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

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Abstract

Campbell et al. (2019) which details two separate experiments which suggest that individuals think of politicians with local roots and that exibit behavioral localism more highly. I was able to replicate the entire article with the exceptions of table 1 and figure 2 because they visuals relating to methodology and not the results themselves. I will be conducting an extension which includes the use of stan_glm instead of lm as well as look at certain subgroups based upon location and party identification. I hope to find cool things:)

Introduction

Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots by Rosie Campbell, Philip Cowley, Nick Vivyan, and Markus Wagner in the *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 subjects to rate hypothetical members of Parliament. The hypothetical members have varying levels of local roots as well as varying levels of "behavioral localism"—their track record of constituency service and if they act more so as a trustee or delegate. In the second study, subjects again considered hypothetical members of Parliament with varying levels of local roots. How, the subjects also received information on their political preferences and partisan loyalties. The first study depicted that the additional information swayed rankings, but local roots still seemed to have an association. The second study agreed with these results stating 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." The remainder of the article discusses the nuances of these results within the frame of the driving question.

Using R, I replicated Campbell et al. (2019). 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]

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 Key (1949). Other notable works include Bowler, Donovan, and Snipp. (1993) and Garand (1988) which highlight the United States and Arzheimer and Evans (2012) as well as Arzheimer and Evans (2014) which highlight Britain. These two articles are particularly important due to Campbell et al. (2019) dealing with the "friends and neighbors" effect in the United Kingdom. These are just a couple of the notable works. Of course, more in way of an actual review is to come.

[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

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 subjects to rate hypothetical members of Parliament. The hypothetical members have varying levels of local roots as well as varying levels of "behavioral localism"—their track record of constituency service and if they act more so as a trustee or delegate. In the second study, subjects again considered hypothetical members of Parliament with varying levels of local roots. How, the subjects also received information on their political preferences and partisan loyalties. The first study depicted that the additional information swayed rankings, but local roots still seemed to have an association. The second study agreed with these results stating 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." The remainder of the article discusses the nuances of these results within the frame of the driving question.

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.[3] All of my code for this paper including the extension is available in my Github repository.[4]

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.

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

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 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[5] instead of the traditional, frequentist lm function used in Campbell et al. (2019). Stan_glm allows for the use or 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.[6] 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[7]. 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 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

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

variation."[8] 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 the NRS social grade of the respondents[9] 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

