Online Appendix for:
Land Lotteries, Long-term Wealth, and Political Selection

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1 1805 and 1807 lotteries

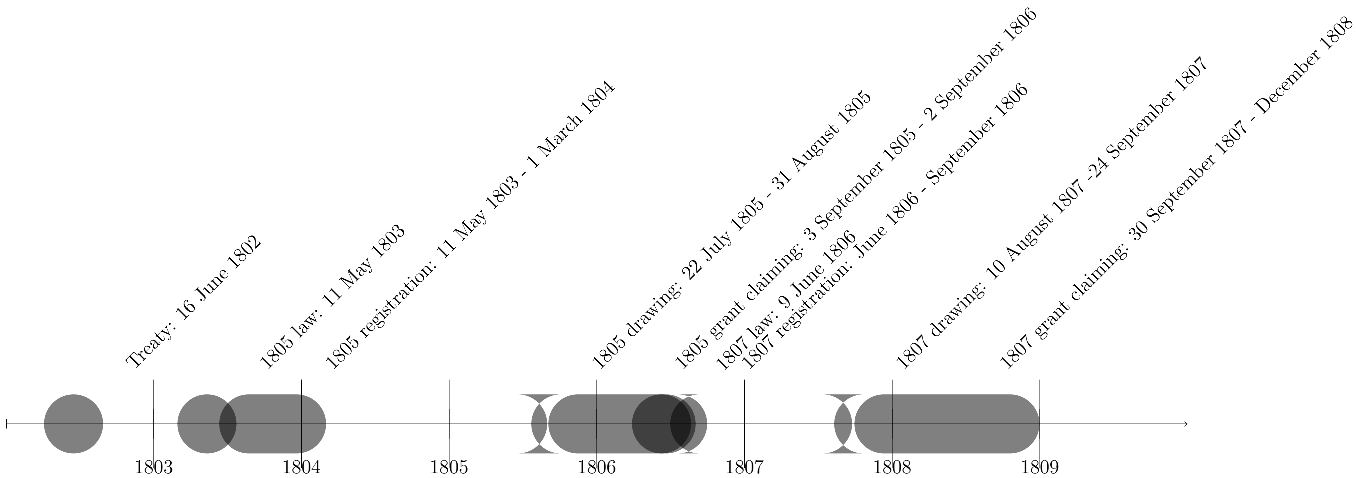


Figure 1: Timeline of 1805 and 1807 lottery events. (Graham, 2010, 2011).

Requirements	No. Draws (1805)	No. Draws (1807)
"Every free male white person, twenty-one years of age and upwards, being a citizen of the United States, and an inhabitant of this State, twelve months immediately preceding the passage of this act, or paid a tax towards the support of government (including such as may be absent on lawful business)" [1]	1	1
"Every free white male person of like description, having a wife, legitimate child or children, under twenty-one years of age"	2	2
"All widows having a legitimate child or children, under the age of twenty-one years, who have resided twelve months in this State, immediately preceding the passage of this act" [2]	2	1
"All families of orphans, under twenty-one years of age, having no parents living" [3]	1	1-2 [4]
"All families of orphans [with three years' residence], under twenty-one years of age, whose father is dead, "	N/A	1
"All free female white persons, who have arrived to the age of twenty-one years or upwards, who have resided in this State [for three years]"	1	N/A

Table 1: Lottery qualifications specified by Acts of 11 May 1803 and 9 June 1806 (Clayton and Adams, 1812). [1] The residency requirement is three years under 1807 lottery rules. An amendment to the 1807 rules also makes provision for persons laboring under accidents or misfortunes. [2] The 1807 lottery rules apply to all widows with three years residence in Georgia. [3] An amendment to the 1805 lottery rules entitles children whose father is dead and mother remarries to draw in the same manner. The 1807 lottery rules apply the three years residency requirement. [4] The 1807 lottery rules specify "families of orphans consisting of more than one" receive two draws and orphan families of "only one" receive one draw.

Table 2: Counties created by 1805 and 1807 lotteries.

Panel A: 1805

Counties	No. Districts	Lot sizes (acres)	Lot length (chains square)	Lot orientation (degrees)	Grant fee ($)	Est. value of lot ($)
Baldwin	5	202.5	45	45 / 60	8.10	839.17
Wayne	3	490	70	13 / 77	19.60	842.64
Wilkinson	5	202.5	45	45 / 60	8.10	811.25

Panel B: 1807

Counties	No. Districts	Lot sizes (acres)	Lot length (chains square)	Lot orientation (degrees)	Grant fee ($)	Est. value of lot ($)
Baldwin	15	202.5	45	45 / 60	12.15	827.35
Wilkinson	23	202.5	45	45 / 60	12.15	799.82

Notes: counties and land lots specified by Acts of 11 May 1803 and 9 June 1806. Lot orientation is degrees from the meridian. Lot values are estimated by averaging the cash value of farms minus the value of farming implements and machinery by the number of (improved and unimproved) acres of land in farms (Haines, 2004; Bleakley and Ferrie, 2013). The 1850 values are deflated to 1805 dollars (Panel A) and 1807 dollars (Panel B) using a historical consumer price index (Officer and Williamson, 2012).

2 Descriptive statistics

2.1 1800 Census

County	White males 16–25	White males 26-44	White males 45+	White male total pop.	White female total pop.	Slave pop. (%)
Bryan	57	64	26	286	242	0.813
Bulloch	158	151	97	871	758	0.141
Burke	726	743	242	3,356	3,167	0.312
Camden	104	131	60	496	440	0.437
Chatham	547	591	175	2,077	1,596	0.699
Columbia	478	516	256	2,848	2,473	0.360
Effingham	94	163	132	716	594	0.368
Elbert	637	689	348	3,709	3,546	0.279
Franklin	463	572	276	3,078	2,814	0.140
Glynn	68	116	60	445	334	0.583
Greene	593	857	295	3,716	3,381	0.340
Hancock	964	952	423	5,205	4,400	0.334
Jackson	563	654	243	3,266	3,062	0.181
Jefferson	311	421	219	2,066	1,942	0.289
Liberty	171	187	71	762	584	0.742

Lincoln	230	317	193	1,745	1,581	0.301
McIntosh	79	117	60	460	371	0.684
Montgomery	286	270	147	1,445	1,297	0.137
Oglethorpe	643	653	341	3,479	3,207	0.316
Richmond	360	370	132	1,503	1,225	0.492
Screven	274	310	82	1,253	1,000	0.254
Warren	605	562	313	3,263	2,989	0.247
Washington	660	678	322	3,739	3,442	0.259
Wilkes	716	830	444	4,184	3,848	0.382
Georgia	9,787	10,910	4,957	53,965	48,298	0.365

Table 3: Summary statistics on selected county-level characteristics in the 1800 Census. ‘Slave pop.’ is the slave population over the total population.

2.2 1820 Census

County	Slave pop. (%)	Slave wealth Gini
Baldwin	0.548	0.668
Bryan	0.739	0.804
Bulloch	0.264	0.829
Burke	0.476	0.872
Camden	0.594	0.820
Chatham	0.635	0.843
Clarke	0.368	0.746
Columbia	0.561	0.670
Effingham	0.450	0.775
Elbert	0.440	0.761
Glynn	0.758	0.765
Greene	0.256	0.664
Hancock	0.534	0.680
Jackson	0.246	0.834
Jefferson	0.437	0.796
Liberty	0.711	0.769
Lincoln	0.455	0.708
McIntosh	0.720	0.830
Montgomery	0.373	0.855
Oglethorpe	0.517	0.670
Richmond	0.568	0.793
Screven	0.448	0.751
Tattnall	0.111	0.842
Warren	0.381	0.748
Washington	0.358	0.800
Wayne	0.363	0.800
Wilkes	0.548	0.664
Wilkinson	0.209	0.853
Georgia	0.412	0.789

Table 4: Summary statistics on selected county-level characteristics in the 1820 Census, for counties existing in 1807. 'Slave pop.' is the slave population over the total population. 'Wealth Gini' is the gini coefficient based on imputed slave wealth (see footnotes to Table OA-5 for the slave value imputation method). Highlighted counties were created by the 1805 and 1807 lotteries.

