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The Impact of Facial Attractiveness on Candidates' Vote Share: Case Study of U.S. House Elections

1. Introduction

This project examines the influence of facial attractiveness on voting outcomes in California's 2018 and 2020 U.S. House elections. Using the "Three Forehead and Five Eyes" standard to measure attractiveness, it analyzes the relationship between a candidate's attractiveness level and vote share. The goal is to determine whether and to what extent facial attractiveness impacts a candidate's electoral performance.

The results indicate that facial attractiveness significantly increases vote share for California candidates, with this effect primarily observed for non-incumbents and non-Democratic candidates. The limited impact on incumbents is likely because voters have more information, such as past performance, to judge them by. Besides, given the Democratic Party's long-standing dominance in the California House of Representatives, which may be attributed to political inertia, electoral systems, demographic factors, and progressive policy orientations, it is unsurprising that the impact of facial attractiveness is more evident for non-incumbent candidates.

2. Data Collection

This project primarily utilizes the U.S. California House of Representatives Election Results from Wikipedia, combined with district demographics from the American Community Survey (ACS) and detailed candidate profiles from websites such as Ballotpedia, Vote Smart, JoinCalifornia, and BallotReady. The research sample is limited to California House candidates from 2018 and 2020 with complete personal characteristics data, totaling 189 samples.

(1) Election Result: Web-scrape from Wikipedia, including district, candidate name, party, votes, incumbent status, photo download url, and year.

(2) Candidate Data

Initially, I hoped to use all U.S. House candidates as my sample, assuming I could directly web-scrape or download comprehensive data. However, I soon encountered several challenges: limited online availability of candidate information, data scattered across multiple websites, and missing candidate photos on Wikipedia. So I had to spend much time manually collecting data and photo from various sources, such as Wikipedia, Ballotpedia, JoinCalifornia, BallotReady, and news websites, etc. Consequently, I narrowed the research scope to focus solely on California, and my sample consists only of candidates with complete information.

(3) District Demographics: Download data (.csv) directly from the U.S. Census Bureau Website. Use ACS 1-year estimates for 2018 and 5-year estimates for 2020, as 1-year estimates are not available for 2020. While 5-year estimates are more reliable, they may smooth out some of the pandemic's impact.

3. Data Cleaning

The collected data is primarily stored in dataframe and .csv formats for Python analysis. I retained only the necessary variables required for analysis, removing irrelevant columns and generating dummy variables for categorical data. Then, I removed samples with missing values in personal characteristic data.

(1) Election Result

A. Scraped Wikipedia pages, cleaned HTML tags.

B. Calculated total votes and vote share for each candidate. Used natural logarithm (ln) of vote share as the dependent variable, because it helps reduce the impact of outliers and avoids difficulties in interpretation. This is because the number of candidates varies across districts, leading to differences in vote share scales. The importance of percentage changes in vote share also varies.

C. Since California has long been dominated by the Democratic Party, to better observe the effect of appearance on non-incumbents (mainly non-Democratic candidates), the "Party" variable was simplified into Democratic and non-Democratic.

(2) Candidate Data

A. Kept accepted photo formats (.jpg, .jpeg, .png, .bmp) unchanged, and converted other formats to .jpg for subsequent analysis. For photos with face angle deviating significantly from frontal view, poor image resolution, or partially obscured, I found alternative photos as replacements.

B. The attractiveness scores are calculated using two methods (HOG + Linear SVM face detector and MMOD CNN face detector), and then appropriately grouped into 3 and 4 levels separately. These grouped score levels used as main explanatory variables.

(3) District Demographics

Classified districts as urban, transitional, or rural based on Median Household Income and total population.

