Online Appendix

Voter Turnout and Selective Abstention in Concurrent Votes

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A Theoretical Derivations

Derivation of Utility Function for $\rho \to 0$

Let us denote the maximum value of U_{ij} by $\max_j U_{ij} =: U_{ij}^{\max}$. All $n \geq 1$ propositions that take the maximum value are denoted by the index $j^{\max}$ where $\arg\max_j U_{ij} =: j^{\max}$.

$$
\begin{aligned}
\lim_{\rho\to 0} U_i &= \lim_{\rho\to 0}\left(\sum_{j=1}^{N} U_{ij}^{1/\rho}\right)^{\rho} - F_i \\
&= \lim_{\rho\to 0} \exp\left(\frac{\ln\left[\sum_{j=1}^{N} U_{ij}^{1/\rho}\right]}{1/\rho}\right) - F_i .
\end{aligned}
$$

We substitute $\rho = 1/\nu$, when ρ approaches 0, ν goes to infinity. We apply Bernoulli-d'Hôpital's rule and divide both sides of the ratio with $U_{ij}^{\max}$. This yields

$$
\begin{aligned}
\lim_{\rho\to 0} U_i &= \lim_{\nu\to\infty} \exp\left(\frac{\left[\sum_{j=1}^{N} U_{ij}^{\nu}\right]^{-1} \sum_{j=1}^{N} U_{ij}^{\nu} \ln U_{ij}}{1}\right) - F_i \\
&= \lim_{\nu\to\infty} \exp\left(\frac{\sum_{j=1}^{N} U_{ij}^{\nu} \ln U_{ij}}{\sum_{j=1}^{N} U_{ij}^{\nu}}\right) - F_i \\
&= \lim_{\nu\to\infty} \exp\left(\frac{n \ln U_{ij}^{\max} + \sum_{j=1, j\neq j^{\max}}^{N} \left(U_{ij}/U_{ij}^{\max}\right)^{\nu} \ln U_{ij}}{n + \sum_{j=1, j\neq j^{\max}}^{N} \left(U_{ij}/U_{ij}^{\max}\right)^{\nu}}\right) - F_i .
\end{aligned}
$$

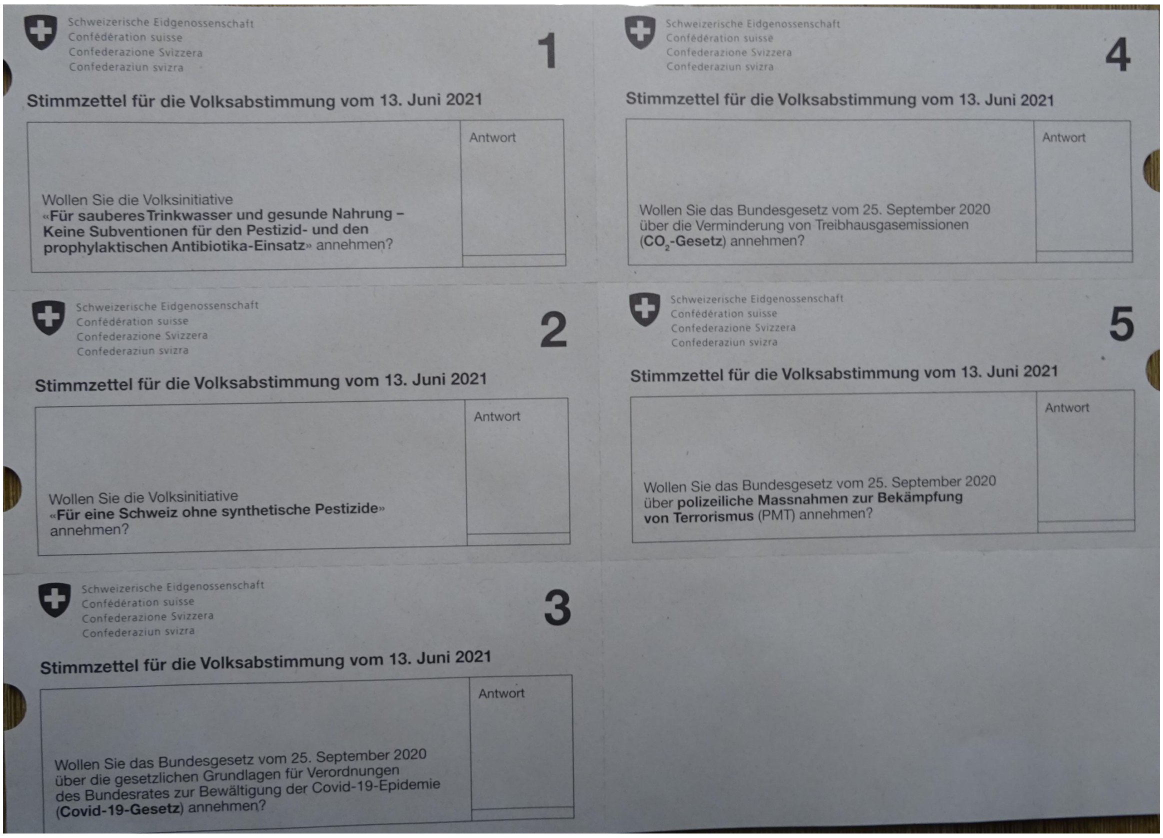
Evaluating the limes of the latter expression yields the desired result

