Real Life Leslie Knopes: Factors Contributing to the Proportion of Women Candidates for Local Office in the United States

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Executive Summary

Much data and research exists about factors influencing the number of women in national politics globally but there is little understanding of these same elements at the local level. In my project, I examine which social, economic, and political factors are most relevant to predicting higher proportions of women candidates for local office in the United States. I employ a gender guessing package on candidate-level precinct returns from the 2018 elections and combine the resulting data with county-level factors related to demography, economics, election history, and reproductive healthcare. Using both LASSO regression and random forest techniques resulted in a low success rate for predicting counties with higher proportion of women candidates, but did isolate a small number of influential factors. This lack of conclusive evidence from this study suggests that demographic and community level factors are not the most influential drivers of women candidates. Instead, untested community-level variables and individual-level factors may be more telling for future research.

Introduction

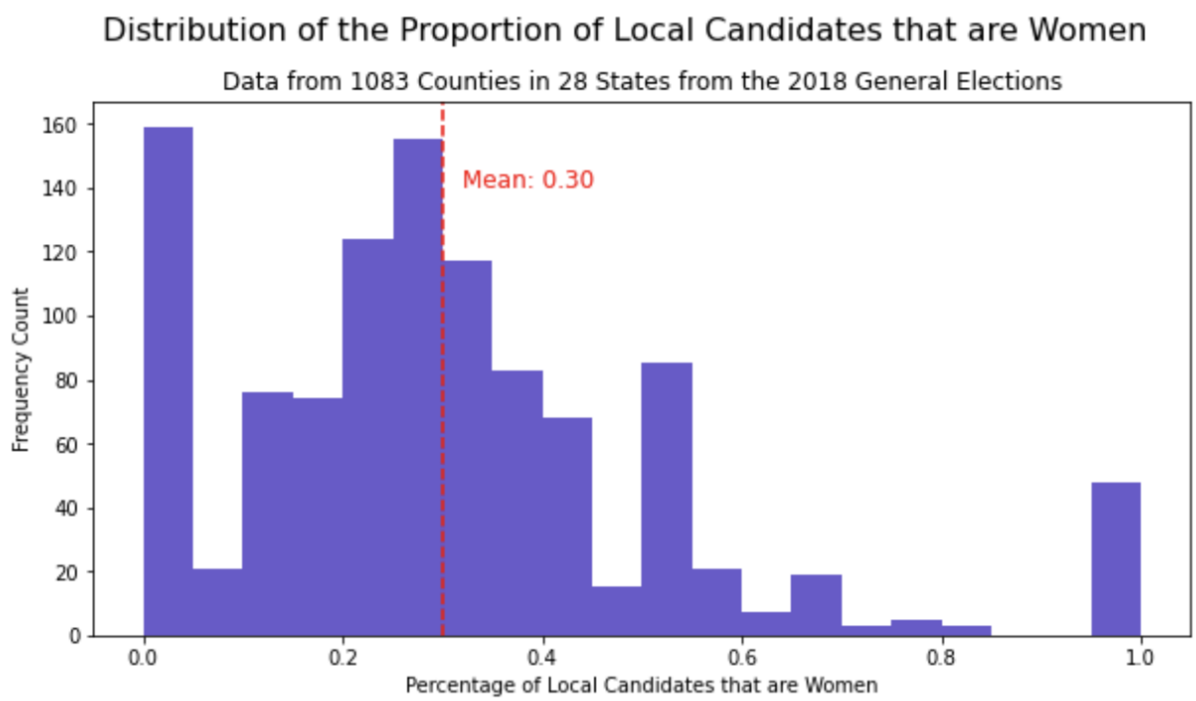
The United Nations tracks data on women in national political positions as part of the Sustainable Development Goals indicator 5.5.1 and recently expanded this to include local level offices (United Nations, n.d.). However, UN data is aggregated at the national level, leaving a relatively small sample size for advanced modeling techniques. Secondly, there is extensive research on factors related to women's representation at the national level, but representation at the local level is understudied (Berevoescu, 2021 & Carroll, 2010). While extensive datasets exist for the number or proportion of women serving in office at national level, data is sparse for local level offices. Finally, most indicators measure the number of women elected officials and not women candidates.