4. Data Analysis and Data Visualization

(1) Descriptive Statistics

Table 1 shows the basic characteristics of all samples and different parties. I found that California is primarily dominated by the Democratic Party, whose candidates have slightly higher scores than Republicans. Next, I analyzed the relationships between candidate characteristics and scores (Table 2). The findings indicate:

A. Female candidates have slightly higher scores than males.

B. There is no much difference in scores between incumbents and non-incumbents.

C. Transitional and urban districts candidates have slightly higher scores compared to those from rural districts.

D. Scores show a slight U-shaped relationship with age, though the differences are small.

Table 1 Descriptive Statistics

	Total		Republican		Democratic		Other	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
ln_vote_share	-0.7237	0.4228	-1.0027	0.383	-0.5087	0.2739	-1.6526	0.369
score	72.5185	7.3619	71.5479	7.974	73.3214	6.9596	67.75	0.9574
Score (CNN)	73.0423	7.236	72.3425	7.411	73.6071	7.2103	70	1.8257
Male	0.672	0.4707	0.7945	0.4068	0.5893	0.4942	0.75	0.5
Female	0.328	0.4707	0.2055	0.4068	0.4107	0.4942	0.25	0.5
Republican	0.3862	0.4882						
Democratic	0.5926	0.4927						
Other	0.0212	0.1443						
Not Incumbent	0.4656	0.5001	0.7534	0.434	0.2589	0.44	1	0
Incumbent	0.5344	0.5001	0.2466	0.434	0.7411	0.44	0	0
Age	54.9048	13.881	53.863	11.6754	55.7143	14.7925	51.25	25.2636
Master & Above	0.5767	0.4954	0.3425	0.4778	0.7232	0.4494	0.75	0.5
College	0.4021	0.4916	0.6027	0.4927	0.2768	0.4494	0.25	0.5
High School	0.0212	0.1443	0.0548	0.2292	0	0	0	0
rural	0.127	0.3338	0.137	0.3462	0.1161	0.3218	0.25	0.5
transition	0.7566	0.4303	0.7534	0.434	0.7589	0.4297	0.75	0.5
urban	0.1164	0.3216	0.1096	0.3145	0.125	0.3322	0	0
N	189	189	73	73	112	112	4	4

Table 2 Candidate Characteristics and Facial Attractiveness Scores

	HOG + Linear SVM			MMOD CNN		
	Mean	Std	N	Mean	Std	N
Male	71.4409	7.6352	127	72.1654	7.0528	127
Female	74.7258	6.2651	62	74.8387	7.331	62
Master & Above	72.7523	6.915	109	72.8991	7.1892	109
College	72.2895	8.071	76	73.4211	7.4499	76
High School	70.5	6.1373	4	69.75	3.7749	4
Republican	71.5479	7.974	73	72.3425	7.411	73
Democratic	73.3214	6.9596	112	73.6071	7.2103	112
Other	67.75	0.9574	4	70	1.8257	4
Not Incumbent	72.7045	7.1441	88	73.4091	7.0035	88
Incumbent	72.3564	7.5784	101	72.7228	7.4527	101
rural	69.2917	9.2618	24	70.375	7.4531	24
transitional	73.028	6.7417	143	73.4196	6.9307	143
urban	72.7273	8.379	22	73.5	8.5899	22
Age: <40	73.75	6.8439	32	73.875	6.8333	32
Age: 40-50	72.6216	7.0567	37	72.7297	7.3924	37
Age: 50-60	71.2857	9.0485	49	72.0204	7.9804	49
Age: 60-70	71.8043	6.6754	46	72.8043	7.1075	46
Age: >70	74.52	5.6356	25	74.88	6.2405	25

Table 3 shows the relationship between candidate facial attractiveness levels and ln vote share. Regardless of whether attractiveness scores are divided into 3 or 4 levels, I observe a generally positive relationship between score levels and ln vote share. Candidates with higher score levels tend to achieve higher vote shares, and as the levels increase, the standard deviation gradually decreases. Figures 1 and 2 present scatter plots of score levels versus ln vote share. These plots also show a generally positive relationship. In addition, non-Democratic candidates display greater variation in both score levels and vote share. In these figures, the Y-axis represents ln vote share, the X-axis represents score groups. Circles size reflects the number of observations, and colors indicate party (Democratic vs. non-Democratic) or incumbent status (incumbent vs. non-incumbent) ratio.