$$
\lim_{\rho\to\infty} U_i = \exp\left(\ln U_{ij}^{\max}\right) - F_i = U_{ij}^{\max} - F_i .
$$

B Additional Tables and Figures

B.1 Additional Descriptive Statistics

Figure B.1: Sample Ballot Paper

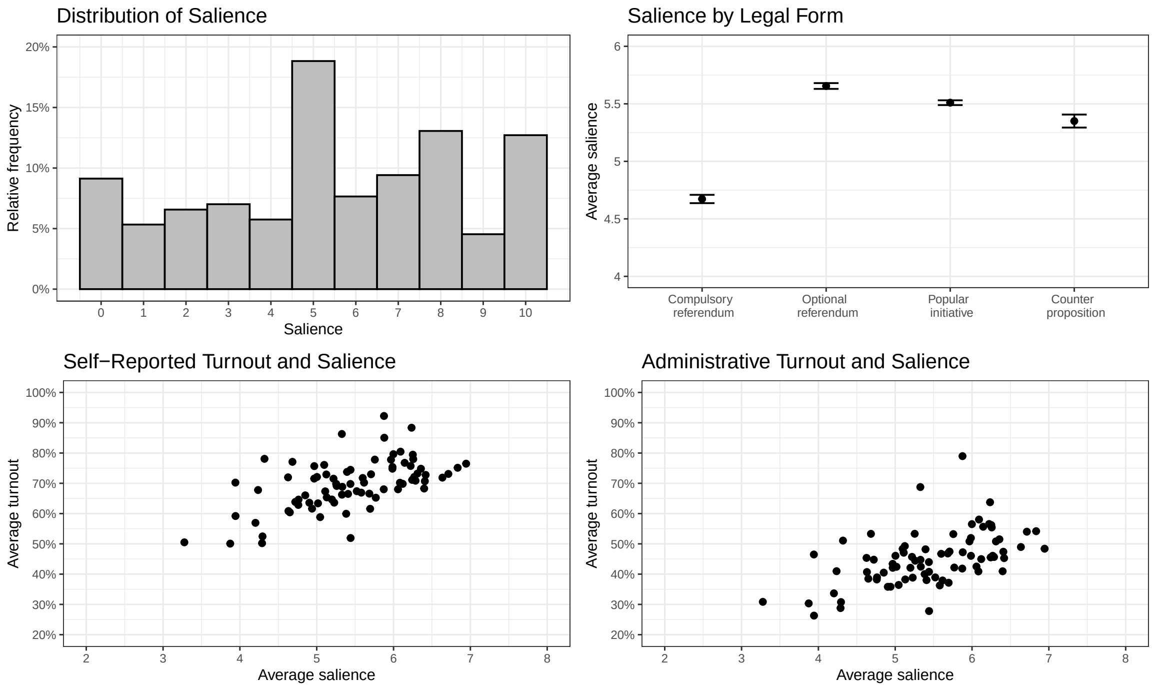


Note: Sample ballot paper from a federal vote from June 13, 2021, with five concurrent propositions.

