

# Online Appendix

Justice Isn't Blind: Attorney Attractiveness and Success in US Federal Court\*

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\*Replication materials are available at the Journal of Law and Courts Dataverse: <https://doi.org/10.7910/DVN/OVMN95>

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## 1 Principles for Human Subjects Research

Three of the four conceptualizations of attractiveness in this project were derived from ratings of attractiveness given by participants of Amazon’s Mechanical Turk (“MTurk”). This research adheres to all Principles and Guidance for Human Subjects Research approved by the APSA Council in Spring 2020. In addition, this research was approved by an Institutional Review Board on August 14, 2020.

In the Summer of 2020, online respondents located in the United States were recruited to participate in an academic research survey. They were informed of the general goals of the research project, informed the project was academic in nature, and told they could opt out at anytime during the survey. They were then prompted for their consent to participate before the survey began. There was no deception involved in the research, no interaction with any political processes, and no identifying information was collected or retained from the respondents. After the answering approximately 20 questions, respondents were paid \$1 in exchange for their participation. With an average survey completion time of less than 10 minutes, this compensation is above average for US-based MTurk participants (see Litman, Robinson and Rosenzweig, 2015).

## 2 Outcome, Treatment, and Control Variables

In all of my analyses, I use the opposition attorney’s attractiveness rating to predict success against the US government. Success is conceptualized by the judge-level, dichotomous dependent variable **Opposition Vote**. The variable is coded as 1 if the judge voted for the opposition attorney’s party on the merits. In the full analysis, 3,290 individual judge votes are included. This variable’s descriptive statistics differ slightly in the analyses with different measures of attractiveness because observations are excluded if the opposition attorney was unable to receive a specific attractiveness rating.

The distributions of the four treatment variables are displayed in Figure A.1. For each variable the mean value is indicated by a dashed red vertical line.

The following covariates are included in both the prediction equation and used in matching. The distributions of the variables differ slightly between the full dataset and the Ninth Circuit dataset.

Table A.1: Descriptive Statistics for Dependent Variables

	Mean	Variance	Minimum	Maximum	N
Opposition Vote (Images)	0.440	0.246	0	1	3,290
Opposition Vote (9th)	0.327	0.220	0	1	1,522
Opposition Vote (Computer)	0.455	0.248	0	1	2,646
Opposition Vote (US)	0.327	0.220	0	1	1,522
Opposition Win (Images)	0.421	0.243	0	1	1,067