Table 3 Facial Attractiveness Levels and ln Vote Share

	ln_vote_share					
	HOG + Linear SVM			MMOD CNN		
score groups	mean	std	N	mean	std	N
4 groups						
below 69.99	-0.7852	0.4742	72	-0.7246	0.417	69
70-74.99	-0.7284	0.4576	49	-0.833	0.5277	46
75-79.99	-0.6626	0.3305	47	-0.6733	0.3653	47
above 80	-0.6388	0.3137	21	-0.623	0.289	27
3 groups						
below 74.99	-0.7622	0.4665	121	-0.768	0.4653	115
75-79.99	-0.6626	0.3305	47	-0.6733	0.3653	47
above 80	-0.6388	0.3137	21	-0.623	0.289	27

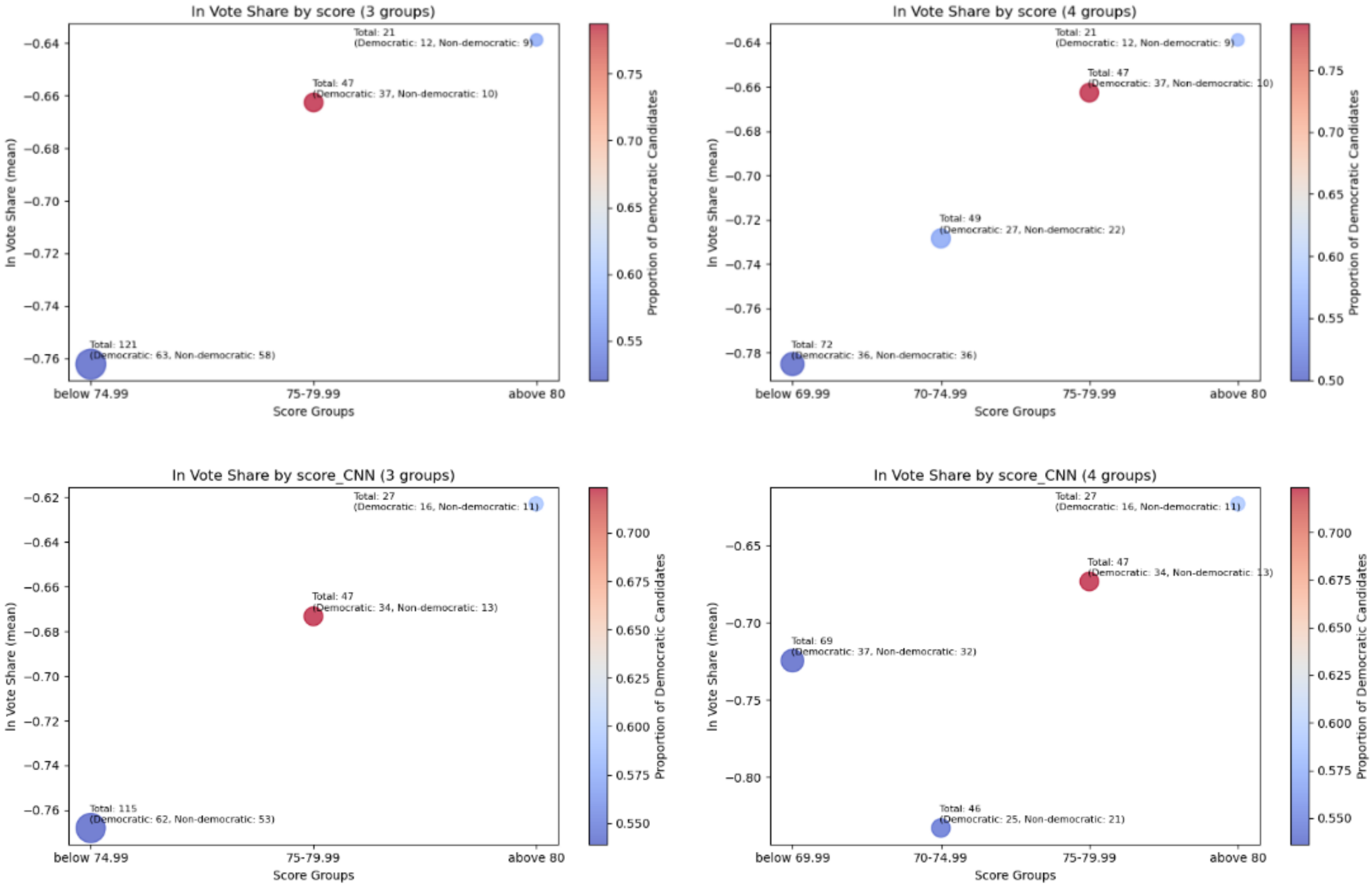

Figure 1　Facial Attractiveness Levels and ln Vote Share (Party Ratio)

