



Tinder Decides: Mate Desirability Influences Votes

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“When Women Run, Women Win”

- ▶ Women win at equal rates to men (e.g., Burrell 1994, Lawless 2015)
- ▶ Partisanship swamps gender in U.S. general elections (Hayes 2011)





...But Which Women Win?

- ▶ After controlling for women's higher qualifications, they receive fewer votes than men (Anzia and Berry 2011, Fulton 2012)

Related queries

1 hot female politicians

2 hottest female politicians

3 pakistani female politicians

4 25 most gorgeous female politicians

Key Question

Does the way in which we evaluate candidates disadvantage women?

Assessing Qualifications is Hard

- ▶ It's hard and time-intensive to figure out who to vote for (Berelson et al. 1954)
- ▶ Lots of evidence that we rely on snap judgments more than we should (Kahneman 2011)
 - ▶ When candidates "look" competent, they are more likely to win (e.g., Todorov et al. 2005, Ahler et al. 2016)
 - ▶ Traditional argument: we substitute easy questions for hard ones

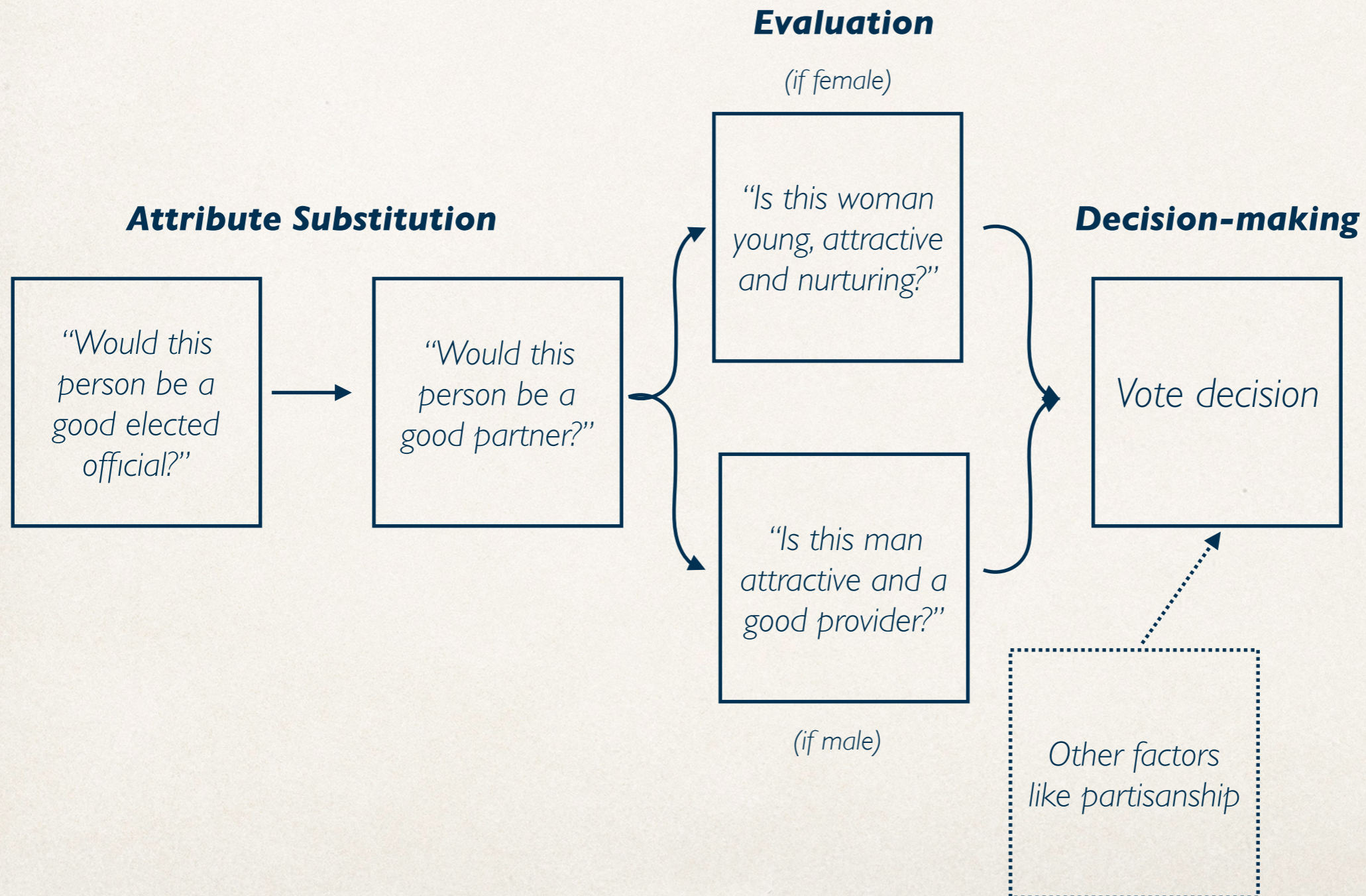
Snap Judgments are Familiar Judgments

- ▶ Problem: many easier questions than how to vote! **How do we know a priori what judgment will be substituted?**
- ▶ One answer: we fall back on a **familiar** person-evaluation strategy—**mate selection**
 - ▶ We “know” and practice how to do this (“Tinder mentality”); we don’t “know” and practice how to vote
 - ▶ Does not have to be for ourselves—we are comparing against a **prototype** (Kahneman and Frederick 2002, Johnson et al. 2008)

Judgments of Mate Desirability

- ▶ General consensus on traits in both evolutionary psychology (e.g., Buss 1989) and social psychology (e.g., Zentner and Eagly 2015)
- ▶ In **female** partners:
 - ▶ Fertility (attractiveness and age) and parenting skills (“motherliness”)
 - ▶ *Asymmetry: much more emphasis on attractiveness and age*
- ▶ In **male** partners:
 - ▶ Fertility (attractiveness—age less a factor) and parenting skills (“fatherliness”)

Candidate Evaluation Process



The Case of Oregon

26 Candidates | Partisan Candidates

State Representative, 29th District



Katie Eyre Brewer

Republican (REP)

Occupation: Certified Public Accountant

Occupational Background: Senior Tax Manager, Harsch Investments and Jones & Roth; Principal, Fordham Goodfellow; Senior Consultant,

PricewaterhouseCoopers; Controller, The Arcand Co.; Senior Tax Specialist, KPMG.

Educational Background: BS, Accounting, Cal State Northridge.

Prior Governmental Experience: Member, Hillsboro Planning Commission.

Community Service: Past Chair, Hillsboro Chamber of Commerce; Domestic Violence, Education Outreach; Crisis Counselor, Washington County Rape Crisis Center.

Family: Married to Bill; children (ages 6-25), Madelyn, Sadie, Nikki, Jacob and Bonnie.

KATIE EYRE BREWER: Let's End the Backless Spending and Debt

State Representative, 29th District



Katie Riley

Democrat (DEM)
Independent (IND)

Occupation: Assistant Professor Emerita

Occupational Background: Assistant Professor, Director of Education, Administrator,

Public Health & Preventive Medicine, OHSU, 1992-2009; Administrator in School of Engineering, other departments, UCLA, 1966-1992.

Educational Background: University of Oregon, B.A.; WSU, M.A; UCLA, Ed.D.

Prior Governmental Experience: Legislative Task Force, Oregon Commission on Children & Families; Washington County Commission on Children and Families; Northwest Regional Education Service District Board; Multnomah County DUII Advisory Committee.

Community Involvement: Past President, Oregon Public Health Association; Hillsboro School District Curriculum Committee.

Data

- ▶ 2000-2014 Oregon state legislative races
 - ▶ Scrape voting pamphlets from the OR Secretary of State's website
 - ▶ Result: 816 candidates, 789 unique photos
 - ▶ 228 unique photos of women
 - ▶ 561 unique photos of men

Study Design

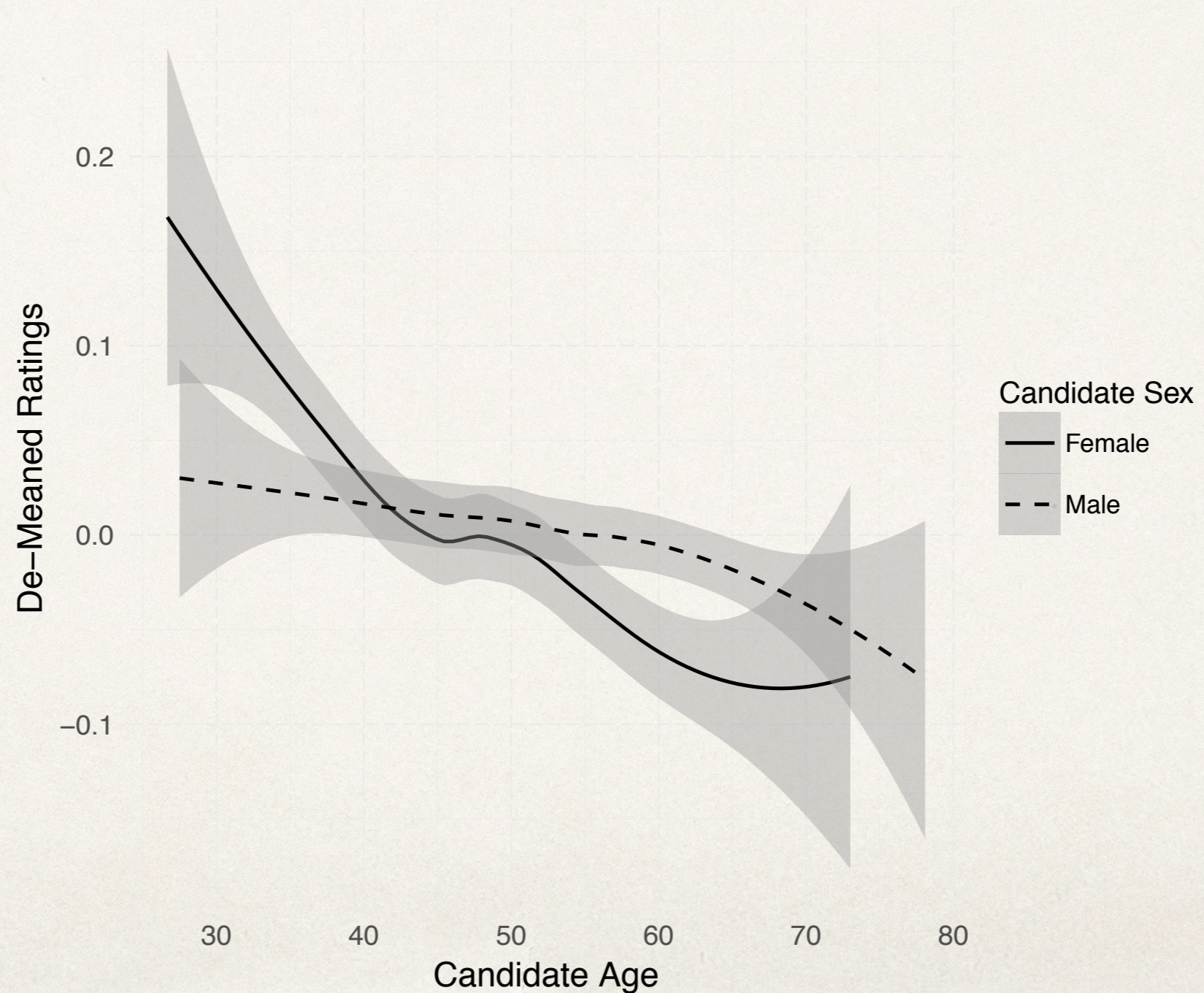
- ▶ **Study 1:** 3,245 survey respondents recruited via MTurk, 529 photos
- ▶ **Study 2:** 7,036 survey respondents recruited via MTurk, 789 photos
- ▶ **Study 3:** 4,551 registered voters recruited via SSI, 187 photos
- ▶ Each respondent rates ~30 randomly drawn photos on a **single** question
 - ▶ **Hypothetical vote:** “how likely would you be to vote for this person?”
 - ▶ Each respondent’s rating is aggregated into a mean candidate rating

Results (summary)

- ▶ Specific mate selection traits (attractiveness and mother/fatherliness) predict willingness to vote for candidates
 - ▶ Holds in both convenience and registered voter samples
- ▶ Lots of potential reasons for correlation between traits, however...one unique prediction of mate selection theory is that women will be penalized much more than men as they age

