Online Appendix for: "The Electoral Implications of Politically Irrelevant Cues under Demanding Electoral Systems"

Taishi Muraoka

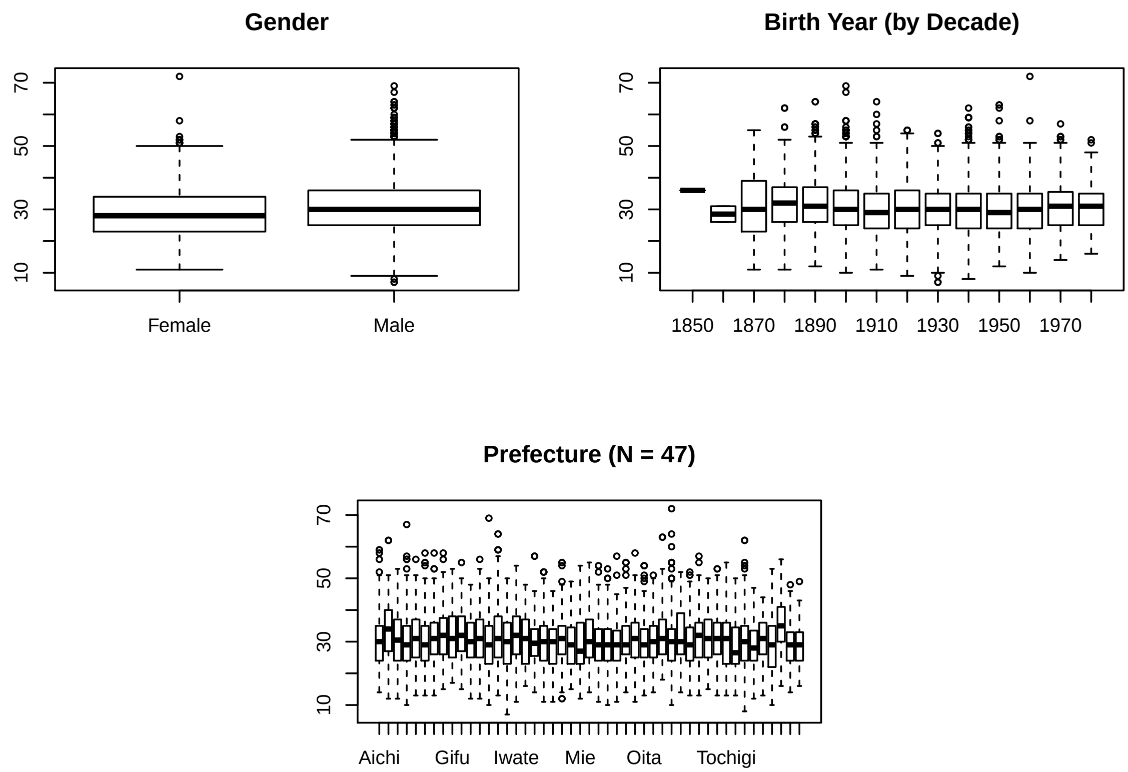
A Placebo Tests

Is candidate name complexity really politically irrelevant? As I mentioned in the main text, it is very difficult to imagine that the number of strokes, which is mostly determined at birth, is systematically related to the performance, policy positions, or personal quality of candidates. Any reader who is familiar with Japanese names may be comfortable with this assumption. Nevertheless, in order to validate this point more formally, I conduct some placebo tests.

First, I examine whether the visual complexity of candidate names is confounded with some background characteristics of candidates using variables available in the JHRED (Reed and Smith 2017). The top left panel of Figure A.1 compares the distributions of the name complexity scores of male and female candidates. It indicates that there is no systematic difference between the two. Next, the top right panel shows the relationship between birth year (by decade) and name complexity. It is not the case that those who were born in earlier decades have more complex names. Finally, the bottom panel shows the distributions of name complexity scores by prefecture in which candidates ran. Again, there is no systematic difference in name complexity scores across regions.

Next, I test whether the visual complexity of candidate names is a significant predictor of ideologies or campaign strategies utilizing data provided by Catalinac (2016; 2018). Catalinac (2016; 2018) assembles over 7,000 campaign manifestos made by individual candidates for the Lower House elections between 1986 and 2009. Using various tools of text analysis, she successfully quantifies two variables: (1) the extent to which candidates em-

Figure A.1: The Distributions of Name Complexity Scores by Gender, Birth Year, and Prefecture



phasized "pork" (or targeted goods instead of general policies) in their manifestos; and (2) the left-right positions of their platforms. The first one measures the proportion of pork in the manifesto, hence taking values between 0 and 1. The second variable measures the ideological position of the candidate based on a continuous scale, with higher values indicate that candidates are more leaning toward the right. The empirical range of this variable is between -4.365 and 5.180 with mean 0.042. To the best of my knowledge, these variables are the most comprehensive measures of campaign strategies and policy positions available at the candidate level. I estimate the effect on name complexity on these two outcomes.