There is much existing analysis on barriers to increasing the number of women in office. The International Republican Institute, a leader on research and programming related to this topic internationally, identified three main categories of barriers to women's participation in public life: the individual, social, and institutional and governmental barriers (International Republican Institute, 2023). Domestic analysis largely has focused on social and economic barriers, but there is an increased attention on the individual motivation to run for office (Lawless, 2010). However, this variable is more difficult to measure based on the data available, although some interesting research has been done on surveys of mayors in the U.S. (Carroll, 2010). Increasingly, reproductive health and abortion are noted as driving factors for women's political participation, even at the municipal level (Epstein, 2023 and Frey, 2022). My study seeks to build on existing research by providing an analysis of the factors related to the proportion of women candidates by county in local elections in the United States in 2018.

Data

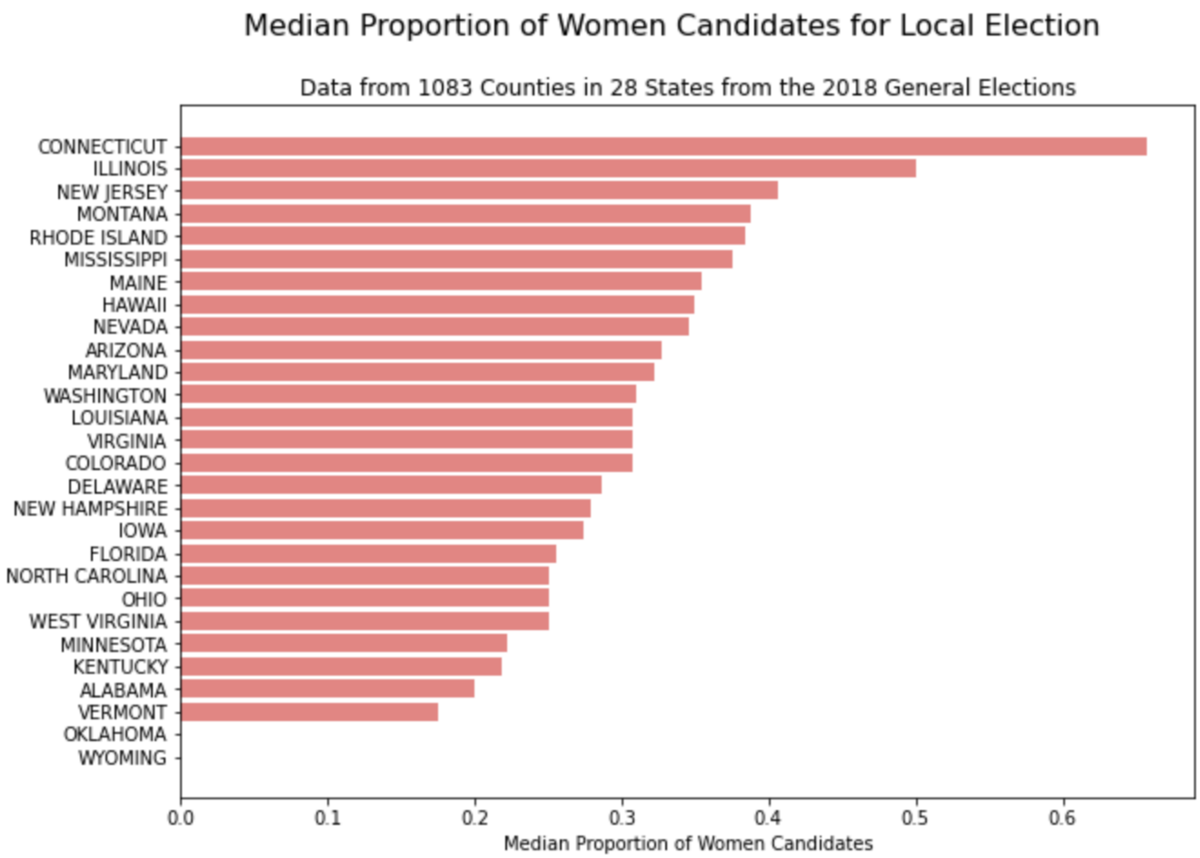
The MIT Election Data + Science Lab has compiled a database on U.S. election data, including detailed information by the precinct level for U.S. local and state government ballots for the 2018 elections (MIT Election Data and Science Lab, 2022). This includes names of candidates on the ballot for a variety of local and state positions as well as the resulting vote counts for each candidate by precinct. The original local dataset includes over 1.8 million rows (candidate-level) for 31 states plus Wasington, DC. After data-cleaning and aggregation, the final dataset contains 1,083 (county-level) rows for 28 states. This includes a total of 24,862 unique candidates for local office, of which 6,883 were classified as women (roughly 28%) using a gender-guessing package in Python. See Appendix I for a more detailed description of the gender-guessing algorithm's methodology. Figure 1 depicts the distribution of the outcome variable in this study, the proportion of local candidates that are women (by county).