Figure A.1: Distribution Plots for Various Measures of Attractiveness

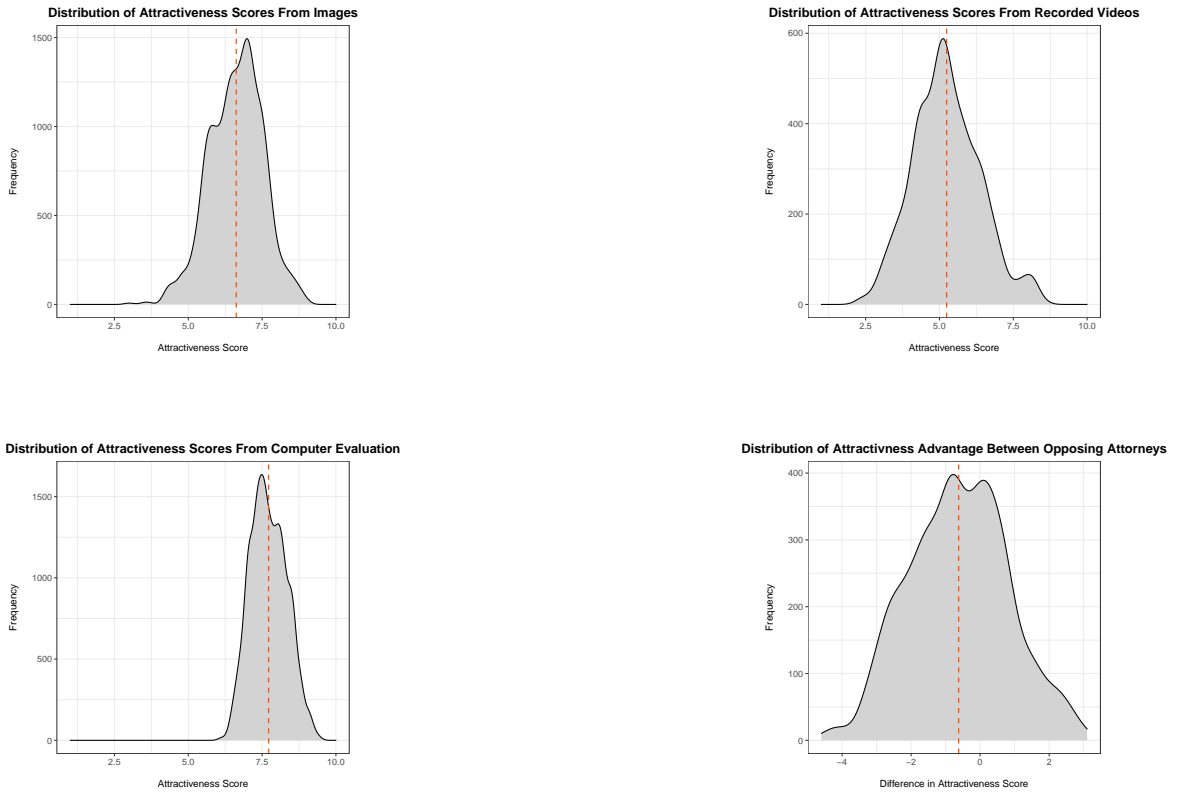


Table A.2: Correlations of Various Measures of Attractiveness

	Images (Humans)	Images (Comp.)	Ninth Cir. Videos	US-Opp. Diff.
Images (Humans)	1			
Images (Comp.)	0.206	1		
Ninth Cir. Videos	0.288	0.317	1	
US-Opp. Diff.	0.223	0.215	0.732	1

- **Experienced Attorney-** Empirical research has shown that experienced attorneys have an advantage in Court of Appeals litigation (e.g., Songer, Sheehan and Haire, 1999). This is a binary variable that is coded as 1 if the opposition attorney has participated in an oral argument at the US Courts of Appeals prior to the present case. The variable was collected using the attorney profile pages from Westlaw.
- **Amicus Advantage-** Collins and Martinek (2010) show that parties with more support from amicus curiae are more likely to win cases at the Court of Appeals. This is a count variable reflecting an opposition attorney's net amicus advantage (or disadvantage) compared to their US opponent. An attorney receives one point for each amicus brief submitted on the merits that supports their party's case. A negative value indicates more amicus briefs were filed in support of the US, a positive value indicates more amicus briefs were filed in support of the opposition. The variable was collected from the case materials available on Westlaw.
- **Elite Law School Graduate-** Attorneys that have attended elite law schools have been shown to have significant advantages when arguing in federal court (e.g. Johnson, Wahlbeck and Spriggs, 2006). This is a binary variable coded as 1 if the attorney graduated from an elite law school. Elite law schools are schools that have consistently ranked in the top 14 of the U.S. News and World Report's Best Law School Rankings from 2010-2020. Each attorney's law school was collected from their professional website or from the relevant bar association records.
- **Opposition Party Resources-** An ordinal variable that proxies that amount of resources the opposition attorney's client has at their disposal. Individuals are coded as 1, businesses or organizations are coded as 2, local governments are coded as 3, and state governments are coded as 4. This coding is consistent with several studies in Court of Appeals analysis (e.g., Cross, 2007; Songer, Sheehan and Haire, 1999). This variable was collected using the party names from the case materials from Federal Judicial Center and Westlaw.
- **En banc-** Cases that are heard en banc are typically salient, more ideological, and more complex (George, 1999). As a result, judges may behave differently with respect to attractive attorneys in these cases. This is a binary variable coded as 1 if the case is being heard en banc and 0 otherwise. This variable was collected using information from the Federal Judicial Center.
- **Unfavorable Judge-** Ideology is perhaps the most explanatory variable in the study of judicial behavior. Cross (2007) confirms that this finding holds at the US Courts of Appeals. This is a binary variable coded as 1 if the judge is ideologically pre-disposed to vote against the opposition attorney. A judge is so disposed if they were appointed by a president from a different party than the lower court judge when the opposition attorney is the appellee OR if they were appointed by a president from the same party as the lower court judge when the opposition attorney is the appellant. The judges' parties and the parties' positions were obtained from the biographical database and the case materials collected from the Federal Judicial Center.
- **Shared Race With Judge-** Psychologists have shown that humans show systematic favoritism to members of their own race (see Meissner and Brigham, 2001, for a review of many of these studies). I account for this possibility in judging by creating this binary variable coded as 1 if the attorney and the judge casting the vote identify as the same race and 0 otherwise. The judge's race was collected from the biographical database from the Federal Judicial Center.