Table A.1 summarizes the results. Models 1 to 3 use the proportion of pork in the campaign manifesto as an outcome, and models 4 to 6 use ideology as a dependent variable. In models 1 and 3, I simply include the measure of name complexity and random effects by

Table A.1: The Effect of Name Complexity on Campaign Strategy and Ideology

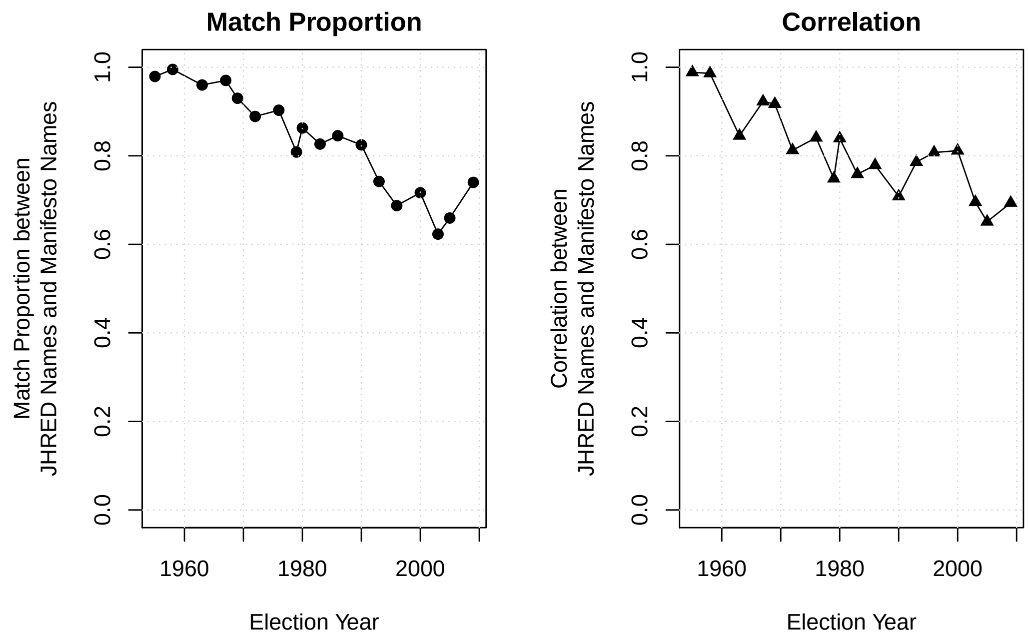
	Proportion of Pork			Ideology		
	(1)	(2)	(3)	(4)	(5)	(6)
Name Complexity	0.001	0.0003	0.0001	0.002	0.0001	0.001
	(0.0005)	(0.0004)	(0.0004)	(0.003)	(0.001)	(0.001)
Name Length		−0.006	−0.006		−0.006	−0.008
		(0.005)	(0.005)		(0.015)	(0.015)
Female		−0.014	−0.013		0.015	0.037
		(0.009)	(0.009)		(0.029)	(0.028)
Birth Year		−0.003**	−0.001**		0.003**	0.0004
		(0.0002)	(0.0002)		(0.001)	(0.001)
District Magnitude			−0.020**			−0.026*
			(0.004)			(0.014)
σ_c	0.191	0.103	0.105	1.21	0.222	0.225
σ_p	–	0.098	0.109	–	0.722	0.752
Election-Year Fixed Effects	No	No	Yes	No	No	Yes
N	7,497	7,491	7,491	7,497	7,491	7,491
Log Likelihood	898.1	2,289.3	2,555.6	−10,319.8	−7,065.8	−6,827.5
AIC	−1,788.3	−4,562.5	−5,079.2	20,647.5	14,147.7	13,686.9

Note: $^{*}p<0.10$; $^{**}p<0.05$. The models are fitted with the `lmer` command in the `lme4` package in `R`. Birth year is transformed so that the minimum value takes 0. σ_c and σ_p indicate the standard deviations of candidate and party random effects, respectively.

candidate. In models 2 and 5, I add some candidate characteristics, including name length, female, and birth year, as well as party random effects. Then, in models 3 and 6, I further add district magnitude and election year fixed effects. The effect of name complexity is not statistically different from 0 in all models. Therefore, there is no systematic evidence that name complexity can predict the ideologies or campaign strategies of candidates. These findings provide some credence to the argument that name complexity contains no politically useful information.

B How often Candidates Simplify Their Names

Figure B.1: Comparing Candidate Names in the JHRED and Manifestos



The fact that some candidates use simplified names in elections poses some measurement and inferential concerns. But, how prevalent is this practice? In order to partly answer this question, I compare candidate names that appear in the JHRED and campaign manifestos that were made by individual candidates. The assumption here is that if candidates chose to put a simplified version of their names on the ballot, they also did the same in their manifestos. I obtain the copies of original manifestos between 1955 and 2009 (except 1960) and randomly pick 50 candidates in each election cycle. Then, I compare the name complexity scores of candidate names in the JHRED and manifestos.

The findings are summarized in Figure B.1. The left panel shows the proportion of name match between the two data sources, whereas the right panel shows the correlation in name complexity scores between the two. The first thing to notice is that in both panels, we see a slight declining trend. Over time, more and more candidates seem to use simplified names, and disagreement between the JHRED and manifestos increases. This may be explained by learning and strategic adjustment in part of candidates. Second, however, both the proportion of name match and the correlation in name complexity scores remain fairly high. For example, the correlation in name complexity scores between the JHRED and manifestos never becomes lower than 0.61, which is the correlation between complexity and difficulty scores (see section E below). Therefore, it seems to be the case that a lot of candidates did not simplify their names, and even if they did, name complexity scores did not change a lot. The main takeaway of this exercise is that we may not have to worry too much about the measurement issue associated with the fact that the JHRED uses candidates' actual names. The fairly high correlation between actual names and those voters saw at the polling station also justifies the reliance on the intention-to-treat effects.