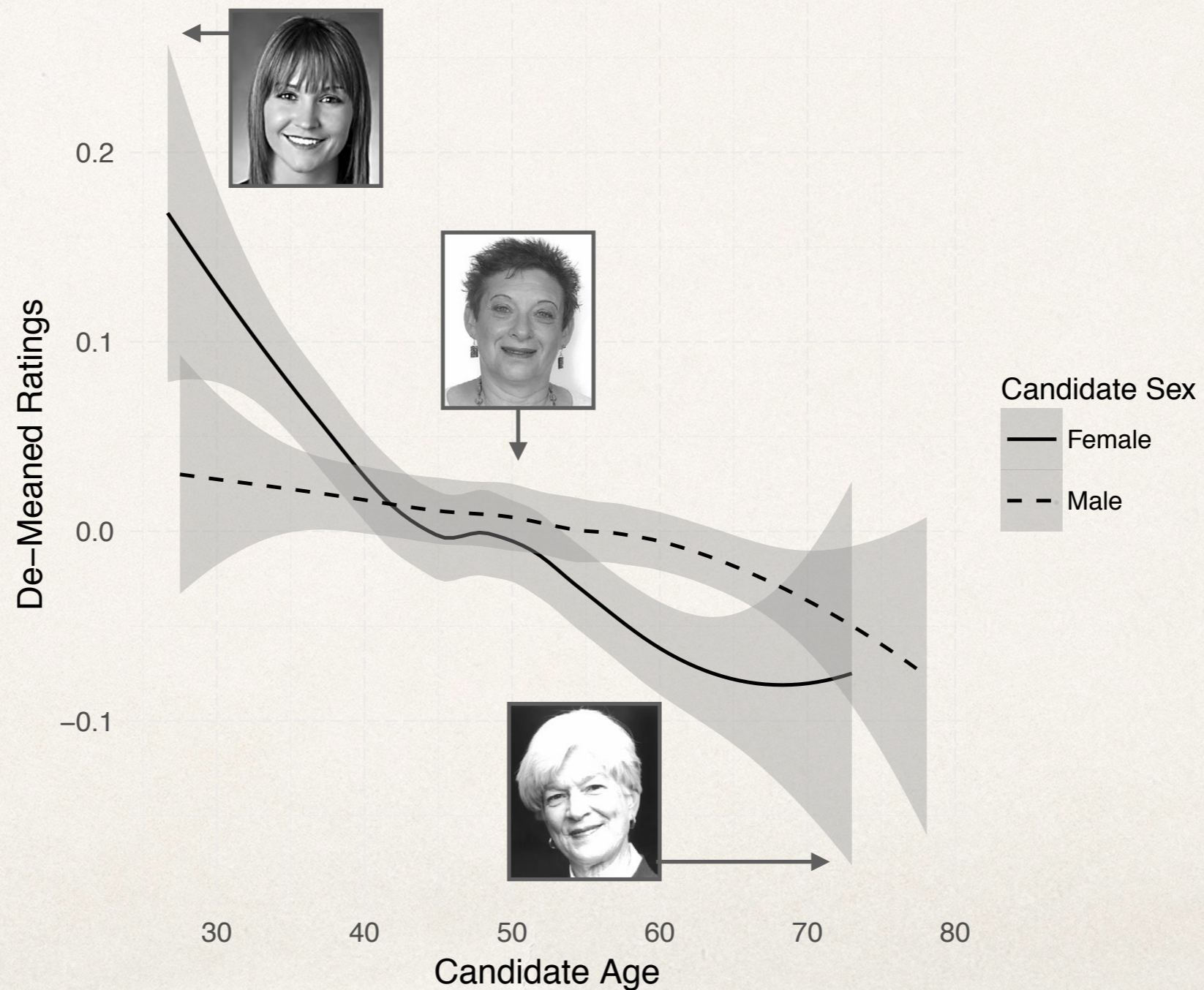
Age Matters More for Women

Hypothetical Vote as a Function of Candidate Age and Sex



Age Matters More for Women

Hypothetical Vote as a Function of Candidate Age and Sex



Implications for Descriptive Representation

- ▶ Older and less conventionally attractive women will be at a disadvantage with voters
 - ▶ Worse news: women tend to be older than men when they run for the first time (Carroll and Sanbonmatsu 2013)
- ▶ Voters may exhibit bias in which women they elect without any intention of discriminating
- ▶ Candidate photos may trigger “Tinder mentality” (gendered, racialized snap judgments based on appearance)

Remaining Questions

▶ Political psychology

- ▶ Is there some minimum amount of information needed to trigger this behavior?

▶ Descriptive representation

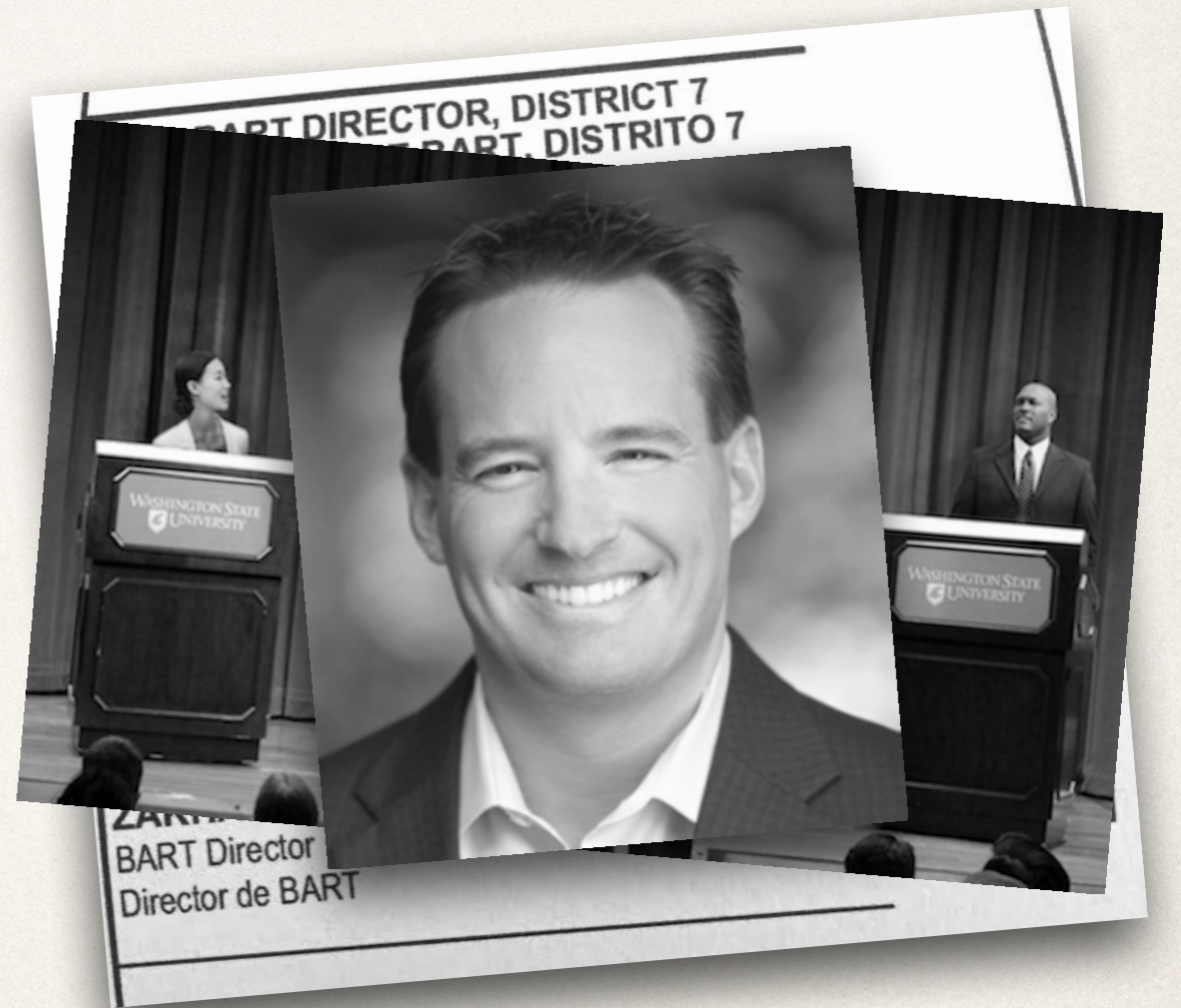
- ▶ Which groups do “neutral” heuristics privilege?

▶ Democratic accountability

- ▶ Can appealing-looking candidates insulate themselves against poor performance?

▶ Electoral rules

- ▶ Does holding many direct elections of candidates (as occurs in U.S.) exacerbate use of snap judgments?



Thanks!

Rachel Bernhard

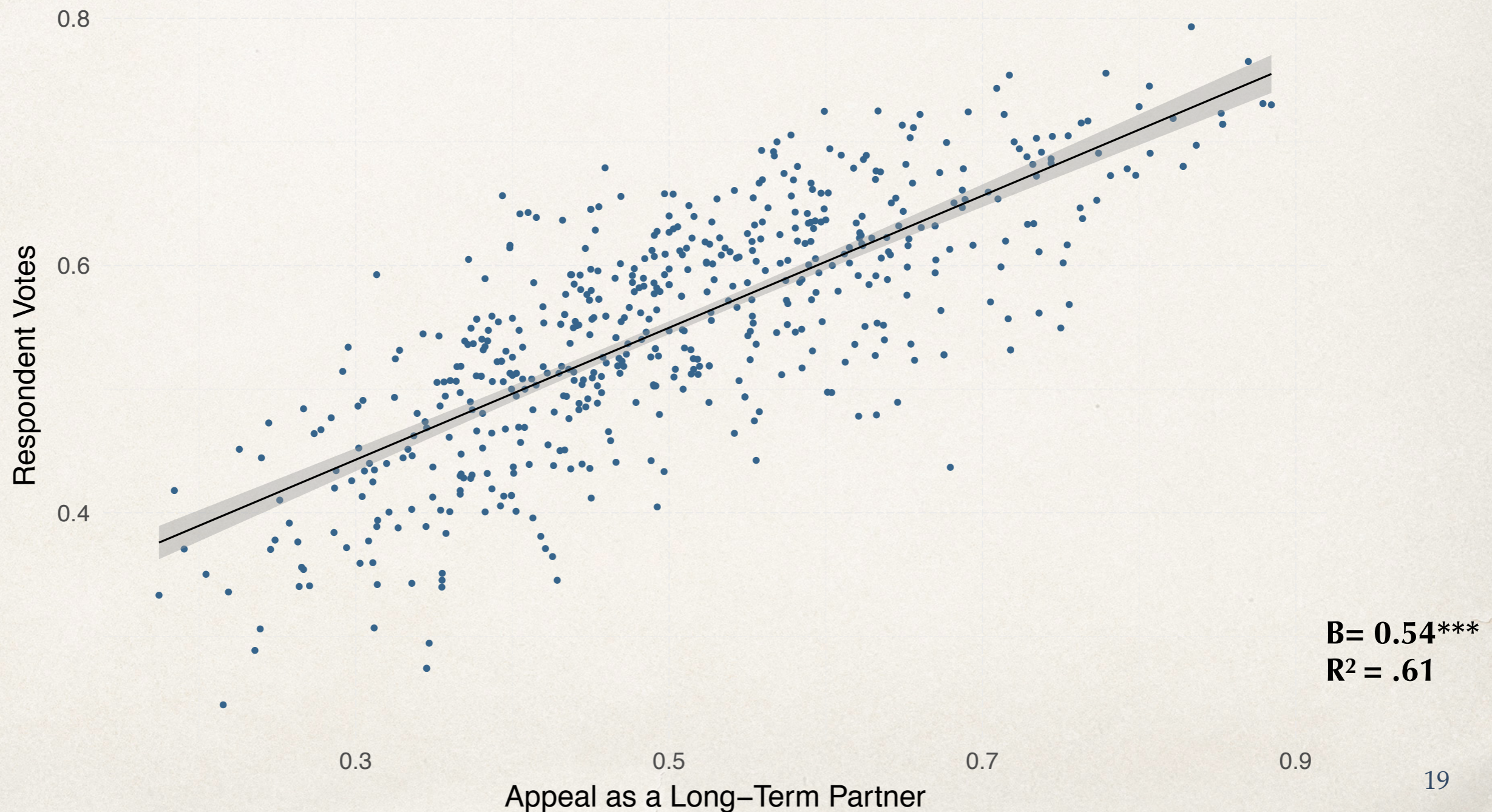
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Study 1: Design

- ▶ **Aim: do people substitute mate desirability for political evaluation?**
- ▶ 3,245 survey respondents recruited via MTurk, 529 photos
 - ▶ Each respondent rates ~30 randomly drawn photos on a **single** question
 - ▶ **Partner appeal:** "how appealing would others find this person as a long-term romantic partner?"
 - ▶ **Hypothetical vote:** "how likely would you be to vote for this person?"
- ▶ Each photo-trait is rated ~57 times, which are aggregated into a mean rating

