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

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Abstract

Campbell et al. (2019) details two separate studies which bolster the cue-based hypothesis of local roots. I successfully replicated all of their results. For my extension, with the first study, I used a Bayesian approach and found a negligible difference but did find heterogeneous effects based upon social class. With the second study, I looked at the interaction between the components and the respondent age groups as well as interaction between the components themselves where I found 18-24 year-olds being less critical of personal views influencing a member of Parliament's policy than their older counterparts and local roots downplaying the negative impact of the trustee model of representation on voter preference.

Introduction

Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots by Rosie Campbell, Philip Cowley, Nick Vivyan, and Markus Wagner in *The Journal of Politics* aims to answer the driving question of, "Why do politicians with strong local roots receive more electoral support?" by running and analyzing two separate studies. The first study uses a "paired profiles factorial vignette design" by asking respondents to rate pairs of hypothetical members of Parliament. The hypothetical members have varying levels of local roots as well as varying levels of "behavioral localism"—if they focus on local or national issues. In the second study,"a conjoint survey experiment," respondents again considered two hypothetical MPs with varying levels of local roots and behavioral localism but had to choose between them. A variable signaling if an MP was chosen or not was regressed against all of the components to determine their average marginal component effects (AMCE)—in other words, the change in probability of an MP being chosen. The first study followed their hypothesis that, "the effects of local roots on voter evaluations of politicians are reduced when voters receive direct information concerning behaviors about which they might otherwise use local roots as a cue." The second study, "showed that even if voters are provided with a rich array of information about politicians' behavior and ideological positioning, the effect of local roots remained positive and notable," confirming the more simplistic first study.

Using R, I was able to replicate all of Campbell et al. (2019). All of the code needed to do the same can be found within the Appendix. The original code can be found in the *The Journal of Politics* Dataverse.[1] All of my code for this paper including the extension is available in my Github repository.[2]

After being able to replicate all of the results from Campbell et al. (2019). Next, in order to bolster their work and find interesting patterns nestled within the data, I delved into their models. With the first study, I used the Bayesian stan_glm instead of frequentist lm for the four models. Ultimately I found a negligible difference. I also looked at the heterogeneity of the treatment effect based upon social class. I found a notable difference between the unskilled working class and the other classes. With the second study, I looked at the interaction between the components and the respondent age groups where I found 18-24 year-olds being less critical of personal views influencing an MP's policy than their older counterparts. I also added an interaction term between local roots and policy influence to the model which aids the cue-based hypothesis in Campbell et al. (2019).

[1] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/C15VOD

[2] https://github.com/SamuelLowry/why_friends_and_neighbors_replication_paper.git

Literature Review

Due to Campbell et al. (2019) being a very recent article, published May 6, 2019, there has not been any follow-up scholarly work on the topic even from the authors themselves. Nevertheless, Campbell et al. (2019) builds off of a rich history of the "friends and neighbors" effect which was first coined by Valdimer Key in his book *Southern Politics*. Key (1949) noted how candidates, "gain support, not primarily for what he stands for or because of his capacities, but because of where he lives."[3] Tatalovich (1975) found the same effect in Mississipi. Across the pond, Gallagher (1980) depicts how the friends and neighbors effect applies to Irish politics. Three years later, Lewis-Beck and Rice (1983) looked at the effect in terms of the home state advantage during presidential elections.

Relevant work referenced in Campbell et al. (2019) includes Bowler, Donovan, and Snipp. (1993) which highlights how the friends and neighbors effect could be due to access to more information about local candidates. Nevertheless, Campbell and Cowley (2014) found that, "voters still tend to prefer politicians with local roots to those without, even when presented with the same amount of information about both."[4] Campbell et al. (2019) comes into play after the suggestion of many such as Gimpel et al. (2008) to look into the cue-based mechanism behind the friends and neighbors effect.