The Relationship between Salience, Information Costs, and Turnout — Figure B.2 presents descriptive statistics on the individual subjective salience and sheds light on how this variable is related to both the legal form of a proposition and turnout. The upper left panel shows the distribution of the measured salience for voters and non-voters. Citizens often choose prominent numbers in the middle and at the tails of the distribution (0, 5, or 10). The mode with a value of 5 is clearly higher than the other values. The upper right panel in Figure B.2 presents the average individual salience for each of the four legal forms of a proposition. Optional referendums and popular initiatives score highest in terms of average salience, followed by counter propositions. Compulsory referendums score lowest in terms of average salience. This relationship between the legal form and salience is qualitatively similar to the relationship between the legal form and administrative turnout in Figure 2, lending support to our salience measure. The individual salience not only depends on the legal form of the proposition but is also associated with turnout. The lower two panels in Figure B.2 demonstrate how the average salience per voting day from the post-vote survey is correlated with self-reported (lower left graph) and administrative turnout (lower right graph). In both graphs, we observe a strong positive statistical correlation of 0.58 and 0.53, respectively.

This comparison of average salience ignores that the concurrent propositions on the same voting day may differ in terms of salience. However, there is a high congruence about which proposition is the most important per voting day among survey participants. The average congruence about the top proposition is 82.7% when there are two concurrent propositions. This means that 82.7% of respondents rate the same proposition as more important on voting days with two propositions. The congruence decreases to 72.6% for voting days with three propositions and 65.2% for voting days with four propositions. The congruence is still 68.2% for voting days with five concurrent propositions.

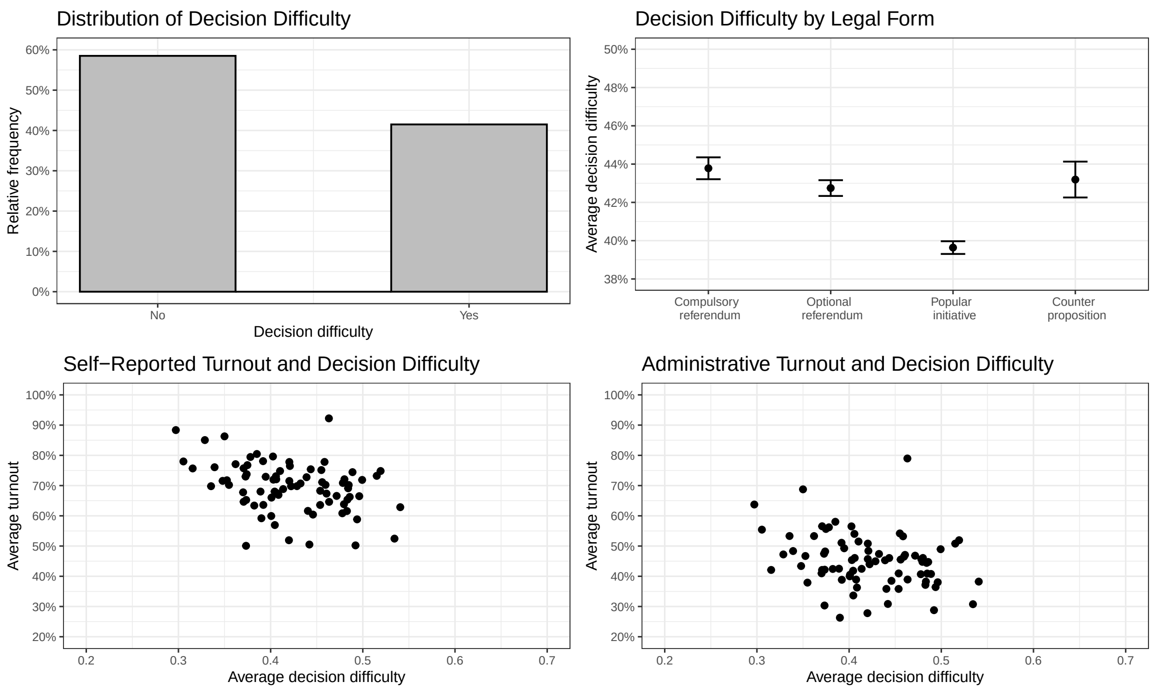
Figure B.2: Individual Subjective Salience