Figure 1: Distribution of the Proportion of Local Candidates that Are Women



The average proportion of women candidates was just 30%, although there were significant numbers of counties with no women and all women. I then examined the proportions at the state level, this time based on the median values instead of the average due to the high number of counties with no women candidates. As seen in Figure 2, only two states (Connecticut and Illinois) had counties with a median of 50% or higher women candidates for local office.

Figure 2: Median Proportion of Women Candidates for Local Election



In addition to the initial dataset, the MIT Election Data + Science Lab compiled an additional dataset with key county-level demographic and voting history factors (including election results for the 2012 and 2016 presidential races) to accompany the 2018 precinct level return data (MIT Election Data and Science Lab, 2022). I also sourced data on key reproductive health indicators such as the number of women potentially in demand of contraception assistance or the number of women's clinics in the county (Guttmacher Institute, n.d.). As a result, I compiled a total of 88 variables (including dummy variables for state and regions) covering key demographic, economic, reproductive health, and political factors. See Appendix II for a full list of the input variables and sources.

Tables 1-4 highlight descriptive statistics for key subsets of the most relevant input variables. Most of the counties in the data are majority white, although there is an average of 11.7% of the population that is Black as well as an average of 6.4 % of the population that is Hispanic and just an average of 4.4% that is foreign-born. There is potential collinearity of these racial and ethnic factors, for example if a county has a large community of Black immigrants who speak Spanish. The average percentage of the county that is rural is roughly balanced at 54.8%. Our data contains two age percentages which allow us to examine counties with majority elderly and majority young populations. Surprisingly the majority of counties voted for Republican presidential candidates in both 2012 and 2016, despite Obama's victory in 2012.

Table 1: Subset of Key Demographic Variables

Subset of Demographic Variables							
Descriptive statistics	Percentage of the population that is:						
	White	Black	Hispanic	Foreign-Born	Age <29	Age >65	Rural
Mean	0.768	0.117	0.064	0.044	0.373	0.172	0.548
Stan. Dev.	0.19	0.167	0.087	0.052	0.05	0.042	0.31
Min	0.132	0.0	0.0	0.0	0.136	0.07	0.0
25%	0.651	0.009	0.016	0.013	0.344	0.146	0.296
50%	0.827	0.038	0.034	0.027	0.37	0.17	0.542
75%	0.924	0.156	0.071	0.054	0.398	0.192	0.8
Max	0.996	0.862	0.832	0.522	0.674	0.531	1.0

Table 2: Subset of Economic Variables

Subset of Economic Variables		
Descriptive statistics	Unemployment Rate	Median Household Income
Mean	0.079	47,023
Stan. Dev.	0.031	13,411
Min	0.0	18,972
25%	0.059	38,089
50%	0.076	44,845
75%	0.095	53,179
Max	0.261	125,672

Table 3: Subset of Political Variables

Subset of Political Variables		
Top Candidate	Count	Percentage
Trump ('16)	863	0.797
Clinton ('16)	217	0.2
Third('16)	3	0.003
Obama ('12)	306	0.283
Romney ('12)	777	0.717

Table 4: Subset of Reproductive Health Variables

Subset of Reproductive Health Variables					
Descriptive statistics	Number of publicly funded clinics	Number of Title X-funded clinics	No. of wom. in need of public support for contraceptive services	No. of women 13-44 with potential demand for contraceptive services	No. of women 20-44 with potential demand for contraceptive services
Mean	3.844	1.5	7,415	14,303	12,658
Stan. Dev.	7.565	2.117	19,621	39,441	35,410
Min	1	0	30	50	40
25%	1	1	950	1,545	1,335
50%	2	1	2,240	3,750	3,230
75%	4	1	6,270	10,735	9,325
Max	175	36	345,310	715,650	645,830

Methodology

Because my primary goal was to understand the relationship between the input variables and my outcome variable (the proportion of women running for local office) rather than prediction, I utilized two techniques: 1) Least Absolute Shrinkage and Selection Operator (LASSO) regression and 2) random forests.

