Milestone Eight

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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:)

Contents

1 Introduction

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.

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]

[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

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 noteable 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 noteable works. Of course, more in way of an actual review is to come.

3 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.

4 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.

5 Extension

I have already been able to replicate all of the results from *Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots* Campbell et al. (2019) by Rosie Campbell, Philip Cowley, Nick Vivyan, and Markus Wagner in the *The Journal of Politics*. The next step is to improve upon their methods and make suggests as to what to do next. My thoughts are below:

1. Use stan_glm instead of lm for study 1
2. Look at heterogeneous effects for study 1
3. Look at population effects for study 2
4. Use a pAMCE for study 2 instead of an AMCE

5.1 Study 1

Table 1: Bayesian Generalized Linear Models Instead of Linear Models

	(1)	(2)	(3)	(4)
Intercept	-0.413 (0.069)	-0.659 (0.141)	-0.415 (0.067)	-0.662 (0.135)
Has Local Roots	0.756 (0.096)	0.760 (0.098)	0.758 (0.097)	0.761 (0.096)
Behavioral Info Given	0.682 (0.085)	0.691 (0.084)		
Treatments Interaction	-0.255 (0.119)	-0.258 (0.118)		
Male		-0.136 (0.056)		-0.140 (0.056)
25-49		0.151 (0.102)		0.160 (0.099)
50-64		0.441 (0.108)		0.420 (0.106)
65+		0.505 (0.112)		0.507 (0.107)
Skilled Working Class		0.028 (0.092)		0.083 (0.090)
Lower Middle Class		0.047 (0.083)		0.060 (0.076)
Middle Class		0.002 (0.085)		0.012 (0.078)
GCSE		0.042 (0.088)		0.049 (0.088)
A Levels		0.116 (0.090)		0.113 (0.087)
University		-0.107 (0.084)		-0.126 (0.077)
Constituency Focus			1.395 (0.098)	1.400 (0.097)
National Focus			-0.006 (0.096)	0.000 (0.093)
Local:Constituency			-0.308 (0.136)	-0.311 (0.137)
Locanl:National			-0.236 (0.136)	-0.242 (0.137)
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

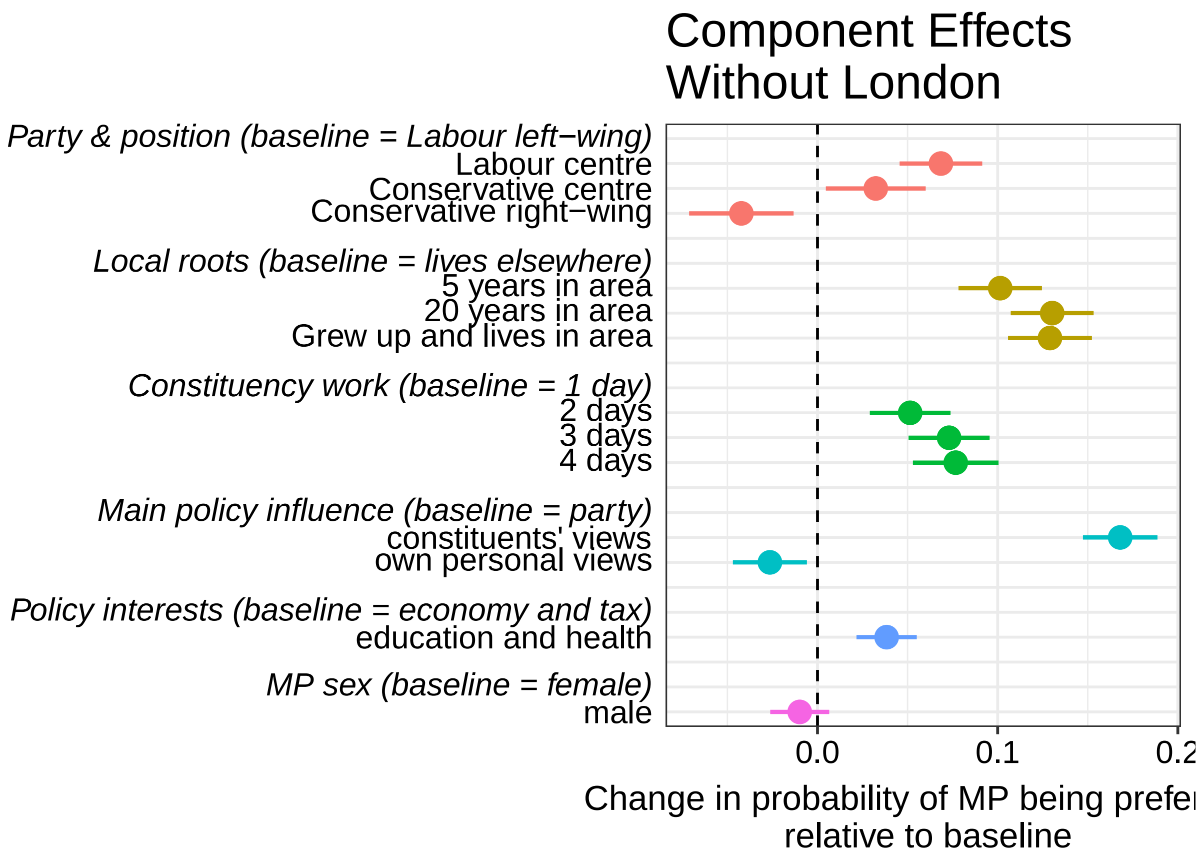
Here, the four models are created using stan_glm instead of the traditional lm. The contents of the parentheses present the MAD SD and not a traditional standard error.

