Making Policy with Data

An Introductory Course on Policy Evaluation

Policy Briefing

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Do Politicians Financially Benefit from Holding Power?

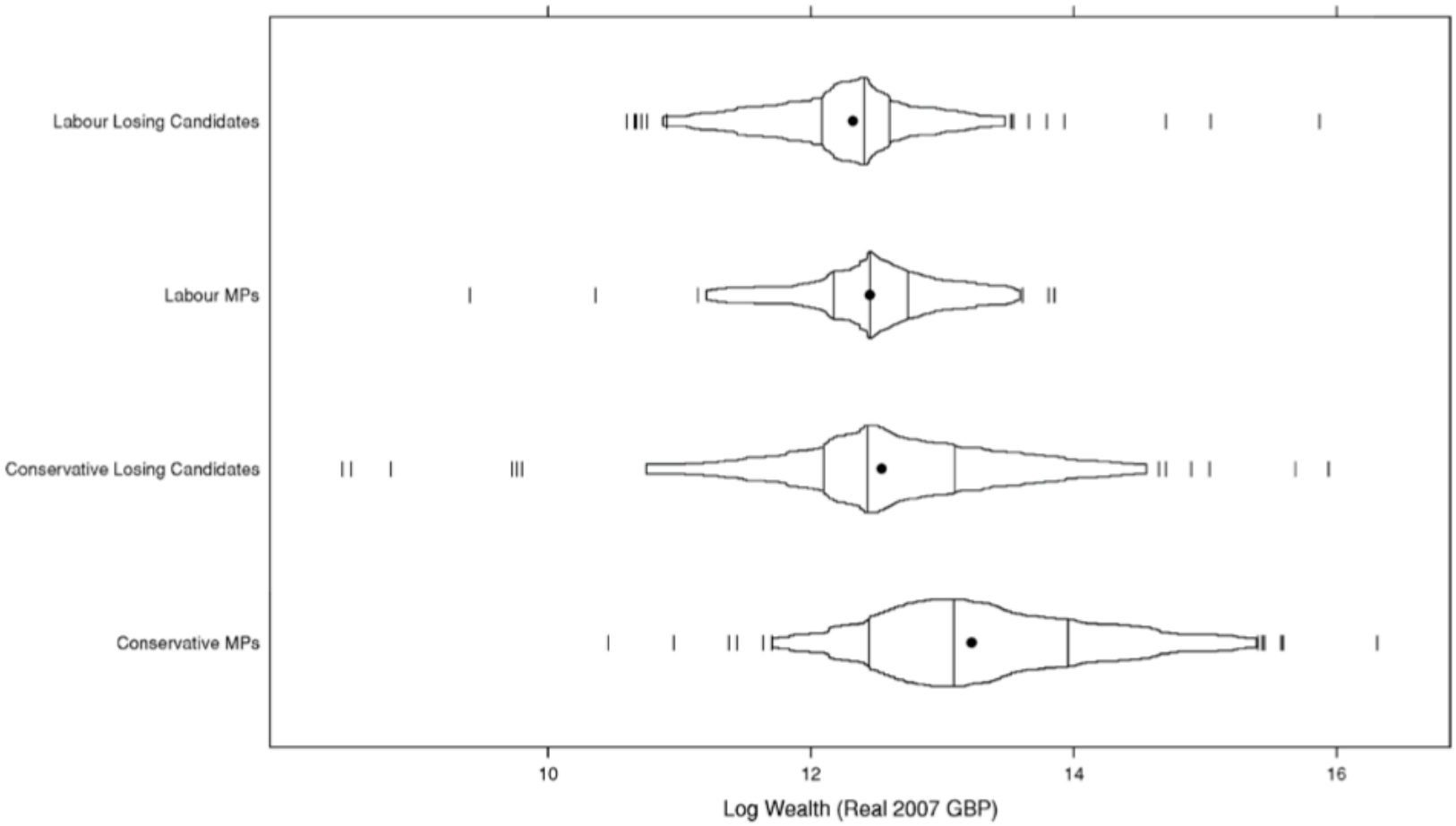
Do Politicians Financially Benefit from Holding Power?