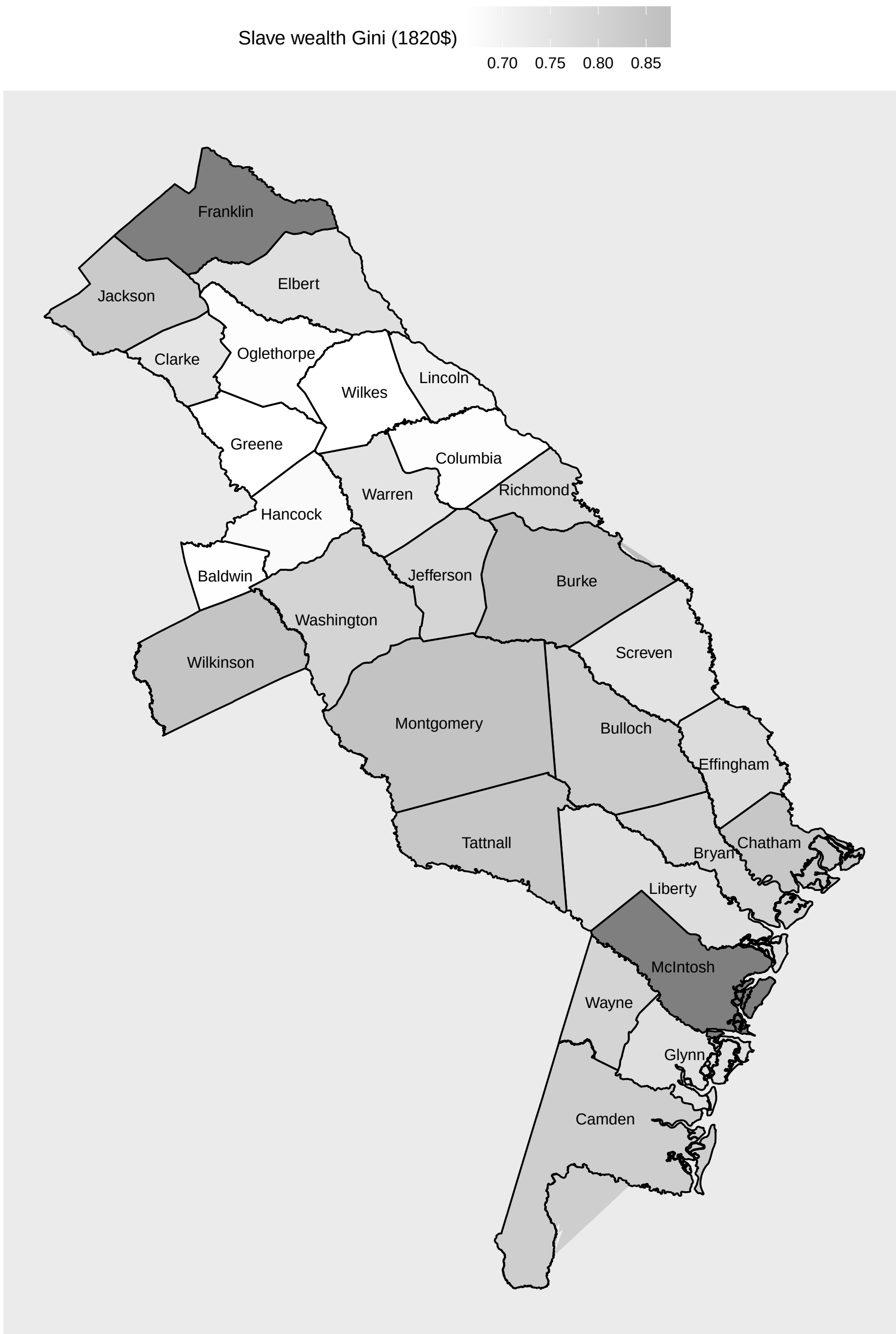


Figure 2: Gini coefficient based on 1820 slave wealth for counties existing in 1807. See footnotes to Table OA-5 for the slave value imputation method.

Table 5: Imputed slave values (1820$), by gender and age group.

	Male	**Female**
Under 14	331	303
14-25	700	642
26-44	425	389
45+	258	236

Notes: Phillips (1905) estimates the average value of male prime field hands (18-30 years old) in Georgia in 1821 is $700. I use the coefficients in Table II of Kotlikoff (1979) to adjust the average price according to age group and gender.

2.3 1850 Census

Variable	N	Min.	Mean	Max.	S.d.
Personal characteristics					
Age	25,506	21	38.042	101	11.195
Literate	25,520	0	0.891	1	0.311
In school	25,520	0	0.001	1	0.038
Real estate value (1850$)	25,520	0	2,324.389	250,000	5,538.743
Surname characteristics					
Surname length	25,520	3	6.224	14	1.560
Surname frequency	25,520	1	36.965	449	74.114
Occupations					
Blacksmith	25,520	0	0.006	1	0.080
Carpenter	25,520	0	0.009	1	0.092
Farmer	25,520	0	0.852	1	0.355
Laborer	25,520	0	0.004	1	0.065
Lawyer	25,520	0	0.009	1	0.093
Mechanic	25,520	0	0.008	1	0.087
Merchant	25,520	0	0.021	1	0.143
Overseer	25,520	0	0.006	1	0.075
Physician	25,520	0	0.014	1	0.117
Reverend	25,520	0	0.009	1	0.093
Teacher	25,520	0	0.005	1	0.067

Table 6: Individual-level summary statistics using sample drawn from the 1850 full-count Census Center (2008); Sarah Flood and Warren (2015). 'Surname length' is the character length of surnames. 'Surname frequency' is the number of times surnames appear in the sample. 'Literate' is a binary variable indicating literacy (can read and write). 'In school' is an indicator variable for individuals currently in school. The occupations dummies indicate contemporary occupational categories. Sample is restricted to male heads of households aged 21 and over who living in Georgia at the time of the census, were born in Georgia, and have non-missing surnames and property value.

County	Log value of farms ($)	Log value of farm equip. ($)	Log total # of farms	Log mean farm value ($)	Log total farm acres	Per acre farm value ($)	Slave pop. (%)	Real estate wealth Gini
Baldwin	13.407	10.341	5.481	7.879	12.343	2.761	0.565	0.594
Bryan	12.636	9.857	5.342	7.230	12.046	1.692	0.656	0.618
Bulloch	12.761	9.724	6.021	6.691	13.122	0.663	0.340	0.546
Burke	14.642	11.794	6.568	8.014	13.171	4.100	0.673	0.677
Camden	13.715	10.242	5.460	8.223	12.240	4.234	0.672	0.802
Chatham	14.513	12.251	4.883	9.520	11.866	12.643	0.587	0.723
Clarke	13.876	11.028	5.991	7.825	12.197	5.051	0.503	0.674
Columbia	14.213	11.682	6.192	7.938	12.613	4.559	0.692	0.555
Effingham	12.646	9.721	5.730	6.861	12.358	1.263	0.478	0.634
Elbert	14.262	11.443	6.690	7.511	12.655	4.691	0.484	0.649
Franklin	13.882	11.335	7.174	6.626	12.900	2.461	0.207	0.666
Glynn	13.544	10.353	4.522	8.980	11.574	6.877	0.858	0.801
Greene	14.385	11.266	6.238	8.101	12.444	6.659	0.633	0.606
Hancock	14.096	11.314	6.096	7.936	12.572	4.307	0.631	0.577
Jackson	13.505	10.856	6.304	7.127	12.203	3.418	0.301	0.523
Jefferson	14.118	11.483	6.288	7.756	12.603	4.227	0.588	0.613
Liberty	13.563	10.400	5.497	8.022	12.743	2.174	0.745	0.707
Lincoln	13.363	10.604	5.609	7.688	11.918	3.970	0.630	0.556
McIntosh	13.485	11.209	4.762	8.615	11.538	6.290	0.768	
Montgomery	11.678	9.094	5.124	6.475	12.140	0.582	0.285	0.683
Oglethorpe	14.437	11.561	6.319	8.060	12.606	5.888	0.642	0.560
Richmond	13.969	10.838	5.606	8.318	11.913	7.468	0.481	0.712
Screven	13.320	10.672	6.211	7.036	13.144	1.109	0.536	0.753
Tattnall	12.345	9.503	5.790	6.495	12.883	0.550	0.258	0.522
Warren	14.335	11.434	6.405	7.873	12.825	4.277	0.492	0.570
Washington	14.102	11.444	6.449	7.580	12.962	2.908	0.488	0.622
Wayne	11.419	8.525	5.147	6.215	11.226	1.146	0.271	0.631
Wilkes	14.112	11.332	6.148	7.899	12.571	4.378	0.684	0.629

Wilkinson	13.723	11.147	6.469	7.175	12.662	2.670	0.331	0.591
Georgia	18.377	15.589	10.854	7.459	16.943	3.938	0.421	0.660