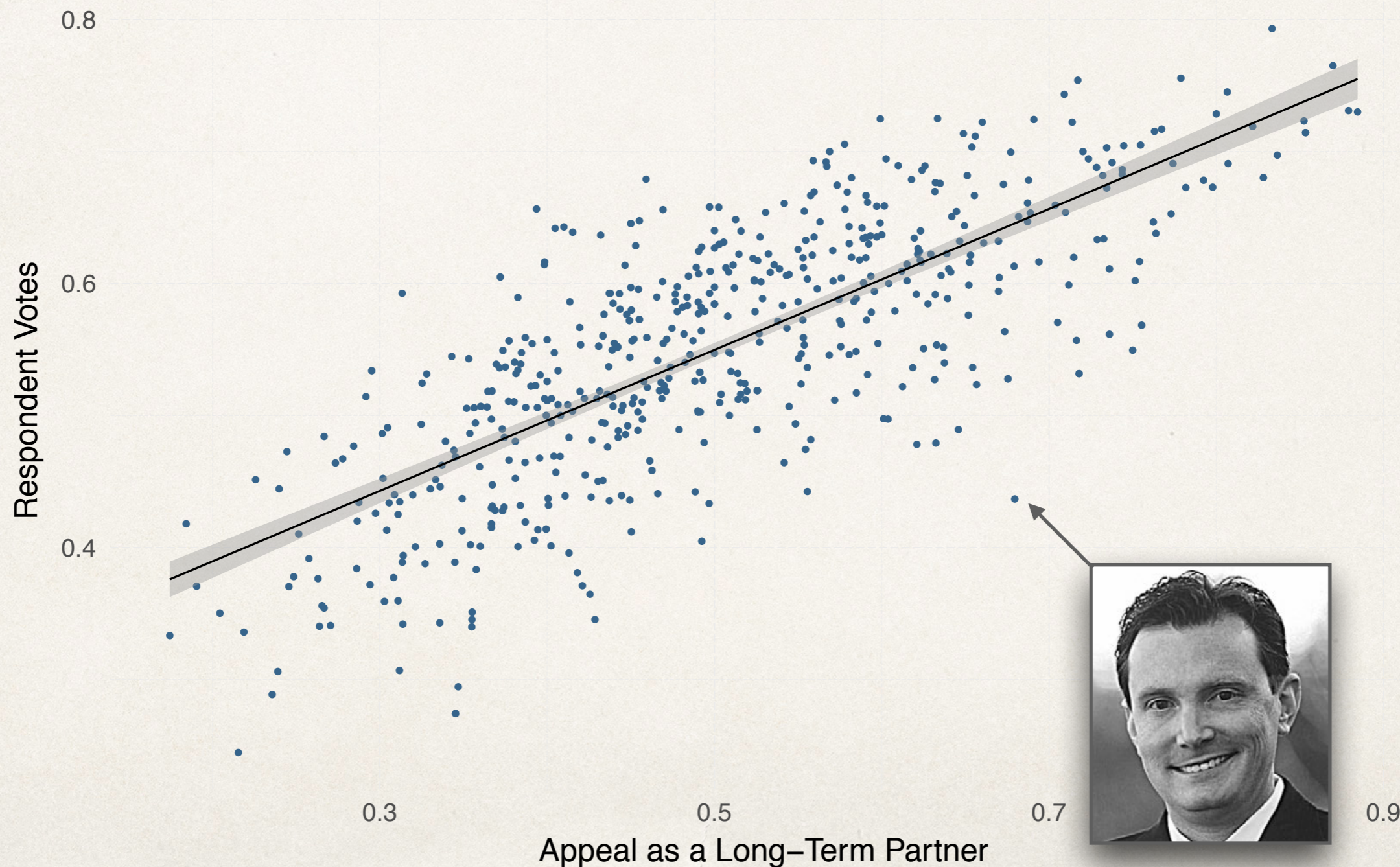
Partner Appeal Predicts Likely Votes

Relationship Between Partner Appeal and Vote Choice



Partner Appeal Predicts Likely Votes

Relationship Between Partner Appeal and Vote Choice

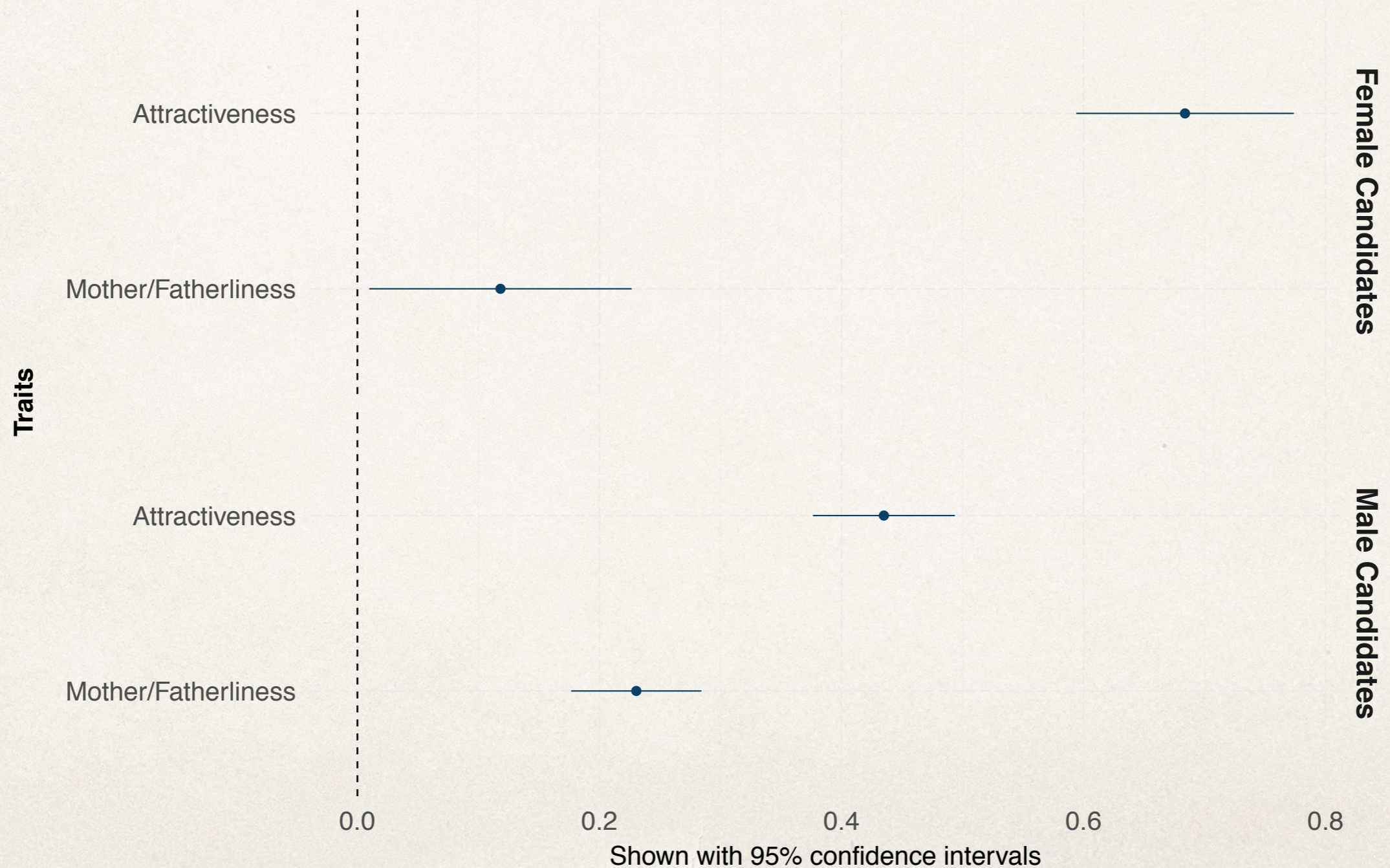


Study 2: Design

- ▶ **Aim: do *specific* mate desirability traits predict vote preference?**
- ▶ **Study 2: 7,036 survey respondents recruited via MTurk, 789 photos**
 - ▶ Each respondent rates ~30 randomly drawn photos on a **single** trait
 - ▶ Traits: attractiveness, motherliness/fatherliness, hypothetical vote
 - ▶ 50+ ratings of each photo-trait, aggregated into mean rating

“Mate” Traits Predict Political Evaluations

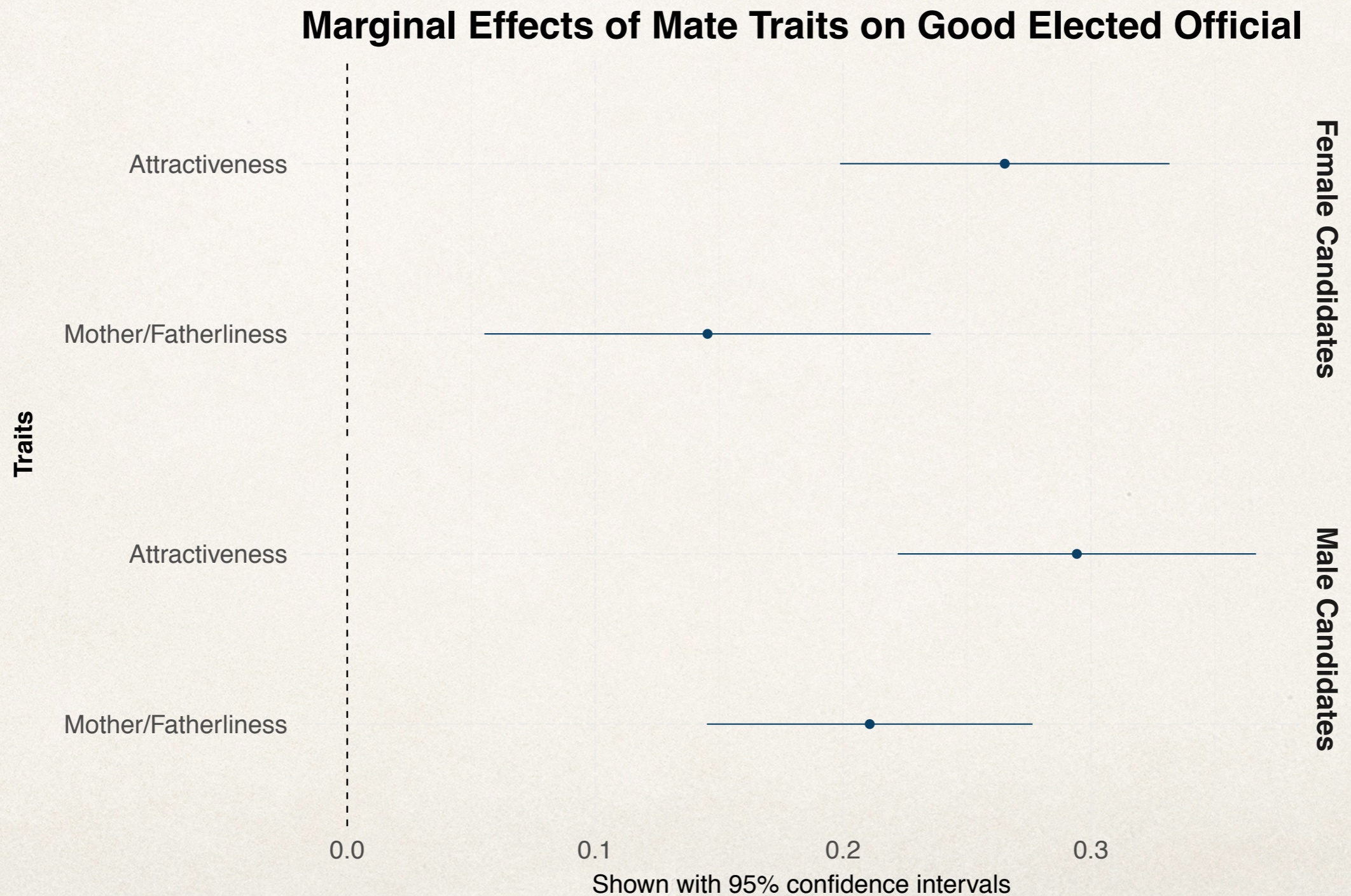
Marginal Effects of Mate Traits on Hypothetical Votes



Study 3

- ▶ **Study 3:** replication with 4,551 registered voters recruited via SSI
 - ▶ Subset of 187 candidate photos rated (4 photos per respondent)

“Mate” Traits Still Predictive



Extra Slides

Literature on Gender Bias

Caveats and Scope

Case and General Empirics

Election Analyses

Study 1: Partner Appeal

Studies 2 and 3: Traits and Age

Studies 2 and 3: Heterogeneity

Other Research:

Candidate Height

Voters' Information Search

Women's Self-Selection

Gender in Local Elections

How Do We Assess Women's Qualifications?

- ▶ Men stereotyped as competent (e.g., Fiske et al. 2002)
- ▶ Women are not assumed to be qualified (Ditonto 2016, Ditonto and Redlawsk 2014, Bernhard and Freeder NP)
- ▶ Giving voters explicit information about qualifications doesn't eliminate this bias for all voters (Mo 2015)
- ▶ After controlling for women's higher qualifications, they receive fewer votes (Anzia and Berry 2011, Fulton 2012)

Caveats and Scope

- ▶ Hard to make causal claims about highly interrelated, difficult-to-manipulate traits
- ▶ Generalizability of Oregon, state legislative elections
- ▶ Results conditional on earlier selection processes

Generalizability

 added 5 new photos. ...
5 hrs · 

Kayin men debating their ideal woman. Key features include: average beauty, average independence, demure, loving, faithful, good at leading the children, and tall. The women we spent the following two days with could be best described as: very independent, brave, decisive, and fantastic story tellers.



The Curious Case of Oregon

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- ▶ Improvements over earlier work:
 - ▶ Voters likely to receive these cues in real life
 - ▶ Better measurement of the cues themselves
 - ▶ Media, PAC confounding much less likely
 - ▶ Much harder to strategically move between districts
 - ▶ Data comes from earlier in the selection pipeline

Predicting Elections from Voting Pamphlets

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Vote Share_D =

$$\begin{aligned} & \beta \cdot \text{Photo}_D + \beta \cdot \text{Photo}_R + \beta \cdot \text{Prior Govt Experience}_D + \beta \cdot \text{Prior Govt Experience}_R + \\ & \beta \cdot \text{Education}_D + \beta \cdot \text{Education}_R + \beta \cdot \text{Occupation}_D + \beta \cdot \text{Occupation}_R + \\ & \text{FEs}(\text{district, year, office}) \end{aligned}$$

Variable Coding

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- ▶ From scraped data:
 - ▶ **Photo:** “how likely would you be to vote for this person?”, 7-pt scale [Study 1]
 - ▶ **Prior Government Experience:** hand-coded, 12-pt scale
 - ▶ **Education:** hand-coded, 4-pt scale
 - ▶ **Occupation:** “how effective a state legislator would someone with this job be if they had no other political experience?”, 5-pt scale

Appearance Predicts Votes in Elections

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Relationship of Information Cues to Real Vote Share	
	<u>Democratic Advantage in Vote Share</u>
Democrat's Appearance	0.243* (0.097)
Opponent's Appearance	-0.434*** (0.089)
Democrat's Prior Government Experience	0.271*** (0.051)
Opponent's Prior Government Experience	-0.324*** (0.052)
Democrat's Education	0.071 (0.049)
Opponent's Education	-0.002 (0.029)
Democrat's Profession	-0.067 (0.112)
Opponent's Profession	-0.269*** (0.077)
District, Year, and Office Fixed Effects?	Yes
Observations	267 races
R ²	0.869

Note: Coefficients are scaled 0-1. Standard errors displayed in parentheses; all SEs are robust (HC1), clustered by election race. Constant and fixed effects coefficients not displayed. *p<0.05; **p<0.01; ***p<0.001

Women's vs. Men's Appearance

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Relationship of Cues to Vote Share

	<u>Female Candidates</u>	<u>Male Candidates</u>	<u>Wald Test of Differences</u>
Appearance	0.554*** (0.163)	0.277 (0.199)	p=0.078
Prior Government Experience	0.390*** (0.075)	0.306*** (0.083)	p=0.000
Education	0.144** (0.049)	-0.037 (0.064)	p=0.004
Helpful Profession	-0.024 (0.134)	0.330* (0.163)	p=0.273
Year and Office Fixed Effects?	Yes		
Observations	267 races (68 female Rs, 97 female Ds, 199 male Rs, 126 male Ds)		
R ²	0.578		