- Hard to study: political power is not randomly assigned
- Eggers and Hainmueller (2009) study the financial return to office in postwar UK
- Two identification strategies:
  - Selection on observables (Matching)
  - Regression discontinuity
- They yield consistent results

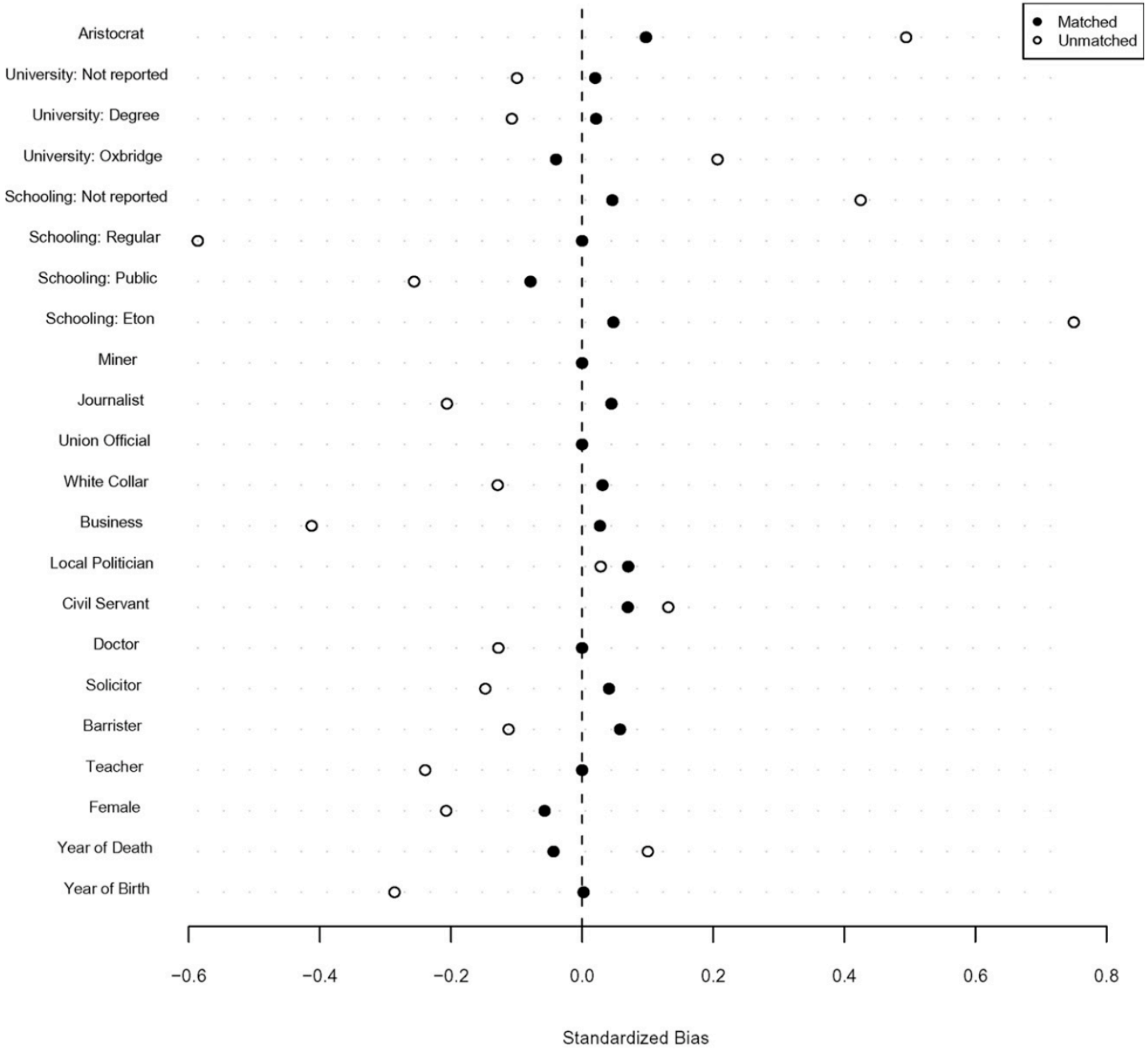
MPs for Sale?