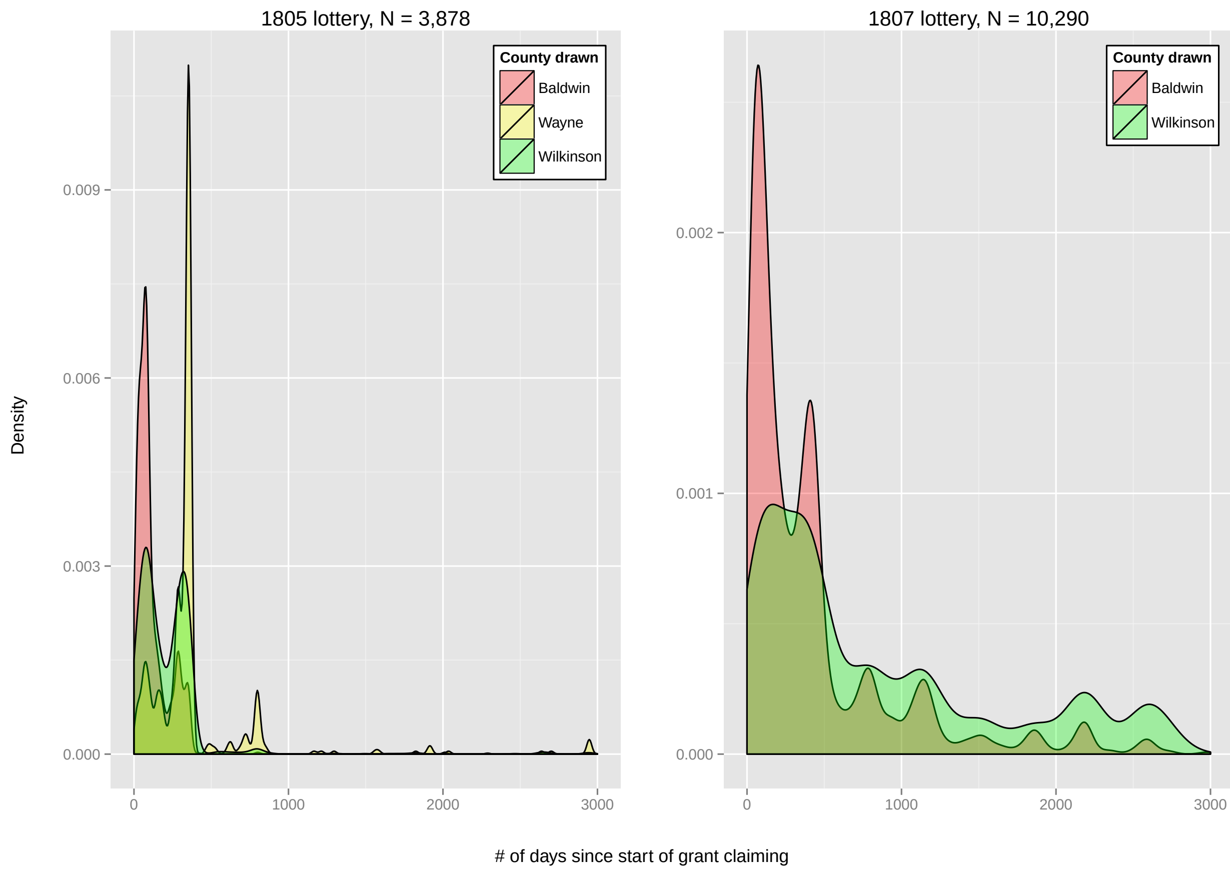
Table 7: Summary statistics on selected county-level characteristics for counties existing in 1807 from the 1850 Census. 'Log total farm acres' is the log of the sum of improved and unimproved acres of land in farms. 'Log average farm value' is the log of the difference between farm value and equipment value, over the total number of farms. 'Per acre farm value' is the difference between farm value and equipment value, over the sum of improved and unimproved acres of farm land. All dollar values are current (1850$). 'Slave pop.' is the slave population over the total population. 'Wealth Gini' is based on real estate values in sample drawn from the 1850 full-count Census (see footnotes to Table OA-6 for sample exclusions).

2.4 1870 Census

County	Taxation	Population	Per-capita taxation
Baldwin	22,870	10,618	2.154
Bryan	2,141	4,015	0.533
Bulloch	3,000	5,668	0.529
Burke	18,000	17,165	1.049
Camden	500	5,420	0.092
Chatham	52,880	31,043	1.703
Clarke	13,500	12,941	1.043
Columbia	732	11,860	0.062
Effingham	1,101	4,755	0.232
Elbert	4,030	10,433	0.386
Franklin	4,000	7,893	0.507
Glynn	9,528	5,376	1.772
Greene	5,200	12,454	0.418
Hancock	6,173	11,317	0.545
Jackson	1,470	11,181	0.131
Jefferson	7,348	12,190	0.603
Liberty	2,074	7,688	0.270
Lincoln	2,144	5,413	0.396
McIntosh	3,795	4,491	0.845
Montgomery	1,162	3,586	0.324
Oglethorpe	8,469	11,782	0.719
Richmond	54,928	25,724	2.135
Screven	3,200	9,175	0.349
Tattnall	1,250	4,860	0.257
Warren	2,300	10,545	0.218
Washington	17,056	15,842	1.077
Wilkes	3,750	11,796	0.318
Wilkinson	11,725	9,383	1.250
Wayne	486	2,177	0.223
Georgia	1,164,304	1,200,000	0.983

Table 8: Summary statistics on selected county-level characteristics in the 1870 Census. ‘Taxation’ is level of county-level non-national taxation; the amount for Georgia reflects total receipts into the state treasury during the fiscal year. ‘Population’ is total population in 1870; ‘Per-capita taxation’ is the ratio of ‘Taxation’ to ‘Population’.

Figure 3: Time lag in filing grants for 1805 and 1807 fortunate drawers.



Notes: grants filed for land reverted to state are excluded. See OA-Fig. 1 for the dates of grant claiming specified by the Acts of 11 May 1803 and 9 June 1806. The legislature extended the grant deadline for each lottery on an annual basis for about a decade.

3 Distribution of response variables

Table 9: Distribution of response variables by treatment and compliance status.

Response	**Group**	**N**	**Min.**	**Mean**	**Max.**	**S.d.**
Candidacy	$\mathcal{C}$	18,313	0	0.012	1	0.110
	$\mathcal{T}$	3,027	0	0.014	1	0.116
	$\mathcal{N}$	299	0	0.010	1	0.100
	all	21,639	0	0.012	1	0.111
Officeholding	$\mathcal{C}$	18,406	0	0.036	1	0.186
(binary)	$\mathcal{T}$	3,044	0	0.036	1	0.186
	$\mathcal{N}$	300	0	0.023	1	0.151
	all	21,750	0	0.036	1	0.185
Officeholding	$\mathcal{C}$	18,406	0.004	0.057	0.910	0.181
(match prob.)	$\mathcal{T}$	3,044	0.004	0.057	0.898	0.180
	$\mathcal{N}$	300	0.004	0.056	0.902	0.181
	all	21,750	0.004	0.057	0.910	0.181
Slave wealth	$\mathcal{C}$	1,811	0	1,943	63,526	4,001
	$\mathcal{T}$	282	0	1,929	25,583	3,355
	$\mathcal{N}$	38	0	1,745	10,412	2,579
	all	2,131	0	1,938	63,526	3,899

Response: 'Candidacy' indicates whether the participant ran for office between 1805 and 1847, inclusive, excluding women, orphans, pretreatment candidates, and pretreatment officeholders. 'Officeholding (binary)' indicates whether the participant held office between 1806 and 1847, inclusive, excluding women, orphans, and pretreatment officeholders. 'Officeholding (match prob.)' is the probability of being matched to the officeholder records for the same restricted sample as the binary case. 'Slave wealth' is the imputed slave wealth for participants matched to the 1820 Census (see footnotes to Table OA-5 for the slave value imputation method). *Group:* $\mathcal{C}$ denotes participants assigned to control; $\mathcal{T}$ denotes treated compliers, or participants assigned to treatment who accept treatment; $\mathcal{N}$ denotes never-treats, or participants assigned to treatment who decline treatment.

4 Power analysis by simulation

The purpose of a power analysis by simulation is to estimate $\mathrm{P}(\text{Reject}\,\mathrm{H}_0|\mathrm{H}_0\,\text{is false})$ at a fixed significance level ($\alpha = 0.05$) and sample size ($N = 21,750$) for different treatment effects $\Delta_{1,\ldots,j}$. In this case N is the size of the observed sample of participants, excluding widows, orphans, and pretreatment officeholders. The simulation proceeds as follows:

1. Take a random sample of size N without replacement from from the observed distribution of treatment assignments, weighted by the observed propensity score, to create a vector of simulated treatment assignments.