The attorney’s race was obtained from the images, videos, and other information displayed on their professional website and/or from their publicly available social media accounts.

- **Shared Gender With Judge-** Boyd, Epstein and Martin (2010) show the effect of gender in gender discrimination cases at the Court of Appeals. To account for the possibility that these effects extend to the treatment of attorneys I create a binary variable coded as 1 if the attorney and the judge casting the vote identify as the same gender and 0 otherwise. The judge’s gender was collected from the biographical database from the Federal Judicial Center. The attorney’s gender was obtained from the images, videos, and other information displayed on their professional website and/or from their publicly available social media accounts.

Table A.3: Descriptive Statistics for Full Dataset Control Variables

	Mean	Variance	Minimum	Maximum	N
Experienced Attorney	0.776	0.174	0	1	3,290
Amicus Advantage	0.264	2.769	-8	17	3,290
Elite Law School Graduate	0.211	0.123	0	1	3,290
Opposition Party Resources	1.606	0.123	1	4	3,290
En banc	0.032	0.003	0	1	3,290
Unfavorable Judge	0.506	0.250	0	1	3,290
Shared Gender With Judge	0.613	0.237	0	1	3,290
Shared Race With Judge	0.688	0.215	0	1	3,290

Table A.4: Descriptive Statistics for Ninth Circuit Dataset Control Variables

	Mean	Variance	Minimum	Maximum	N
Experienced Attorney	0.936	0.060	0	1	1,522
Amicus Advantage	0.841	7.928	-3	16	1,522
Elite Law School Graduate	0.307	0.213	0	1	1,522
Opposition Party Resources	1.647	0.698	1	4	1,522
En banc	0.036	0.035	0	1	1,522
Unfavorable Judge	0.503	0.250	0	1	1,522
Shared Race With Judge	0.619	0.236	0	1	1,522
Shared Gender With Judge	0.559	0.247	0	1	1,522

The following covariates are included only in the creation of the matched dataset. They account for systematic effects of the survey respondent’s race and gender on their evaluation of an attorney’s appearance:

- **Shared Gender with Respondent-** Psychologists have found gender effects perceptions of attractiveness (e.g., Leder et al., 2010). To account for possible biases in the sample of

respondent’s that rate an attorney’s appearance I created an ordinal variable that captures the amount of same-gendered respondents that evaluated an attorney’s appearance as a percent. To aid in matching, this variable is then coarsened into quartiles with a value of 1 indicating a low number of same-gendered respondents rating an attorney and a value of 4 indicating a high number of same-gendered respondents. The respondent’s gender was self-reported in a series of demographic questions prior to their rating of images in an online survey. The attorney’s gender was obtained from the images, videos, and other information displayed on their professional website and/or from their publicly available social media accounts.

- **Shared Race with Respondent**-To account for own-race favoritism in the rating of attorneys by respondents (Meissner and Brigham, 2001), I create this ordinal variable that captures the amount of same-race survey respondents that evaluated an attorney’s appearance as a percent. To aid in matching, this variable is then coarsened into quartiles with a value of 1 indicating a low number of same-race survey respondents rating an attorney and a value of 4 indicating a high number of same-race survey respondents. The respondent’s race was self-reported in a series of demographic questions prior to their rating of images in an online survey. The attorney’s race was obtained from the images, videos, and other information displayed on their professional website and/or from their publicly available social media accounts.

Table A.5: Descriptive Statistics for Full Dataset Matching-Only Variables

	Mean	Variance	Minimum	Maximum	N
Shared Gender with Respondent	2.526	1.221	1	4	3,290
Shared Race with Respondent	2.546	1.227	1	4	3,290

### 3 Pre-Matching Regression Results

Table A.6: The Effect of Attractiveness on Receiving a Judge’s Vote (Pre-Matching)

	<i>Dependent Variable:</i>			
	Opp. Attorney Vote			
	(1)	(2)	(3)	(4)
Attract. Rating (Images)	0.123*			
	(0.041)			
Attract. Rating (Computer)		0.222*		
		(0.068)		
Attract. Rating (9th)			0.191*	
			(0.050)	