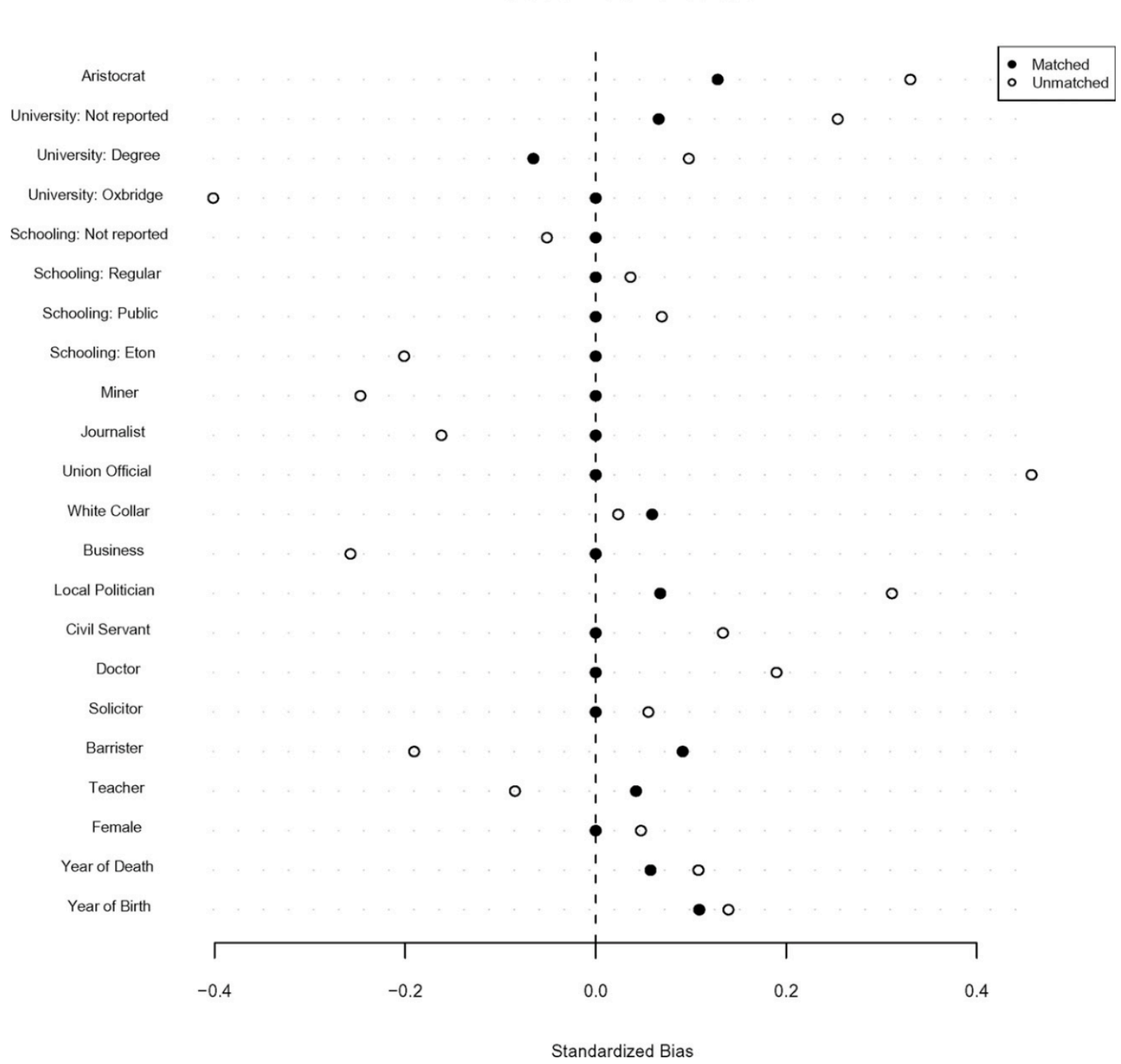
MPs' Wealth at Death

FIGURE 2. Distributions of (Log) Wealth at Death by Party for Winning and Losing Candidates to House of Commons 1950–1970