Paper Review

Campbell et al. (2019) aims to answer the driving question of, "Why do politicians with strong local roots receive more electoral support?" by running and analyzing two separate studies. The first study uses a "paired profiles factorial vignette design" by asking respondents to rate pairs of hypothetical MP on a scale from 0-10. The hypothetical members, named Nick and Philip, have varying levels of local roots as well as varying levels of "behavioral localism"—if they focus on local or national issues. Philip's score was then subtracted

[3]Quoted in Campbell et al. (2019)

[4]Quote from page 938 of Campbell et al. (2019). It is the authors' summary of their own work, so I thought that it would beat any summary I came up with.

from Nick's score, as Nick always had local roots. Nick's resulting relative score was then used as the dependent variable in the models. In the second study,"a conjoint survey experiment," respondents again considered two hypothetical MPs with varying levels of local roots and behavioral localism but had to choose between them. In this case, though, more components were added in order to see if something other than localism was at play. The total list includes party, level of local roots, days a week focused on constituency work, policy influence, and policy focus. A variable signaling if an MP was chosen or not was regressed against all of the components to determine their AMCE—in other words, the change in probability of an MP being chosen. A plethora of further information on conjoint analysis can be found in Hainmueller, Hopkins, and Yamamoto (2014), but all in all it allows for the inference of causal relationships.

The first study followed their hypothesis that, "the effects of local roots on voter evaluations of politicians are reduced when voters receive direct information concerning behaviors about which they might otherwise use local roots as a cue." In other words, behavioral localism matters more to people than local roots. Therefore it takes precedent over local roots when it comes to voter preferences. Local roots are merely a cue. The second study, "showed that even if voters are provided with a rich array of information about politicians' behavior and ideological positioning, the effect of local roots remained positive and notable," confirming the more simplistic first study. In addition, it showed a resounding preference for MPs being influenced by constituents over personal views.

Replication

Using R, I was able to replicate all of Campbell et al. (2019). All of the code needed to do the same can be found within the Appendix. The original code can be found in the *The Journal of Politics* Dataverse.[5] All of my code for this paper including the extension is available in my Github repository.[6]

[5] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/C15VOD
[6] https://github.com/SamuelLowry/why_friends_and_neighbors_replication_paper.git

Extension

I was able to replicate all of the results from Campbell et al. (2019). Next, in order to bolster their work and find interesting patterns nestled within the data, I delved into their models. Ultimately, I deemed the following four worthy enough to write about—two per study.

Study 1

1. Using the Bayesian stan_glm instead of frequentist lm for the four models
2. Looking at the heterogeneity of the treatment effect based upon social class

Study 2

1. Looking at the interaction between the components and the respondent age groups
2. Adding an interaction term between local roots and policy influence to the model

Study 1

In Table 1, the four models from the first study were created using the Bayesian stan_glm function from the rstanarm package[7] instead of the traditional, frequentist lm function used in Campbell et al. (2019). Stan_glm allows for the use of priors, but in this case they are not used. While stan_glm uses a Gaussian process in order to construct its models, due to not including a prior, the difference between the coefficients is practically nonexistent.[8] There is a difference, though, between the standard errors. Campbell et al. (2019) uses "robust standard errors". In this case, they used the vcovHC function from the sandwich package[9]. VcovHC calculates heteroscedasticity consistent standard errors. As described in Long and Ervin (2000), "heteroscedasticity occurs when the variance of the errors varies across observations." In an ordinary least squares regression, this can lead to bias due to differing variance across different groups. VcocHC seeks to account for this difference leading to "robust", unbiased standard errors. Stan_glm on the other hand outputs median absolute

[7] https://cran.r-project.org/web/packages/rstanarm/index.html
[8] Compare Table 1 to Table 2 in the Appendix
[9] https://cran.r-project.org/web/packages/sandwich/sandwich.pdf