Note: Coefficients are scaled 0-1. Standard errors displayed in parentheses; all SEs are robust (HC1), clustered by election race. Estimates are precision-weighted across Democratic and Republican candidates (e.g., "Appearance" is the precision-weighted average of Democratic Appearance and Opponent Appearance). Constant, Male_{DEM}, Male_{REP}, Male_{DEM}*Male_{REP}, and fixed effects coefficients not displayed. Wald test of differences based on joint test. *p<0.05; **p<0.01; ***p<0.001

Women's vs. Men's Appearance

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Relationship of Cues to Democratic Vote Share			
	<u>Female Candidates</u>	<u>Male Candidates</u>	<u>Wald Test of Differences</u>
Democrat's Appearance	0.453* (0.223)	0.184 (0.273)	p=0.324
Opponent's Appearance	-0.671** (0.239)	-0.382 (0.291)	p=0.322
Democrat's Prior Government Experience	0.250** (0.087)	0.242* (0.099)	p=0.932
Opponent's Prior Government Experience	-0.796*** (0.148)	-0.461*** (0.154)	p=0.031
Democrat's Education	0.188** (0.068)	-0.102 (0.105)	p=0.006
Opponent's Education	-0.097 (0.070)	-0.002 (0.082)	p=0.247
Democrat's Helpful Profession	-0.061 (0.170)	0.377 (0.217)	p=0.044
Opponent's Helpful Profession	0.037 (0.217)	-0.269 (0.247)	p=0.216
Year and Office Fixed Effects?	Yes		
Observations	267 races (68 female Rs, 97 female Ds, 199 male Rs, 126 male Ds)		
R ²	0.578		

Note: Coefficients are scaled 0-1. Standard errors displayed in parentheses; all SEs are robust (HC1), clustered by election race. Constant, Male_{DEM}, Male_{REP}, Male_{DEM}*Male_{REP}, and fixed effects coefficients not displayed. *p<0.05; **p<0.01; ***p<0.001

Sample

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- ▶ Not all 789 unique photos included in every study: discovered later that district boundaries in Oregon shifted between 2000 and 2002
 - ▶ 529 unique photos rated on all traits and used in regressions
 - ▶ 365 male candidates, 164 female candidates
- ▶ In study with registered voters, only 187 unique photos used to retain power
 - ▶ Largest photos from the dataset selected
 - ▶ 91 male candidates, 96 female candidates

Study 1: Example

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How appealing would others find this person as a long-term partner?

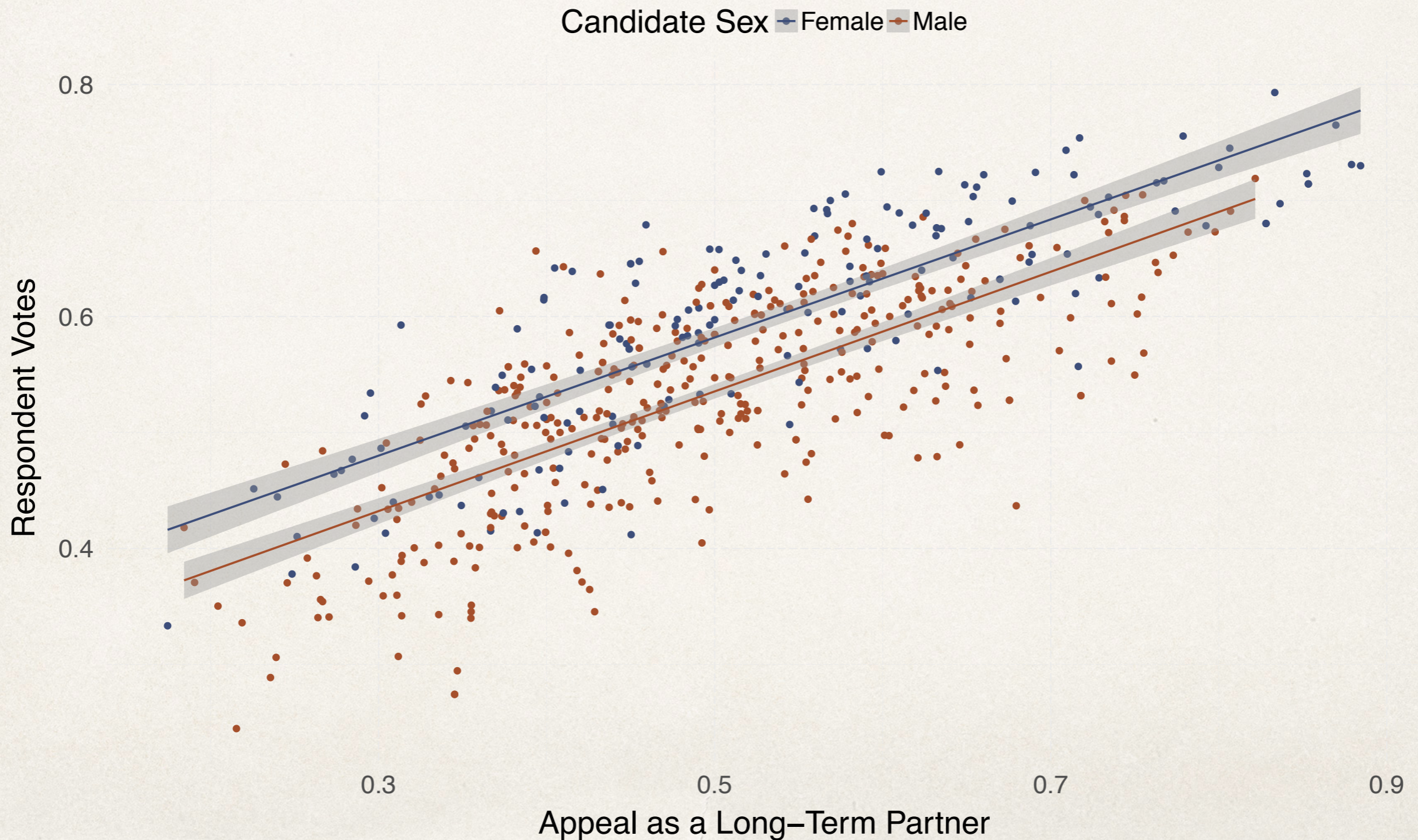
<i>Extremely appealing</i>	<i>Moderately appealing</i>	<i>Slightly appealing</i>	<i>Neither appealing nor unappealing</i>	<i>Slightly unappealing</i>	<i>Moderately unappealing</i>	<i>Extremely unappealing</i>
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Appeal Predictive for Both Sexes

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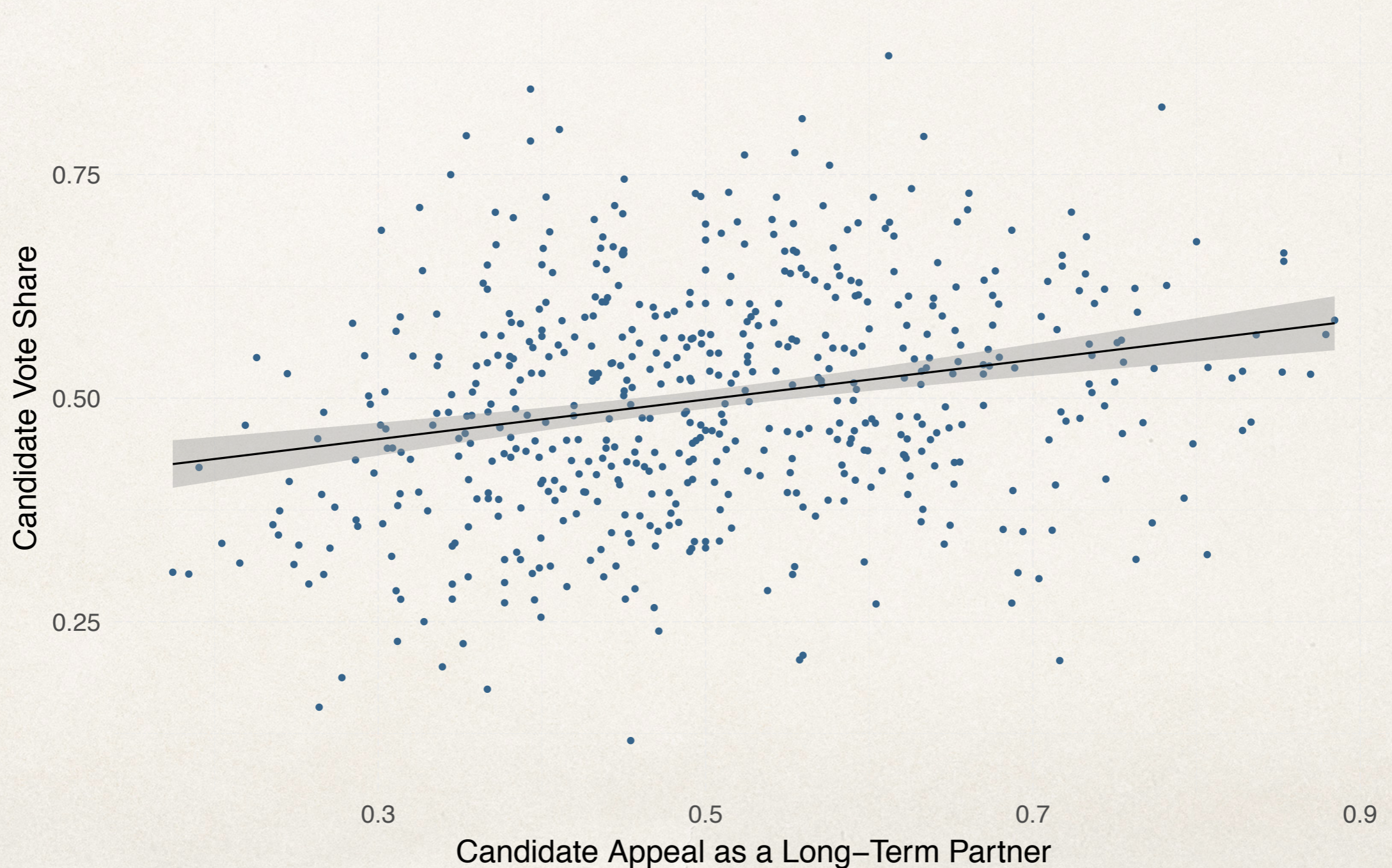
Relationship Between Partner Appeal and Vote Choice, by Candidate Sex



Partner Appeal Predicts Real Votes

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Relationship Between Partner Appeal and Real Votes in Oregon



Study 2: Design

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- ▶ **Secondary aim: rule out strongest alternative explanations**
- ▶ Respondents also rated candidates on competence, dominance, and gender typicality (all shown to predict election outcomes)

Gender Stereotypes vs. Mate Prototypes

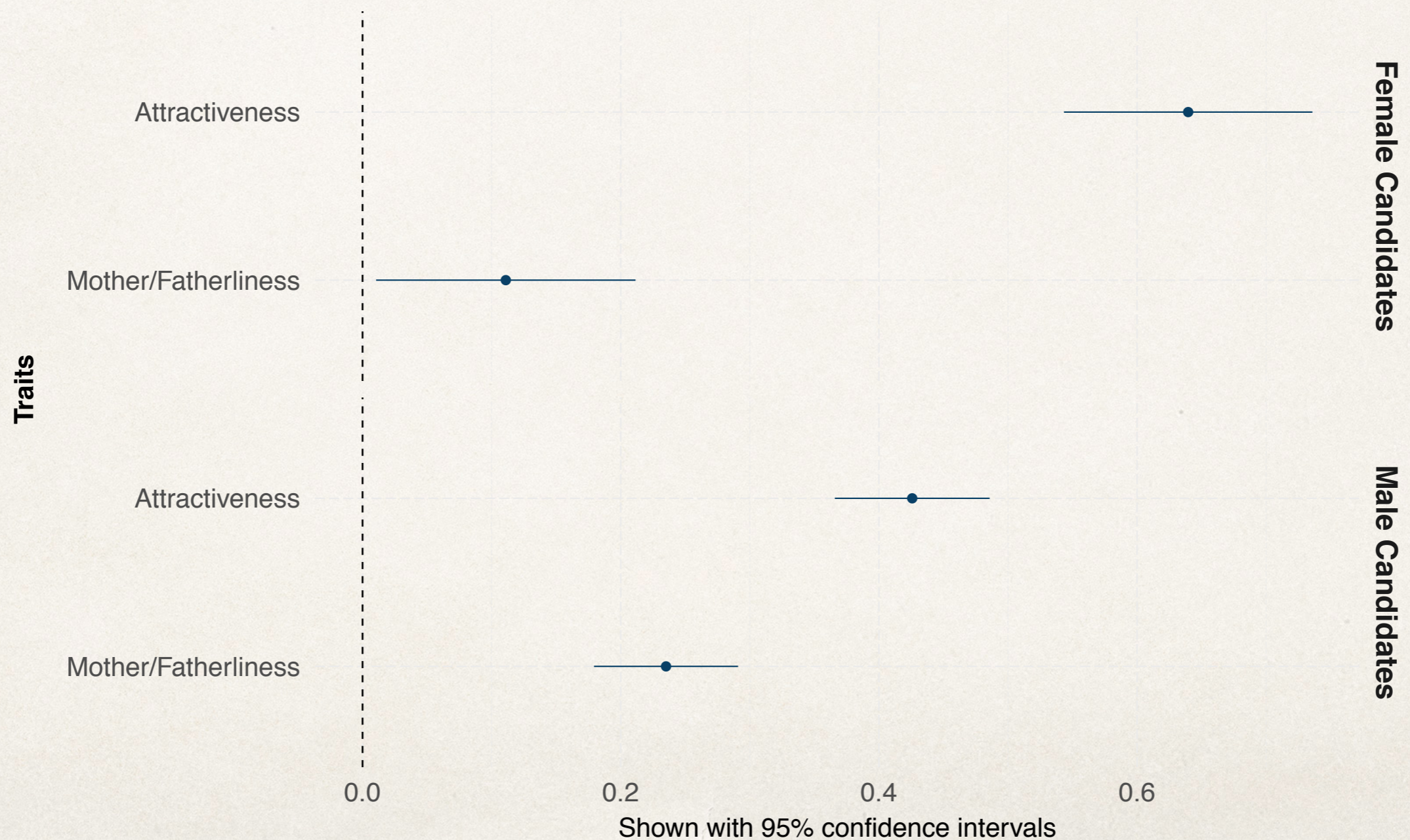
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- ▶ In Study 3, a subset of respondents rated candidates on the short-form Bem Sex Role Inventory (BSRI) traits
 - ▶ 10 stereotypically masculine traits
 - ▶ 10 stereotypically feminine traits
 - ▶ Affectionate, aggressive, assertive, compassionate, defends own beliefs, dominant, eager to soothe hurt feelings, forceful, gentle, has leadership abilities, independent, loves children, sensitive to the needs of others, strong personality, sympathetic, tender, understanding, warm, willing to take a stand, willing to take risks
- ▶ Goal: assess whether gender stereotyping plays an (independent?) role, distinguish between the two