Table 2: Model depicting Heterogeneous Effects

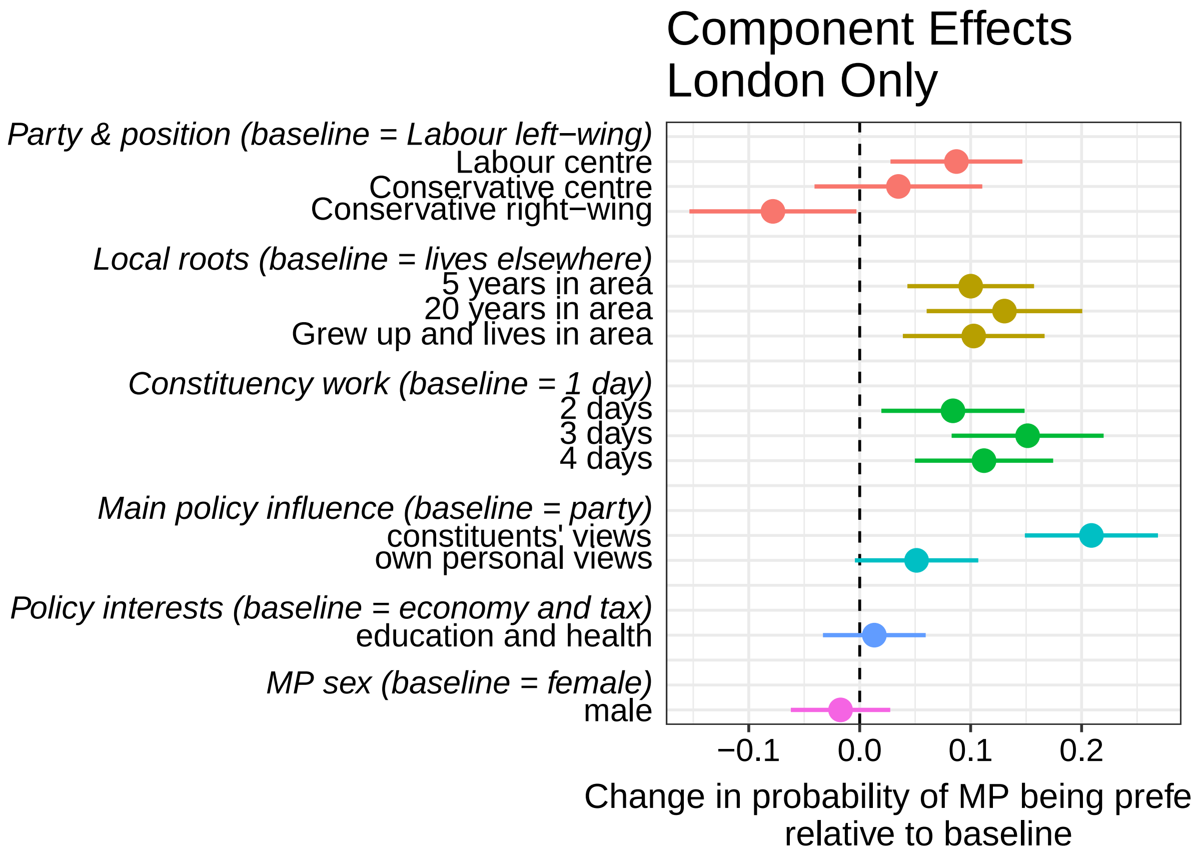
Statistic	Mean	St. Dev.
X.Intercept.	−0.366	0.132
localtreatLocal.roots	0.224	0.182
behtreatConst..focus	1.397	0.097
behtreatWestmin..focus	−0.004	0.096
agegrp25.49	−0.134	0.134
agegrp50.64	−0.031	0.141
agegrp65.	0.074	0.147
localtreatLocal.roots.behtreatConst..focus	−0.313	0.135
localtreatLocal.roots.behtreatWestmin..focus	−0.226	0.136
localtreatLocal.roots.agegrp25.49	0.426	0.182
localtreatLocal.roots.agegrp50.64	0.765	0.196
localtreatLocal.roots.agegrp65.	0.723	0.202
sigma	1.983	0.020