Table 1: Bayesian Generalized Linear Models Instead of Linear Models

	(1)	(2)	(3)	(4)
Intercept	-0.412 (0.068)	-0.660 (0.139)	-0.411 (0.067)	-0.660 (0.131)
Has Local Roots	0.755 (0.095)	0.757 (0.097)	0.754 (0.093)	0.761 (0.097)
Behavioral Info Given	0.683 (0.083)	0.691 (0.084)		
Treatment Interaction	-0.254 (0.120)	-0.256 (0.119)		
Male		-0.136 (0.057)		-0.141 (0.054)
25-49		0.148 (0.097)		0.161 (0.093)
50-64		0.440 (0.103)		0.419 (0.103)
65+		0.504 (0.110)		0.508 (0.104)
Skilled Working Class		0.031 (0.093)		0.082 (0.091)
Lower Middle Class		0.046 (0.081)		0.058 (0.077)
Middle Class		0.003 (0.083)		0.012 (0.079)
GCSE		0.046 (0.086)		0.044 (0.080)
A Levels		0.121 (0.090)		0.109 (0.087)
University		-0.104 (0.074)		-0.130 (0.079)
Constituency Focus			1.397 (0.097)	1.402 (0.096)
National Focus			-0.007 (0.095)	0.003 (0.095)
Local:Constituency			-0.311 (0.134)	-0.316 (0.135)
Local:National			-0.231 (0.136)	-0.240 (0.135)
nobs	5203	5203	5203	5203
algorithm	sampling	sampling	sampling	sampling
pss	4000.000	4000.000	4000.000	4000.000
nobs.1	5203.000	5203.000	5203.000	5203.000
sigma	2.068	2.060	1.992	1.983

Table 1: Here stan_glm is used to construct the models instead of lm. The difference between the coefficients is negligible. The standard errors are slightly larger, though, due to stan_glm outputting MAD SD. The dependent variable is the relative rating of Nick compared to Philip.

deviation (MAD SD) in the standard error parentheses. In order to get the MAD SD, the median absolute deviation is scaled by 1.483 which, according to Gelman, Hill, and Vehtari (2020), "reproduces the standard error in the special case of a the normal distribution". Gelman, Hill, and Vehtari (2020) describes MAD SD as a, "more stable measure of variation."[10] In both cases, the standard errors are more robust than the traditional standard error. Nevertheless, the MAD SD tends to be larger than the robust standard error used in Campbell et al. (2019). All in all, the difference between the use of lm and stan_glm in this case is largely negligible.

In Figure 1, stan_glm was used to create four models from subsets of the data based upon