“Mate” Traits Still Predictive

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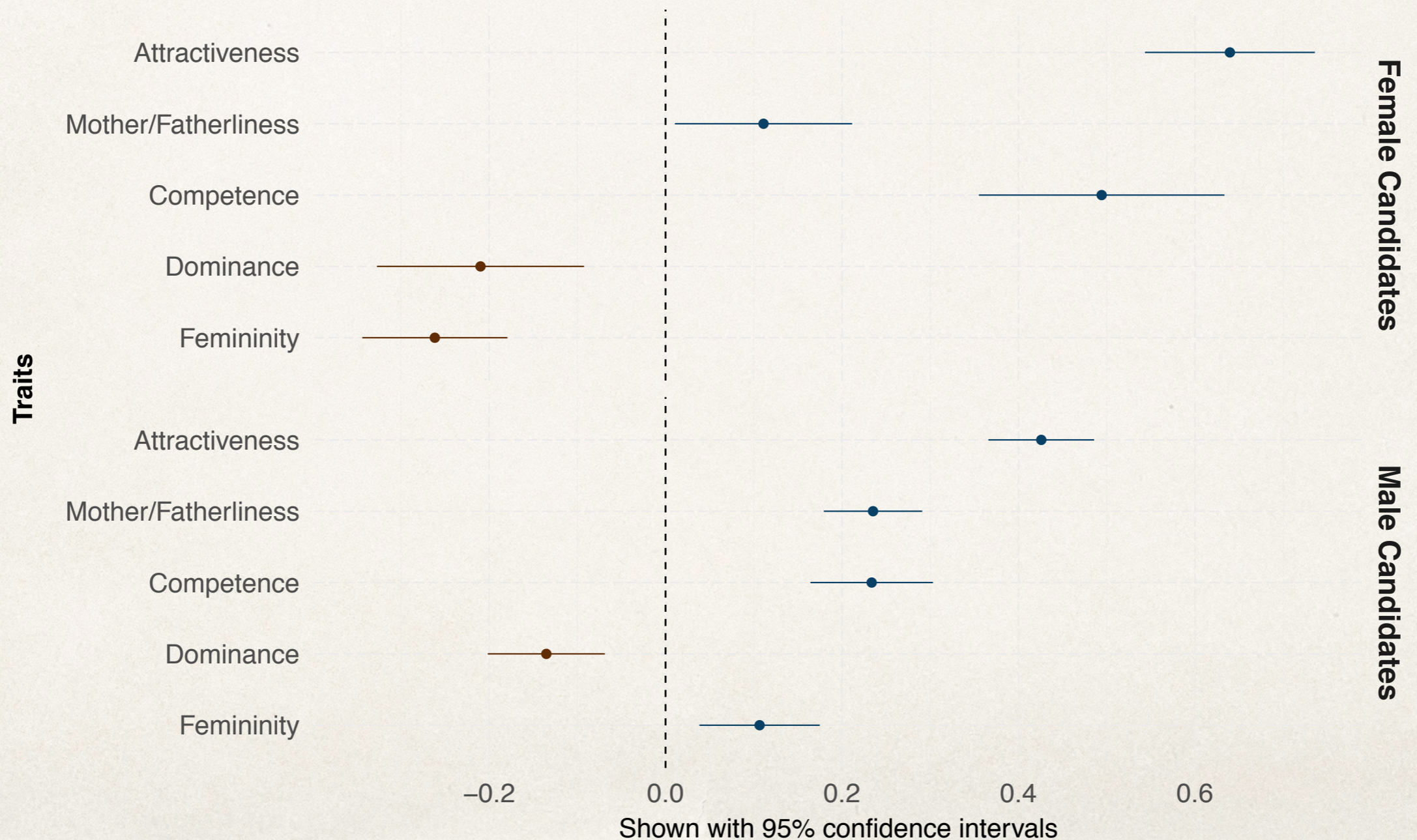
Marginal Effects of Mate Traits on Hypothetical Votes, Including Competence, Dominance, and Femininity



All Traits Shown

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Marginal Effects of Mate Traits on Hypothetical Votes, Including Competence, Dominance, and Femininity



Study 3: Design

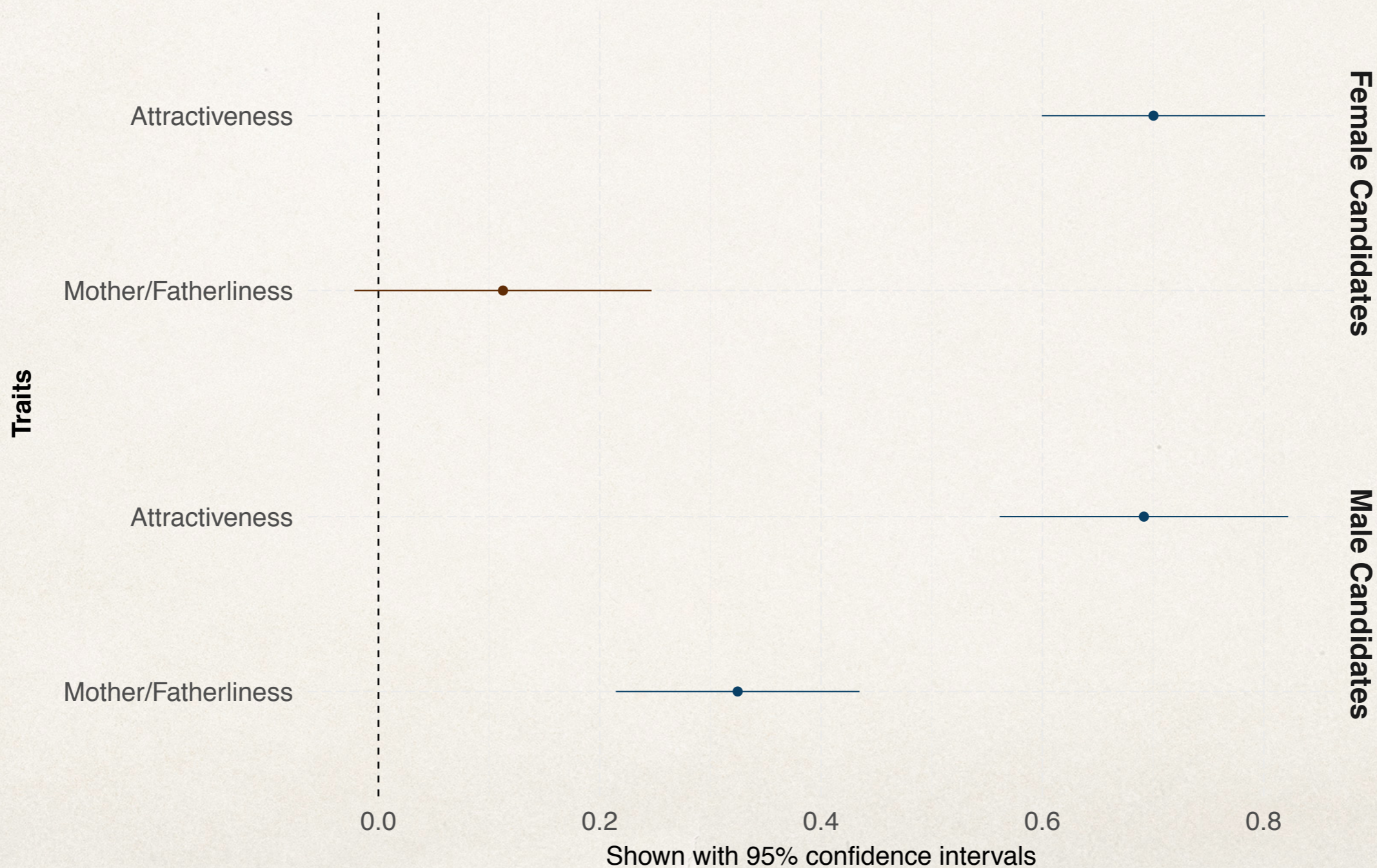
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-
- ▶ **Aim: replicate Study 2 with registered voters**
 - ▶ 4,551 registered voters recruited via SSI, 187 photos
 - ▶ Respondents rate 4 randomly drawn candidates on each trait (different 4 for each trait)
 - ▶ Traits: attractiveness, mother/fatherliness, and good elected official
 - ▶ 47+ ratings of each photo-trait, aggregated into mean rating

"Mate" Traits Maintain Correlations

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Marginal Effects of Mate Traits on Hypothetical Vote



Testing Best Alternative Explanation

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Partner Appeal vs. Competence

Dependent variable:

Willingness to Vote for Candidate

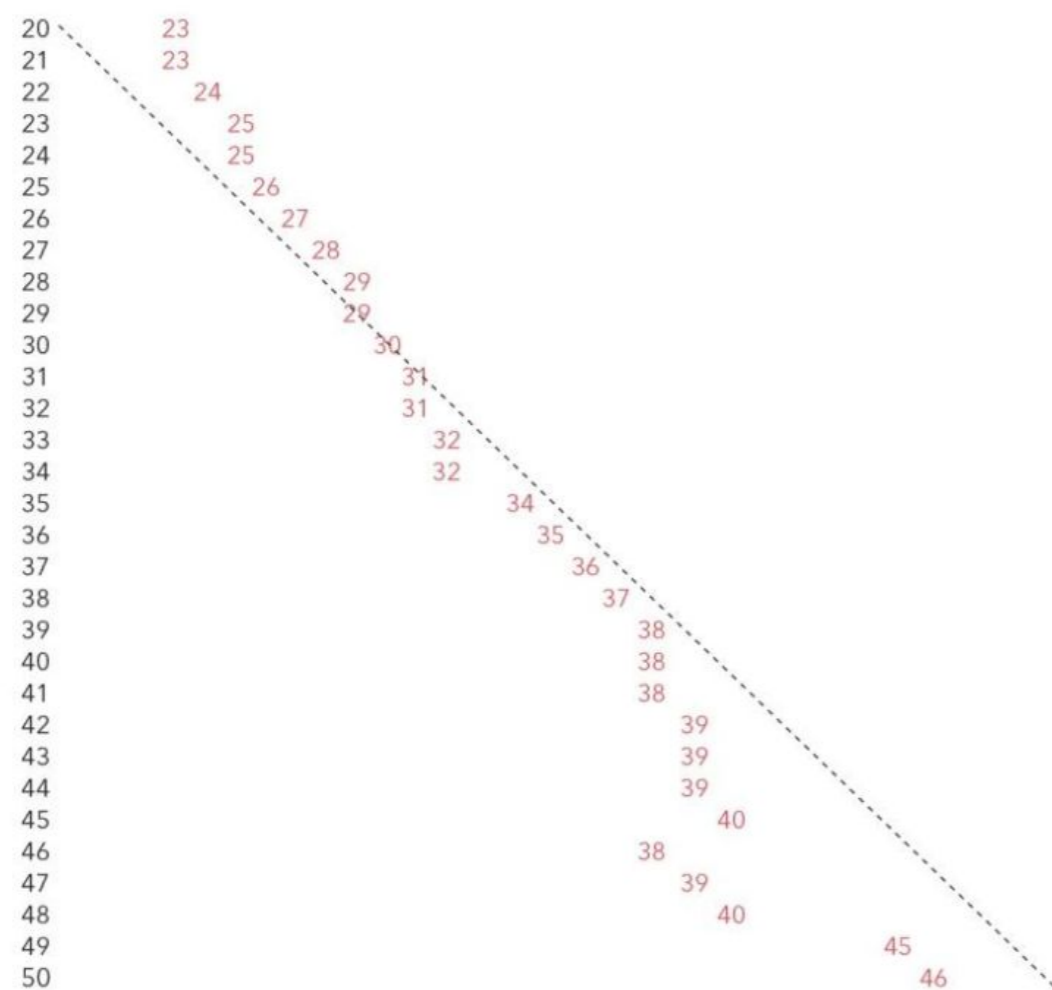
	Female Candidates	Male Candidates	Female Candidates	Male Candidates	Female Candidates	Male Candidates
Appeal as a Partner	.509*** (.026)	.516*** (.025)			.288*** (.029)	.343*** (.022)
Perceived Competence			.806*** (.040)	.735*** (.035)	.486*** (.045)	.491*** (.031)
Constant	.327*** (.015)	.277*** (.012)	.059* (.027)	.050* (.023)	.120*** (.022)	.041* (.018)
Observations	172	381	172	381	172	381
R ²	.688	.539	.705	.541	.815	.720
Adjusted R ²	.686	.538	.704	.540	.813	.718
Residual Std. Error	.054 (df = 170)	.062 (df = 379)	.052 (df = 170)	.062 (df = 379)	.042 (df = 169)	.048 (df = 378)
F Statistic	374.425*** (df = 1; 170)	443.360*** (df = 1; 379)	407.059*** (df = 1; 170)	447.434*** (df = 1; 379)	371.816*** (df = 2; 169)	485.523*** (df = 2; 378)