Note: Box percentile plots. Box shows empirical distribution function from .05 to .95 quantile; vertical lines indicate the .25, .5, and .75 quantile, respectively. Observations outside the .05–.95 quantile range are marked by vertical whiskers. The dot indicates the mean.


Conservative Candidates
Matched
Unmatched
Aristocrat
University: Not reported
University: Degree
University: Oxbridge
Schooling: Not reported
Schooling: Regular
Schooling: Public
Schooling: Eton
Miner
Journalist
Union Official
White Collar
Business
Local Politician
Civil Servant
Doctor
Solicitor
Barrister
Teacher
Female
Year of Death
Year of Birth
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
Standardized Bias


Labour Candidates
Matched
Unmatched
Aristocrat
University: Not reported
University: Degree
University: Oxbridge
Schooling: Not reported
Schooling: Regular
Schooling: Public
Schooling: Eton
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Standardized Bias

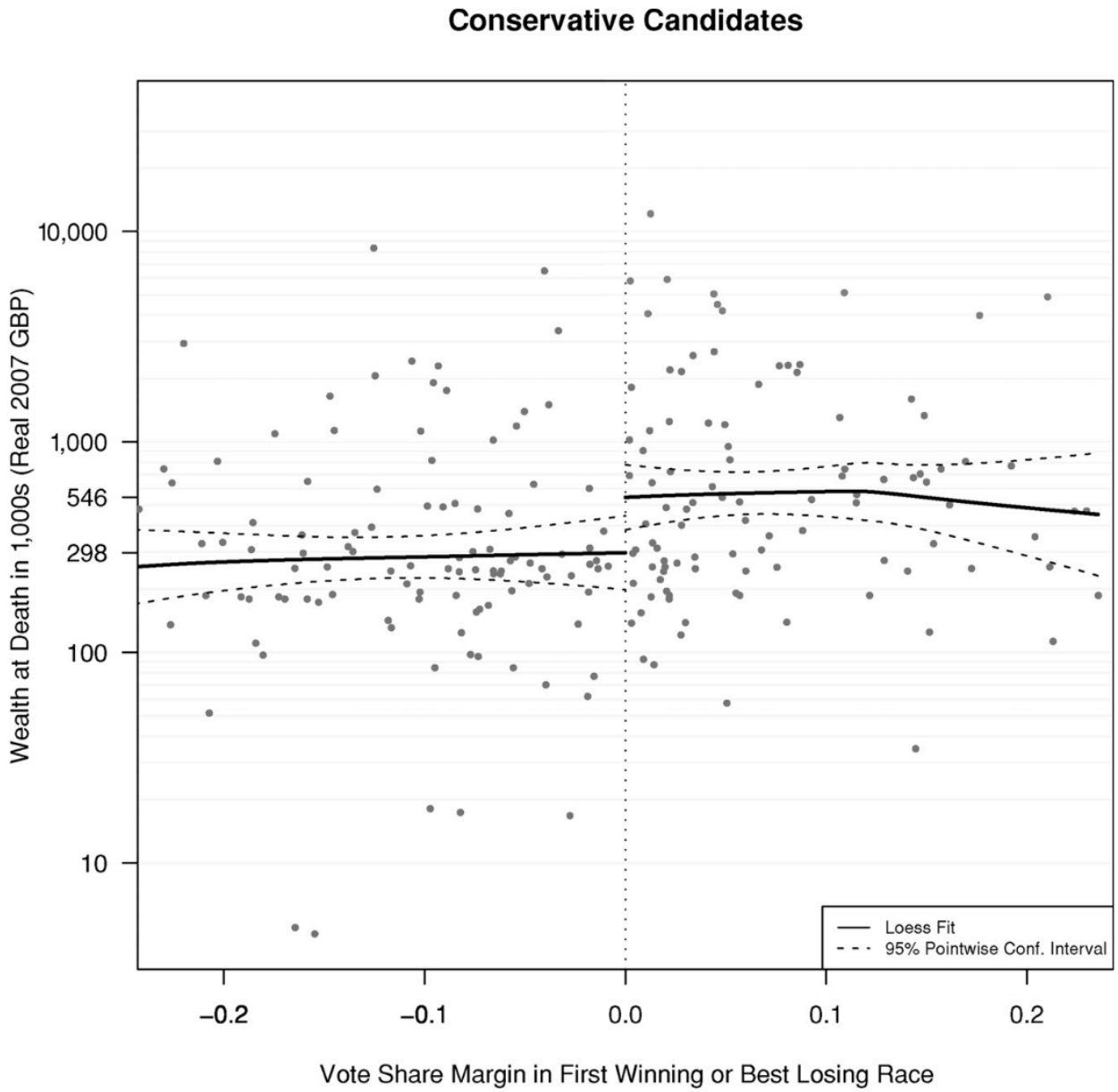
Effect of Serving in House of Commons on Wealth (Matching)