Note: The upper left panel presents the distribution of the individual subjective salience, which ranges from 0 (not important) to 10 (very important). The upper right panel shows the average salience by the legal form of the proposition, where the error bars illustrate the 95% confidence interval of the mean. The lower left panel presents the relationship between the average individual self-reported salience and the average individual turnout per voting day, and the lower right panel presents the relationship between the average individual salience per voting day from survey data and the average turnout from administrative data.

The second part of the cost-benefit calculus in our theoretical model consists of the voting costs. Since we do not directly observe individual voting costs, we use the answer to the survey question on the difficulty of the vote choice as a proxy for voting costs. Figure B.3 presents descriptive statistics about our empirical measure of voting costs. The upper left panel shows the distribution of the vote choice difficulty for voters and non-voters. Over 58% of our respondents stated not to have had difficulties in their vote choice. The upper right panel presents the average difficulty for each of the four legal forms of a proposition. There is no statistically significant difference among the average difficulty of compulsory referendums, optional referendums, and counter propositions, but the figure suggests that individuals have fewer difficulties forming their opinion about popular initiatives. A possible explanation for this pattern is the fact that political actors advertise popular initiatives more aggressively than the other legal forms and therefore, citizens have fewer difficulties to decide. As expected, the two lower graphs show that self-reported average turnout (lower left graph) and administrative turnout (lower right graph) are both negatively related to the average difficulty of the citizens per voting day with a correlation coefficient of -0.35 and -0.27, respectively.

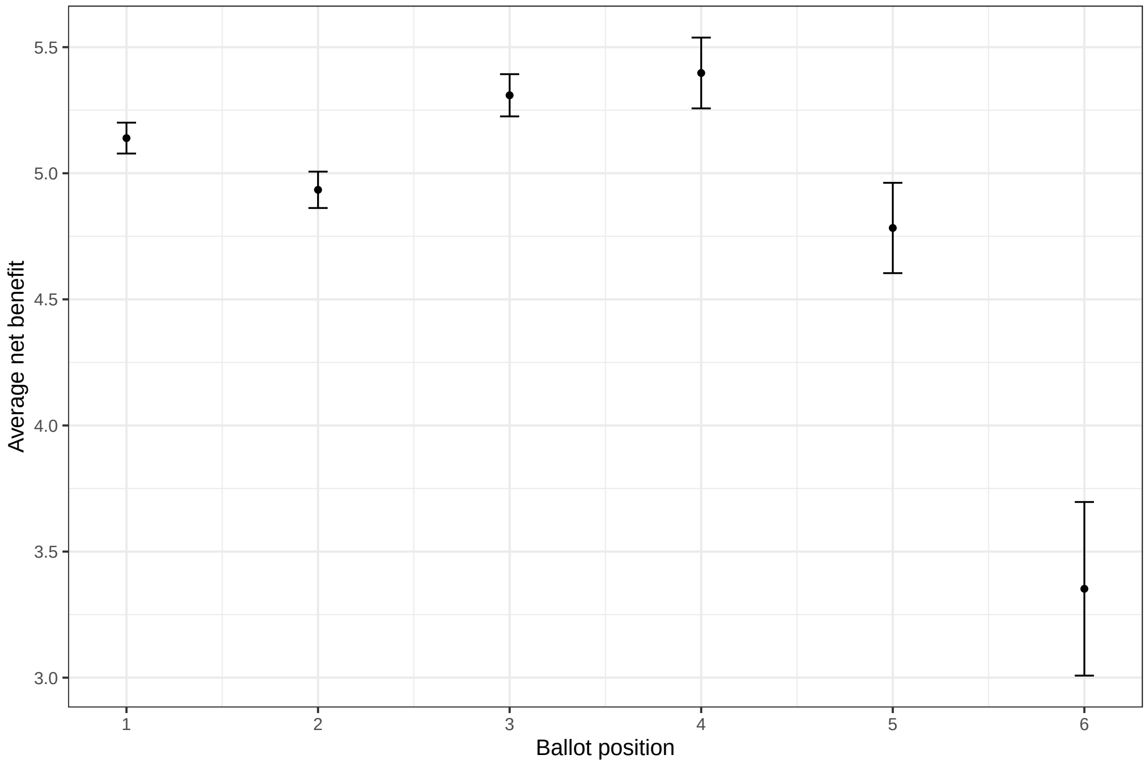
Figure B.3: Individual Vote Choice Difficulty