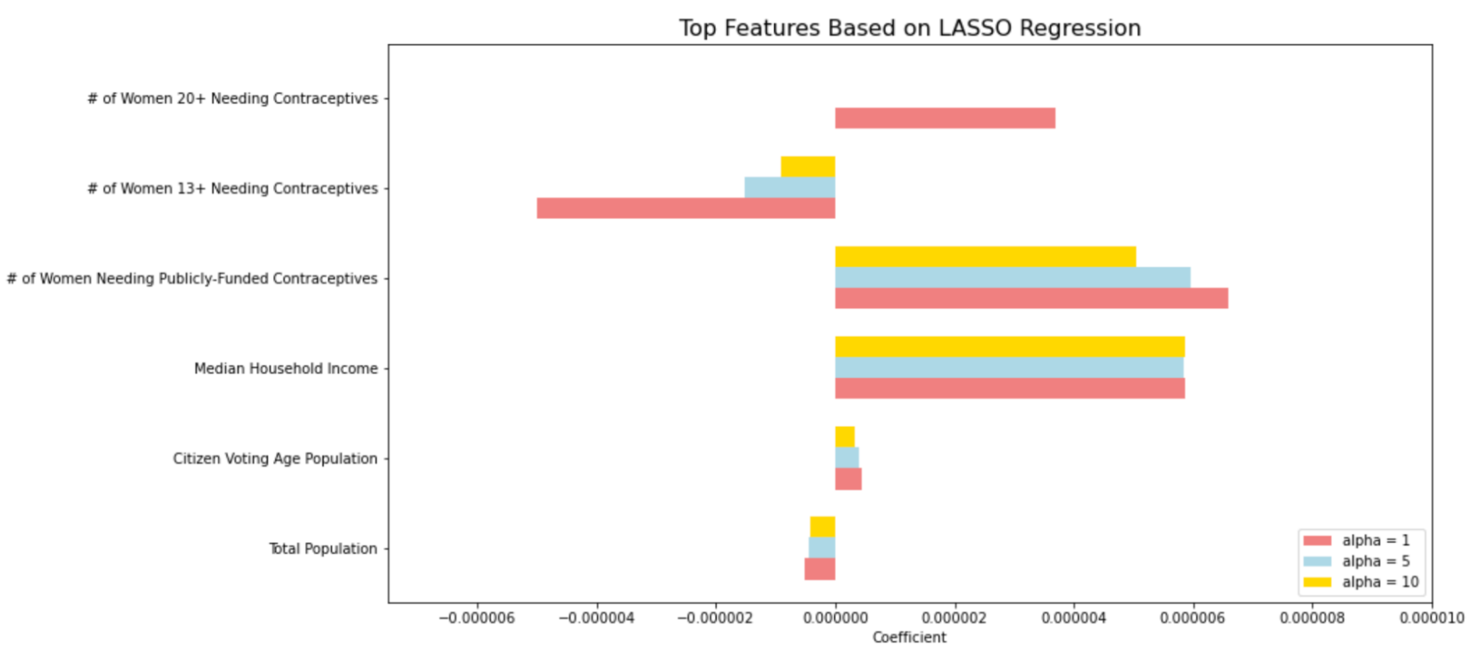
The LASSO algorithm performs a standard Ordinary Least Squares (OLS) regression but applies a penalty based on a user-defined tuning parameter to shrink certain coefficients to zero. Thus LASSO regression not only assists in regularizing our model, but also performs variable selection (James et al., 2021). This method served useful in isolating which of my 88 independent variables had the strongest predictive nature. This technique is frequently used in medical research but has been used previously in political science research, such as the use of LASSO regression to perform variable selection of over 70 variables to predict the gender wage gap in the United States (Boeheim & Stoellinger, 2021). Because LASSO regression is a parametric technique based on OLS, it can perform poorly if the relationship between the features and outcome variables are non-linear.

Random forests are a non-parametric technique based on decision trees, which predict the outcome variable by splitting the data based on the independent variable values (resulting in an output resembling a family tree). Although the researcher can set hyperparameters such as max-depth or node purity to reduce overfitting, a useful technique is to employ random forests by building multiple, decorrelated trees on multiple training samples. (James et al., 2021). Using a random forest approach improves prediction accuracy while still maintaining strong interpretability by identifying variable importance (James et al., 2021). This variable importance role is most relevant to my research. Previously, random forests have been used by researchers across sectors to both identify variable importance and predict an outcome. For example, Genuer et al. demonstrated how random forests can be used in algorithms to both rank and select variables to maintain both interpretation and prediction power (Genuer et al., 2010).