Opp-US Atty. Attract. Diff.				0.078* (0.039)
Experienced Atty.	-0.219* (0.088)	-0.135 (0.099)	-0.115 (0.230)	-0.154 (0.230)
Net Amicus Adv.	0.194* (0.038)	0.244* (0.044)	0.005 (0.029)	-0.0001 (0.029)
Elite Law School Atty.	0.401* (0.080)	0.379* (0.090)	0.432* (0.125)	0.445* (0.125)
Opp. Resources	0.372* (0.052)	0.396* (0.059)	-0.254* (0.084)	-0.256* (0.084)
En banc	1.820* (0.255)	1.819* (0.259)	0.969* (0.374)	0.896* (0.373)
Unfavorable Judge	-0.136* (0.073)	-0.131 (0.082)	-0.258* (0.112)	-0.267* (0.112)
Shared Gender Judge	-0.022 (0.075)	0.036 (0.085)	-0.011 (0.113)	-0.028 (0.112)
Shared Race Judge	-0.137* (0.079)	-0.117 (0.089)	-0.115 (0.115)	-0.114 (0.115)
Constant	-1.520* (0.313)	-2.532* (0.558)	-1.191* (0.391)	-0.080 (0.266)
Observations	3,290	2,646	1,522	1,522

*Note:* all logistic regression models; one-sided t-tests; \*p<0.05

## 4 Balance and Post-Matching Results

Table A.7: Balance Statistics After CBPSM (Image-Based Treatment)

	<i>Pearson Correlation Between Treatment and Covariates</i>	
	Before Matching	After Matching
Experienced Attorney	-0.058	0.000
Amicus Advantage	0.006	-0.000
Elite Law School Graduate	0.084	-0.000
Opposition Party Resources	-0.053	-0.000
En banc	0.072	-0.000
Unfavorable Judge	0.016	-0.000
Shared Gender With Judge	-0.076	0.000
Shared Race With Judge	-0.029	0.000
Shared Race with Resp.	-0.126	0.000
Shared Gender with Resp.	-0.006	0.000

Table A.8: Balance Statistics After CBPSM (Computer-Based Treatment)

	<i>Pearson Correlation Between Treatment and Covariates</i>	
	Before Matching	After Matching
Experienced Attorney	-0.121	-0.000
Amicus Advantage	0.061	0.000
Elite Law School Graduate	0.135	0.000
Opposition Party Resources	0.021	0.000
En banc	0.081	0.000
Unfavorable Judge	0.006	-0.000
Shared Gender With Judge	-0.042	0.000
Shared Race With Judge	-0.018	-0.000



Table A.9: Balance Statistics After CBPSM (Video-Based Treatment)

	<i>Pearson Correlation Between Treatment and Covariates</i>	
	Before Matching	After Matching
Experienced Attorney	-0.061	-0.000
Amicus Advantage	-0.037	-0.000
Elite Law School Graduate	0.010	-0.000
Opposition Party Resources	-0.036	-0.000
En banc	-0.036	0.000
Unfavorable Judge	-0.014	0.000
Shared Gender With Judge	-0.061	-0.000
Shared Race With Judge	-0.056	-0.000
Shared Race with Resp.	-0.041	0.000
Shared Gender with Resp.	-0.010	-0.000

Table A.10: Balance Statistics After CBPSM (Opp-US Difference Treatment)

	<i>Pearson Correlation Between Treatment and Covariates</i>	
	Before Matching	After Matching
Experienced Attorney	-0.075	-0.014
Amicus Advantage	0.070	0.013
Elite Law School Graduate	0.003	-0.001
Opposition Party Resources	0.027	0.007
En banc	0.087	0.014
Unfavorable Judge	0.027	0.004
Shared Gender With Judge	-0.042	-0.003
Shared Race With Judge	-0.108	-0.015
Shared Race with Resp.	-0.065	-0.010
Shared Gender with Resp.	-0.049	-0.010

Table A.11: Balance Statistics After CBPSM at the Case-Level (Image-Based Treatment)

	<i>Pearson Correlation Between Treatment and Covariates</i>	
	Before Matching	After Matching
Experienced Attorney	-0.063	-0.000
Amicus Advantage	0.017	0.000
Elite Law School Graduate	0.080	0.000
Opposition Party Resources	-0.043	-0.000
En banc	0.031	0.000
Unfavorable Panel	-0.044	0.000
Shared Gender With Panel	-0.094	0.000
Shared Race With Panel	-0.060	-0.000
Shared Race with Resp.	-0.130	-0.000
Shared Gender with Resp.	-0.017	0.000