Comparing this table to table 2 of Campbell et al. (2019), there is not a change in regards to the treatment, but there is a notable difference specifically with the treatment having a greater effect on older people.

5.2 Study 2



Component Effects
Without London
Party & position (baseline = Labour left−wing)
Labour centre
Conservative centre
Conservative right−wing
Local roots (baseline = lives elsewhere)
5 years in area
20 years in area
Grew up and lives in area
Constituency work (baseline = 1 day)
2 days
3 days
4 days
Main policy influence (baseline = party)
constituents' views
own personal views
Policy interests (baseline = economy and tax)
education and health
MP sex (baseline = female)
male
0.0
0.1
0.2
Change in probability of MP being prefe
relative to baseline



I also wanted to look at the urban/rural divide, so I compared London, the only completely urban region within the UK with the rest of the UK regions. These tables appear to be almost identical and can be compared to figure 3 of Campbell et al. (2019).

This has yet to be completed, but study 2 utilizes AMCE in their analysis of the conjoints. Nevertheless, as pointed out in Cuesta, Egami, and Imai (2020), "MCE critically relies upon the distribution of the other attributes used for the averaging. Although most employ uniform distribution, which equally weights each profile, both the actual distribution of profiles in the real world and the distribution of theoretical interest are often far from uniform." Therefore they propose the use of pAMCE using the factorEx R package which takes population into account. I aim to utilize this instead of AMCE as a further extension.

These extensions hopefully better the article as a whole and clarify its implications.

6 Conclusion

There is little difference between the stan_glm and the lm. I have yet to figure out the pAMCE. More is to come!

7 References

Arzheimer, Kai, and Jocelyn Evans. 2012. “Geolocation and Voting: Candidate-Voter Distance Effects on Party Choice in the 2010 Uk General Election in England.” Political Geography. 31 (5): 301–10.

———. 2014. “Candidate Geolocation and Voter Choice in the 2013 English County Council Elections.” Research; Politics. 1 (2): 1–9.

Bowler, Shaun, Todd Donovan, and Joseph Snipp. 1993. “Local Sources of Information and Voter Choice in State Elections.” American Politics Quarterly. 21 (4): 473–89.