Note: Coefficients are scaled 0-1. * p<0.05; ** p<0.01; *** p<0.001

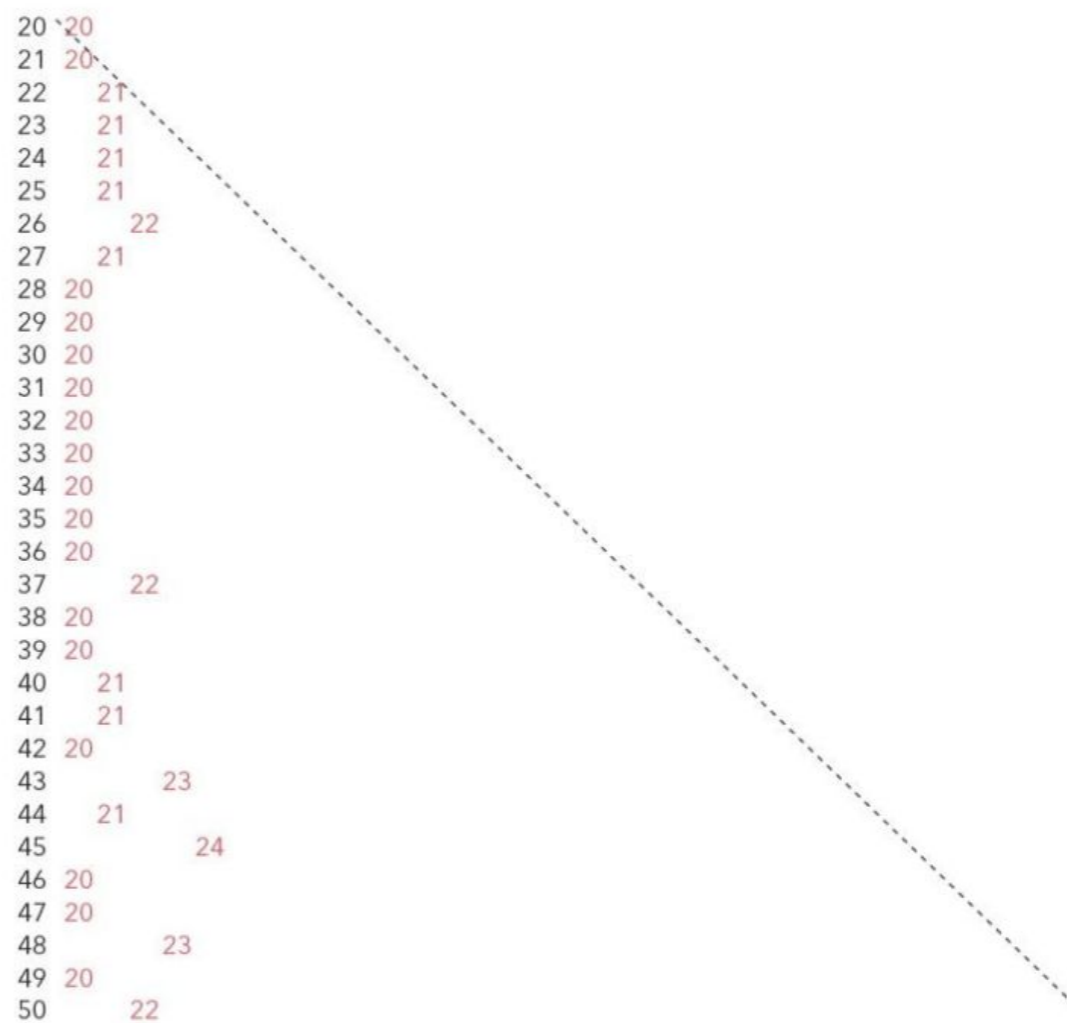
OkCupid Age Data

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a woman's age vs. the age of the men who look best to her



a man's age vs. the age of the women who look best to him



Age Matters

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Candidate Evaluations by Age and Sex

	<i>Dependent variable:</i>		
	Partner Appeal	Perceived Competence	Likely Vote
Age	-.011*** (.001)	-.003*** (.001)	-.005*** (.001)
Male	-.227*** (.056)	-.240*** (.045)	-.242*** (.043)
Male*Age	.005*** (.001)	.005*** (.001)	.004*** (.001)
Constant	1.050*** (.047)	.811*** (.037)	.851*** (.036)
Observations	548	548	548
R ²	.326	.052	.191
Adjusted R ²	.322	.047	.187
Residual Std. Error (df = 544)	.114	.092	.087

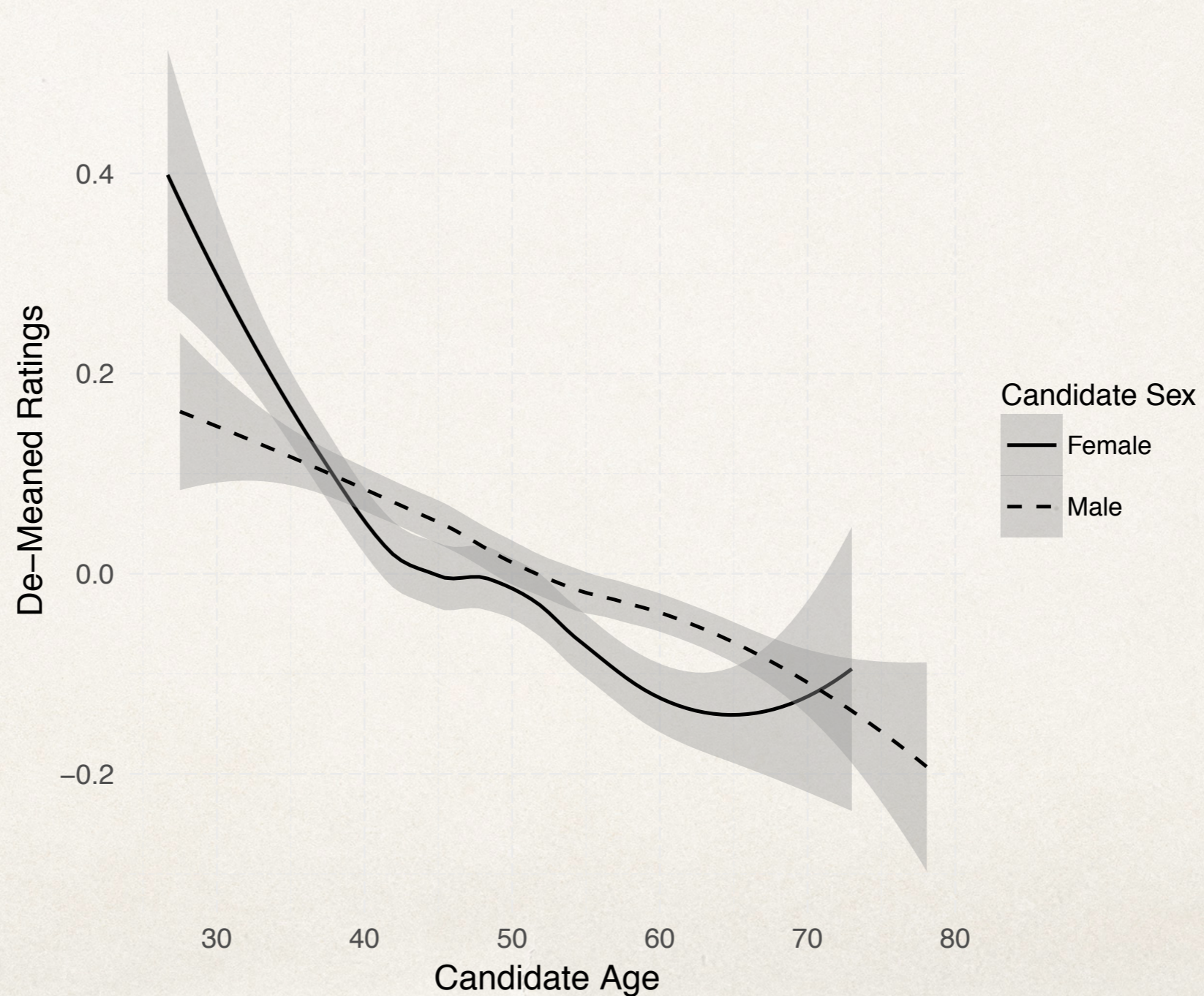
Note:

Age is in years. * p<0.05; ** p<0.01; *** p<0.001

Age Matters More for Women

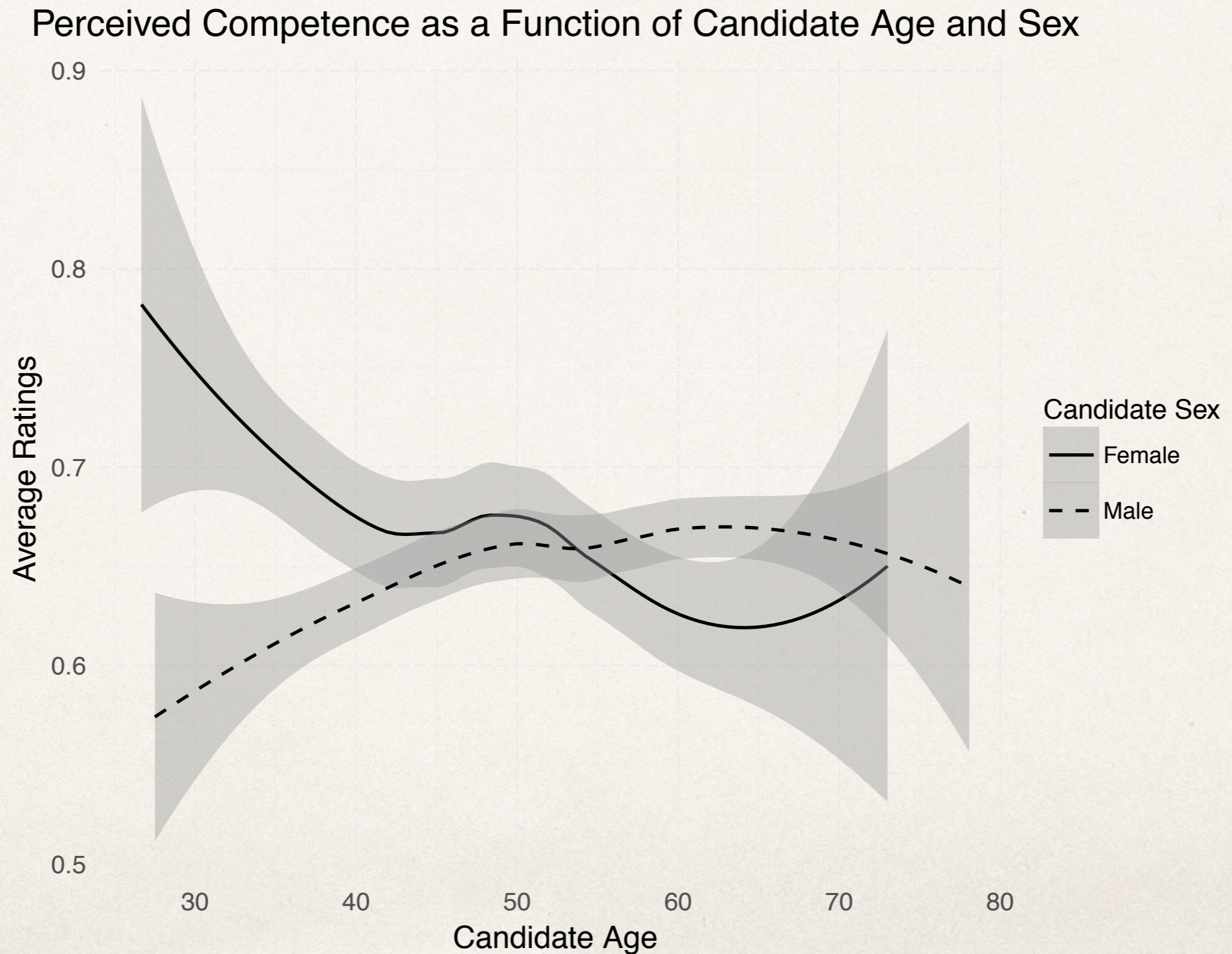
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Partner Appeal as a Function of Candidate Age and Sex