Table A.12: The Effect of Attractiveness on Receiving a Judge's Vote (After CBPSM)

	<i>Dependent variable:</i>			
	Opp. Attorney Vote			
	(1)	(2)	(3)	(4)
Attractiveness Rating (Images)	0.107* (0.040)			
Attractiveness Rating (Comp.)		0.255* (0.067)		
Attractiveness Rating (9th)			0.191* (0.050)	
Opp-US Attorney Attractiveness Diff.				0.087* (0.041)
Experienced Attorney	-0.193* (0.087)	-0.158 (0.098)	0.005 (0.233)	-0.189 (0.243)
Amicus Advantage	0.187* (0.037)	0.204* (0.040)	-0.010 (0.029)	-0.025 (0.030)
Elite Law School Graduate	0.389* (0.080)	0.352* (0.089)	0.409* (0.126)	0.459* (0.123)

Opp. Party Resources	0.379* (0.051)	0.406* (0.059)	-0.265* (0.086)	-0.148* (0.083)
En banc	2.159* (0.266)	1.980* (0.265)	1.369* (0.345)	0.891* (0.405)
Unfavorable Judge	-0.105 (0.073)	-0.103 (0.081)	-0.296* (0.113)	-0.234* (0.111)
Shared Gender With Judge	-0.012 (0.075)	0.011 (0.084)	-0.045 (0.113)	-0.047 (0.112)
Shared Race With Judge	-0.163* (0.079)	-0.117 (0.089)	-0.161 (0.115)	-0.088 (0.115)
Constant	-1.459* (0.301)	-2.757* (0.540)	-1.159* (0.381)	-0.223 (0.275)
Observations	3,290	2,646	1,522	1,522

*Note:* all logistic regression models; one-sided t-tests; \*p<0.05

Table A.13: Predicted Probability of Receiving a Judge’s Vote (After CBPSM)

Treatment Variables	Covs.	Lower Bound	<b>Pr(Receiving Vote)</b>	Upper Bound
Attract. (Img.) = 3	Mean	0.286	<b>0.351</b>	0.423
Attract. (Img.) = 5	Mean	0.366	<b>0.402</b>	0.438
Attract. (Img.) = 7	Mean	0.434	<b>0.454</b>	0.474
Attract. (Img.) = 9	Mean	0.456	<b>0.507</b>	0.558
Attract. (Comp.) = 3	Mean	0.119	<b>0.204</b>	0.325
Attract. (Comp.) = 5	Mean	0.220	<b>0.294</b>	0.379
Attract. (Comp.) = 7	Mean	0.385	<b>0.415</b>	0.446
Attract. (Comp.) = 9	Mean	0.495	<b>0.542</b>	0.588
Attract. (9th) = 3	Mean	0.196	<b>0.240</b>	0.290
Attract. (9th) = 5	Mean	0.287	<b>0.312</b>	0.337
Attract. (9th) = 7	Mean	0.347	<b>0.390</b>	0.443
Attract. (9th) = 9	Mean	0.388	<b>0.483</b>	0.579
Opp-US Diff. = -4.5	Mean	0.189	<b>0.254</b>	0.331
Opp-US Diff. = -1.5	Mean	0.273	<b>0.306</b>	0.341
Opp-US Diff. = 1.5	Mean	0.325	<b>0.364</b>	0.404
Opp-US Diff. = 3	Mean	0.330	<b>0.394</b>	0.462

Table A.14: The Effect of Attractiveness on Winning a Case (After CBPSM)

	(1)	(2)
	Pre-Matching	Post-CBPSM
	<i>Dependent variable:</i>	
	Opposition Party Win	
Attractiveness Rating (Images)	0.124* (0.071)	0.126* (0.071)
Experienced Attorney	-0.180 (0.153)	-0.165* (0.152)
Amicus Advantage	0.158* (0.063)	0.143* (0.061)
Elite Law School Graduate	0.361* (0.140)	0.363* (0.140)
Opposition Party Resources	0.368* (0.089)	0.370* (0.089)
En banc	1.503* (0.851)	1.855* (0.891)
Unfavorable Panel	0.084 (0.128)	0.078 (0.128)
Shared Gender With Panel	-0.019 (0.137)	0.041 (0.138)
Shared Race With Panel	-0.064 (0.152)	-0.055 (0.152)
Constant	-1.728* (0.557)	-1.821* (0.530)
Observations	1,067	1,067