C Vote Share Data

Table C.1: The Descriptive Statistics of Vote Share Data

	SNTV Data				
	N	Mean	SD	Min	Max
Vote Share	17,998	12.329	7.945	0.003	84.367
Name Complexity	17,998	30.474	8.393	7	69
Average Letter Complexity	17,998	7.680	1.976	2.25	16.333
Name Difficulty	17,998	20.739	7.214	5	49
Average Name Difficulty	17,998	5.204	1.675	1	12.5
Name Length	17,998	3.997	0.629	2	7
Number of Candidates	17,998	9.179	3.586	2	26
District Magnitude	17,998	4.093	0.839	1	6
SD of Name Complexity	17,998	8.022	2.159	0.707	18.046
	SMDP Data				
	N	Mean	SD	Min	Max
Vote Share	7,867	26.630	19.149	0.119	95.302
Name Complexity	7,867	30.186	7.940	7	72
Average Letter Complexity	7,867	7.732	1.946	2.5	15.667
Name Difficulty	7,867	21.027	7.038	5	53
Average Letter Difficulty	7,867	5.382	1.743	1	12
Name Length	7,867	3.935	0.579	2	8
Number of Candidates	7,867	4.010	1.072	2	9
SD of Name Complexity	7,867	7.184	3.364	0.000	29.698

Data come from Reed and Smith (2017). Complexity scores and difficulty scores are calculated based on an online dictionary of Japanese letters (http://kanji.jitenon.jp).

D Alternative Models

Table D.1: Alternative Specifications

	Vote Share			
	(1)	(2)	(3)	(4)
	SNTV All	SMDP All	SNTV LDP-Only	SNTV LDP-Only
Name Complexity	-0.035^{*}	0.028	-0.013	-0.003
	(0.009)	(0.023)	(0.015)	(0.027)
Name Complexity × Number of LDP Candidates				-0.003
				(0.007)
Name Length	0.380^{*}	0.407	0.071	0.072
	(0.117)	(0.307)	(0.198)	(0.199)
Number of LDP Candidates			-1.398^{*}	-1.310^{*}
			(0.068)	(0.212)
District Magnitude			-3.009^{*}	-3.010^{*}
			(0.127)	(0.127)
σ_c	4.324	7.503	3.910	3.890
σ_p	4.113	10.850	–	–
District-Year Fixed Effects	Yes	Yes	–	–
Election-Year Fixed Effects	–	–	Yes	Yes
N	17,998	7,867	6,201	6,201
Log Likelihood	$-47,926$	$-22,574$	$-17,831$	$-17,835$
AIC	100,299	49,348	35,709	35,719

Note: $^{*}p<0.05$. The models are fitted with the `lmer` command in the `lme4` package in `R`. σ_c and σ_d indicate the standard deviations of candidate and election-district random effects, respectively.

In models 1 and 2 of Table D.1, I use an alternative specification of the effect of name complexity on vote share. Instead of including district-level controls and election-year fixed effects, I use district-year fixed effects. This specification yields the same results. Under SNTV, the effect of name complexity on vote share is negative and statistically different from 0. Its effect size is slightly greater than the one reported in model 2 of Table 1. By contrast, under SMDP, the effect of name complexity is not statistically different from 0, and its sign is incorrect, consistent with the result of model 2 in Table 2. In short, the main findings are robust even when I exploit within-district variation in name complexity.

Next, is the effect of name complexity under SNTV observed even when I focus on LDP candidates? It may be the case that voters with strong attachment to the LDP first decide to vote for the party and then pick whoever has the simplest name (perhaps because it is the easiest to write or because they want to minimize the chance that they make writing errors). To test this, I estimate models that include only LDP candidates.

In model 3 of Table D.1, I run a model that is similar to model 2 in Table 1, except that it does not include party random effects and that it controls for the number of LDP candidates instead of the number of candidates in the district. The effect of name complexity is negative but not statistically different from 0. In model 4, I run a model that includes the interaction term between name complexity and the number of LDP candidates, which is similar to model 1 in Table H.1 below. Although the interaction term shows a negative sign, the marginal effect of name complexity is not statistically reliable across the entire range of the number of LDP candidates.

Therefore, there is no strong evidence to support the possibility that voters first choose their favorite party (the LDP) and then write the simplest name from that party. One reason for the null results may be that this type of voter (i.e., strong party identifier) is the one who successfully finds and uses partisan cues to make vote choice even in highly demanding information environments. Therefore, he/she may be resilient to the influence of visual name complexity. Another reason may be that after sorting out candidates from different parties, these voters may randomly pick a candidate that they vote for (for example, based on ballot order). In short, there are some reasons to expect that my argument does not apply to voters with strong partisan attachment.

E Alternative Measure: Name Difficulty Score

As I discussed in the main text, the use of the number of strokes is not without limitation because candidate names in the JHRED may be different from what voters saw at the polling station in some cases. In order to partly overcome this concern, I use an alternative measure of the explanatory variable and demonstrate that the findings are robust to the different operationalization/conceptualization of candidate name complexity.

In particular, I employ the measure of *candidate name difficulty*. In Japan, a public interest incorporated foundation called the Japan Kanji Aptitude Testing Foundation (*Nihon Kanji Nōryoku Kentei Kyōkai*: 日本漢字能力検定協会) conducts various examinations related to the understanding of Japanese. Its Kanji Aptitude Tests (*Kanji Kentei*: 漢字検定) assess people's abilities to read and write *kanji* and classify *kanji* letters into 13 groups (grades) based on their difficulty. Those *kanji* that Japanese people learn in their lower school grades are assigned to tests with lower grades. Therefore, *kanji* letters in tests with higher grades are generally more difficult to recognize and reproduce and also less commonly used in daily life.