Age Improves Ratings of Men's Competence

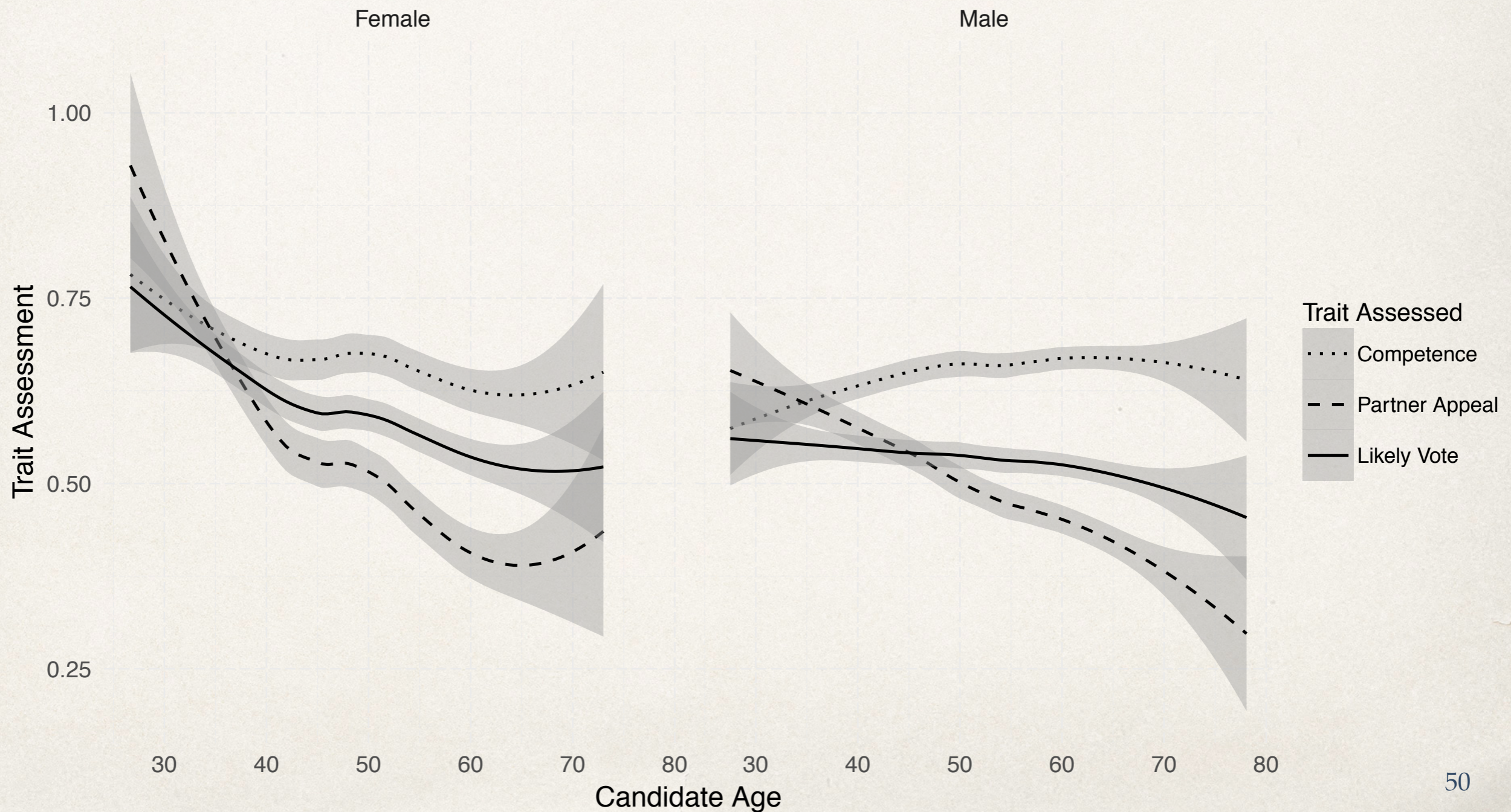
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Age Matters More for Women

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Evaluations as a Function of Candidate Age and Sex



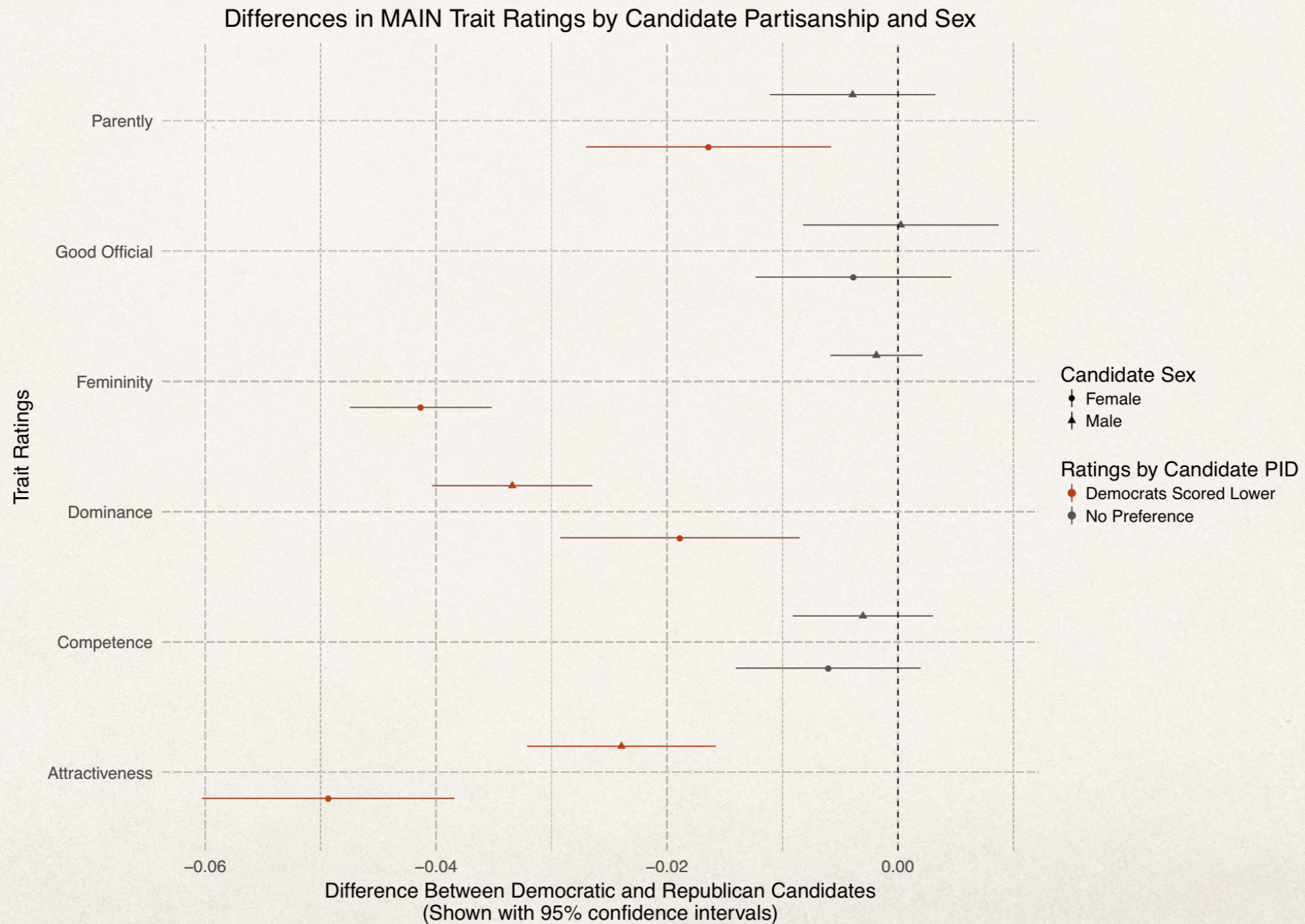
Study 4: Design

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- ▶ **Aim: provide a better measure of professional qualifications**
 - ▶ 906 MTurk respondents
 - ▶ Each rates 10 randomly drawn occupations (99 unique occupations total)
 - ▶ Rating: "how effective a state legislator would someone with this job be if they had no other political experience?"
 - ▶ ~91 occupation ratings are aggregated into mean rating

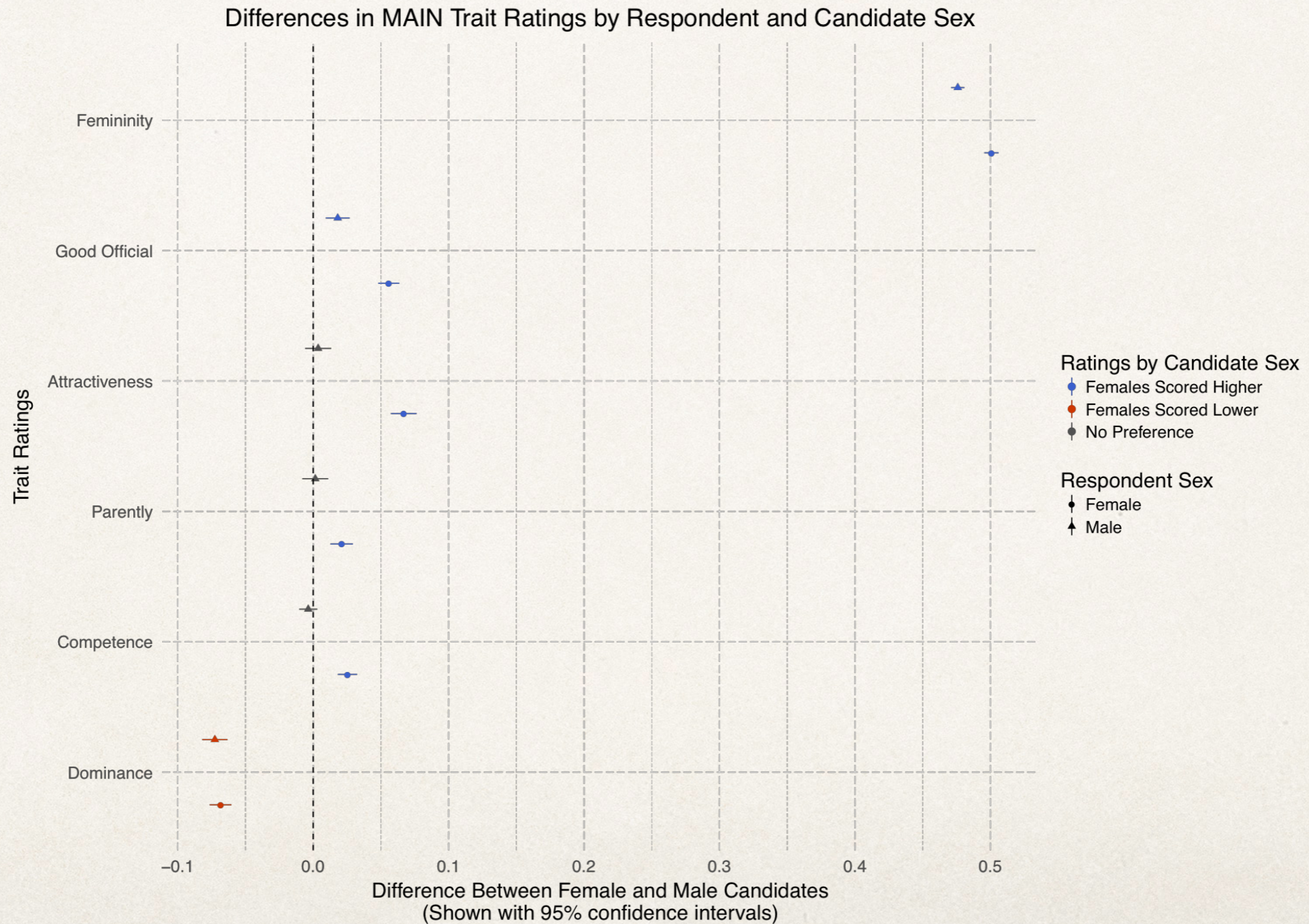
Differences Between Candidates: Gender and PID

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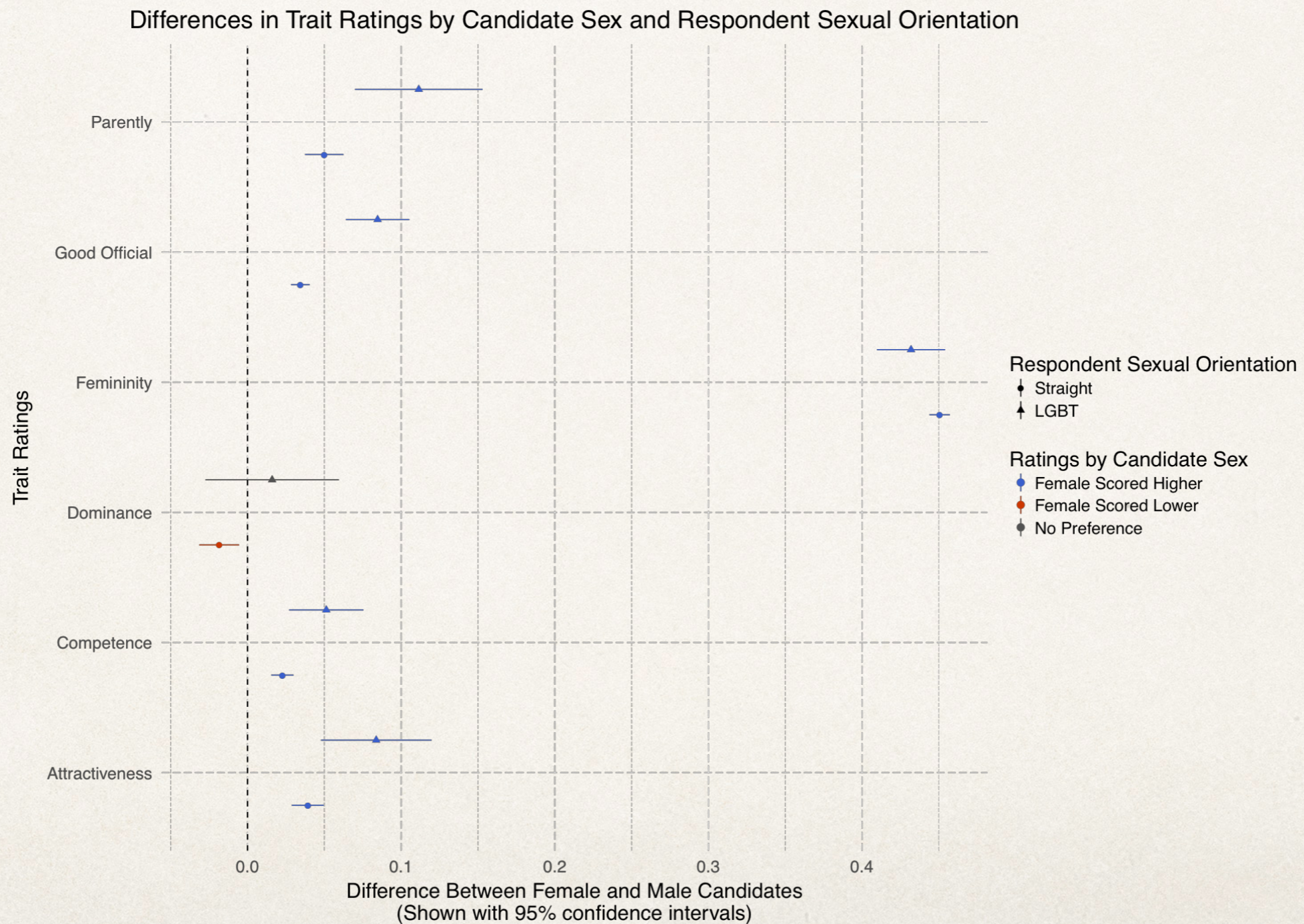
Differences Between Respondents: Gender