*Note:* all logistic regression models; one-sided t-tests; \*p<0.05

Table A.15: Predicted Probability of Winning a Case (After CBPSM)

Treatment Variables	Covs.	Lower Bound	<b>Pr(Winning Case)</b>	Upper Bound
Attract. (Img.) = 3	Mean	0.211	<b>0.312</b>	0.435
Attract. (Img.) = 5	Mean	0.309	<b>0.368</b>	0.432
Attract. (Img.) = 7	Mean	0.395	<b>0.429</b>	0.463
Attract. (Img.) = 9	Mean	0.403	<b>0.492</b>	0.581

## 5 Robustness Checks

### 5.1 Coarsened Exact Matching

To perform Coarsened Exact Matching, I dichotomized the image-based treatment variable to create a “high attractiveness” indicators. A high attractiveness score is a score that is more than one standard deviation above the average attractiveness score of attorneys in a given sample. Table A.16 displays the descriptive statistic for this variables.

Although CEM has many advantages as discussed in the main text, it is also severe in its pruning of observations. For this reason the **En banc**, **Shared Gender with Respondent**, and **Shared Race with Respondent** variables are not used in this analysis.

Table A.16: Binary Treatment Variables

	Mean	Std. Dev.	Scorer	Image Source	Circuit(s)
High Attract. Rating (Images)	0.144	0.352	Humans	Websites	All
High Attract. Rating (Computer)	0.171	0.377	Computer	Websites	All
High Attract. Rating (9th)	0.164	0.370	Humans	Court Video	9th
Attractiveness Advantage	0.347	0.476	Humans	Court Video	9th

Table A.17: The Effect of Attractiveness on Receiving a Judge's Vote (After CEM)

	<i>Dependent variable:</i>			
	Opp. Attorney Vote			
	(1)	(2)	(3)	(4)
High Attract. Rating (Images)	0.458*			
	(0.131)			
High Attract. Rating (Computer)		0.292*		
		(0.115)		
High Attract. Rating (9th)			0.345*	
			(0.153)	
Attract. Advantage				0.432*
				(0.125)
Experienced Attorney	-0.049	0.076	-0.440*	-0.489*
	(0.148)	(0.102)	(0.256)	(0.259)
Amicus Advantage	1.308*	0.237*	0.035	-0.062
	(0.262)	(0.062)	(0.036)	(0.051)
Elite Law School Graduate	0.124	0.325*	0.093	0.313*
	(0.133)	(0.091)	(0.143)	(0.132)
Opp. Party Resources	0.594*	0.476*	-0.109	-0.206*
	(0.108)	(0.066)	(0.124)	(0.107)
Unfavorable Judge	-0.161	-0.168	0.029	-0.201
	(0.118)	(0.088)	(0.127)	(0.123)
Shared Gender Judge	0.009	-0.074	-0.084	0.023
	(0.120)	(0.091)	(0.128)	(0.125)
Shared Race Judge	-0.037	-0.104	-0.039	-0.022
	(0.129)	(0.094)	(0.131)	(0.127)
Constant	-1.323*	-1.053*	-0.212	-0.163
	(0.233)	(0.161)	(0.275)	(0.273)
Observations	1,315	2,265	1,189	1,297

*Note:* all logistic regression models; one-sided t-tests; \*p<0.05

Table A.18: The Effect of Attractiveness on Winning a Case (After CEM)

	(1)	(2)
	Pre-Matching	Post-CEM
	<i>Dependent variable:</i>	
	Opposition Party Win	
High Attractiveness Rating (Images)	0.357* (0.178)	0.302* (0.183)
Experienced Attorney	-0.192 (0.153)	-0.034 (0.169)
Amicus Advantage	0.152* (0.062)	0.448* (0.143)
Elite Law School Graduate	0.367* (0.140)	0.253* (0.148)
Opposition Party Resources	0.360* (0.089)	0.227* (0.109)
En banc	1.592* (0.851)	2.254* (1.149)
Unfavorable Panel	0.079 (0.128)	0.203 (0.140)
Shared Gender With Panel	-0.025 (0.137)	-0.049 (0.142)
Shared Race With Panel	-0.062 (0.152)	-0.162 (0.171)
Constant	-0.939* (0.246)	-0.761* (0.263)
Observations	1,067	901