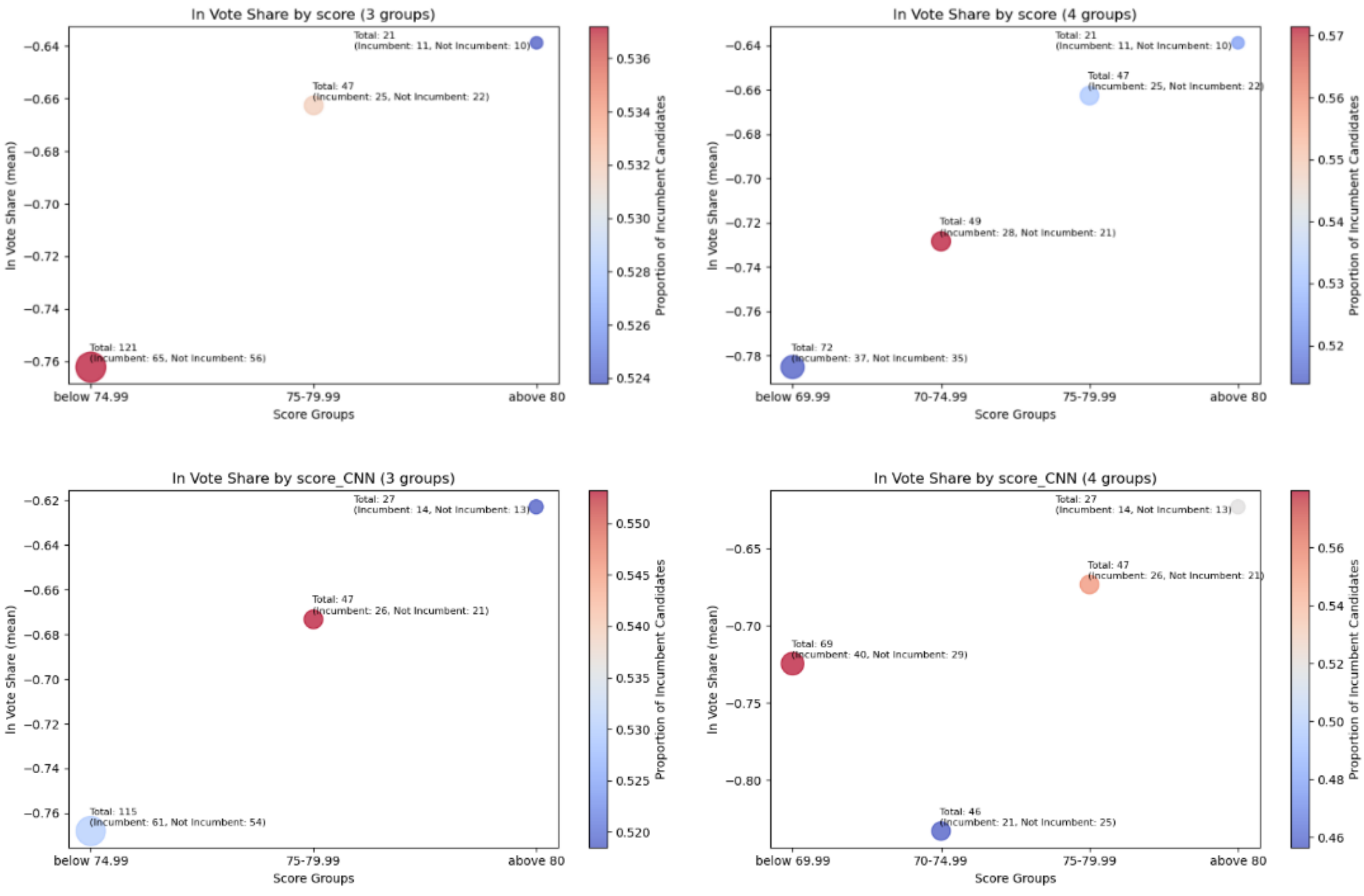

Figure 2 Facial Attractiveness Levels and ln Vote Share (Incumbent Ratio)

(2) Face Detection

I use two models from the dlib C++ Library for face detection: the HOG + Linear SVM face detector and the Max-Margin (MMOD) CNN face detector. These are combined with the "68 points Face landmark Detection" to perform the "Three Forehead and Five Eyes[1]" analysis and an calculate attractiveness score for each candidate. The 68 points Face landmark Detection is primarily suitable for near frontal photos, so it may be less accurate in score calculation for photos where the face angle deviates significantly from the front view. Since it does not include points for detecting the hairline, I only compute the ratio of the middle and lower courts, as well as the five eyes ratio. Faces closer to this standard receive higher scores, and these scores are then grouped into different levels.

(3) OLS Regression

I use the natural logarithm (ln) of vote share as the dependent variable, with score level as the primary explanatory variable. There are two types of scores (derived from two different

[1] Three Courts: The face length is divided into three equal parts: From the hairline to the line between the eyebrows; From the eyebrow line to the bottom of the nose; From the bottom of the nose to the tip of the chin.
Five Eyes: The width of the face is divided into five equal parts: From the outer corner of the right eye to the right edge of the face; The width of the right eye; The space between the eyes; The width of the left eye; From the outer corner of the left eye to the left edge of the face.