Table E.1: The Kanji Aptitude Tests and the Difficulty Scores of Japanese Letters

Test Grade	Difficulty Score
Hiragana/Katakana (ひらがな/カタカナ)	1
Kanji Aptitude Test	
Grade 10 (漢検１０級)	2
Grade 9 (漢検９級)	3
Grade 8 (漢検８級)	4
Grade 7 (漢検７級)	5
Grade 6 (漢検６級)	6
Grade 5 (漢検５級)	7
Grade 4 (漢検４級)	8
Grade 3 (漢検３級)	9
Grade Semi-2 (漢検準２級)	10
Grade 2 (漢検２級)	11
Grade Semi-1 (漢検準１級)	12
Grade 1/Semi-1 (漢検１級/準１級)	13
Grade 1 (漢検１級)	14
Not Included in Kanji Aptitude Test (漢検対象外)	15

Based on the Kanji Aptitude Tests, I score the difficulty of each *kanji* letter as summarized in Table E.1. First, I assign the score of 1 to *hiragana* and *katakana*, which are the simplest forms of Japanese. Next, I give the score of 2 to *kanji* letters that are included in the lowest level of the Kanji Aptitude Test (Grade 10). Similarly, *kanji* letters in the Kanji Aptitude Test Grade 9 receive the score of 3, the letters in the Kanji Aptitude Test Grade 8 receive the score of 4, and so on. *Kanji* letters in the most difficult test (Grade 1) receive the score of 14, and those letters that are not included in any of the tests—mainly because they are not daily used and too difficult—receive 15. To obtain the test grade of each *kanji*, I rely on an online Japanese dictionary.[1]

After scoring the difficulty levels of the letters, I sum up the difficulty scores of the letters used in the candidate name, as I did when I constructed name complexity scores in the main text. The correlation between complexity and difficulty scores is only moderately high ($r = 0.61$). This is partly because not all letters with a large number of strokes are considered difficult in the Kanji Aptitude Tests. The only moderately high correlation suggests that if candidate name difficulty predicts vote share, it is even stronger evidence that some Japanese voters' decisions are distorted by politically irrelevant cues associated with candidate names.[2] It also suggests that the main findings may be robust to the presence of some measurement errors.

I believe that the difficulty measure is inferior to the measure of candidate name complexity for several reasons. First, unlike the total number of strokes, which is easy to count, voters do not know which letter is in which test grade. They only have a rough sense of which letter is more difficult than others. Therefore, knowing which name is more complex at a glance should be more consistent with the cognitive process of voters at the polling station than knowing which name is more difficult. Second, strictly speaking, the current coding rules are arbitrary. For example, there is no reason to believe that the difficulty of *kanji* letters increases by one as test grades go up.

[1] See `http://kanji.jitenon.jp`.

[2] The only moderately high correlation also implies that candidates who are disadvantaged due to high name complexity may not always be the same as those who are disadvantaged due to high name difficulty.

Table E.2: The Effect of Name Difficulty on Vote Share under SNTV

	Vote Share					
	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	All	All	First-Time Candidates	First-Time Candidates
Name Difficulty	−0.020	−0.017			−0.025	
	(0.006)	(0.009)			(0.010)	
Name Length	0.270	0.257			0.257	
	(0.069)	(0.108)			(0.117)	
Average Letter Difficulty			−0.082	−0.074		−0.099
			(0.023)	(0.036)		(0.039)
Number of Candidates (log)	−7.715	−7.030	−7.723	−7.032	−5.699	−5.692
	(0.182)	(0.159)	(0.182)	(0.159)	(0.285)	(0.287)
District Magnitude	−1.181	−0.826	−1.181	−0.825	−0.586	−0.587
	(0.056)	(0.069)	(0.058)	(0.069)	(0.091)	(0.093)
σ_c	–	4.056	–	4.056	–	–
σ_p	4.394	4.095	4.387	4.101	3.919	3.908
Election-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	17998	17,998	17,998	17,998	5,993	5,993

Note: The outcome is the vote share of the candidate. Models 1 to 4 use all observations under SNTV, while models 5 and 6 only use first-time runners. Average letter difficulty = name difficulty/name length. Standard deviations of the parameter posteriors are in parentheses.

The results based on name difficulty scores are summarized in Table E.2, where I replicate the SNTV models in Table 1. In model 1, which does not include candidate random effects, the posterior mean of the coefficient on name difficulty is −0.20 with a 95% credible interval of [−0.032, −0.008]. In model 2, I add candidate random effects. This model yields the statistically significant effect of name difficulty with a 90% credible interval of [−0.032, −0.002]. In models 3 and 4, I use average letter difficulty, or the mean difficulty of the letters used in the candidate name. In these models, 95% credible intervals are [−0.127, −0.035] and [−0.144, −0.001], indicating that both effects are statistically reliable. Finally, models 5 and 6 include only first-time candidates. In both models, the effect of name difficulty is statistically reliable with 95% credible intervals of [−0.045, −0.007] and [−0.174, −0.024], respectively. Overall, the results are similar even when I use the alternative measure based on name difficulty. Although not presented, the effect of name difficulty is not statistically reliable when I use the SMDP observations.

F Alternative Explanations

One threat to my argument is a possibility that some parties in Japan recognize the electoral advantage of simpler names and strategically allocate candidates with simpler names in more cognitively demanding districts. If so, the findings in the main text might reflect not voter behavior but party strategies. However, this explanation is unlikely to be the case. In Japan, it is common for parties, especially the LDP, to nominate candidates who are local to the district. Assuming that parties have a limited candidate pool in each district, it should not be always possible for them to nominate best-qualified candidates with very simple names.