Note: The upper left panel presents the distribution of the vote choice difficulty for a proposition. The upper right panel presents the average difficulty by the legal form of the proposition, where the error bars illustrate the 95% confidence interval of the mean. The lower left panel presents the relationship between the average difficulty and the average self-reported turnout, and the lower right panel presents the relationship between the average self-reported average difficulty from the survey data and the average turnout from administrative data.

Net Benefit and Ballot Position — Figure B.4 presents the average net benefit of all propositions with the same position on the ballot. The findings indicate that there is no clear pattern between the net benefit and the position of the proposition on the ballot.

Figure B.4: Average Net Benefit by Ballot Position



Note: The graph shows the average net benefit by the ballot position of the propositions. The error bars indicate the 95% confidence interval.

B.2 Probability of Being Decisive

A key parameter in the cost-benefit calculus presented in equation (1) is the probability of being decisive, denoted as p. Empirically, it is challenging to directly estimate this parameter because we cannot observe how individuals perceive the closeness of the referendums in advance. To illustrate that the probability of being decisive is reflected in the salience measure, as discussed in Section 6.1, we examine the relationship between the ex-post closeness of the votes and the average salience in Table B.1.

In this analysis, the dependent variable is the average individual salience for each proposition, while the explanatory variable represents the absolute difference between a proposition's "yes" share and 50%, the threshold required to obtain a majority of the votes cast. A larger value for this difference indicates a less closely contested decision. The regression results presented in column (1) do not include any fixed effects or control variables, whereas the regression in column (2) accounts for voting day fixed effects. In both models, the standard errors are one-way clustered by voting day.

The findings reveal that the average salience of the proposition decreases for less closely contested propositions. This suggests that the probability of being decisive is indeed captured within the individual salience measure of the propositions. In essence, when the vote results are closer, the salience tends to be higher.

Table B.1: Association Between Salience and Ex-Post Closeness of the Referendum

	Dependent variable: Salience	
	(1)	(2)
Distance	-0.020^{***}	-0.021^{**}
	(0.008)	(0.009)
Voting day FE	No	Yes
Observations	228	228

Note: The dependent variable in both columns is the aggregated average salience per proposition at the federal level. The variable "Distance" measures the distance in absolute terms between the share of the yes votes and 50%. Column (1) does not include any control variables nor fixed effects and column (2) includes voting day fixed effects. The standard errors in parentheses are one-way clustered by voting day. *** p<0.01, ** p<0.05, * p<0.1.

B.3 Estimation of Utility Parameters

We use the voting days with single propositions to estimate the coefficients τ and γ of equation (4) and present the results in Table B.2. Column (1) presents the results of the maximum likelihood estimation of equation (4) without any covariates. The coefficient for τ is -1.1 and the coefficient for γ, which is simply the constant, is -3.4. Adding covariates results in $\tau = -0.9$ and the net fixed costs for a 50-year-old male voter, who is married, with a university degree, a high political knowledge, and considers himself a center voter are -2.2. We use age and the indicator variables male, married, university, and political knowledge to construct the individual net fixed costs. The net fixed costs vary in the sample between -7.5 and -0.01, indicating that the fixed costs exceed the consumption benefit induced by civic duty for all individuals and the sample average is -3.6.