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Differences Between Respondents: LGBTQ

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High Standards

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- ▶ **Does candidate height affect voter evaluations?**
- ▶ Empirical strategy: run experiments manipulating perceived height of candidates, varying candidate gender and ethnicity



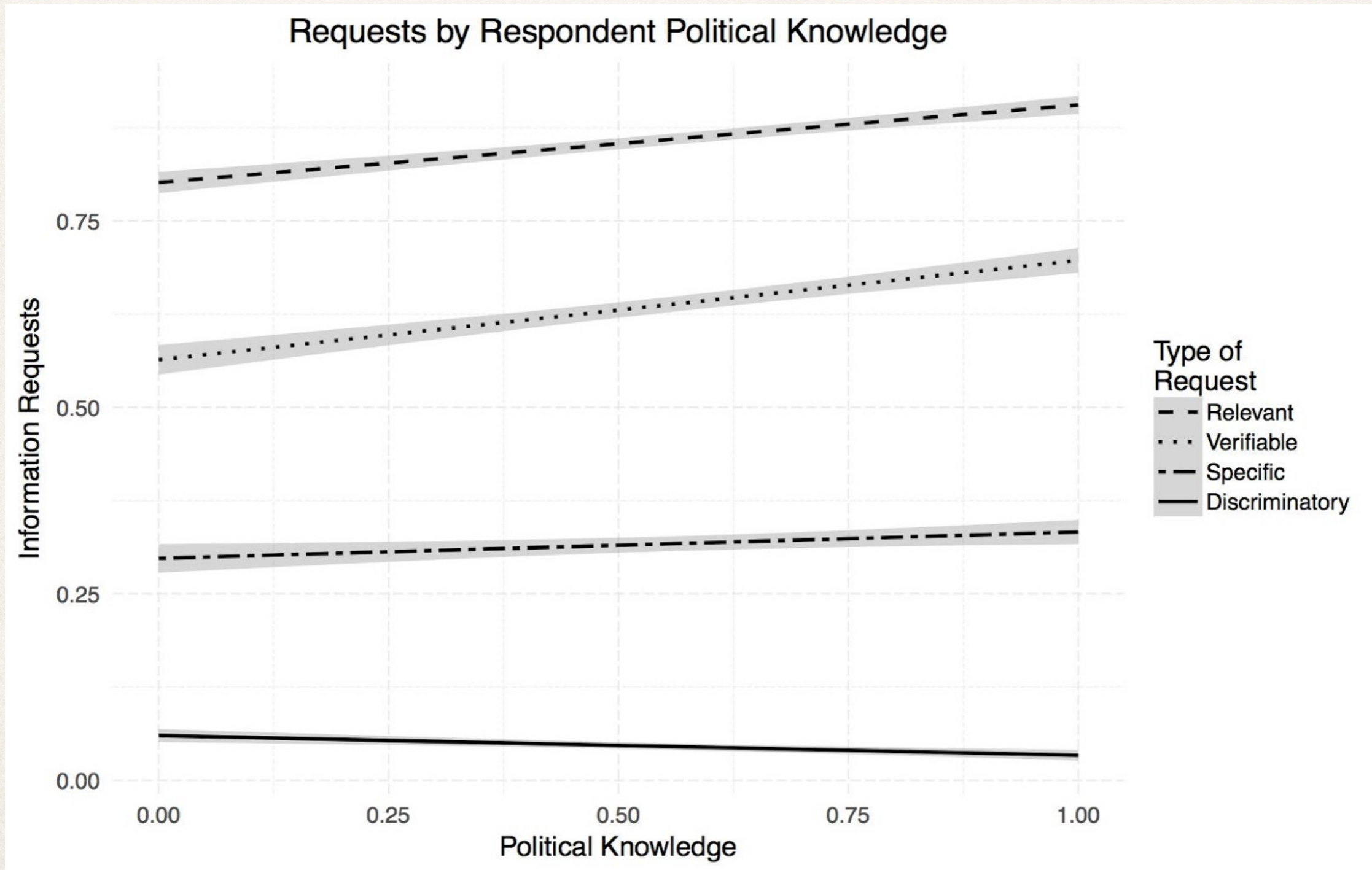
The More You Know

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- ▶ **What information do voters search for?**
- ▶ **Can they use it efficiently?**
- ▶ **Do they want to know different things about different kinds of candidates?**
- ▶ Empirical strategy: experiments asking voters in open-ended text boxes what they want to know, varying office, race, and gender

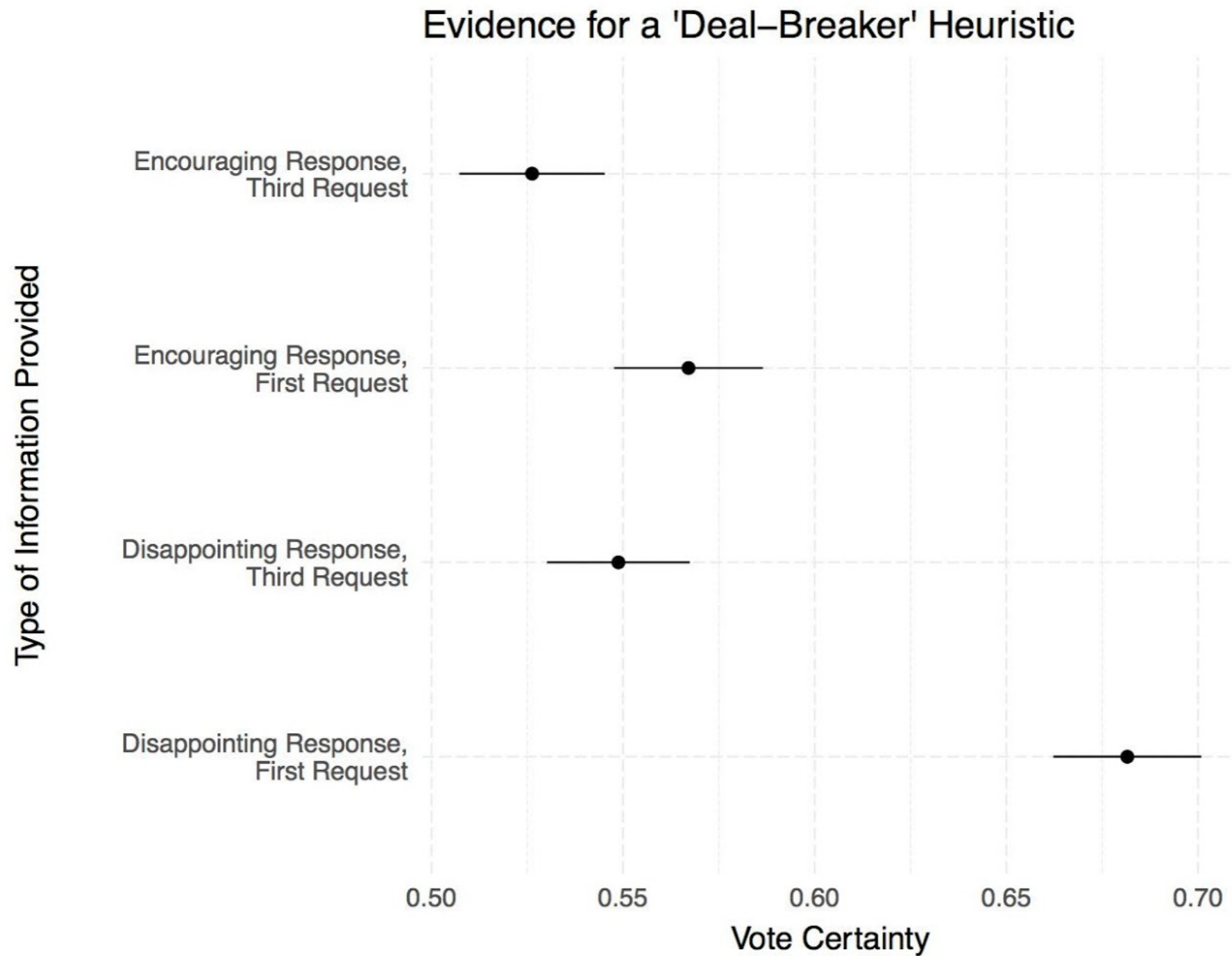
The More You Know

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The More You Know

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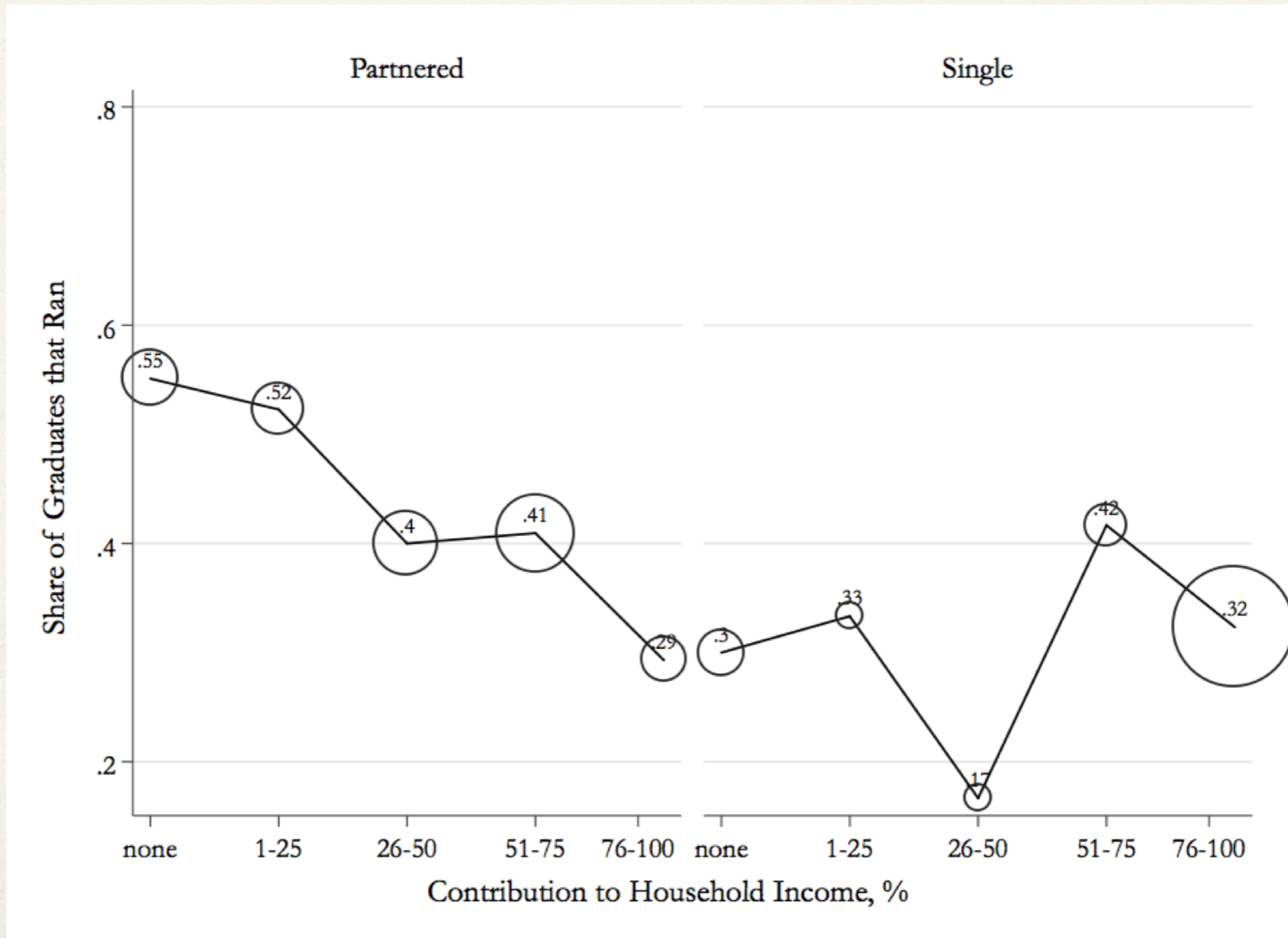
To Emerge?

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- ▶ **Which women actually run for office?**
- ▶ **How do they make the decision to run?**
- ▶ Empirical strategy: study women in the process of making that decision (before, during, after)
 - ▶ National survey and ethnographic work with a women's candidate training organization

To Emerge?

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Gender Stereotyping in Elections

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- We know voters hold gender stereotypes, and that less informed voters are more likely to rely on stereotypes, but literature not yet clear whether women are disadvantaged at the ballot box
- **How can we vary voter information and sophistication in real elections?**
 - ▶ Empirical strategy: compare how women fare in local races held during off-cycle (high attention to local races) vs. on-cycle (low attention to local races)

Gender Stereotyping in Elections

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City Council Elections vs. Mayoral Elections	Non-Incumbents (1)	“” + City FE (2)	“” + Mixed-Sex (3)
Female	0.026 (0.013)	0.025 (0.014)	0.031 (0.015)
On-cycle	0.009 (0.009)	0.027 (0.012)	0.01 (0.009)
Female × On-cycle	0.027 (0.018)	0.031 (0.019)	0.028 (0.020)
Mayor	0.066 (0.024)	0.047 (0.017)	0.082 (0.033)
Female × Mayor	-0.035 (0.037)	-0.028 (0.035)	-0.062 (0.043)
On-cycle × Mayor	-0.068 (0.027)	-0.044 (0.020)	-0.089 (0.039)
Female × On-cycle × Mayor	-0.073 (0.049)	-0.079 (0.049)	-0.054 (0.061)
<i>(Intercept and controls for incumbents and competitiveness of race not shown here)</i>			
City fixed effects?	No	Yes	No
R-squared	0.10	0.14	0.08
Observations	18,323	18,323	13,849

Notes: Standard errors clustered by city in parentheses. Dependent variable = 1 if candidate won and =0 if candidate lost.