[10] See page 67 of Gelman, Hill, and Vehtari (2020) for more details

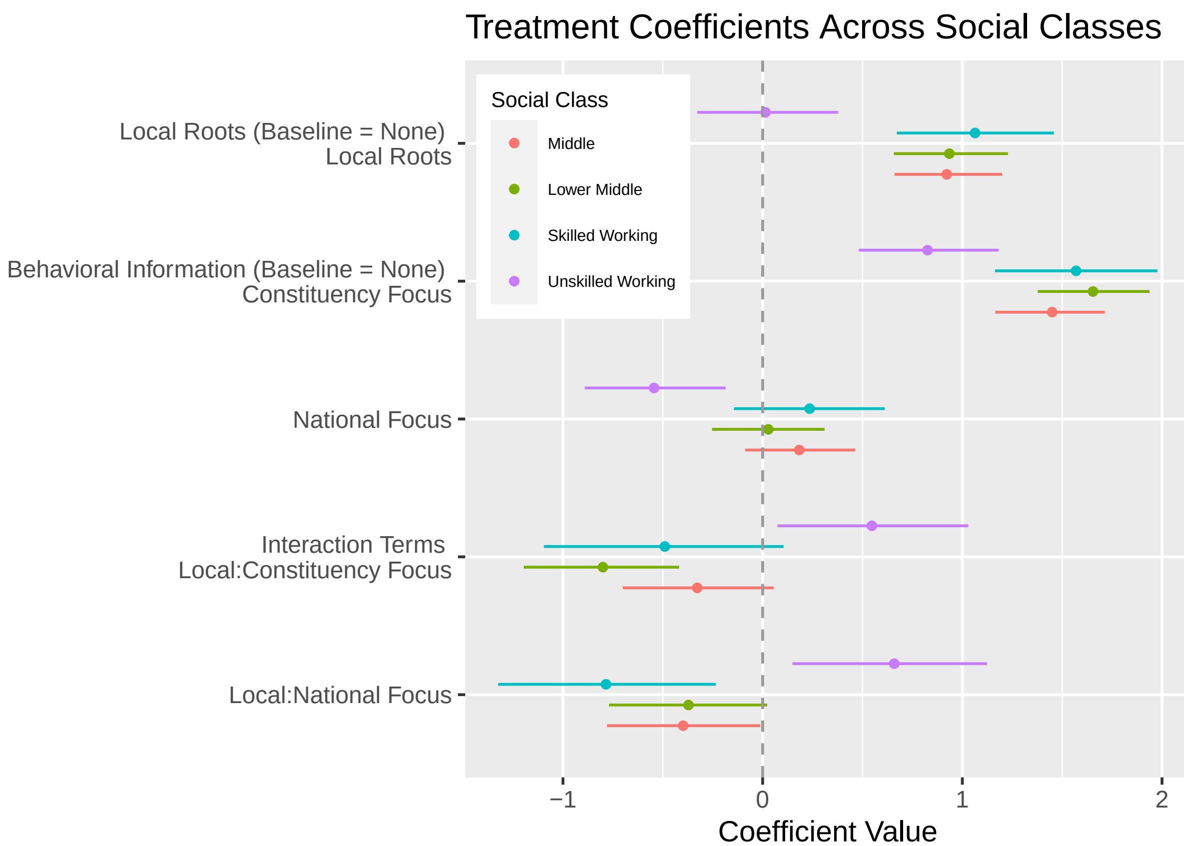

Figure 1: Stan_glm model of the interaction between the treatment effects by social class. The lines denote 95% credible intervals. The treatments affect the unskilled working class in a notably different manner.

the NRS social grade of the respondents[11] in order to discover heterogeneous effects. The unskilled working class stands out from the rest. The local roots treatment does not definitively positively impact their rating of Nick unlike the other classes. In addition, while the other classes are not definitively deterred by behavior indicative of a national focus, the unskilled working class is. Nevertheless, the median constituency focus coefficient is notably lower for the unskilled working class than the other classes. Thus, the unskilled working class more so rejects a focus on national policies than endorses a focus on local politics compared to the other classes. The interaction terms are also different. For both the local roots constituency focus group and the local roots national focus group the slope is larger for the unskilled working class unlike the other classes—granted, the 95% credible just peeks over zero for some of the other classes.[12] The treatment effects are notably different by class.

Study 2

In Figure 2, the AMCE from the second study are depicted amongst subsets of respondent age. Hainmueller, Hopkins, and Yamamoto (2014), the landmark paper on conjoint analysis, outlines two types of interaction within conjoint studies. The first involves two components interacting. The second involves a component interacting with respondent attributes. Here, the latter is occurring, as seen by the notable difference between the age groups in the component effect of personal views being a policy influence. For all age groups except 18-24 year-olds, the AMCE is negative—granted, the 95% confidence interval crosses zero for both 40-59 year-olds and the 60+ group. The 18-24 year-old respondents were definitively swayed in their selection an MP by personal views having an influence on the MP's politics, as the 95% confidence interval does not cross zero. This is especially interesting because policy influence between personal views and constituents' views elicits the greatest difference amongst the AMCE when all respondents are analyzed together.[13]

In Figure 3, the average component interaction effects (ACIE) between local roots and policy influence are shown in addition to the AMCE depicted in Campbell et al. (2019). In regard to

[11] AB = Middle, C1 = Lower Middle, C2 = Skilled Working, DE = Unskilled Working
[12] See page 128-129 of Gelman, Hill, and Vehtari (2020) for further information on interaction
[13] See Figure 3