models), each further divided into 3 levels and 4 levels respectively. The model controls for various demographic characteristics, such as age, gender, education level, political party, incumbent status, district types (urban, transitional, rural), and year fix effects. Furthermore, I analyze whether the relationship between attractiveness levels and vote share differs across political parties or incumbent status through subgroup analyses or by adding interaction terms into the model.

5. Conclusion

Table 4 shows that facial attractiveness has a significant positive effect on vote share, while controlling for variables such as gender, age, party affiliation, and district characteristics. Regarding differences in political party and incumbent status, Democratic and incumbent candidates have significantly higher vote shares. (The regression results using 4 score levels also indicate a positive relationship, but with smaller coefficients and lower significance levels.)

Table 4 Effects of Facial Attractiveness on ln Vote Share (Total Sample)

	(1)	(2)	(3)	(4)	(5)	(6)
score level	0.050^{**}		0.050^{**}		0.050^{**}	
	(-0.023)		(-0.024)		(-0.024)	
score level (CNN)		0.054^{**}		0.054^{**}		0.056^{**}
		(-0.022)		(-0.023)		(-0.023)
Democratic	0.257^{***}	0.260^{***}	0.244^{***}	0.246^{***}	0.244^{***}	0.247^{***}
	(-0.044)	(-0.045)	(-0.052)	(-0.052)	(-0.051)	(-0.051)
Incumbent	0.486^{***}	0.487^{***}	0.484^{***}	0.486^{***}	0.484^{***}	0.486^{***}
	(-0.047)	(-0.048)	(-0.048)	(-0.049)	(-0.048)	(-0.048)
Education FE			V	V	V	V
City FE					V	V
N	189	189	189	189	189	189
R^2	0.653	0.655	0.654	0.656	0.656	0.658
Adjusted R^2	0.639	0.641	0.637	0.639	0.634	0.637

*p<0.1; **p<0.05; ***p<0.01
Note: All regressions include year fixed effects, and additional controls include age, gender, party, and incumbent status.