Table B.2: Maximum Likelihood Estimation of τ and γ

	Dependent variable: Turnout	
	(1)	(2)
τ	-1.056^{***}	-0.863^{***}
	(0.067)	(0.072)
Male		0.097
		(0.072)
Married		0.629^{***}
		(0.074)
Age		0.054^{***}
		(0.002)
University		0.501^{***}
		(0.089)
Political knowledge		2.166^{***}
		(0.091)
Left-Right		-0.034^{*}
		(0.019)
Constant	-3.394^{***}	-8.131^{***}
	(0.047)	(0.170)
Observations	9,816	9,816

Note: The dependent variable is individual self-reported turnout (0/1). The table reports the results of a maximum likelihood estimation of equation (3) using the voting days with single propositions. *Male*, *Married*, *University*, and *Political knowledge* are binary indicator variables and *Political ideology* is a scale from 0 (left) to 10 (right). The standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.4 Robustness Tests

Functional Form — In our main analysis, turnout and selective abstention are binary outcome variables. To estimate the effect of U^{sum} and U^{max} on turnout and the effect of the proposition net benefit and the ballot position on selective abstention, we use linear probability models. To probe the robustness of our results with respect to the functional form, we test whether our results are robust when we estimate a logistic regression. The results in columns (1) and (3) of Table B.3 provide evidence that our main findings on turnout and selective abstention are robust to an alternative functional form of the regression equation.

Binary Utility Measure — Our theoretical model in Section 3 predicts that an individual will go to the polls if the utility of voting is strictly positive. Our main results support the theoretical model, although the empirical analysis relies on continuous utility measures. As a robustness test, we create binary utility measures for the sum over all proposition net benefits, $1\{U^{sum} > 0\}$ and for the maximum proposition net benefit of a voting day, $1\{U^{max} > 0\}$. We present the effect of these binary utility measures on turnout in column (2), where we find results that support our main findings in Table 3.

Identifying Assumption in Selective Abstention Regression — The interpretation of the findings on the impact of the ballot position on selective abstention in Table 4 crucially depends on the institutional details of how propositions are arranged on the ballot. As discussed in Section 4, it is a common practice of the Federal Chancellery first to consider a proposition's legal form and then the day when it meets the legal requirements. In our sample of 96 voting days, the propositions with the same legal form are not chronologically ordered on 17 voting days. We drop these voting days as a robustness test and present the results in column (4) of Table B.3. The point estimate for the net benefit remains almost identical. This suggests our results are not sensitive to excluding voting days where the Federal Chancellery deviates from its common practice.

Table B.3: Robustness Tests

	Dependent variable:			
	Turnout		Selective abstention	
	(1)	(2)	(3)	(4)
U^{sum}	0.719***			
	(0.053)			
U^{max}	1.916***			
	(0.133)			
$1\{U^{sum}>0\}$		9.552***		
		(1.527)		
$1\{U^{max}>0\}$		22.354***		
		(1.755)		
Net benefit			-1.089***	-1.110***
			(0.027)	(0.108)
Ballot position			0.680***	1.246***
			(0.062)	(0.384)
Linear model	No	Yes	No	Yes
Logit model	Yes	No	Yes	No
Observations	53,218	53,218	125,475	98,828