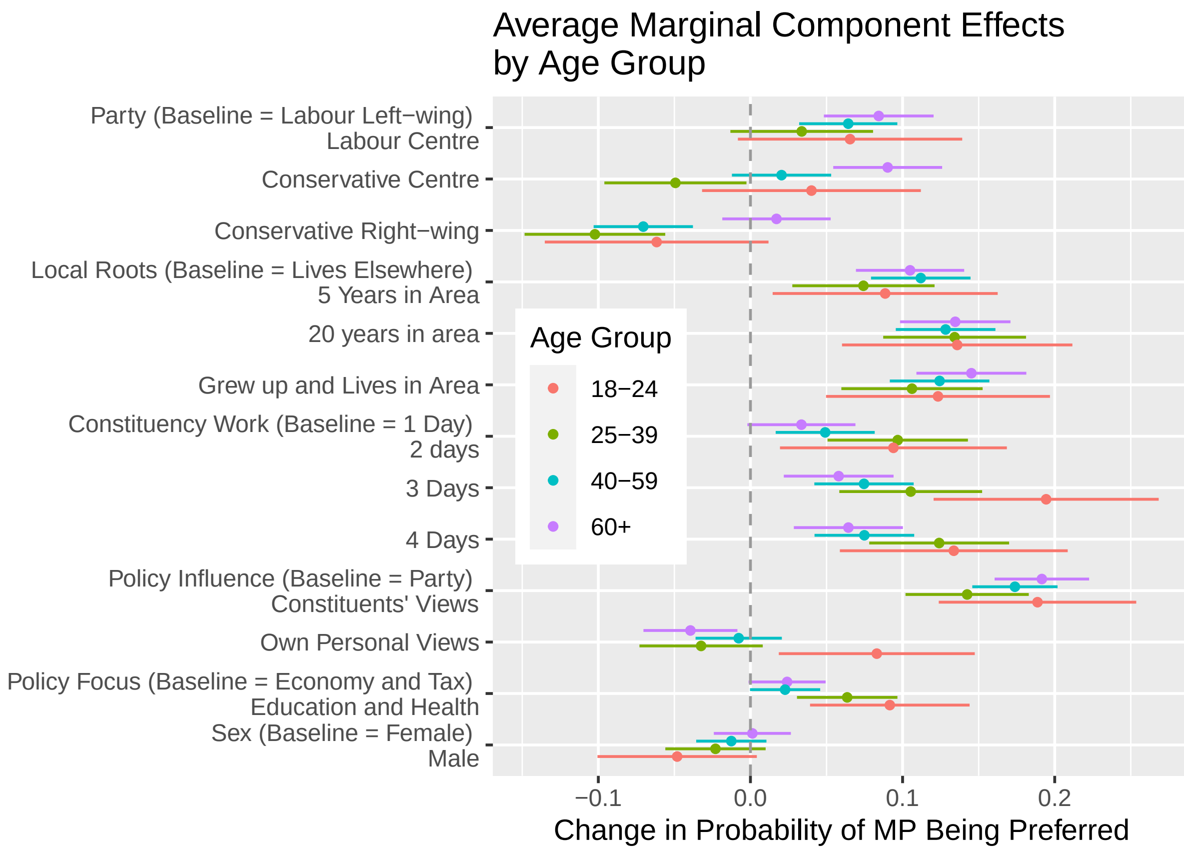

Figure 2: The average marginal component effects from the second study depicted amongst subsets of respondent age. Lines denote a 95% confidence interval. There is a notable difference amongst 18-24 year-olds in regard to personal views influencing an MP's policies.