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

[9] AB = Middle, C1 = Lower Middle, C2 = Skilled Working, DE = Unskilled Working

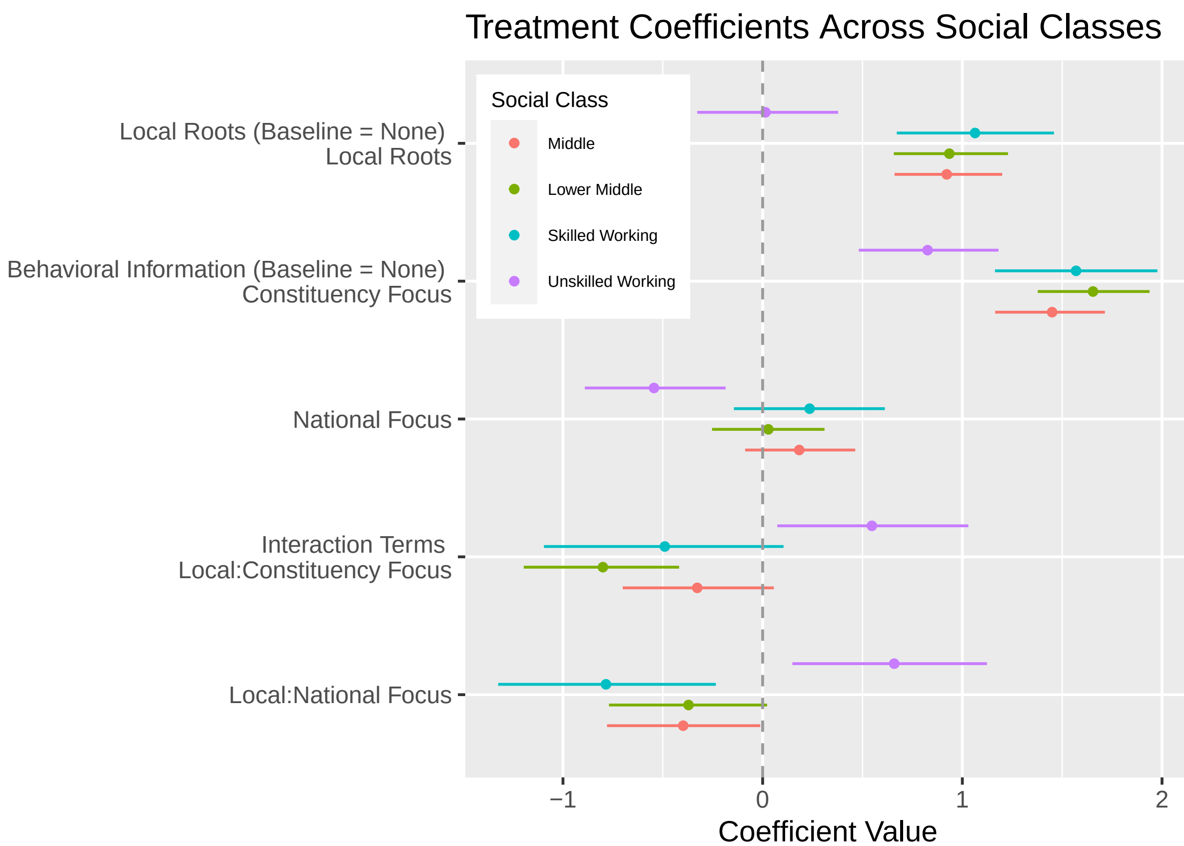

Figure 1: Stan_glm model of the interaction between the treatment effects by social class. The lines denote 95% credible intervals. The treatments affect the unskilled working class in a notably different manner.

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 polices 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.[10] The treatment effects are notably different by class.