Campbell, Rosie, Philip Cowley, Nick Vivyan, and Markus Wagner. 2019. “Why Friends and Neighbors? Explaining the Electoral Appeal of Local Roots.” The Journal of Politics. 81(3), 937-951.

Cuesta, Brandon de la, Naoki Egami, and Kosuke Imai. 2020. “Improving the External Validity of Conjoint Analysis: The Essential Role of Profile Distribution.”

Garand, James. 1988. “Localism and Regionalism in Presidential Elections: Is There a Home State or Regional Advantage.” Western Political Quarterly. 41 (1): 85–103.

Key, Valdimer. 1949. “Southern Politics.” New York: Knopf.

A Appendix of Replicated Graphics

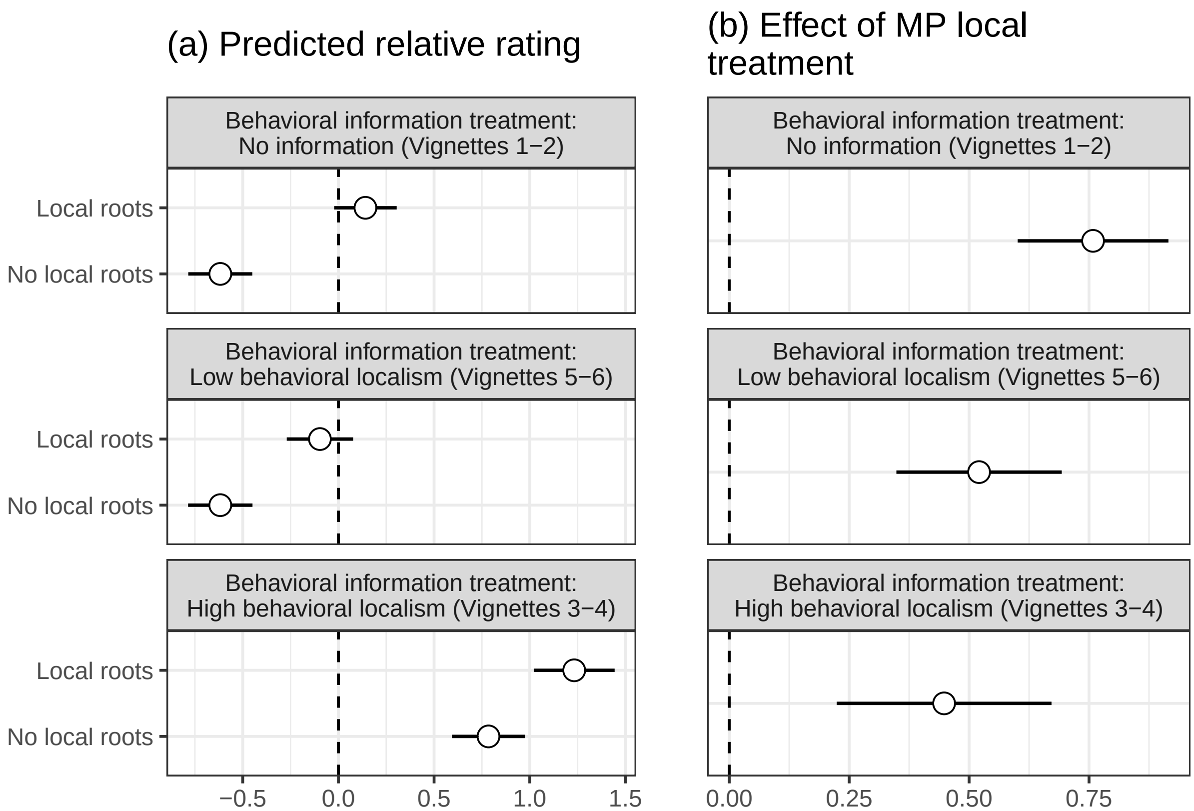
I was able to replicate table 2, figure 1, and figure 3. They are below. I was unable to replicate table 1 and figure 2 because they were not data related. They were merely visualizations displaying content about methods and experimental design. Table 1 depicts written descriptions of the hypothetical Members of Parliament present to subject. Figure 2 depicts a screenshot of the survey.