Table 5, examining the differences between Democratic and non-Democratic candidates, reveals that facial attractiveness has a significant positive effect only on the vote share of non-Democratic candidates. Moreover, the score levels derived from the CNN model show a larger effect. (The subgroup analyses by incumbent status show consistent results.)

Table 5 Effects of Facial Attractiveness on ln Vote Share (Subgroups: by Party)

	Not Democratic (1)	Democratic (2)	Not Democratic (3)	Democratic (4)
score level	0.080*	0.012		
	(-0.048)	(-0.025)		
score level (CNN)			0.090*	0.024
			(-0.051)	(-0.025)
Incumbent	0.548***	0.437***	0.531***	0.442***
	(-0.07)	(-0.066)	(-0.072)	(-0.067)
N	77	112	77	112
R^2	0.407	0.631	0.412	0.634
Adjusted R^2	0.317	0.599	0.323	0.602

*p<0.1; **p<0.05; ***p<0.01
Note: All regressions include year fixed effects, and additional controls include age, gender, education level, party, incumbent status, and district type.

Table 6 Effects of Facial Attractiveness on ln Vote Share (Interaction)

	(1)	(2)		(3)	(4)
score level	0.105**		score level	0.093**	
	(-0.045)			(-0.041)	
score level:Incumbent	-0.099**		score level:Democratic	-0.074	
	(-0.05)			(-0.049)	
score level (CNN)		0.108**	score level (CNN)		0.088**
		(-0.045)			(-0.043)
score level (CNN):Incumbent		-0.097*	score level (CNN):Democratic		-0.054
		(-0.051)			(-0.052)
Incumbent	0.629***	0.637***	Democratic	0.354***	0.332***
	(-0.096)	(-0.1)		(-0.101)	(-0.105)
N	189	189	N	189	189
R^2	0.662	0.664	R^2	0.659	0.66
Adjusted R^2	0.638	0.642	Adjusted R^2	0.636	0.637

*p<0.1; **p<0.05; ***p<0.01
Note: All regressions include year fixed effects, and additional controls include age, gender, education level, party, incumbent status, and district type.

Furthermore, I analyze the effects on different political parties and incumbent status. Using the score (CNN) as an example, in Table 6, regressions 1 & 2 show that when the score level increases by 1, non-incumbent candidates have a significantly larger increase by 0.099 in their ln vote share compared to incumbents. Regressions 3 & 4 indicate that when the score level increases by 1, non-Democratic candidates present a larger increase in their ln vote share compared to Democratic candidates, with a difference of 0.074 (not significant). These results highlight a notable disparity in how facial attractiveness affects incumbent versus non-incumbent candidates.

In conclusion, incumbents, often Democrats, have a strong advantage in vote share. However, the attractiveness effect may provide a small boost to challengers, potentially offsetting some of the incumbent advantage.

6. Future Work

(1) More diverse facial attractiveness evaluation standards should be adopted, including a certain degree of manual scoring. This could help achieve greater objectivity and robustness in the attractiveness assessment.

(2) The sample size for this project is too small. Expanding the sample to include all U.S. House candidates from every state would increase the reliability of the results.

(3) It would be interesting to explore which types of voters are more influenced by candidate appearance.

(4) With a nationwide sample, it would be possible to examine the interaction between attractiveness and urban / rural districts to understand how this relationship varies across different geographical contexts.

(5) Candidate data is too scattered across different sources. Although I could not find a comprehensive dataset this time, it would be more efficient if I could find an existing database in future research.