Findings

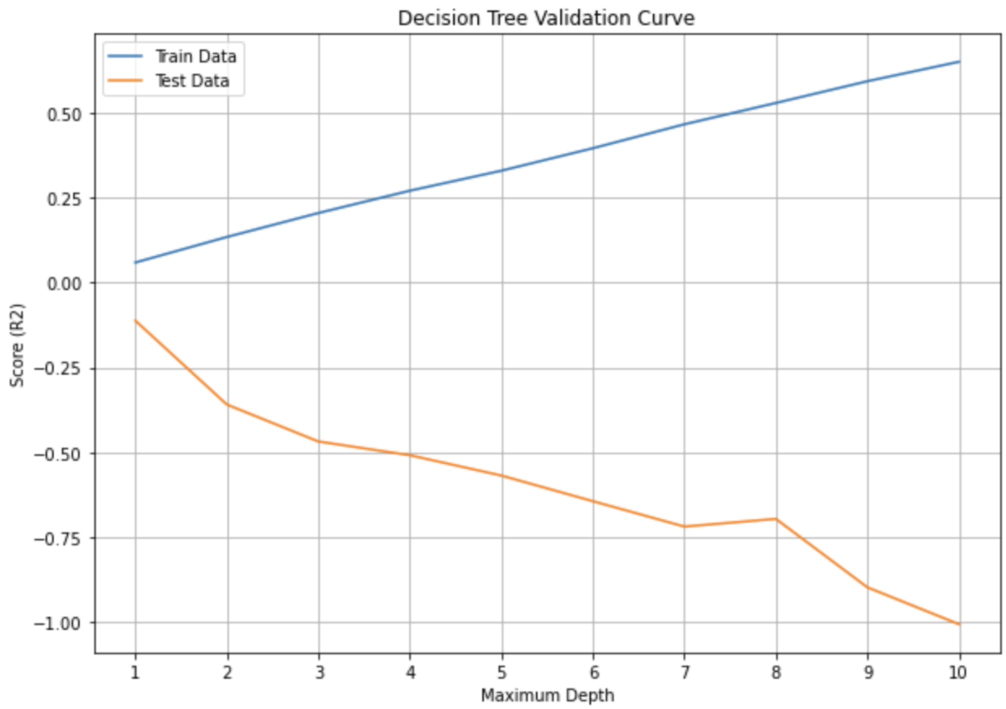
First, I used LASSO regression to isolate the most relevant variables. For hyperparameter tuning, I experimented with alphas of 1, 5, and 10 (which control the penalties introduced to reduce variables to zero). These had very similar results, reducing all but 5 or 6 of the 88 original variables to zero. Notably, these remaining variables are largely related to population metrics (particularly for women) as well as one indicator measuring mean household income. However, the magnitude of the coefficients of the remaining variables were so small, suggesting the lack of a meaningful impact on the outcome variable. This is confirmed by the poor R2 score which suggests that these variables overall are poor predictors of the proportion of women candidates. Figure 3 shows the coefficients of the variables remaining after applying the LASSO regression method.

