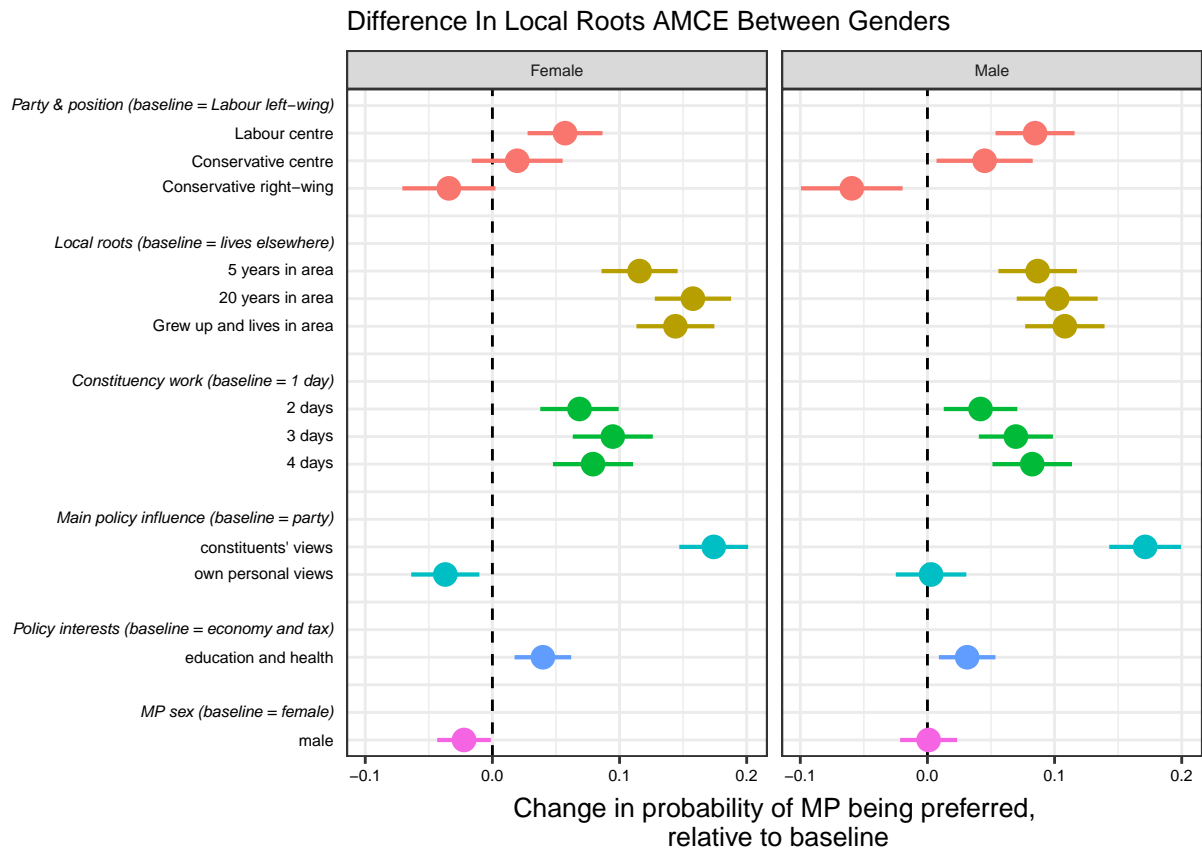
10　D.

Figure 5: Estimated average marginal component effects of each MP attribute level compared to the baseline level of the attribute. In contrast to the original article, I subset the data by gender. Males pay slightly less attention to local roots than females. From the original study, MPs with any level of local roots were 10% and 13% more likely to be chosen by respondents. From my tests, males showed a lower response of only about a 10% increase for the 20 year as well as grew up in the area levels of local roots whereas the effect on females exceeded 15 %. The change in probability of a candidate being preferred due to local roots for men was about 1/3 less than that for women.
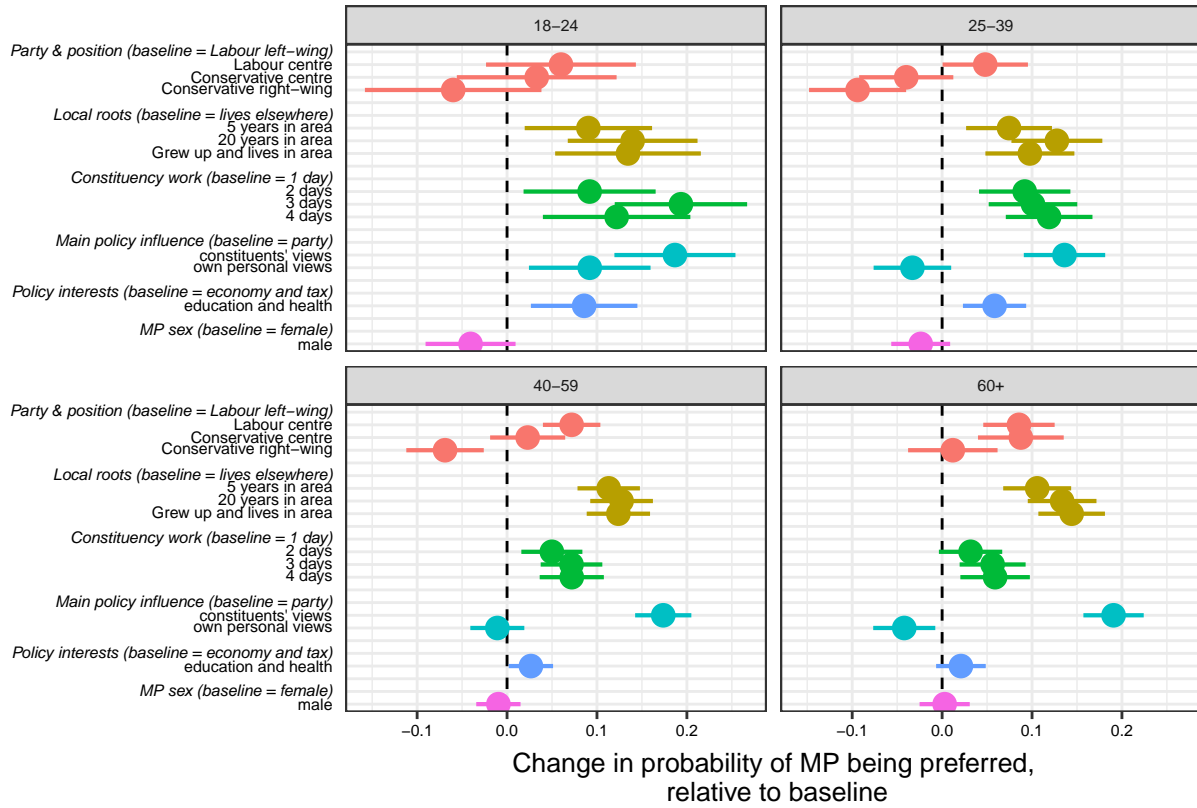
Figure 6: Estimated average marginal component effects of each MP attribute level compared to the baseline level of the attribute. In contrast to the original article, I subset the data by age. The results between the age groups were much more varied and there was not a distinct trend in the older a voter is the more likely they will chose a candidate based on local roots. All the results agreed with those of the first article in that the magnitude of the local roots effect is constistanlty amongst the largest across all the attributes

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