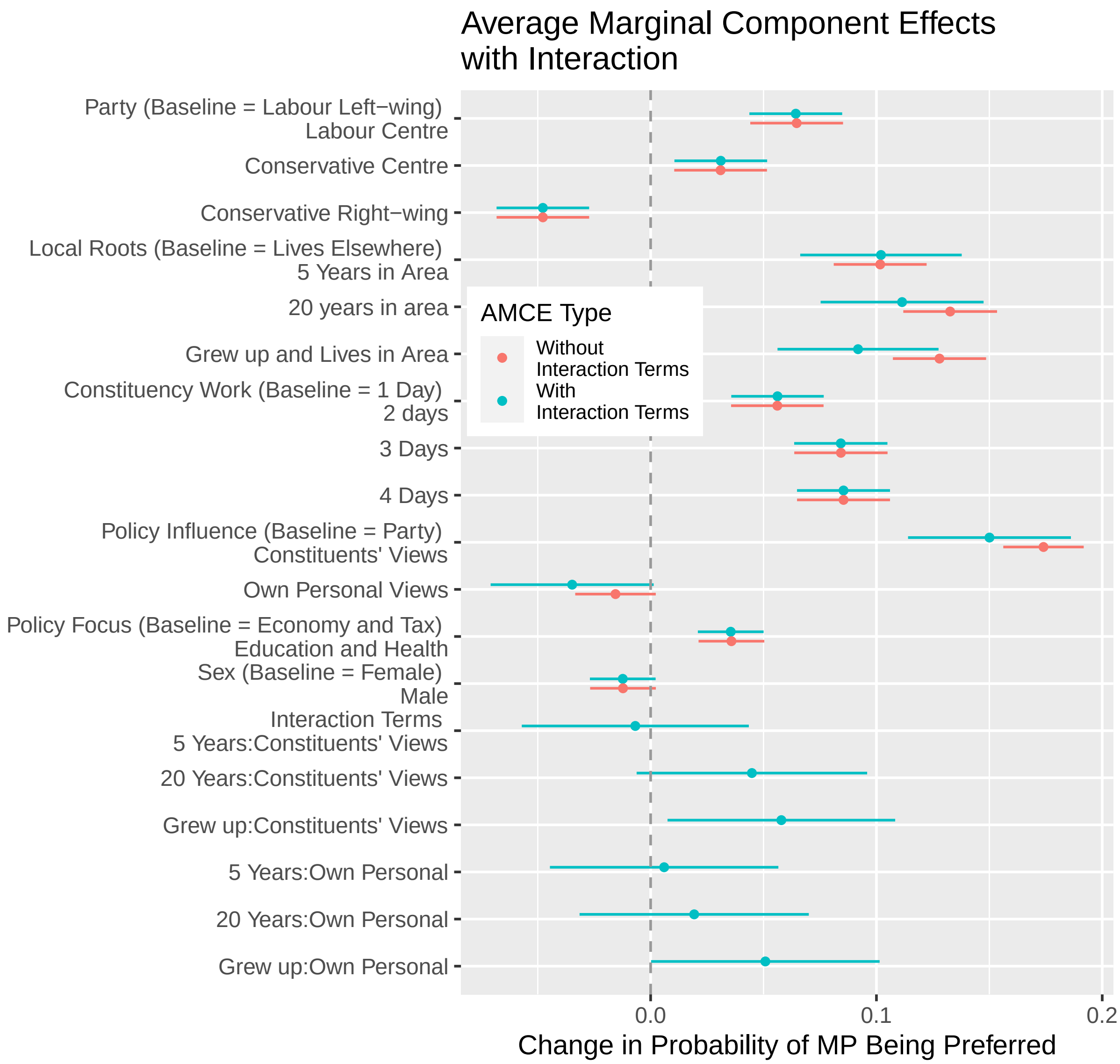

Figure 3: The average marginal component effects from the second study with and without interaction between local roots and policy influence. Lines denote a 95% confidence interval. The average component interaction effects demonstrate how local roots can downplay the negative impact of personal views influencing policy.

Hainmueller, Hopkins, and Yamamoto (2014), the first type of interaction is seen here. The ACIE display how local roots in part negate the negative effect of personal views influencing policy. The interaction term for the MPs that grew up and live in the area and that allow constituents to influence policy and the interaction term for MPs that grew up and live in the area and that allow their own personal views influence policy are both positive and significant at a 95% confidence level. In other words, local roots, the subject of Campbell et al. (2019), excuses what is otherwise seen as undesirable. Nevertheless, it may not be a case of excusing what respondents otherwise see as bad. Instead, respondents could claim that they trust an MP's personal views more if they are from the same area.

Conclusion

In conclusion, I was able to replicate all of Campbell et al. (2019). Then I delved into their models. The use of stan_glm instead of lm within the first study is largely negligible. The heterogeneity of the treatment effect based upon social class, on the other hand, exposed a firm rejection of the trustee model by the unskilled working class. It also depicted their difference in regard to the interaction terms. With the second study, the interaction between the components and the respondent age groups exposed the fact that 18-24 year-olds are less critical of personal views influencing an MP's policy than their older counterparts. In addition, the interaction term between local roots and policy influence supports the cue-based hypothesis from Campbell et al. (2019). Even when an MP was serving in a trustee model, that was slightly overlooked due to local roots. It is quite possible that local roots acted as a cue to the respondents allowing them to be more likely to trust MPs whose policy is influenced by their own views.

Ultimately, my extension of Campbell et al. (2019) does not contradict their findings but instead bolsters them. Granted, it did find some heterogeneous effects. Thus, we rely on local roots when other information is missing, or we view it as a lens that can excuse the trustee model of representation. Campbell et al. (2019) focuses mostly on behavioral localism and not the motivation behind that behavior. Therefore, more research could be done in order to determine the relationship between the trustee model of representation and local roots.