2. Simulate response values with Δ_j as the difference-in-means between the simulated treated and control units. Generate random values from the binomial distribution with the probability of success on each trial equal to the mean of the response in the observed sample.

3. Perform a randomization test on the simulated data and extract the p value.

Repeat the simulation $\mathcal{I}$ times and calculate power of the test by dividing the count of the number of p values that are less than α over $\mathcal{I}$. Normally, 80% power is required to justify a study. Fig. 4 provides the results of power analysis simulations for the officeholding response.

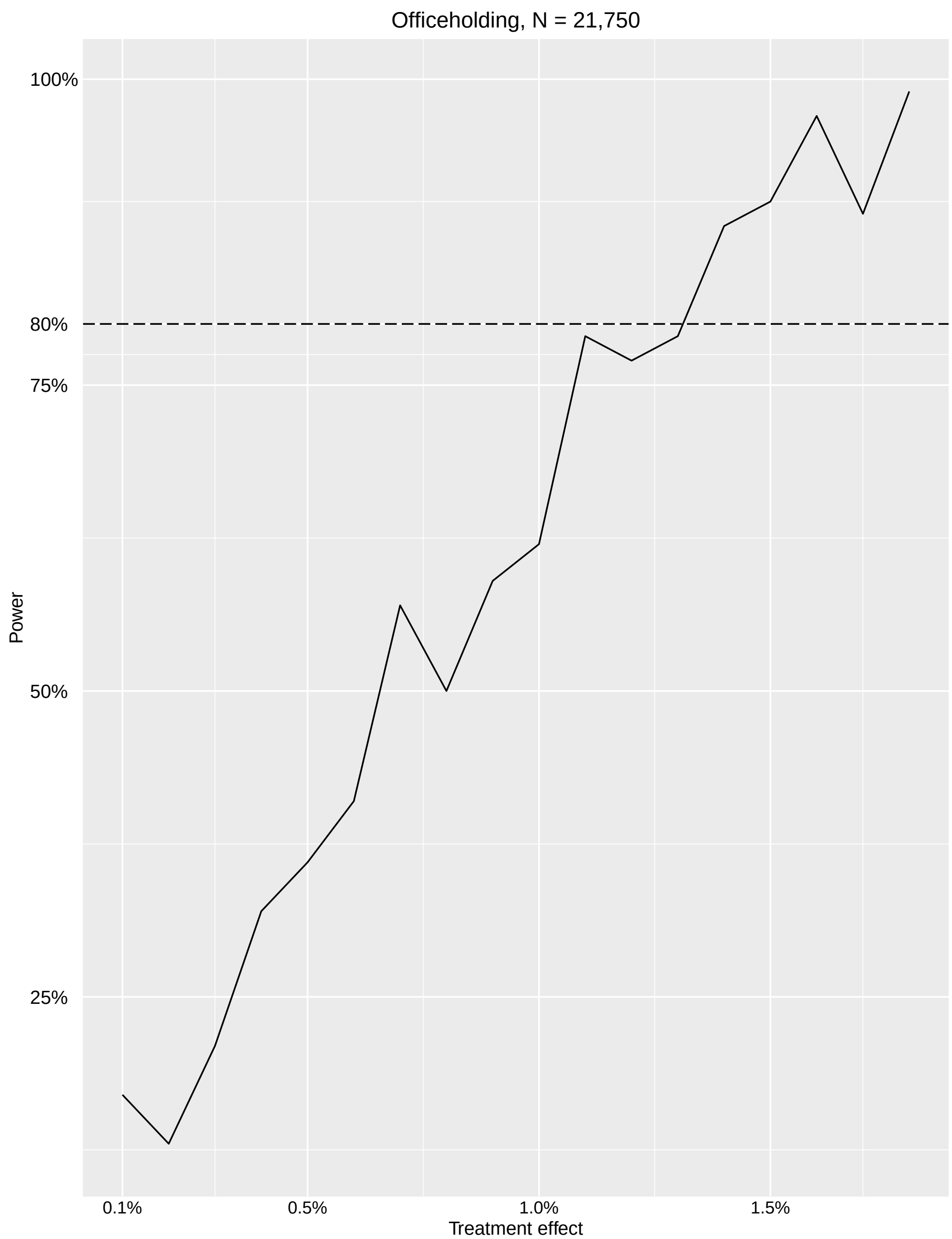
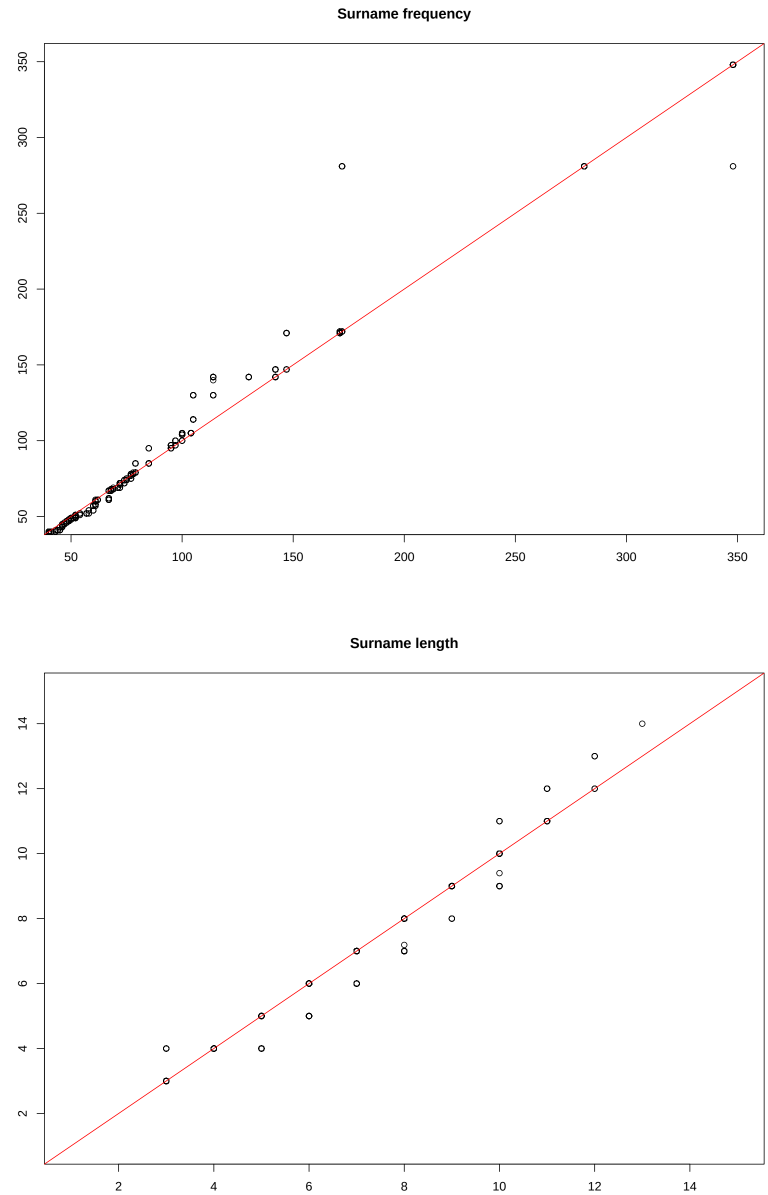


Figure 4: Power analysis by simulation ($\mathcal{I} = 100$ iterations) for continuous and binary response variables. The horizontal line indicates the 80% power that is normally required to justify a study. p values are calculated using a two-sided randomization test ($\mathcal{L} = 100$ iterations) for δ^*_{ITT}.