Study 2

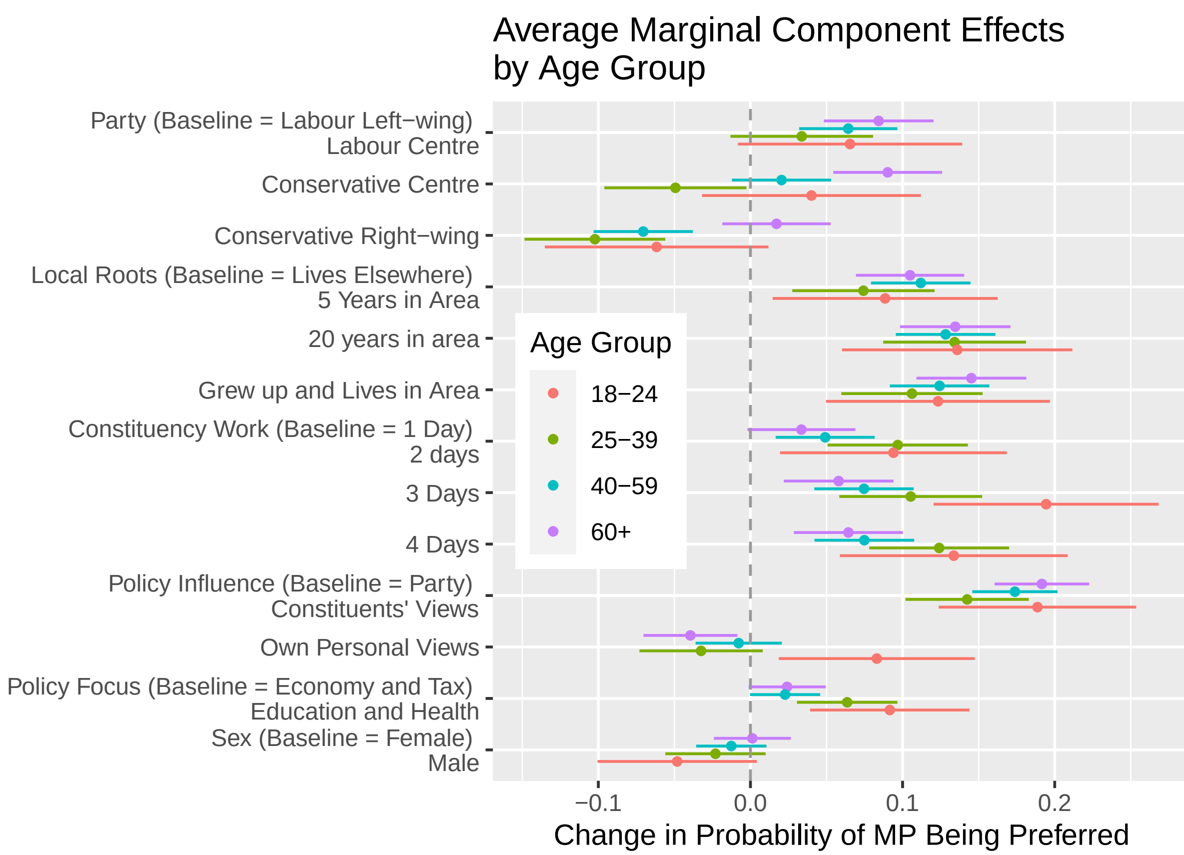

Figure 2: The average marginal component effects from the second study depicted amongst subsets of respondent age. Lines denote a 95% confidence interval. There is a notable difference amongst 18-24 year-olds in regards to personal views influencing an MP's policies.

[10]See page 128-129 of Gelman, Hill, and Vehtari (2020) for further information on interaction

In Figure 2, the average marginal component effects 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 average marginal component effect 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 average marginal component effects when all respondents are analysed together.[11]

In Figure 3, the average component interaction effects between local roots and policy influence are shown in addition to the average marginal component effects depicted in Campbell et al. (2019). In regards to Hainmueller, Hopkins, and Yamamoto (2014), the first type of interaction is seen here. The average component interaction effects 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