TABLE 3. Matching Estimates: Effect of Serving in House of Commons on (Log) Wealth at Death

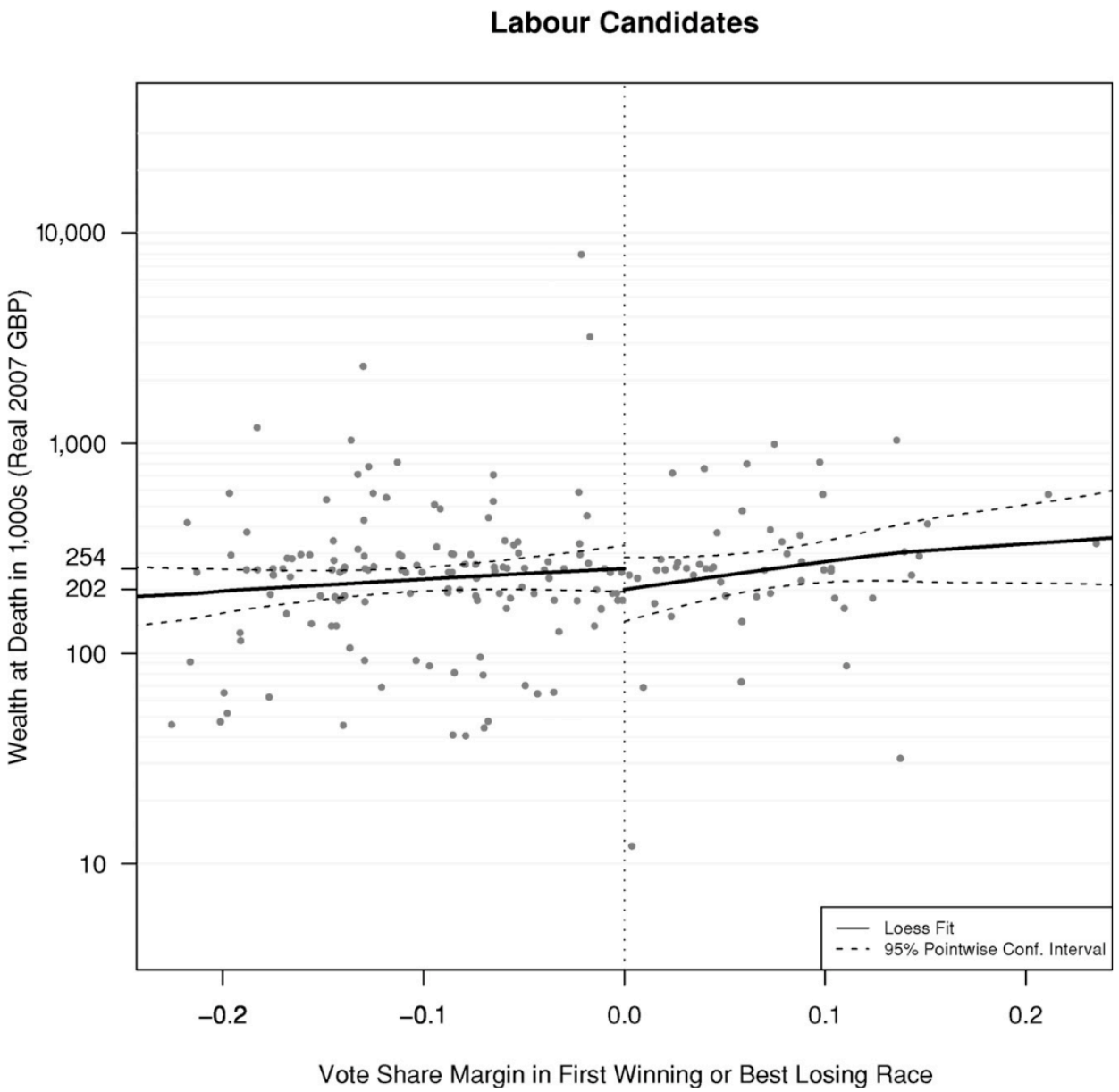
	Conservative Party			Labour Party		
	OLS ATE	Matching ATE	Matching ATT	OLS ATE	Matching ATE	Matching ATT
Effect of serving	0.54	0.86	0.95	0.16	0.14	0.13
Standard error	0.20	0.26	0.34	0.12	0.18	0.15
Covariates	×	×	×	×	×	×
Percent wealth increase	71	136	155	17	15	13
95% Lower bound	15	41	31	−6	−19	−15
95% Upper bound	153	293	398	48	63	52