Figure 3: Coefficients of Remaining Variables from LASSO Regression



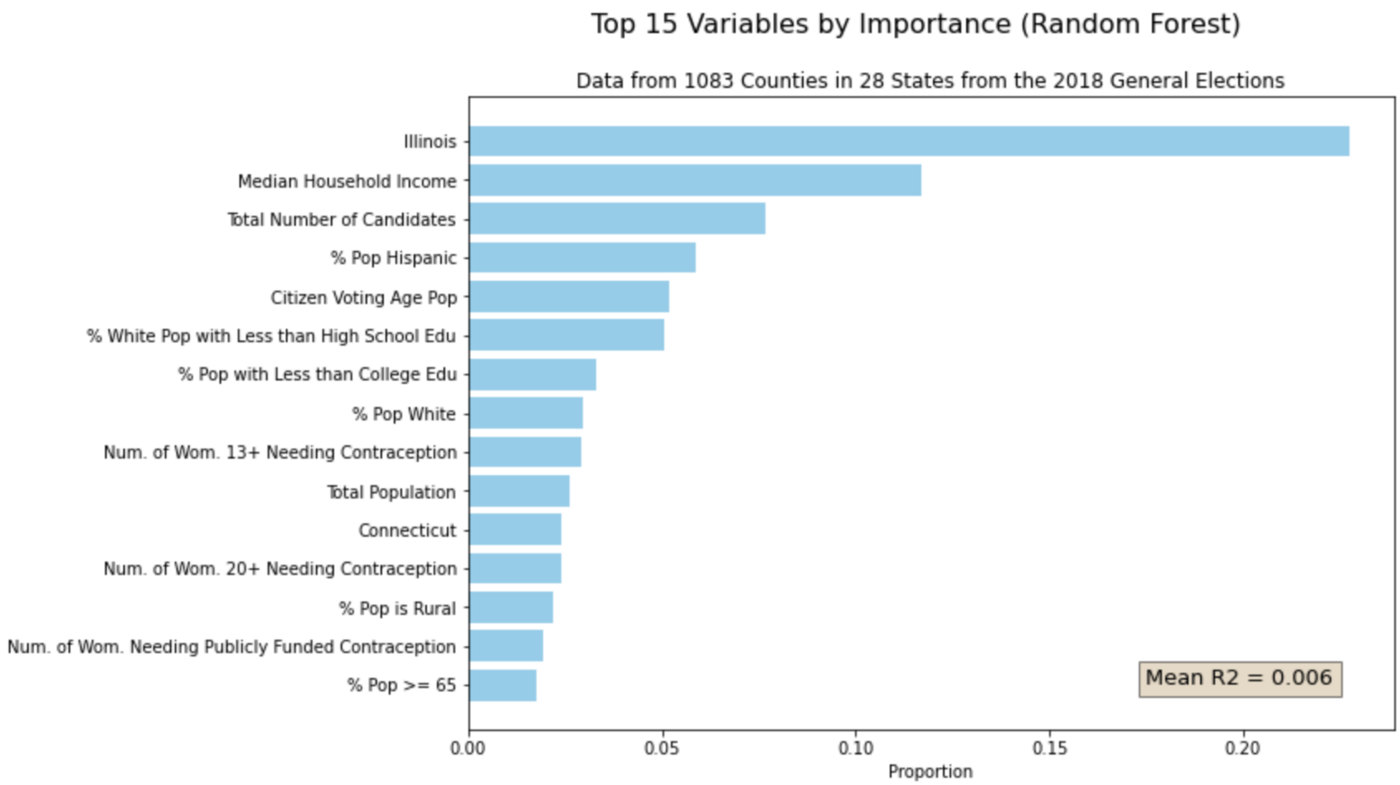
Next, I employed the random forest technique, starting first with building one decision tree to explore hyperparameter tuning. Figure 4 demonstrates hyperparameter tuning for the depth of the decision tree (i.e. how many times it would split) and how this affected the test data. As demonstrated in Figure 4, although the training score improved with increased depth, the test performance score was consistently low, suggesting an overall poor model.

Figure 4: Hyperparameter Tuning - Decision Tree Max Depth Validation Curve



However, as previously mentioned, building random forests can help increase performance. I then built a random forest using 750 iterations and a maximum depth of 3 (based on the initial validation curve) to prevent overfitting. I also used a five-fold cross-validation and calculated the mean R2 score. However, like the LASSO regression results, the resulting R2 score was so low (0.006) as to not be significantly impactful. However it is notable that some of the top 15 variables of importance in the random forest were also present in the LASSO regression, including median household income and female population related statistics. Notably the dummy variable for Illinois was most relevant, likely because our earlier exploratory analysis demonstrated Illinois and Connecticut were the only two states with median county proportions of more than 50%. Of interest, none of the political variables, such as whether the county primarily voted for Trump or Clinton in the 2016 elections, were in the top predictors for either model. Figure 5 shows the variable importance for the top 15 variables in my random forest.

Figure 5: Variable Importance (Random Forest)



Conclusion

Overall, my findings do not support a strong relationship among community-level demographic, economic, political, and reproductive health factors on the proportion of women running for local office. Although some variables were influential in both models, the magnitude and scores were so nominal as to not have meaningful applications for policy. However, there are a number of other untested variables which may be relevant and were not among the 88 features variables. For example, these might include data on social attitudes, the existence of "role models" of previously elected officials, childcare access, or domestic violence rates. Alternatively, the lack of evidence in this study suggests that research based on individual-level data (such as that of a candidate survey) might provide more relevant insight. However, the resulting dataset from my study does provide new information in a scarce data landscape on the count and proportion of women running for local government positions in the United States.

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Appendix I: Implementation Appendix

Since data is scarce on women candidates at the local level, I utilized the Python package "gender-guesser" to classify the gender of each candidate name in the MIT election dataset. This package intakes a single name (such as Margaret) and outputs the gender classification of "male", "female", "mostly-male", "mostly-female", "andy" (if equal likelihood to be male or female), or "unknown" if the name is not found in the database. I calculated the proportion of women as the number of women (as identified by the package as 'female" or "mostly-female") divided by the total number of candidates in each county. This package is based on the underlying data from the program "gender" which includes a dictionary of gender-match-data for about 40,000 names, primarily from European countries, the United States, China, India, and Japan ("Gender-Guesser", 2016). This was last updated in 2016 so information should be relatively accurate for 2018 data. The "gender-guesser" package successfully classified 94.5% of all names in my dataset. Once I aggregated the data to the county-level, I removed counties with 50% or higher "unknown" or "andy" values.