[11] See Figure 3

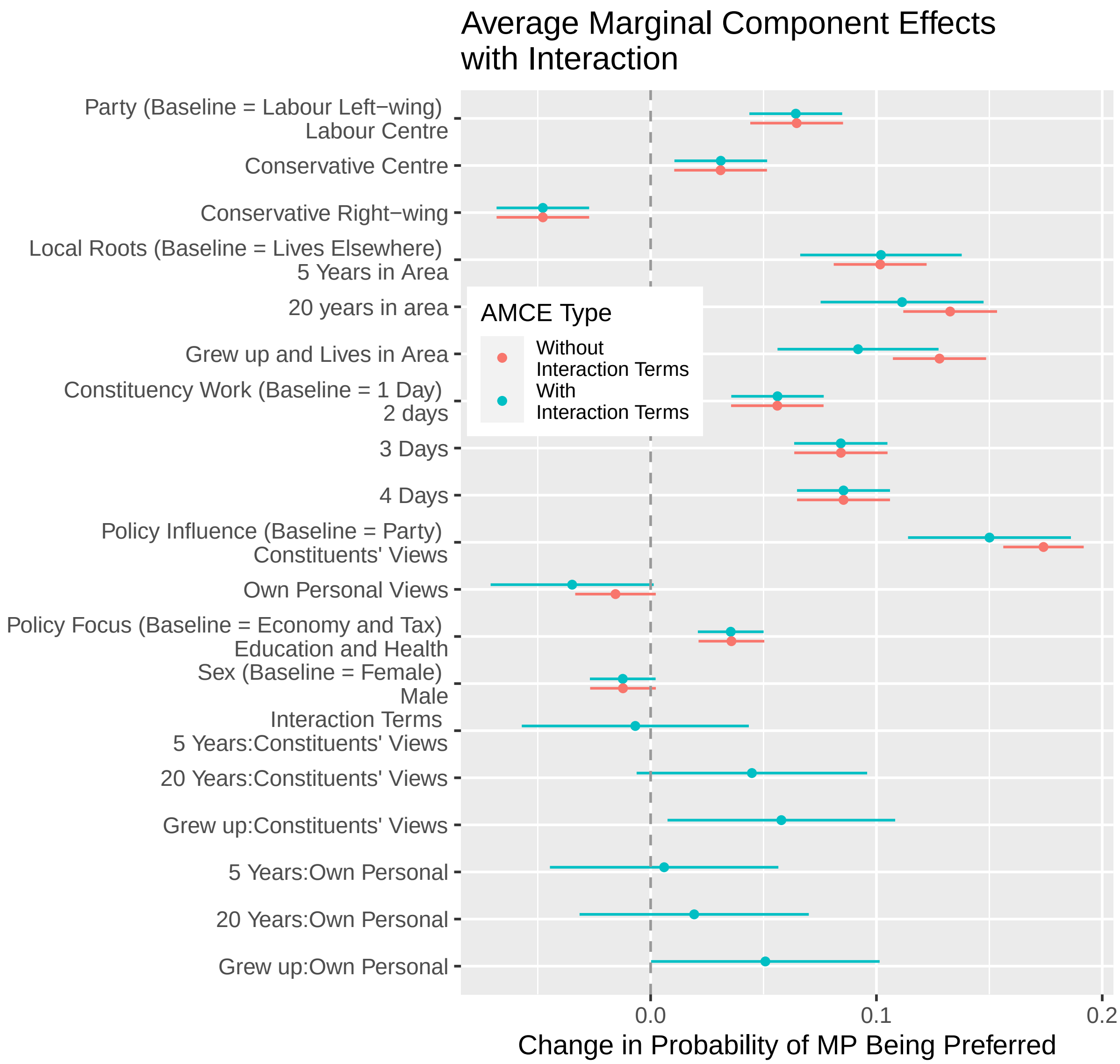

Figure 3: The average marginal component effects from the second study with and without interaction between local roots and policy influence. Lines denote a 95% confindence interval. The average component interaction effects demonstrate how local roots can downplay the negative impact of personal views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

References

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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 Members of Parliament 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