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Appendix of Replicated Graphics

I was able to replicate Table 2, Figure 1, and Figure 3 from Campbell et al. (2019). I was unable to replicate Table 1 and Figure 2 because they were not data related. They were merely visualizations displaying content about methods and experimental design. Table 1 depicts written descriptions of the hypothetical MPs present to subject. Figure 2 depicts a screenshot of the survey. The replicated table and figures are below.

Table 2

	(1)	(2)	(3)	(4)
Intercept	-0.412^{***}	-0.661^{***}	-0.412^{***}	-0.664^{***}
	(0.057)	(0.128)	(0.057)	(0.125)
Local roots	0.755^{***}	0.759^{***}	0.755^{***}	0.758^{***}
	(0.080)	(0.080)	(0.080)	(0.080)
Behavioral localism information	0.683^{***}	0.691^{***}		
	(0.078)	(0.079)		
Behavioral localism: High (vs. no info)			1.395^{***}	1.402^{***}
			(0.098)	(0.098)
Behavioral localism: Low (vs. no info)			-0.007	-0.0002
			(0.085)	(0.086)
Local roots X Behavioral info.	-0.253^{**}	-0.257^{**}		
	(0.110)	(0.110)		
Local roots X High behavioral localism			-0.311^{**}	-0.311^{**}
			(0.140)	(0.139)
Local roots X Low behavioral localism			-0.233^{*}	-0.238^{**}
			(0.119)	(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

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Caption from Campbell et al. (2019): "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."