*Note:* all logistic regression models; one-sided t-tests; \*p<0.05



## 5.2 Replication of Full Analysis with Weighted Scores

In order to account for differences in demographic characteristics of serving US Courts of Appeals judges and survey respondents responsible for assigning attractiveness scores, I assigned weights to attractiveness scores based on a respondent’s self-reported gender and race. In this weighted sample, the amount of influence held by each gender-race combination is identical to the influence held by that combination in the sample of US Courts of Appeals judges included in this analysis. The relevant treatment variable is **Weighted Attractiveness Rating (Images)**, a continuous variable that is an average of the weighted scores, unique to each attorney. In total, 1,185 attorneys received ratings for this analysis.

Table A.19: Descriptive Statistics for Weighted Attractiveness in Full Analysis

	Mean	Variance	Minimum	Maximum	N
Weighted Attract. Rating (Images)	6.501	0.971	2.824	9.355	3290

Table A.20: The Effect of Weighted Attractiveness on Receiving a Judge’s Vote

	(1)	(2)
	Pre-Matching	Post-CBPSM
	<i>Dependent variable:</i>	
	Opp. Attorney Vote	
Weighted Attractiveness Rating (Images)	0.071* (0.037)	0.070* (0.036)
Experienced Attorney	-0.225* (0.088)	-0.201* (0.087)
Amicus Advantage	0.194* (0.038)	0.199* (0.038)
Elite Law School Graduate	0.410* (0.080)	0.379* (0.080)
Opposition Party Resources	0.368* (0.052)	0.375* (0.051)
En banc	1.850* (0.255)	2.038* (0.259)

Unfavorable Judge	-0.135* (0.073)	-0.129* (0.073)
Shared Gender With Judge	-0.028 (0.075)	-0.009 (0.075)
Shared Race With Judge	-0.138* (0.079)	-0.156* (0.079)
Constant	-1.156* (0.287)	-1.182* (0.274)
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Observations	3,290	3,290

*Note:* all logistic regression models; one-sided t-tests; \*p<0.05

### 5.3 Analysis with Additional Covariates

As an additional robustness check, the following variables used in alternative model specifications articulated in Courts of Appeals literature were collected for supplementary analysis.

- **Unfavorable Judge Ideology-** This is a continuous variable that accounts for the ideological difference between the lower court and the Court of Appeals judge when she is pre-disposed to vote against the opposition party. The judge’s disposition is determined identically to the binary variable **Unfavorable Judge**. The appellate ideological measures were taken from the January 5, 2021 update of the Judicial Common Space scores (see Epstein et al. 2007 for the full derivation) and the district court scores were taken from Boyd (2015).<sup>1</sup>
- **Supreme Court Clerk-** A binary variable coded as 1 if the opposition attorney was a law clerk for one of the justices on the United States Supreme Court. This information was collected from the attorney’s professional website and/or from their publicly available social media accounts.
- **Circuit Court Clerk-** A binary variable coded as 1 if the opposition attorney was a law clerk at the same circuit that is hearing the present case. This information was collected from the attorney’s professional website and/or from their publicly available social media accounts.
- **Circuit Fixed Effects-** To account for unique effects that may be based on the rules, customs, or traditions of any particular circuit, circuit fixed effects are included for matching and empirical analysis.

<sup>1</sup>But also see Giles, Hettinger, and Peppers (2001) for the methodology Boyd used to compile the database.

Table A.21: The Effect of Attractiveness on Receiving a Judge's Vote (Add. Covariates)

	(1)	(2)
	Pre-Matching	Post-CBPS
	<i>Dependent variable:</i>	
	Opp. Attorney Vote	
Attractiveness Rating (Images)	0.124* (0.049)	0.119* (0.049)
Experienced Attorney	-0.215* (0.102)	-0.191* (0.105)
Amicus Advantage	0.243* (0.061)	0.190* (0.061)
Elite Law School Graduate	0.224* (0.100)	0.235* (0.103)
Opposition Party Resources	-0.012 (0.067)	-0.013 (0.069)
En banc	1.894* (0.291)	2.198* (0.300)
Unfavorable Judge Ideology	-0.119 (0.365)	0.094 (0.363)
Shared Gender With Judge	0.008 (0.087)	0.029 (0.090)
Shared Race With Judge	-0.139 (0.091)	-0.189* (0.094)
Supreme Court Clerk	0.515* (0.208)	0.438* (0.217)
Circuit Court Clerk	-0.023 (0.236)	-0.102 (0.250)
Circuit Fixed Effects	✓	✓
Constant	5.952* (1.089)	5.745* (1.072)
Observations	3,290	3,290