Appendix II: Independent Features

Note that each variable is calculated at the county level.

#	Variable Name	Description	Source	Notes
1.	total_population	Total population	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
2.	cvap	Citizen Voting Age Population	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
3.	white_pct	Percentage of the population that is white	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
4.	black_pct	Percentage of the population that is Black	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
5.	hispanic_pct	Percentage of the population that is Hispanic	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
6.	nonwhite_pct	Percentage of the population that is not-white	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
7.	foreignborn_pct	Percentage of the population that is foreign-born	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
8.	female_pct	Percentage of the population that is female	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
9.	age29andunder_pct	Percentage of the population that is less than 29 years of age	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
10.	age65andolder_pct	Percentage of the population that is less than 29 years of age	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
11.	clf_unemploy_pct	Unemployment population for civilian labor force	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
12.	lesshs_pct	Percentage of the population	2012-2016	Pulled from MIT

		with an education of less than a regular high school diploma	(ACS 5-Year Estimates)	2018 Election Analysis Dataset
13.	lesscollege_pct	Percentage of the population with an education of less than a bachelor's degree	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
14.	lesshs_whites_pct	White population with an education of less than a regular high school diploma as a percentage of total population	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
15.	lesscollege_whites_pct	White population with an education of less than a bachelor's degree as a percentage of total population	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
16.	rural_pct	Percentage of the population that is rural	2010 IPUMS NHGIS, University of Minnesota	Pulled from MIT 2018 Election Analysis Dataset
17.	median_hh_inc	Median household income in the past 12 months (in 2016 inflation-adjusted dollars)	2012-2016 (ACS 5-Year Estimates)	Pulled from MIT 2018 Election Analysis Dataset
18.	pres_16_CLINTON	Dummy variable for Hilary Clinton receiving the highest presidential candidate vote totals in 2016	2016 MEDSL Election Returns Dataverse	Derived from MIT 2018 Election Analysis Dataset
19.	pres_16_THIRD	Dummy variable for a third party candidate receiving the highest presidential candidate vote totals in 2016	2016 MEDSL Election Returns Dataverse	Derived from MIT 2018 Election Analysis Dataset
20.	pres_16_TRUMP	Dummy variable for Donald Trump receiving the highest presidential candidate vote totals in 2016	2016 MEDSL Election Returns Dataverse	Derived from MIT 2018 Election Analysis Dataset
21.	pres_12_OBAMA	Dummy variable for Barack Obama receiving the highest presidential candidate vote totals in 2012	2012 MEDSL Election Returns Dataverse	Derived from MIT 2018 Election Analysis Dataset
22.	pres_12_ROMNEY	Dummy variable for Mitt Romney receiving the	2012 MEDSL Election	Derived from MIT 2018

		highest presidential candidate vote totals in 2012	Returns Dataverse	Election Analysis Dataset
23.	no_wom_demand_contracep_pub	Number of women who likely need public support for contraceptive services and supplies, aged 13-44, 2016	Guttmacher Institute	
24.	total_titlex_clinics	Total Title X-funded clinics, 2015	Guttmacher Institute	
25.	no_wom_dem_contracep_13	Total no. of women aged 13-44 with potential demand for contraceptive services and supplies, 2016	Guttmacher Institute	
26.	no_wom_dem_contracep_20	Total no. of women aged 20-44 with potential demand for contraceptive services and supplies, 2016	Guttmacher Institute	
27.	total_pub_clinics	Total publicly funded clinics, 2015	Guttmacher Institute	
28.	DUM_no_PP_clinics	Dummy variable for the presence of Planned Parenthood clinics, 2015	Guttmacher Institute	Derived from count data
29.	DUM_no_PP_clinics_titlex	Dummy variable for the presence of Planned Parenthood clinics with Title X funding, 2015	Guttmacher Institute	Derived from count data
30.	DUM_no_fed_centers	Dummy variable for the presence of federally qualified health centers, 2015	Guttmacher Institute	Derived from count data
31.	DUM_no_fed_centers_titlex	Dummy variable for the presence of federally qualified health centers with Title X funding, 2015	Guttmacher Institute	Derived from count data
32.	DUM_no_HD_clinics	Dummy variable for the presence of health department clinics, 2015	Guttmacher Institute	Derived from count data
33.	DUM_no_HD_clinics_titlex	Dummy variable for the presence of health department clinics with Title X funding, 2015	Guttmacher Institute	Derived from count data