I formally test the possibility of parties' strategic nomination by running bivariate regressions of candidate name complexity on district magnitude. The expectation is that if strategic allocation exists, there should be a negative association between district magnitude and candidate name complexity. In this analysis, I use district magnitude, instead of the number of candidates, as a predictor assuming that each party has no direct control over the exact number of candidates in the district. I focus on candidates in six main parties under SNTV (LDP = the Liberal Democratic Party; JSP = the Japan Socialist Party or the Left Socialist Party; Komei = the Komei Party; DSP = the Democratic Socialist Party; JCP = the Japan Communist Party; and Reform = the Democrats or Reform Party).[3] Further, I include only first-time candidates. The rationale is the following. Because candidates with simpler names are more likely to win the election, they are also more likely to be nominated again in the same district in the next election. As a result, if I include rerunning candidates, the estimated effect of district magnitude will suffer from reverse causality.

Table F.1 shows the regression results. The signs of the coefficients on district magnitude are negative except for model 1, but none of them is statistically discernible from 0. Further, these slopes are nearly flat (slope coefficients < 1), and R^2s are essentially 0. Therefore, there is no evidence for the strategic allocation of candidates with simpler names in more cognitively demanding districts. Given these results, it is more likely the case that voters,

[3] See Reed and Smith 2017 for more detail.

Table F.1: The Effect of District Magnitude on Name Complexity under SNTV

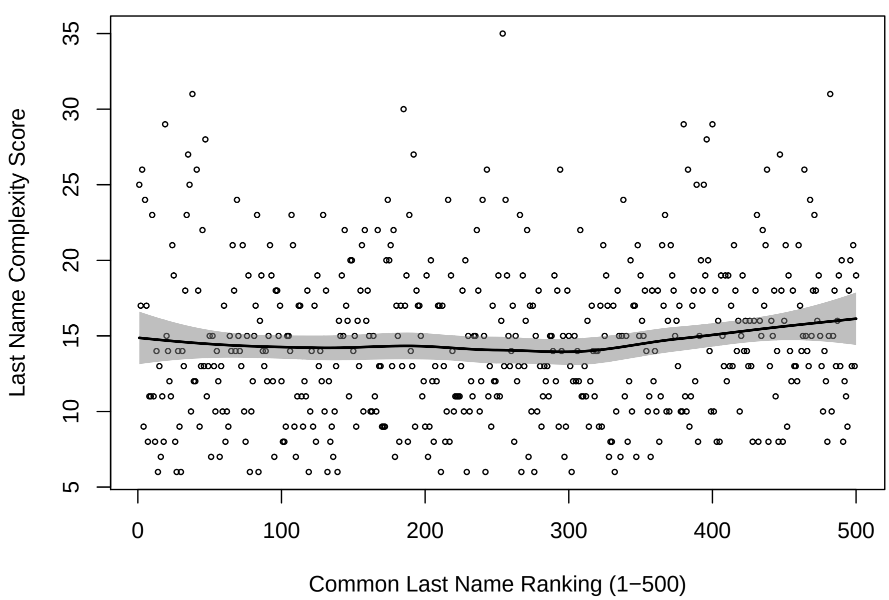
	Name Complexity					
	(1)	(2)	(3)	(4)	(5)	(6)
	LDP	JSP	Komei	SDP	JCP	Reform
District Magnitude	0.388	−0.124	−0.545	−0.477	−0.259	−0.269
	(0.243)	(0.316)	(0.706)	(0.485)	(0.329)	(0.374)
Intercept	29.435	30.759	33.193	31.649	31.841	32.013
	(1.017)	(1.312)	(3.040)	(2.027)	(1.327)	(1.558)
N	1,693	957	205	425	816	760
R^2	0.002	0.0002	0.003	0.002	0.001	0.001

Note: $^*p<0.05$. The models estimate the relationship between district magnitude and name complexity score. The unit of analysis is the legislative candidate in each of six main parties under SNTV. Duplicated candidates are omitted (each candidate appears in the data only once).

rather than parties, drive the link between candidate name complexity and election outcomes.

Second, in line with Fukumoto and Miwa (2018), one might argue that voters are just picking a candidate whose last name is familiar to them. However, this explanation may invalidate my argument and findings only when last names that are common to voters are negatively correlated with name complexity scores (i.e., more common last names have a lower number of strokes).

Figure F.1: 500 Common Last Names and Name Complexity Scores



However, this is unlikely to be the case for several reasons. First, I measure name complexity scores based not on the last names of candidates but on their entire names. Given the fact that there are numerous first names, it is unlikely the case that candidates with certain last names systematically receive lower or higher complexity scores. Second, even when I focus on only the number of strokes in people's last names, there seems to be no relationship between commonality and complexity. In Figure F.1, I show the relationship between 500 most common last names in Japan and their complexity scores.[4] The x-axis is the ranking of these names (from 1st to 500th), and the y-axis is complexity scores. As the fitted loess curve shows, there is essentially no relationship between the commonality of last names and their complexity scores.

[4] Source: https://myoji-yurai.net/prefectureRanking.htm.