Figure 1

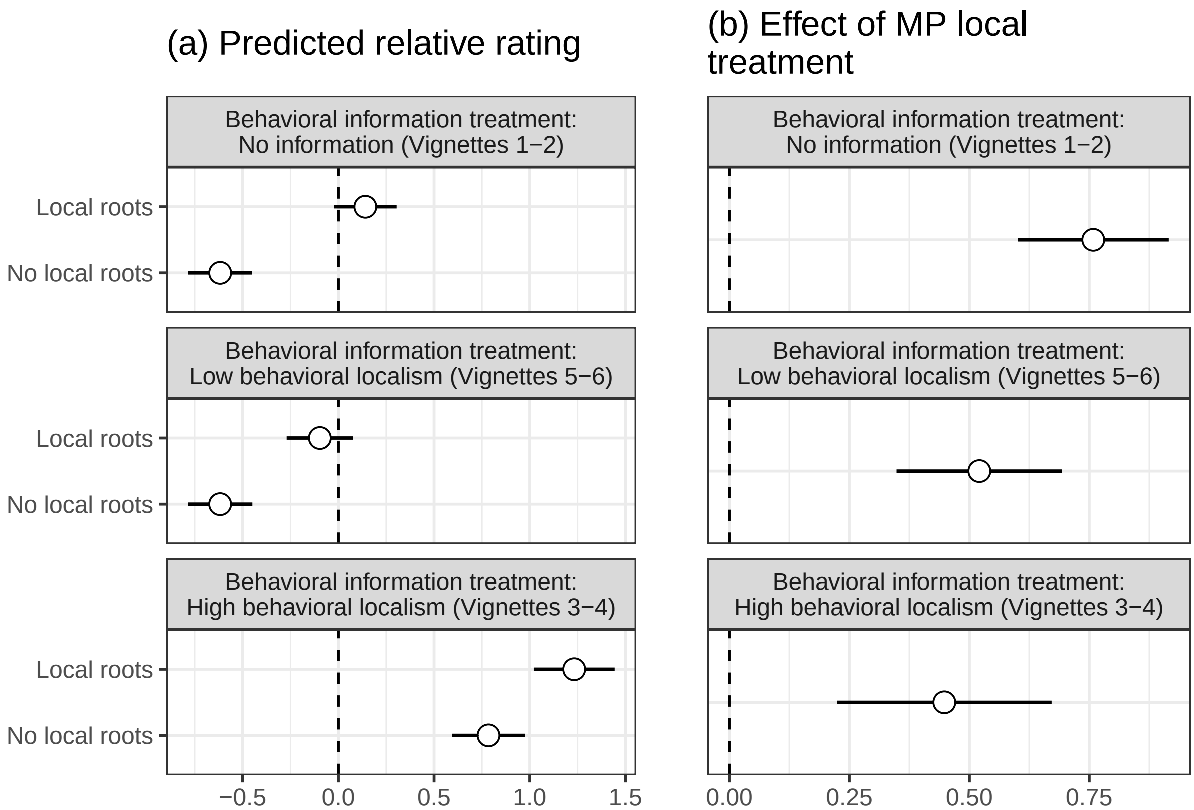

Figure 1. Effects of local roots conditional on behavioral information treatments (study 1). A, Predicted relative rating of MP Nick (MP Nick rating minus MP Philip rating) as the MP local roots treatment varies, with all control variables held constant at their modal value in the sample. Top, predicted 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.

Figure 3

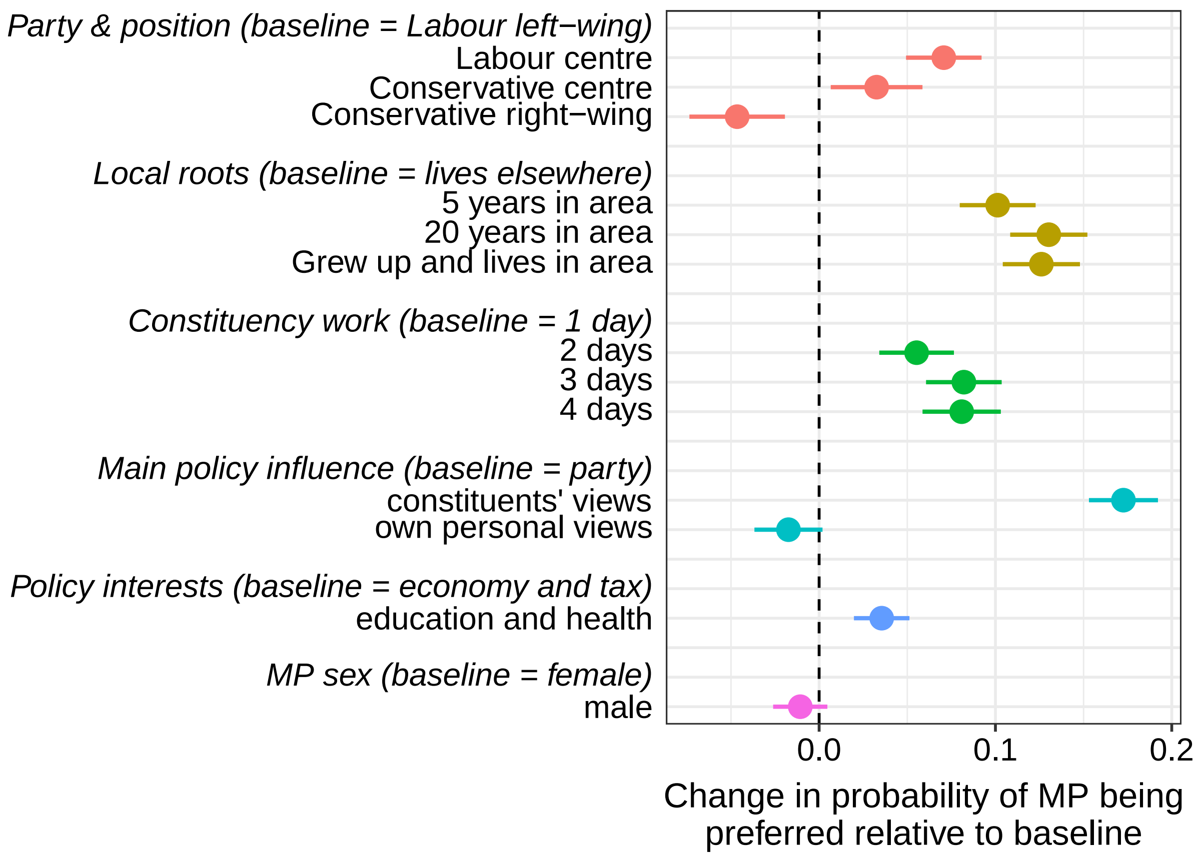

Figure 3. Estimated average marginal component effects of each MP attribute level compared to the baseline level of the attribute, estimated via ordinary least squares regression, with standard errors clustered by respondent. Bars show 95% confidence intervals