*Note:* all logistic regression models; one-sided t-tests; \*p<0.05

## 5.4 Race and Gender Effects

In the main analysis I accounted for the influence of race and gender on attractiveness ratings by controlling for the influence of judges and survey respondents sharing gender and/or race with an opposition attorney. While this approach accounts for certain theoretical expectations on the effect of race and gender on attractiveness ratings, it does not allow for a clean matching of attorneys on disparate races and genders.

In the analysis below I first match opposition attorneys on their gender via the binary variable *Female Attorney*, coded as 1 if the opposition attorney is a female, and race via the binary *Non-White Attorney*, coded as 1 if the opposition attorney identifies as non-white. When these variables are added to the full analysis as matching covariates and additional control variables the effect of attractiveness on success holds.

Table A.22: The Effect of Attractiveness on Receiving a Judge’s Vote with Additional Race and Gender Considerations

	(1)	(2)
	Pre-Matching	Post-CBPS
	<i>Dependent variable:</i>	
	Opp. Attorney Vote	
Attractiveness Rating	0.105* (0.032)	0.072* (0.041)
Female Attorney	0.201 (0.099)	0.209* (0.099)
Non-White Attorney	-0.070 (0.136)	0.048 (0.137)
Experienced Attorney	-0.209* (0.088)	-0.196* (0.088)
Amicus Advantage	0.192* (0.038)	0.219* (0.041)
Elite Law School Graduate	0.407* (0.081)	0.437* (0.080)
Opposition Party Resources	0.372* (0.052)	0.380* (0.052)
En banc	1.825* (0.256)	2.127* (0.265)

Unfavorable Judge Ideology	-0.137* (0.073)	-0.141* (0.073)
Shared Gender With Judge	0.020 (0.078)	0.053 (0.078)
Shared Race With Judge	-0.148 (0.090)	-0.176* (0.091)
Constant	-1.458* (0.317)	-1.301* (0.314)
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Observations	3,290	3,290

*Note:* one-sided t-tests; \*p<0.05

Given additional potential theoretical expectations on the asymmetric effect of attractiveness on success, conditional on gender, I also examined conditional effects in the model reported below. Although the individual attractiveness advantage given to attorneys based on their gender is mixed, there is some preliminary evidence of a three-way conditional effect of greater advantages being extended to female attorneys with a high attractiveness score when arguing before male judges.

Table A.23: Models of the Effect of Attractiveness, Conditional on Attorney and Judge Gender, on Receiving a Judge's Vote at the US Courts of Appeals.

	(1)	(2)
	Pre-Matching	Post-CBPS
	<i>Dependent variable:</i>	
	Opp. Attorney Vote	
Attractiveness Rating * Male Judge * Female Attorney	0.355* (0.210)	0.480* (0.205)
Attractiveness Rating	0.108 (0.083)	0.119 (0.084)
Male Judge	-0.214 (0.667)	-0.081 (0.675)
Female Attorney	2.629* (1.189)	2.715* (1.134)

Attractiveness Rating * Male Judge	0.028 (0.101)	0.010 (0.102)
Attractiveness Rating * Female Attorney	-0.326* (0.170)	-0.335* (0.162)
Male Judge * Female Attorney	-2.732* (1.475)	-3.669* (1.447)
Experienced Attorney	-0.218* (0.088)	-0.201* (0.088)
Amicus Advantage	0.188* (0.038)	0.198* (0.039)
Elite Law School Graduate	0.406* (0.081)	0.333* (0.080)
Opposition Party Resources	0.378* (0.052)	0.372* (0.053)
En banc	1.784* (0.258)	1.839* (0.269)
Unfavorable Judge Ideology	-0.134* (0.073)	-0.159* (0.073)
Shared Race With Judge	-0.128 (0.080)	-0.133* (0.079)
Constant	-1.466* (0.564)	-1.525* (0.571)
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Observations	3,290	3,290

*Note:* one-sided t-tests; \*p<0.05

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