Notes: $N = 223$ for the Conservative Party, $N = 204$ for the Labour Party; for the ATT estimation, there are 104 treated units for the Conservative Party and 61 for Labour. Covariates include all covariates listed in Table 2. ATT = average treatment effect for the Treated, ATE = average treatment effect, OLS = ordinary least squares. Matching results are from 1 : 1 Genetic Matching with postmatching regression adjustment. Standard errors are robust for the OLS estimation and Abadie-Imbens for matching.

A Regression Discontinuity Design



A Regression Discontinuity Design



Effect of Serving on Wealth (RDD)

TABLE 4. Regression Discontinuity Design Results: Effect of Serving in House of Commons on (Log) Wealth at Death

	Conservative Party		Labour Party	
Effect of serving	0.61	0.66	−0.20	−0.25
Standard error	(0.27)	(0.37)	(0.26)	(.26)
Covariates		x		x
Percent wealth increase	83	94	−18	−23
95% Lower bound	8	−7	−52	−65
95% Upper bound	212	306	31	71

Note: Effect estimates at the threshold of winning $\tau_{RDD} = E[Y(1) - Y(0) \mid Z = 0]$. Estimates without covariates from local polynomial regression fit to both sides of the threshold with bootstrapped standard errors. Estimates with covariates from local linear regression with rectangular kernel (equation 2); bandwidth is 15 percentage point of vote share margin with robust standard errors. For the Conservative Party, $N = 223$ for the estimates without covariates, and $N = 165$ with covariates. For the Labour Party, $N = 204$ for the estimates without covariates, and $N = 164$ with covariates.