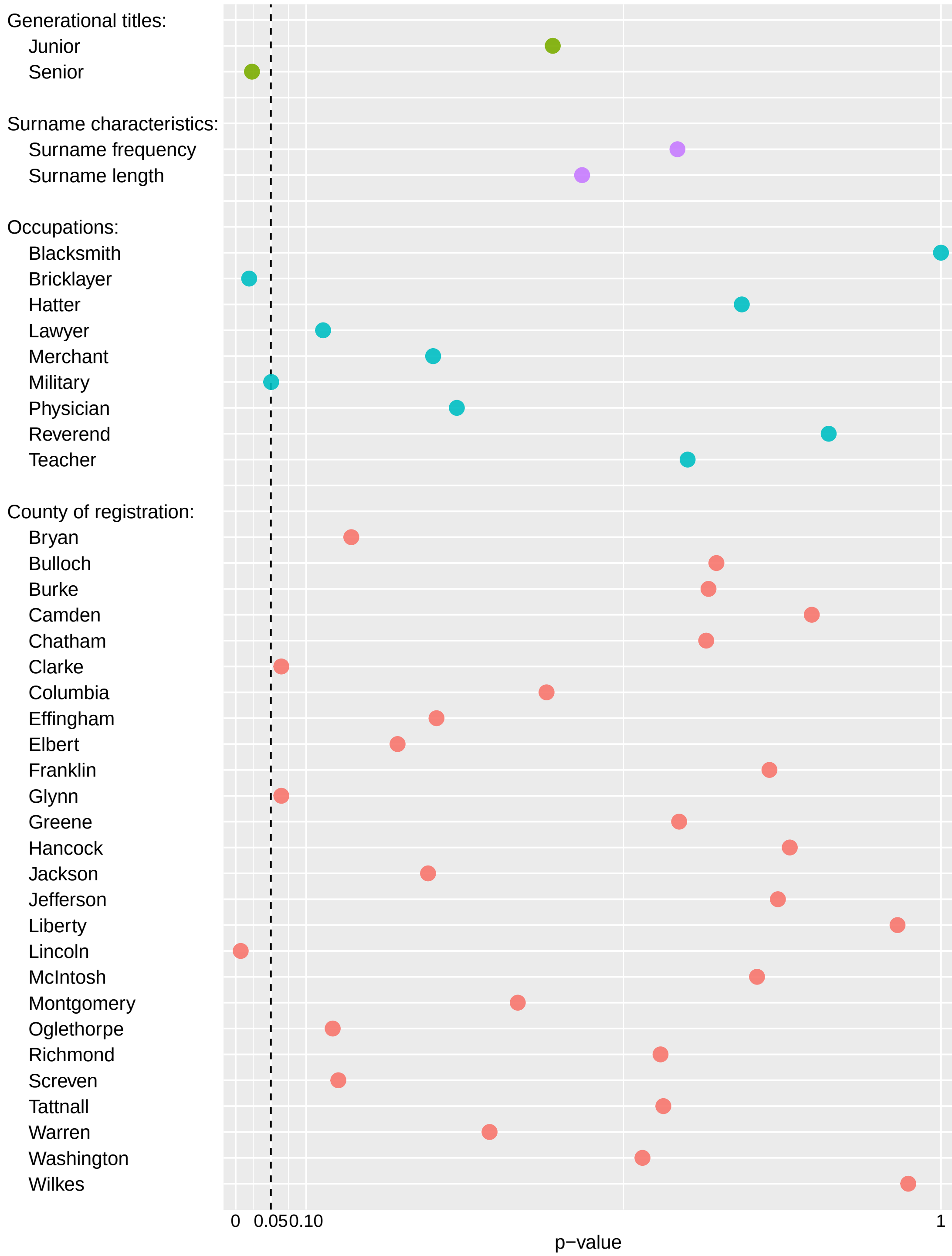
5 Balance of pretreatment covariates

Figure 5: Normal QQ plots of surname characteristics by treatment assignment for all lottery participants ($N = 23,927$).



Notes: 'Surname frequency' is the number of times surnames appear in the lottery records. 'Surname length' is the character length of surnames.

Figure 6: Balance in treatment assignment for all lottery participants ($N = 23,927$).



Note: p values are calculated using a two-sided randomization test ($\mathcal{L} = 10,000$ iterations) for δ^*_{ITT}. See Section OA-7.1 for a description of how p values are obtained. 'Surname frequency' is the number of times surnames appear in the sample. 'Surname length' is the character length of surnames. 'Military' indicates participants listed with a military rank (i.e., Captain, Colonel, General, or Major).

6 Record linkage

I employ a machine learning approach to link lottery participants with officeholder and census records. First, I link the fortunate drawer records from the 1807 lottery with officeholders based on the exact match of surname and Soundex code of the first name, and then manually deduplicate the matched records. Second, I train an ensemble of algorithmic models on the 1807 records to classify correct matches, using participant characteristics (e.g., surname frequency) and match characteristics (e.g., the Euclidean distance between participants' county of registration and officeholders' constituency) as features of the model. The 10-fold cross-validated risk estimate on the training set is under 3%.[1] Lastly, I use the ensemble fit to automatically deduplicate 1805 participant records matched with officeholders on the basis of surname and Soundex code of the first name, using a prediction threshold of 50% to classify correct matches.

7 Estimation of treatment effects

7.1 ITT effects

Under the Neyman (1923) potential outcomes framework, each $i = \{1, ..., N\}$ participants have two potential outcomes, Y_{1i} and Y_{0i}, which represent participant i's response to treatment and control groups, respectively. $Z_i \in \{0, 1\}$ indicates i's treatment assignment and $\boldsymbol{Z}$ indicates the treatment assignments for all N participants. The observed response is thus a function of treatment assignment and potential outcomes, $Y_i = Z_i Y_{1i} + (1 - Z_i) Y_{0i}$.

Let Y^T be the average response in the treatment group and Y^C be the average response in the control group. The intention-to-treat (ITT) estimator for the sample average treatment effect is the difference between these two sample quantities:[2]

[1] Section OA-9.1 provides information on the record link ensemble's candidate learners, weights, and risk estimates.

[2] Section OA-7.2 describes the procedure for obtaining an estimate of the effect of treatment-on-the-treated (TOT).

$$\delta^*_{\text{ITT}} = Y^T - Y^C = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{Z_i Y_{1i}}{N_t/N} - \frac{(1-Z_i)Y_{0i}}{N_c/N}\right), \tag{1}$$

where N_t and N_c are the number of treated and control participants, respectively. The probability of receiving treatment is determined by the number of draws registered by participant i, and the total number of registered draws (tickets) and prizes:

$$\text{P}(Z_i = 1) = \begin{cases} \frac{\#\text{Prizes}}{\#\text{Tickets}} & \text{if } i \text{ has one draw} \\ 2\left(\frac{\#\text{Prizes}}{\#\text{Tickets}}\right) & \text{if } i \text{ has two draws.} \end{cases} \tag{2}$$

The potential outcomes framework implicitly makes the following assumption:

Assumption 1. *Stable unit treatment value assumption (SUTVA). (i.) No interference:* $Y_{i\boldsymbol{Z}}$ *varies with* Z_i*, but does not vary with other elements of* $\boldsymbol{Z}$*. (ii.) No hidden variations in treatment:* $Y_{i\boldsymbol{Z}}$ *for all* i *and* $\boldsymbol{Z}$ *is well-defined.*

Interference undermines the framework because it creates more than two potential outcomes per participant, depending on the treatment assignment of other participants (Rubin, 1990). No hidden variations in treatment is required to ensure that each participant has the same number of potential outcomes (Imbens and Rubin, 2015). Assumption 1 (i.) is violated in the estimation of the treatment effect on officeholding if, for instance, treatment confers treated participants a competitive advantage over control participants in head-to-head contests for elective office. Assumption 1 (ii.) is violated if, for instance, variation in the quality of land prizes creates more than two potential outcomes per participant.

The potential outcomes framework explicitly requires random assignment:

Assumption 2. *Random treatment assignment:* $\text{P}(Z_i|Y_{i\boldsymbol{Z}}) = \text{P}(Z_i)$ *for all* i*.*

Assumption 2 will not hold if $\text{P}(Z_i = 1)$ is affected by factors exogenous to Eq. (2).

Randomization p value Given assumptions 1-2, I use Monte Carlo sampling from a randomization distribution of δ^*_{ITT} to estimate an exact two-sided p value (Ernst, 2004).

7.2 TOT effects

Following closely Freedman's [2006] notation, let α denote the fraction of *always-treats* in the study population — participants who accept treatment regardless of their assignment — and γ be the fraction of never-treats. Let β be the fraction of compliers —those who comply with their assignment — and θ denote the fraction of *defiers* — those who behave contrary to their assignment.

Assumption 3. *Single crossover:* $\alpha = \theta = 0$ *and* $\beta > 0$.