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

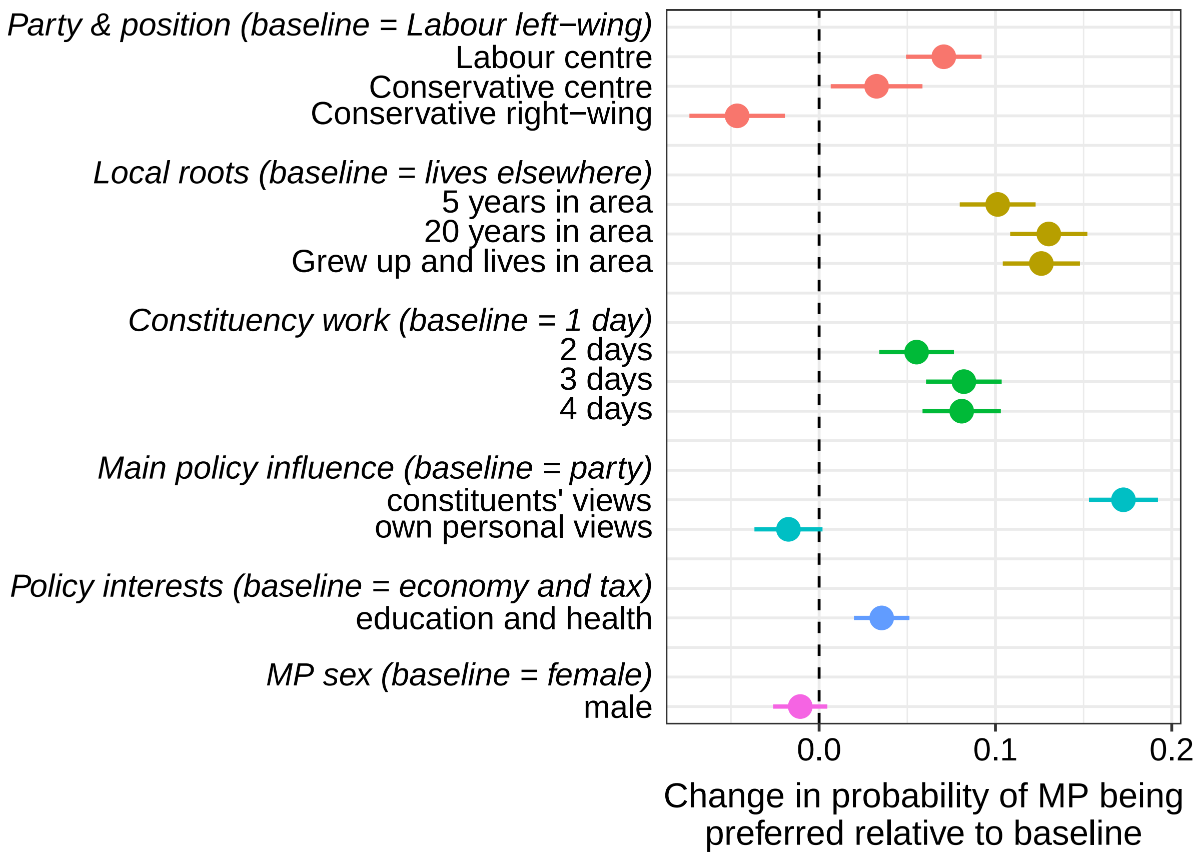
Note from Campbell et al. (2019): "All models estimated via ordinary least squares. Dependent variable is respondent relative rating of MP Nick (the 0–10 rating of Nick minus that of Philip). Robust standard errors in parentheses. N p 5,203."

Figure 1



Caption from Campbell et al. (2019): "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



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