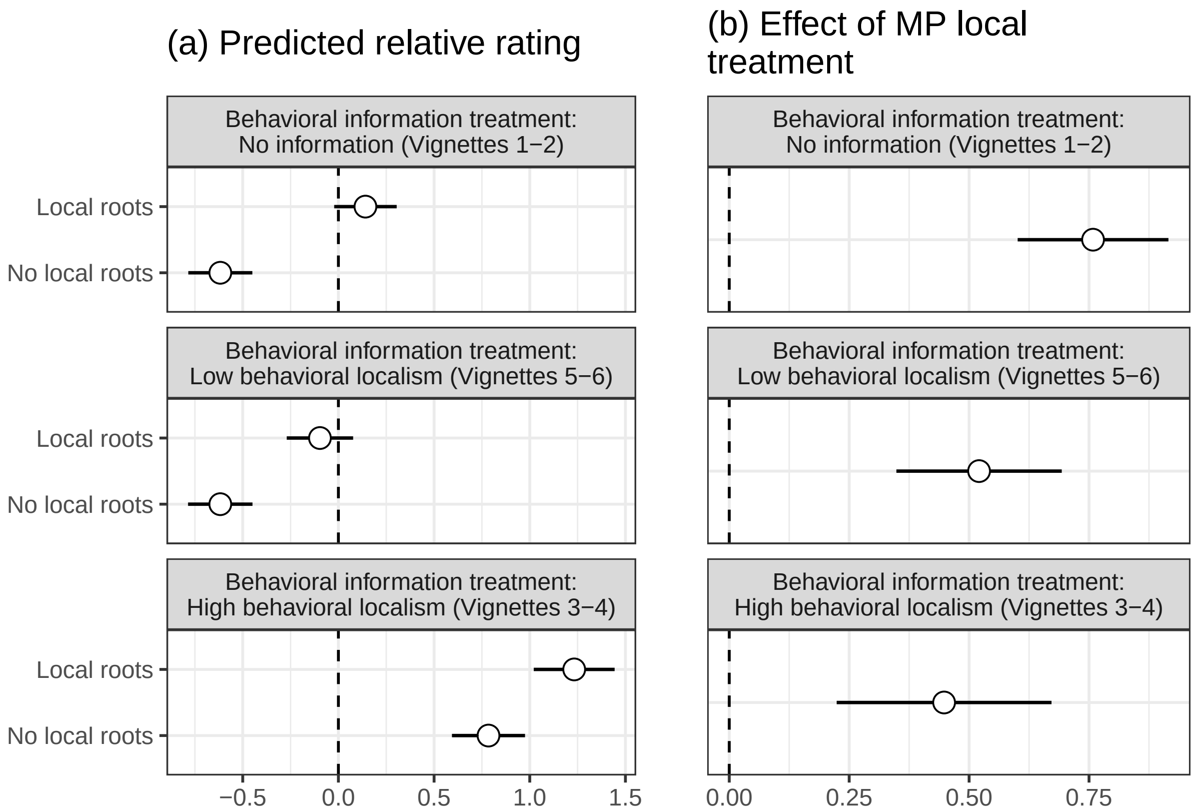

Figure 1. Effects of local roots conditional on behavioral information treatments (study 1). A, Predicted relative rating of MP Nick (MP Nick rating minus MP Philip rating) as the MP local roots treatment varies, with all control variables held constant at their modal value in the sample. Top, predicted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

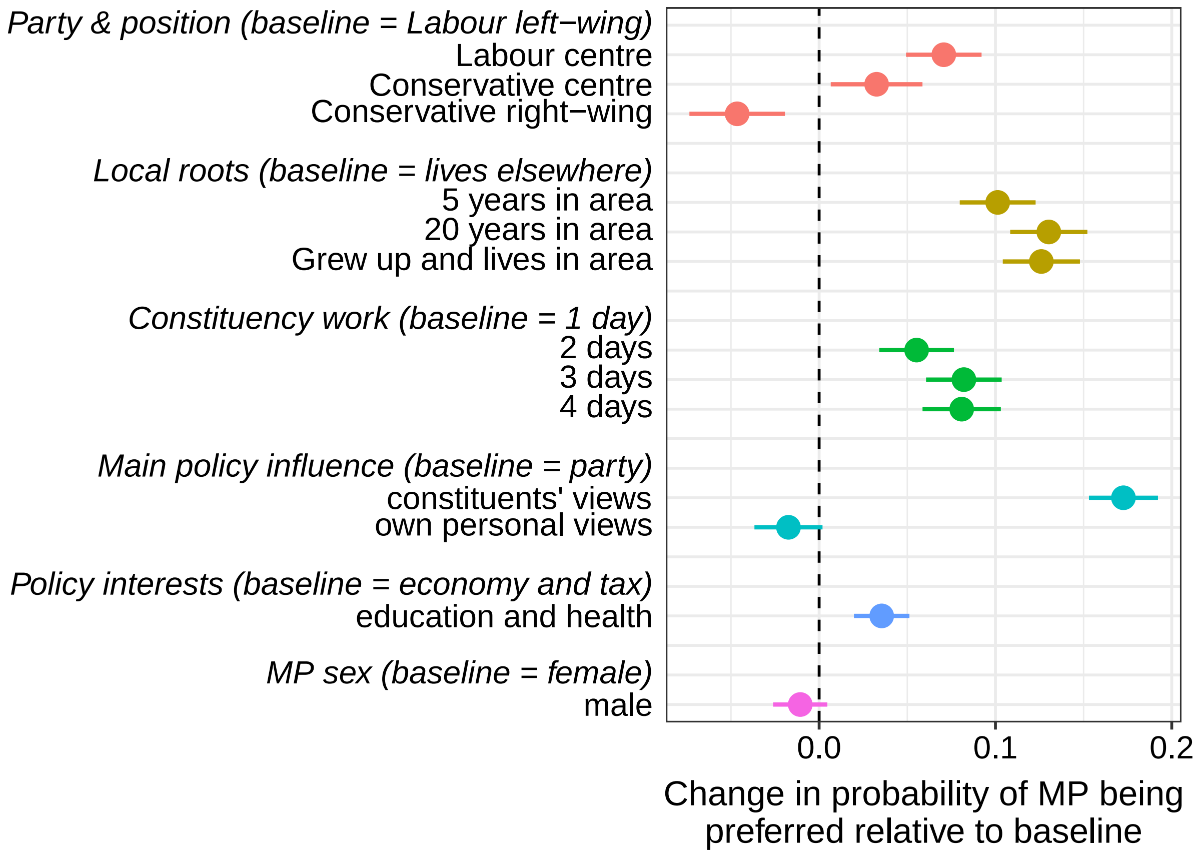

Figure 3. Estimated average marginal component effects of each MP attribute level compared to the baseline level of the attribute, estimated via ordinary least squares regression, with standard errors clustered by respondent. Bars show 95% confidence intervals