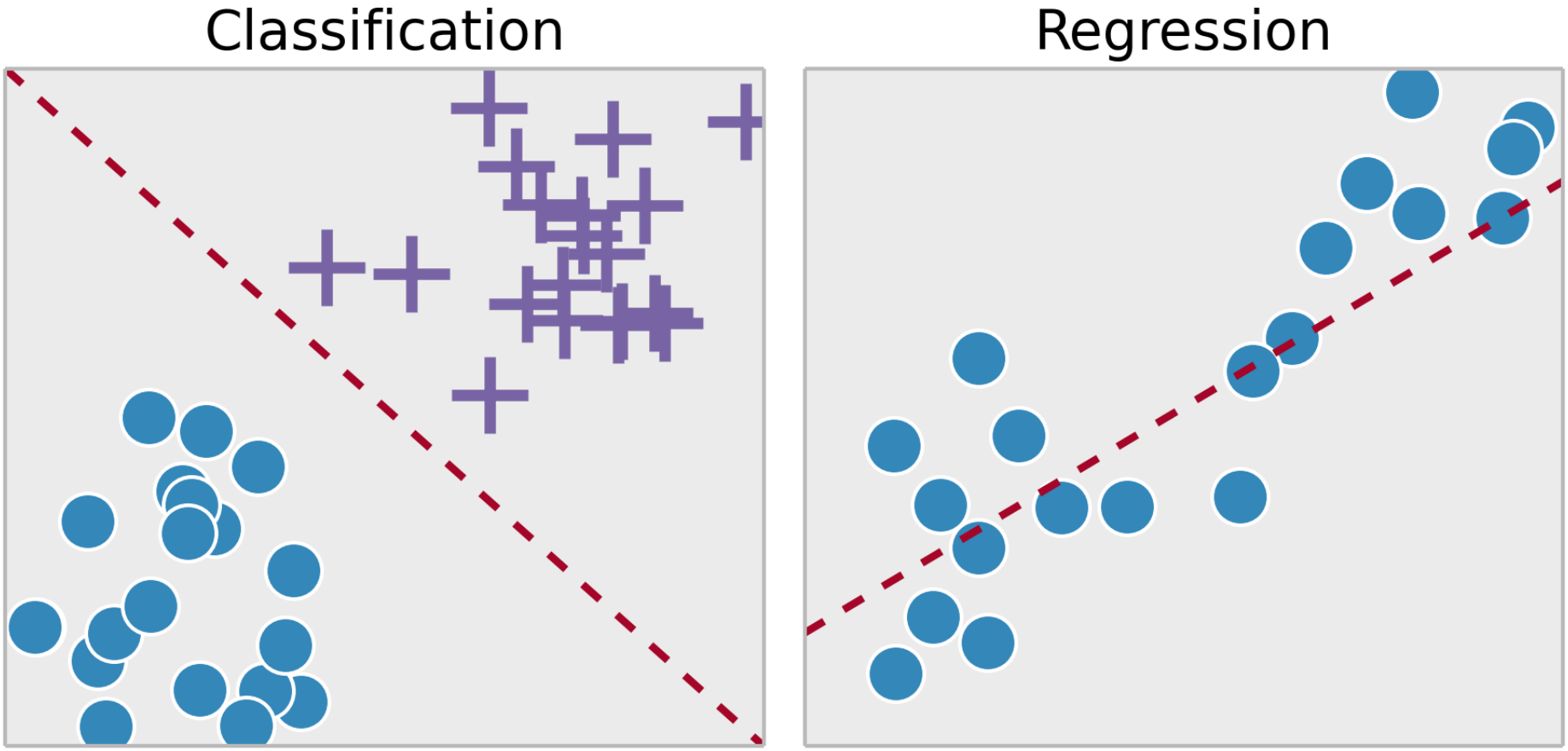
Buzzword:

Supervised and Unsupervised Learning

Supervised and Unsupervised Learning

- Two biggest categories of algorithms in machine learning (statistical learning)
- Supervised learning: learning patterns from **labeled** data
- Unsupervised learning: learning patterns from **unlabeled** data

Supervised Learning



Unsupervised Learning: e.g. Clustering