34.	DUM_no_hosp_clinics	Dummy variable for the presence of hospital-based clinics, 2015	Guttmacher Institute	Derived from count data
35.	DUM_no_hosp_clinics_titlex	Dummy variable for the presence of hospital-based clinics with Title X funding, 2015	Guttmacher Institute	Derived from count data
36.	DUM_no_other_clinics	Dummy variable for the presence of other clinics, 2015	Guttmacher Institute	Derived from count data
37.	DUM_no_other_clinics_titlex	Dummy variable for the presence of other clinics with Title X funding, 2015	Guttmacher Institute	Derived from count data
38.	REGION_midwest	Dummy variable if state is in East North Central or West North Central Division	Census Regions and Divisions	Derived based on state name
39.	REGION_northeast	Dummy variable if state is in New England or Middle Atlantic Division	Census Regions and Divisions	Derived based on state name
40.	REGION_south	Dummy variable if state is in South Atlantic, East South Central, or West South Central Division	Census Regions and Divisions	Derived based on state name
41.	REGION_west	Dummy variable if state is in the Mountain or Pacific Division	Census Regions and Divisions	Derived based on state name
42.	DIVISIONS_east_north_central	Dummy variable if state is Illinois, Indiana, Michigan, Ohio or Wisconsin	Census Regions and Divisions	Derived based on state name
43.	DIVISIONS_east_south_central	Dummy variable if state is Alabama, Kentucky, Mississippi orTennessee	Census Regions and Divisions	Derived based on state name
44.	DIVISIONS_middle_atlantic	Dummy variable if state is New Jersey, New York or Pennsylvania	Census Regions and Divisions	Derived based on state name
45.	DIVISIONS_mountain	Dummy variable if state is Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah or Wyoming	Census Regions and Divisions	Derived based on state name
46.	DIVISIONS_new_england	Dummy variable if state is	Census	Derived based on

		Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont	Regions and Divisions	state name
47.	DIVISIONS_pacific	Dummy variable if state is Alaska, California, Hawaii, Oregon or Washington	Census Regions and Divisions	Derived based on state name
48.	DIVISIONS_south_atlantic	Dummy variable if state is Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia or West Virginia	Census Regions and Divisions	Derived based on state name
49.	DIVISIONS_west_north_central	Dummy variable if state is Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota and South Dakota	Census Regions and Divisions	Derived based on state name
50.	DIVISIONS_west_south_central	Dummy variable if state is Arkansas, Louisiana, Oklahoma and Texas	Census Regions and Divisions	Derived based on state name
51.	ruralurban_cc_1.0	Counties in metro areas of 1 million population or more	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
52..	ruralurban_cc_2.0	Counties in metro areas of 250,000 to 1 million population	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
53.	ruralurban_cc_3.0	Counties in metro areas of fewer than 250,000 population	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
54.	ruralurban_cc_4.0	Urban population of 20,000 or more, adjacent to a metro area	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
55.	ruralurban_cc_5.0	Urban population of 20,000 or more, not adjacent to a metro area	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
56.	ruralurban_cc_6.0	Urban population of 2,500	2013 USDA	Pulled from MIT

		to 19,999, adjacent to a metro area	Economic Research Service	2018 Election Analysis Dataset
57.	ruralurban_cc_7.0	Urban population of 2,500 to 19,999, not adjacent to a metro area	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
58.	ruralurban_cc_8.0	Completely rural or less than 2,500 urban population, adjacent to a metro area	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
59.	ruralurban_cc_9.0	Completely rural or less than 2,500 urban population, not adjacent to a metro area	2013 USDA Economic Research Service	Pulled from MIT 2018 Election Analysis Dataset
60. - 88.	*Dummies for states*	Alabama, Arizona, Colorado, Connecticut, Delaware, Florida, Hawaii, Illinois, Iowa, Kentucky, Louisiana, Maine, Maryland, Minnesota, Mississippi, Montana, Nevada, New Hampshire, New Jersey, North Carolina, Ohio, Oklahoma, Rhode Island, Vermont, Virginia, Washington, West Virginia, Wyoming	MIT Local Precinct-Level Returns 2018	