G Invalid Vote Data and Analysis

Table G.1: The Descriptive Statistics of Invalid Votes Data

	SNTV Data				
	N	Mean	SD	Min	Max
Invalid Votes	1,633	1.191	0.672	0.326	6.687
Average Name Complexity	1,633	30.337	3.465	16	46
Number of Candidates	1,633	7.215	1.990	2	22
District Magnitude	1,633	3.945	0.884	1	6
	SMDP Data				
	N	Mean	SD	Min	Max
Invalid Votes	2,095	2.789	1.318	0.619	15.256
Average Name Complexity	2,095	30.188	4.243	18	45
Number of Candidates	2,095	3.755	0.979	2	9

Table G.2: The Effect of District-Level Name Complexity on Invalid Votes

	Proportion of Invalid Votes (log)	
	(1)	(2)
	SNTV	SMDP
Average Name Complexity	0.005	−0.001
	(0.003)	(0.002)
Number of Candidates (log)	−0.201	−0.418
	(0.033)	(0.029)
District Magnitude	−0.014	
	(0.017)	
σ_d	0.203	0.203
Election-Year Fixed Effects	Yes	Yes
N	1,633	2,095

Note: The outcome is the logged proportion of invalid votes in the district. Standard deviations of the parameter posteriors are in parentheses.

Data come from Mori and Mizusaki (2012) and Reed and Smith (2017). The two data sources are matched perfectly. Models 1 and 2 in Table G.2 correspond to the results of the first and second rows in Figure 1, respectively.

In this section, I also describe the criteria of vote invalidation in more detail. In Japan, votes are counted at each polling station. Prior to the election, the central electoral commission notifies the criteria for judging valid and invalid votes for some expected writing mistakes. However, in reality, it is often the case that some votes cannot be judged based on the notified standards. In such a case, officials at each polling station determine whether these votes are valid or not. For the purpose of illustration, I focus on the example of 松丸まこと (Makoto Matsumaru), who was a candidate for the 2015 Adachi-ward council election (a ward in Tokyo).

First, if voters write his name without any error, their voters will be valid. Second, if they write the name using simplified scripts (*hiragana* or *katakana*), their votes will be valid. For example, they can simplify his last name from 松丸 to まつまる and write まつまるまこと on the ballot paper. Third, even when they write only the last or first name of the candidate, 松丸 or まこと, their votes will be counted. However, if there is more than one candidate with the same last or first name, those votes that partially identify the name of the candidates will be proportionally allocated to the candidates according to the ratio of other unquestionable votes (Horiuchi 2005). For instance, suppose that there are two Matsumarus in the district, and Makoto Matsumaru (松丸まこと) receives 60 votes whereas Taro Matsumaru (松丸太郎) receives 40 votes. If there are ten votes with only Matsumaru (松丸) written on the ballot, Makoto Matsumaru's total number of votes will be $60 + 10 \times 60/100 = 66$, and Taro Matsumaru's total number of votes will be $40 + 10 \times 40/100 = 44$.

In principle, voters are not allowed to put information other than a candidate name on the ballot paper. For example, if voters write "I vote for 松丸まこと" or "stupid 松丸まこと," their votes will be invalidated. An extreme example of this is that the addition of one tiny line on the ballot paper may lead to invalidation. In a similar vein, writing the nickname of a candidate will not be allowed. Only exceptions for this rule are the candidate's occupation, address, and title (e.g., Mr.). Voters are allowed to put them along with the candidate name, granted that they are accurate.

Most importantly, what kinds of writing errors are considered as invalid votes? A rule of thumb is that simple and obvious mistakes will not lead to invalidation. However, when mistakes become unreasonable or handwriting becomes too difficult to recognize, votes are likely to be invalidated. Below are some examples from actual votes for 松丸まこと in the 2015 Adachi-ward council election, some of which were valid but other were not.[5]

Figure G.1: Valid Mistakes

First, all of the five votes in Figure G.1 incorrectly wrote the name of 松丸まこと. For instance, the left-most vote forgot one stroke and wrote 松九, and the next vote reversed the letters in the last name and wrote 丸松. Despite some mistakes, they were all counted as valid votes. Second, by contrast, the vote in Figure G.2 was invalidated as it wrote 丸山 instead of 松丸. The examples in Figure G.1 and Figure G.2 show that simple mistakes do not automatically lead to invalidation, but it is not always clear where to draw the line between valid and invalid mistakes.

Third, three ballot papers in Figure G.3 are the examples of votes that are difficult to recognize due to bad handwriting. Nevertheless, all of these votes were counted as proper votes for 松丸まこと. Fourth, the two examples in Figure G.4 were also supposed to be votes for 松丸まこと. However, these votes were regarded as invalid votes. These examples show that some writing errors are tolerated. But, again, it is not always clear where to draw the line between valid and invalid votes because many decisions seem to depend on the discretion of those who count votes at the polling station (yet it is also clear that they try to reduce uncounted votes as much as they can). These examples also demonstrate that even

[5]Source: https://withnews.jp/article/f0160604001qq000000000000000G00110101qq000013492A.

Figure G.2: Invalid Mistakes

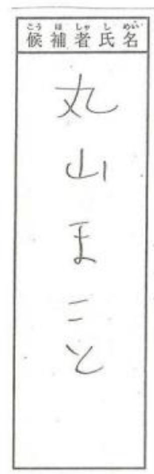


Figure G.3: Valid Votes that Are Difficult to Recognize

though 松丸 does not seem to be too difficult to write, some Japanese people make writing mistakes that may lead to invalidation. It is not too hard to imagine that when they have to write even more complex letters and names, the chance of writing errors and invalidation will be greater.

Finally, apart from the examples above, there are several other instances in which votes may be invalidated. First, when voters mistakenly write a candidate name, and that name matches with the name of a well-known person (e.g., celebrity), these votes may be invalidated. Second, given the fact that political inheritance is fairly common in Japan (Smith

Figure G.4: Invalid Votes that Are Difficult to Recognize

2018), some voters may mistakenly write the name of a candidate's father, who used to be a politician. In this case, their votes will be invalidated. Finally, it is possible that when they try to simplify a candidate's name, some voters mispronounce it. For example, in the above example, the correct way to pronounce 松丸 is "Matsumaru," which corresponds to まつまる in simplified scripts. However, some voters might mistakenly pronounce 松丸 as "Shougan" because there are several ways to read/pronounce the same *kanji*. Then, they might write しょうがん (Shougan) instead of まつまる (Matsumaru) on the ballot paper, which may be considered as an invalid vote. In this way, simplification based on wrong pronunciation may increase the chance of invalidation.