Assumption 3, which can be verified with the data, ensures there are no always-treats and no defiers in the study population, so that $\beta + \gamma = 1$. Y^C is a mix of the average response of compliers assigned to control ($\mathcal{C}$) and the average response of never-treats ($\mathcal{N}$):

$$Y^C = \beta\mathcal{C} + \gamma\mathcal{N} \tag{3}$$

$$\mathcal{C} = \frac{Y^C - \gamma\mathcal{N}}{\beta}. \tag{4}$$

Due to random assignment, the mix is the same in the treatment group:

$$\mathcal{T} = \frac{Y^T - \gamma\mathcal{N}}{\beta}, \tag{5}$$

where $\mathcal{T}$ is the average response of compliers assigned to treatment. The average effect of treatment on the compliers is estimated taking the difference between Eq. (5) and Eq. (4):

$$\delta^*_{\text{TOT}} = \mathcal{T} - \mathcal{C} = \frac{Y^T - Y^C}{\beta}. \tag{6}$$

7.3 Heterogeneous treatment effects

Following Grimmer et al.'s [2014] notation, let $\boldsymbol{X}$ be a $N \times p$ vector of pretreatment covariates, $\boldsymbol{Z}$ a length-N vector representing treatment assignment, and $\boldsymbol{\Psi}$ a $N \times q$ vector representing number of draws in the lottery. In the current application, $\boldsymbol{X}$, $\boldsymbol{Z}$, and $\boldsymbol{\Psi}$ are binary vectors.

Given Assumptions 1-2, I estimate the conditional average treatment effect (CATE), which measures how treatment effects vary across each covariate:

$$\phi(\boldsymbol{Z}, \boldsymbol{\Psi}, \boldsymbol{x}) = \mathrm{E}[Y(\boldsymbol{Z}) - Y(0) | \boldsymbol{\Psi}, \boldsymbol{X} = \boldsymbol{x}]. \tag{7}$$

Estimating Eq. (7) on the observed data may lead to estimates that are reflective of random variation in the sample, rather than systematic variation in the response to treatment, especially when the covariate group is small. Instead, I employ a weighted ensemble method, where each $m = \{1, 2, ..., M\}$ ensemble candidates estimate the response surface:

$$g_m(\boldsymbol{Z}, \boldsymbol{\Psi}, \boldsymbol{x}) = \mathrm{E}[Y | \boldsymbol{Z}, \boldsymbol{\Psi}, \boldsymbol{x}]. \tag{8}$$

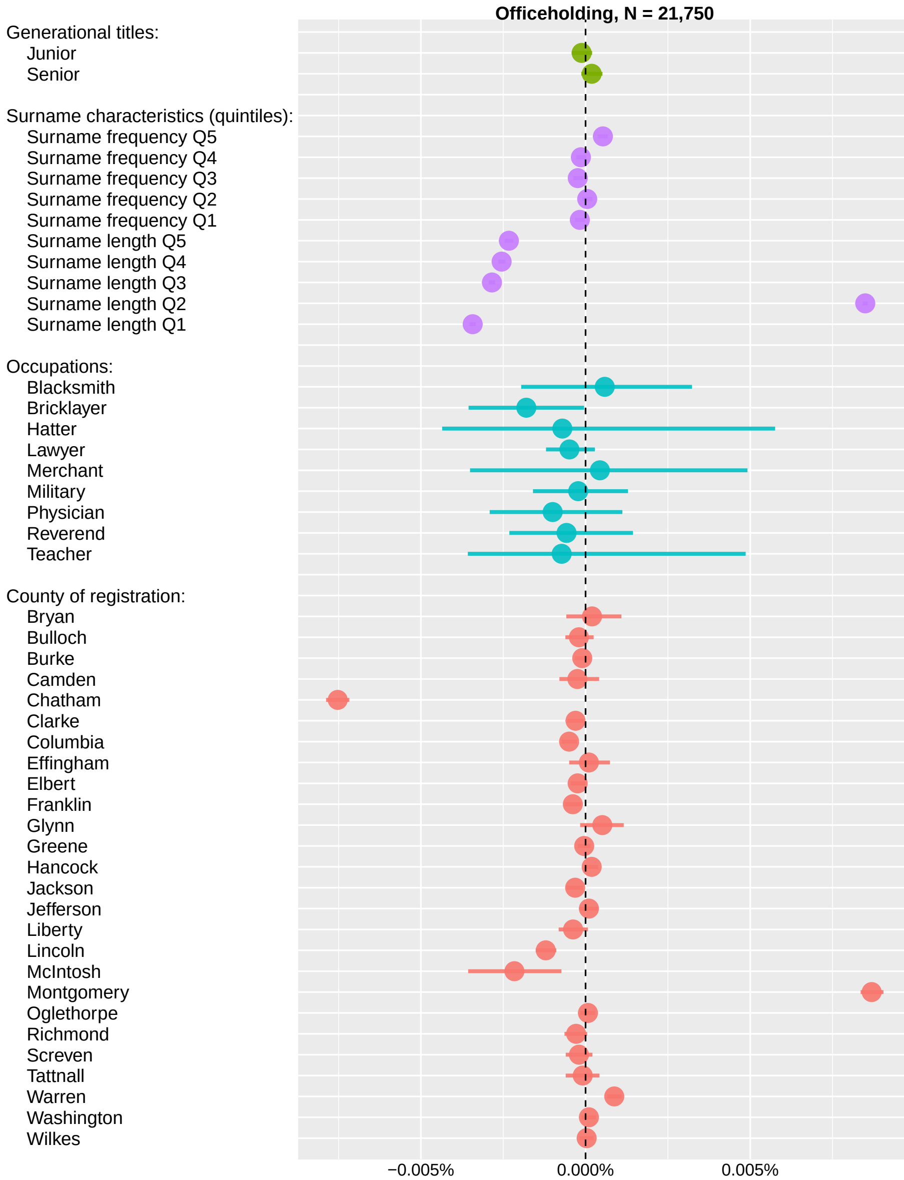
Heterogeneous treatment effects are estimated by taking differences across response surfaces:

$$\hat{\phi}(\boldsymbol{Z}, \boldsymbol{\Psi}, \boldsymbol{x}) = \sum_{m=1}^{M} w_m g_m(1, \boldsymbol{\Psi}, \boldsymbol{x}) - \sum_{m=1}^{M} w_m g_m(0, \boldsymbol{\Psi}, \boldsymbol{x}), \tag{9}$$

where weights $\boldsymbol{w} = \{w_1, w_2, ..., w_M\}$ are attached to each candidate learner. Weights are selected based on the out-of-sample predictive performance of each candidate learner during 10-fold cross-validation (van der Laan et al., 2007).

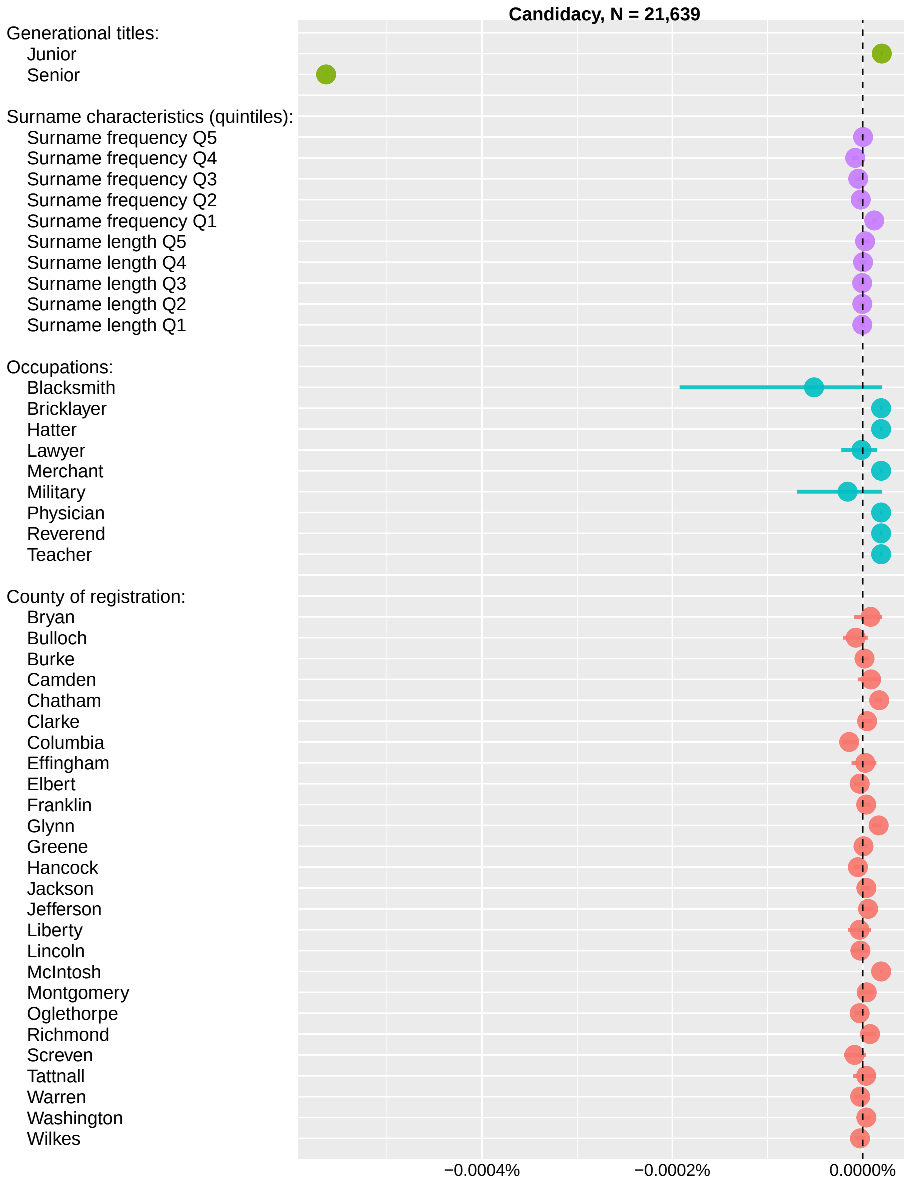
8 Heterogeneous treatment effect estimates

Figure 7: Heterogeneous treatment effects on officeholding according to pretreatment covariates.



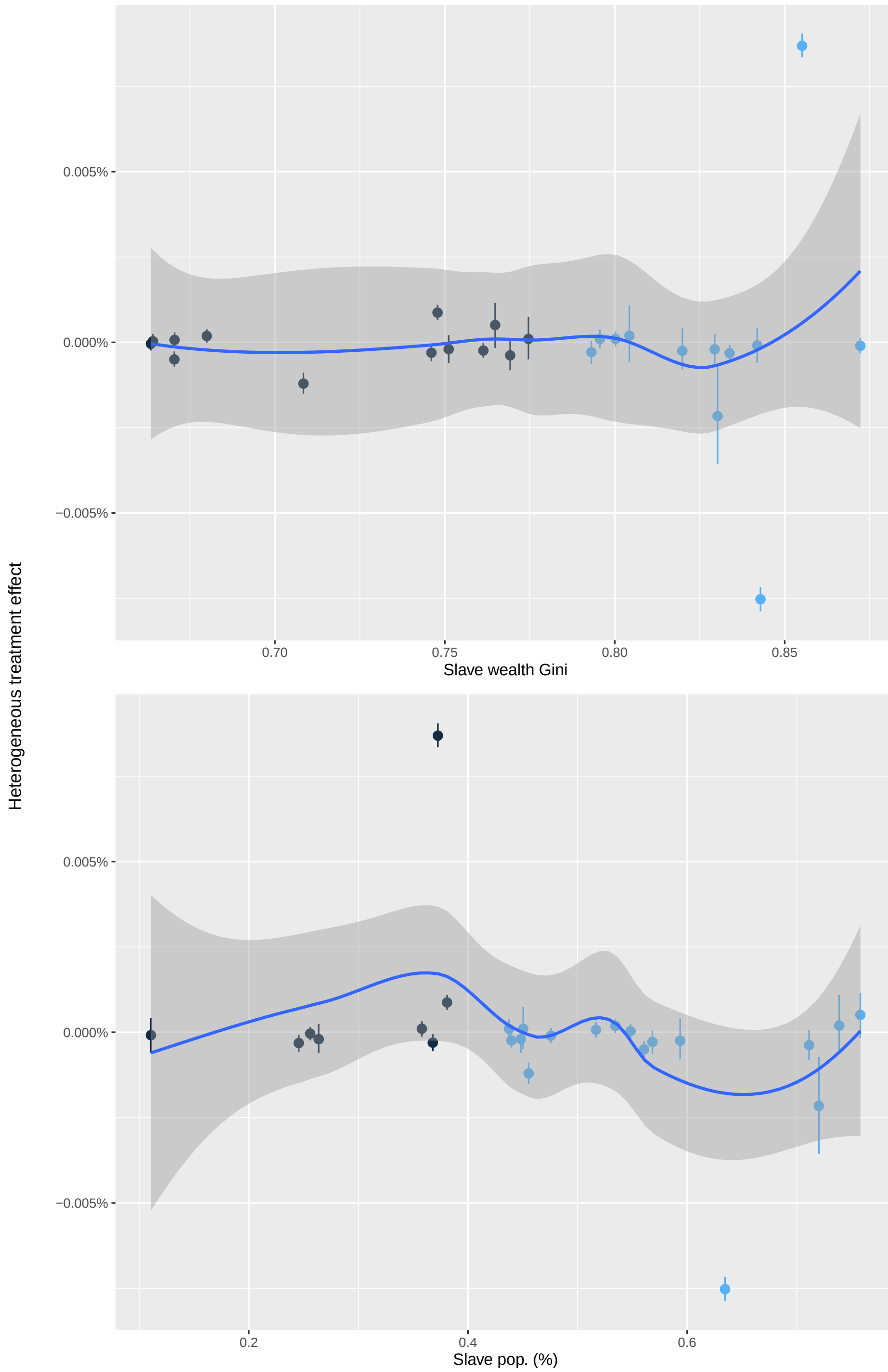
Notes: ensemble method used to estimate response surfaces for participants, given their treatment assignment, number of draws, and pretreatment covariates. Horizontal lines represent 95% bootstrap confidence intervals constructed using 10,000 bootstrap samples. See footnotes to Table 9 for response variable definitions. Covariate groups with insufficient observations to produce treatment effect estimates or confidence intervals are removed.

Figure 8: Heterogeneous treatment effects on candidacy according to pretreatment covariates.



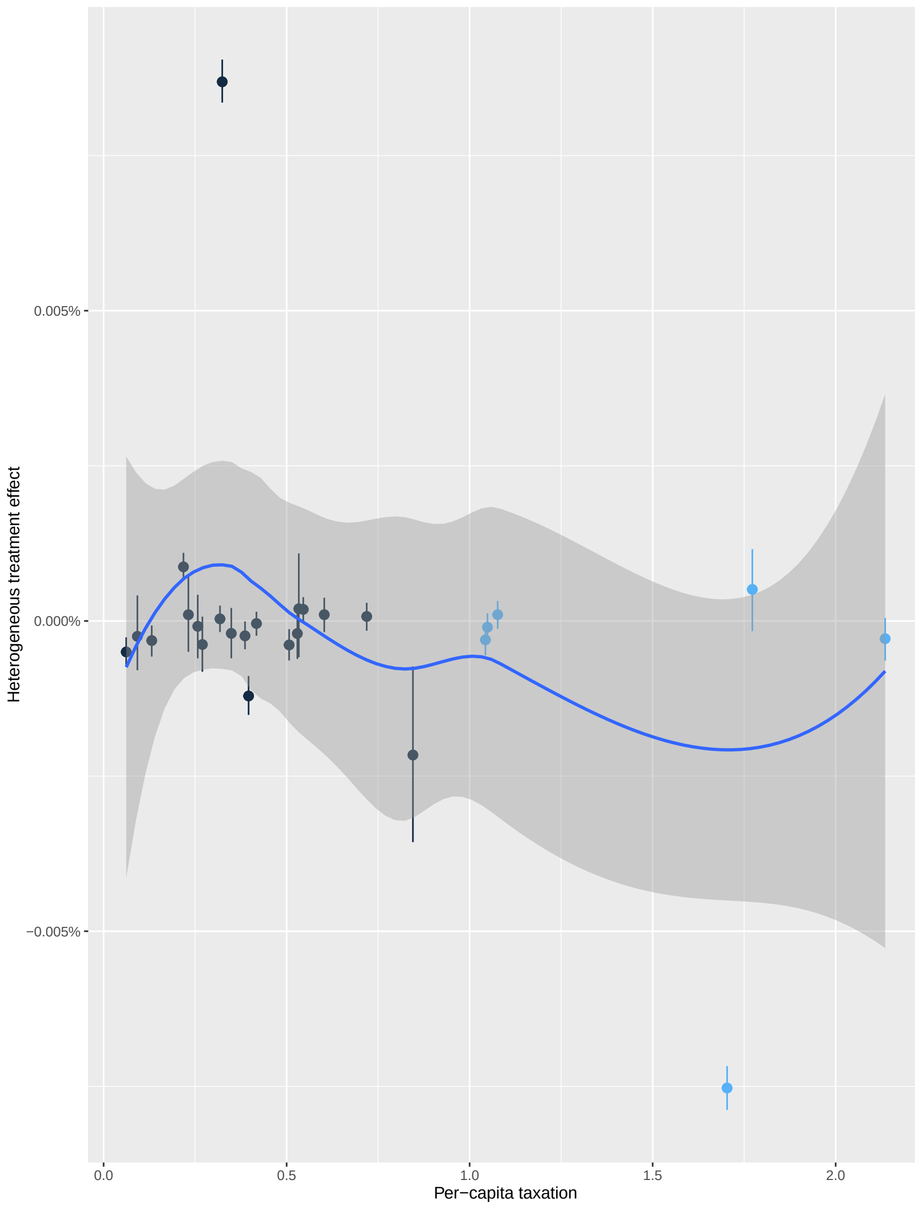
Notes: see footnotes to Fig. 7.