In summary, this section describes the basic criteria of invalidation, providing some examples from actual invalid votes. It is often difficult to determine whether a vote is valid or not. In fact, there have been a number of lawsuits that challenged the decisions of invalidation. Write-in ballots seem to heighten not only the costs of voting among voters but also the costs of election administration.

H Heterogeneous Effects within SNTV and SMDP

Table H.1: The Interaction Models of Name Complexity

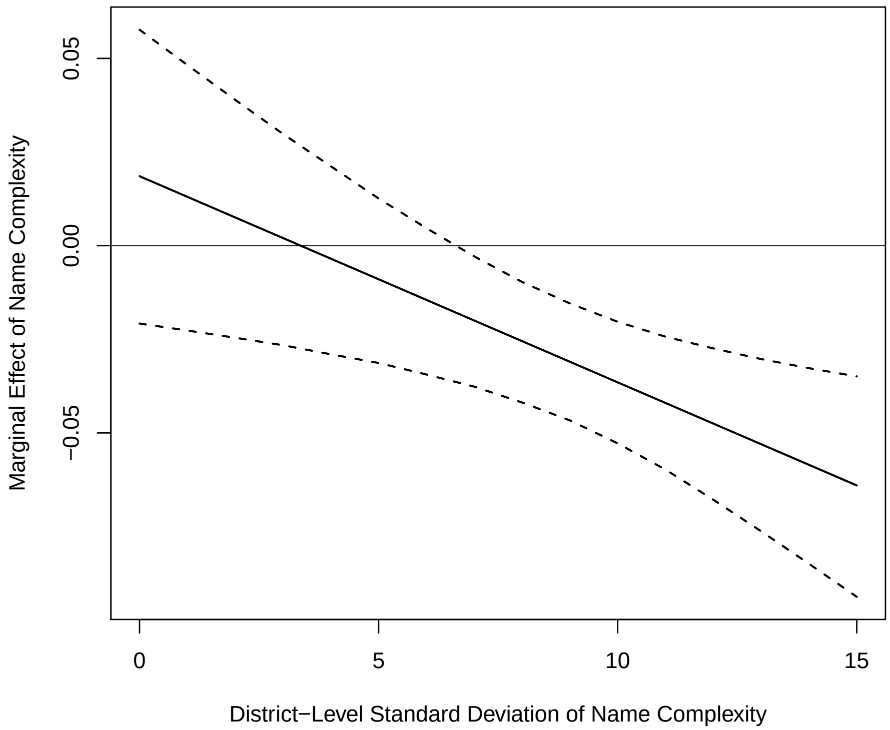
	Vote Share			
	(1)	(2)	(3)	(4)
	SNTV	SNTV	SMDP	SMDP
Name Complexity	0.019	0.019	0.084	0.007
	(0.031)	(0.020)	(0.069)	(0.037)
Name Complexity × Number of Candidates (log)	−0.022		−0.046	
	(0.014)		(0.048)	
Name Complexity × SD of Name Complexity		−0.006		0.001
		(0.002)		(0.004)
Name Length	0.349	0.361	0.259	0.271
	(0.109)	(0.110)	(0.252)	(0.246)
Number of Candidates (log)	−6.369	−7.029	−15.267	−16.692
	(0.434)	(0.160)	(1.524)	(0.456)
District Magnitude	−0.822	−0.819		
	(0.071)	(0.071)		
SD of Name Complexity		0.143		−0.013
		(0.064)		(0.113)
sigma_c	4.049	4.050	6.373	6.369
sigma_p	4.095	4.081	10.703	10.672
Election-Year Fixed Effects	Yes	Yes	Yes	Yes
N	17,998	17,998	7,867	7,867

Note: Model 1 corresponds to the one presented in Figure 2, and model 2 is the one presented in Figure H.1. Models 3 and 4 test the same interaction effects under SMDP. The marginal effect of name complexity in models 3 and 4 are visualized in Figure H.2. Standard deviations of the parameter posteriors are in parentheses.

The second source of heterogeneous effect under SNTV may be variation in candidate name complexity within the district. If all candidates have equally simple or complex names, the visual complexity of candidate names is not discernible. In such a situation, the cognitive process of voters is unlikely to be affected by name complexity. By contrast, the coexistence of both very simple and complex names may magnify the impact of name complexity by highlighting the contrast between these names. Therefore, the negative effect of name complexity should be greater when there is a larger variation in the complexity of candidate names within the district.

To test this, I calculate the standard deviation of name complexity by district and add its interaction with name complexity in model 2 of Table 1. Although using variance leads to the same results, I opt for standard deviation because its distribution approximates normality.