Figure 9: Heterogeneous treatment effects on officeholding according to county of registration, by 1820 county characteristics.



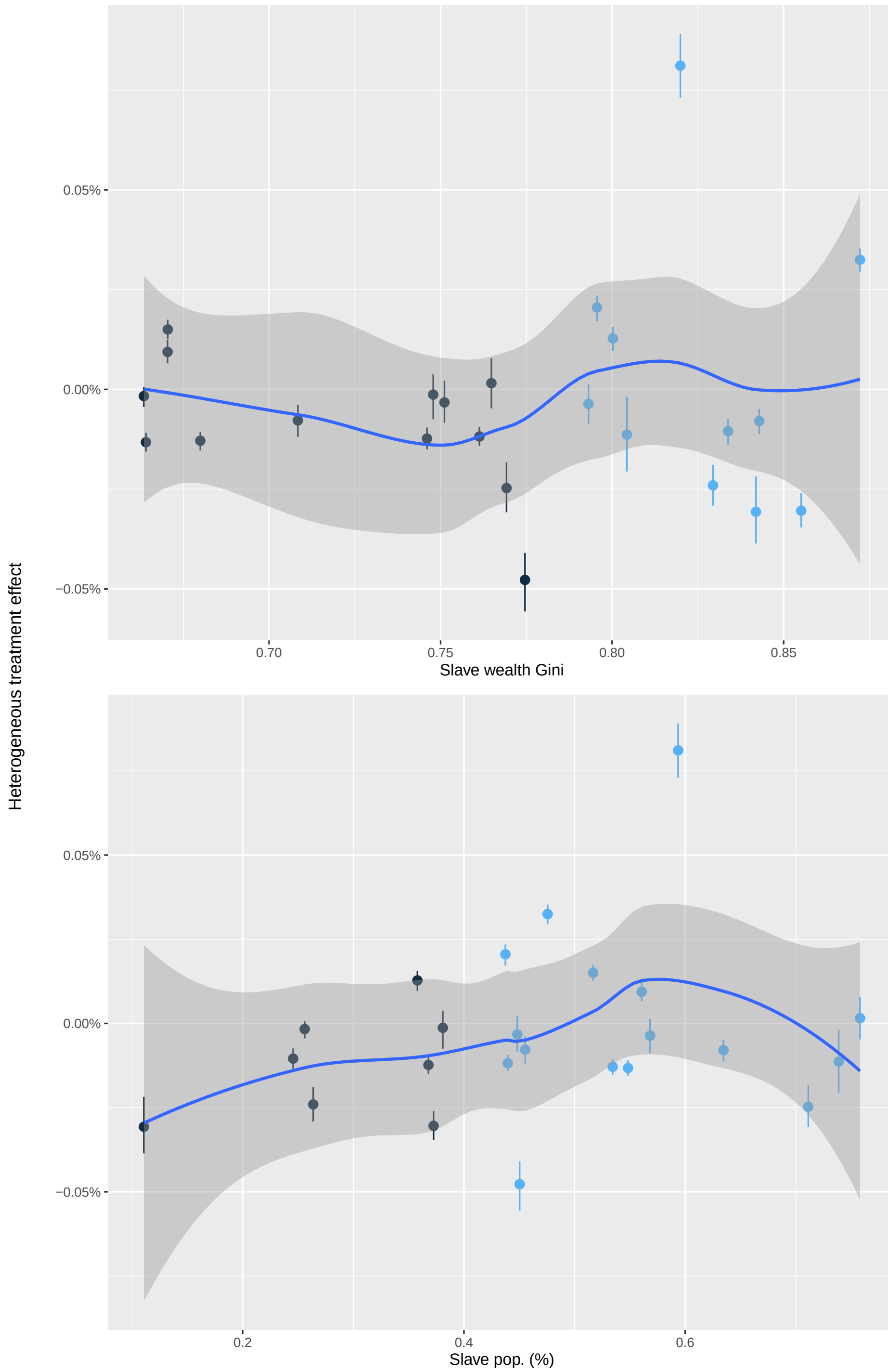
Notes: see footnotes to Fig. 7. Table OA-4 report slave wealth Gini coefficients and slave population shares by county derived from the 1820 Census. Lighter colored observations represent counties above the statewide slave wealth Gini coefficient or slave population share. The line and shaded area is a LOESS-smoothed estimate of the heterogeneous treatment effect and its standard error.

Figure 10: Heterogeneous treatment effects on officeholding according to county of registration, by per-capita taxation in 1870



Notes: see footnotes to Fig. 7. Table OA-8 report levels per-capita taxation by county, derived from the 1870 Census. Lighter colored observations represent counties above the statewide per-capita tax level. The line and shaded area is a LOESS-smoothed estimate of the heterogeneous treatment effect and its standard error.

Figure 11: Heterogeneous treatment effects on 1820 slave wealth according to county of registration, by 1820 county characteristics.



Notes: see footnotes to Fig. 9.

9 Ensemble characteristics

9.1 Record classification

Table 10: Record classification ensemble.

Algorithm	Parameters	Risk	Weight
Super Learner (`SuperLearner`)	default	0.023	-
Lasso regression (`glmnet`)	$\alpha = 1$	0.023	0.243
GLM with elasticnet regularization (`glmnet`)	$\alpha = 0.25$	0.023	0
GLM with elasticnet regularization (`glmnet`)	$\alpha = 0.5$	0.023	0
GLM with elasticnet regularization (`glmnet`)	$\alpha = 0.75$	0.023	0
Neural network (`nnet`)	default	0.066	0
Random forests (`randomForest`)	default	0.026	0
Random forests (`randomForest`)	mtry = 1	0.03	0.45
Random forests (`randomForest`)	mtry = 5	0.025	0.305
Random forests (`randomForest`)	mtry = 10	0.025	0
Ridge regression (`glmnet`)	$\alpha = 0$	0.025	0

Notes: cross-validated risk and weights used for each algorithm in Super Learner prediction ensemble for record classification model. 'Risk' is the 10-fold cross-validated risk estimate based on mean squared error for each algorithm. 'Weight' is the coefficient for the Super Learner, which is estimated using non-negative least squares based on the Lawson-Hanson algorithm.

9.2 Heterogeneous treatment effects

Candidacy

Algorithm	Parameters	Risk	Weight
Generalized boosted models (`gbm`)	default	0.012	1
Random forests (`randomForest`)	default	0.012	0
Random forests (`randomForest`)	mtry = 1	0.012	0
Random forests (`randomForest`)	mtry = 5	0.012	0
Random forests (`randomForest`)	mtry = 10	0.012	0

Officeholding

Algorithm	Parameters	Risk	Weight
Generalized boosted models (`gbm`)	default	0.034	1
Random forests (`randomForest`)	default	0.036	0
Random forests (`randomForest`)	mtry = 1	0.035	0
Random forests (`randomForest`)	mtry = 5	0.035	0
Random forests (`randomForest`)	mtry = 10	0.035	0

Slave wealth			
Algorithm	Parameters	Risk	Weight
Generalized additive models (`gam`)	degree = 2	0.003	0
Generalized additive models (`gam`)	degree = 3	0.003	0
Generalized additive models (`gam`)	degree = 4	0.003	0
Generalized linear models (`glm`)	default	0.003	0
Random forests (`randomForest`)	default	0.003	0
Random forests (`randomForest`)	mtry = 1	0.003	1
Random forests (`randomForest`)	mtry = 5	0.003	0
Random forests (`randomForest`)	mtry = 10	0.004	0

Notes: cross-validated risk and weights for each algorithm in response model ensembles. Ensemble method used to estimate response surfaces for participants, given their treatment assignment, number of draws, and pretreatment covariates.

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