Figure H.1: Heterogeneous Name Complexity Effect by the Distribution of Name Complexity under SNTV



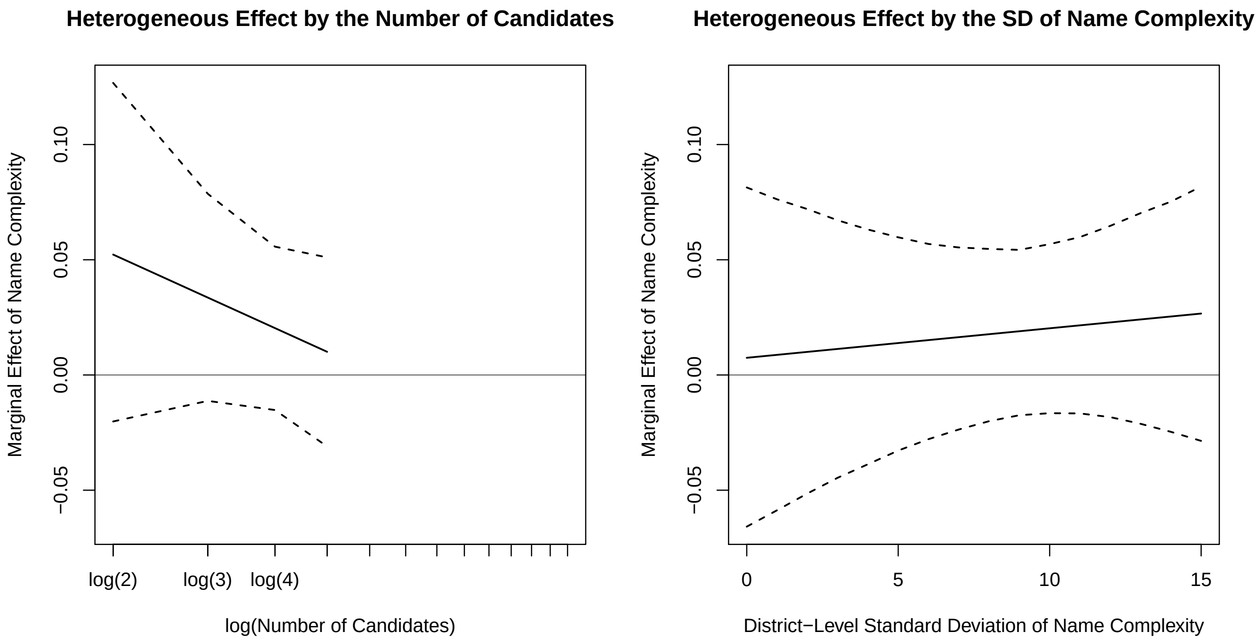
Note: The figure shows the marginal effect of name complexity on vote share conditional on the district-level standard deviation of name complexity under SNTV. Dashed lines indicate a 95% credible interval.

Also, note that the correlation between the number of candidates and the standard deviation of name complexity is low ($r = 0.09$). Therefore, the two interaction models capture different aspects of the heterogeneous effects.

The estimated marginal effect of name complexity for a given standard deviation of name complexity is presented in Figure H.1. As expected, the slope shows a negative sign, and the effect of name complexity is not statistically different from 0 when there is little variation in name complexity among candidates in the same district. By contrast, when there is greater within-district variation in name complexity, the effect of name complexity is negative and statistically reliable.

How about the heterogeneous effects of name complexity within SMDP? The left panel of Figure H.2 shows the marginal effect of name complexity on vote share by the number of candidates under SMDP based on model 3 of Table H.1. The range of the x-axis is limited to the 0th to 90th percentiles of the number of candidates under SMDP (2-5). Although the effect of name complexity is not statistically reliable for the entire range, the slope of the marginal effect is negative, indicating that if the number of candidates was very large, the effect of name complexity on vote share would become negative even under SMDP. Of course, this scenario is unlikely to happen due to the institutional constraint imposed by the electoral rule.

Figure H.2: The Marginal Effect of Name Complexity on Vote Share under SMDP



The right panel also shows the marginal effect of name complexity conditional on the variation in name complexity in the SMDP district based on model 4 of Table H.1. Contrary to the expectation, the slope of the marginal effect shows a positive sign. However, the effect is not statistically discernible from 0 for the entire range of the standard deviation of name complexity. This reaffirms the argument that under less cognitively demanding electoral systems, the effect of name complexity is likely to be null.

I Ballot Paper and Name Display at the Polling Station

Figure I.1: Ballot Paper

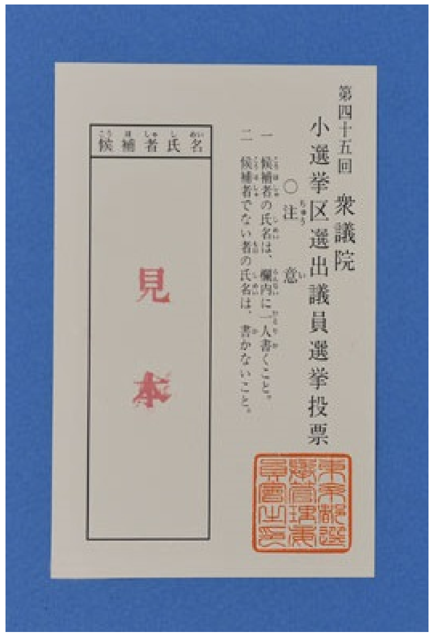


Figure I.1 shows a write-in ballot used in the 2009 Lower House election.[6] Voters write the name of their favored candidate inside the box on the left. Candidate names are not printed on the ballot, but voters see the list of candidates at the voting booth.

Figure I.2 shows the list of candidates that voters saw at the polling station in Fukuoka 3rd District in the 2009 Lower House election.[7] There were 4 candidates. The first row shows candidate names, and the second row indicates their party affiliations.

[6]Source: https://www.jiji.com/jc/v2?id=20090721_dai45kaisosenkyo_05photo.
[7]Source: http://katsuo-ukiukiukie.a-thera.jp/article/1822156.html.

Figure I.2: An Example of the Candidate List