Note: Column (1) presents the marginal effects of a logistic regression where the dependent variable is self-stated turnout (0 or 1) and the marginal effects are retransformed to a scale from 0 to 100. Column (2) presents the effect of the binary utility measures where the dependent variable is turnout, re-scaled from 0 to 100. The dependent variable in column (3) is an individual self-stated indicator variable, indicating whether a voter casts an empty vote, re-scaled from 0 to 100. The presented effects are the marginal effects of the logistic regression. The regression in column (4) excludes the voting days, where the propositions of the same legal are not chronologically ordered on the ballot. We control for socio-economic characteristics at the individual level. The robust standard errors with two-way clustering by canton and voting day (in columns (2) and (4)) and with one-way clustering by voting day (in columns (1) and (3)) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Ordered Net Benefits and Administrative Turnout — Table B.4 presents the effect of the ordered net benefits on administrative turnout. The outcome variable is the average turnout at the cantonal and voting day level for voting days with the same number of concurrent propositions. The ordered net benefits are also aggregated at the cantonal and voting day level. Column (1) includes all voting days with only one proposition, column (2) all voting days with two concurrent propositions, and column (3) those with three concurrent propositions.[1] The results in columns (1)-(3) are consistent with the findings in Figure 3, that higher net benefits are more relevant determinants of the individual turnout decision.

Table B.4: Effect of Ordered Net Benefits on Administrative Turnout

	Dependent variable: Turnout		
	(1)	(2)	(3)
U^{1st}	2.938***	1.505	1.087
	(1.065)	(1.034)	(0.777)
U^{2nd}		0.270	−0.609
		(0.733)	(1.254)
U^{3rd}			0.771
			(0.968)
# of propositions	1	2	3
# of voting days	11	22	26
Observations	281	1,084	1,935

Note: The dependent variable for all three regressions is the average administrative turnout at the cantonal and voting day level. We control for gender, marital status, age, education, political knowledge, and political ideology by including the average shares at the cantonal and voting day level of these variables. The robust standard errors with two-way clustering by canton and voting day are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Binary Utility Measures and Turnout — Since our theoretical model in Section 3 predicts that an individual will go to the polls if the utility of voting is strictly positive, we create binary utility measures for a robustness test. We first order the proposition net benefits per voting day and then create an indicator for each proposition net benefit that equals one if the net benefit is strictly positive. Table B.5 presents the results of estimating equation (6) with these binary utility measures. The results in Table B.5 support the finding that the propositions with the highest net benefit have a stronger marginal effect on turnout than propositions with lower net benefits.

1. Voting days with more than three concurrent propositions do not allow for precise estimations due to a lack of statistical power and are therefore excluded.

Table B.5: Effect of Ordered Net Benefits on Turnout with Binary Utility Measures for Voters

	Dependent variable: Turnout				
	(1)	(2)	(3)	(4)	(5)
$1\{U^{1st} > 0\}$	20.649***	14.745***	15.599***	13.297***	13.709***
	(2.001)	(3.169)	(4.150)	(2.775)	(3.993)
$1\{U^{2nd} > 0\}$		10.878***	10.161***	3.220	12.274**
		(1.574)	(3.111)	(4.399)	(4.433)
$1\{U^{3rd} > 0\}$			4.303**	6.614	0.551
			(1.545)	(3.739)	(4.304)
$1\{U^{4th} > 0\}$				6.530*	7.503**
				(2.689)	(2.952)
$1\{U^{5th} > 0\}$					7.176***
					(1.963)
# of propositions	1	2	3	4	5
# of voting days	11	22	26	7	11
Observations	9,816	16,801	21,211	6,079	7,966

Note: The dependent variable is individual self-reported turnout, re-scaled from 0 to 100 and the utility measures are binary. All regressions include canton and year fixed effects. The robust standard errors in parentheses in columns (1)-(5) are two-way clustered by canton and voting day. *** p<0.01, ** p<0.05, * p<0.1.

Ordered Net Benefits and Turnout with Logistic Regression — Since the main analysis consists of a binary outcome variable and relies on a linear probability model, we test in a further robustness test whether the results that the highest proposition net benefit is the most relevant determinant of turnout holds when we apply logistic regressions. Table B.6 presents how each individual ordered proposition net benefit affects turnout by estimating a logistic regression with each proposition net benefit of a respondent as a separate independent variable. The results indicate that the main pattern is robust to a change in the functional form.

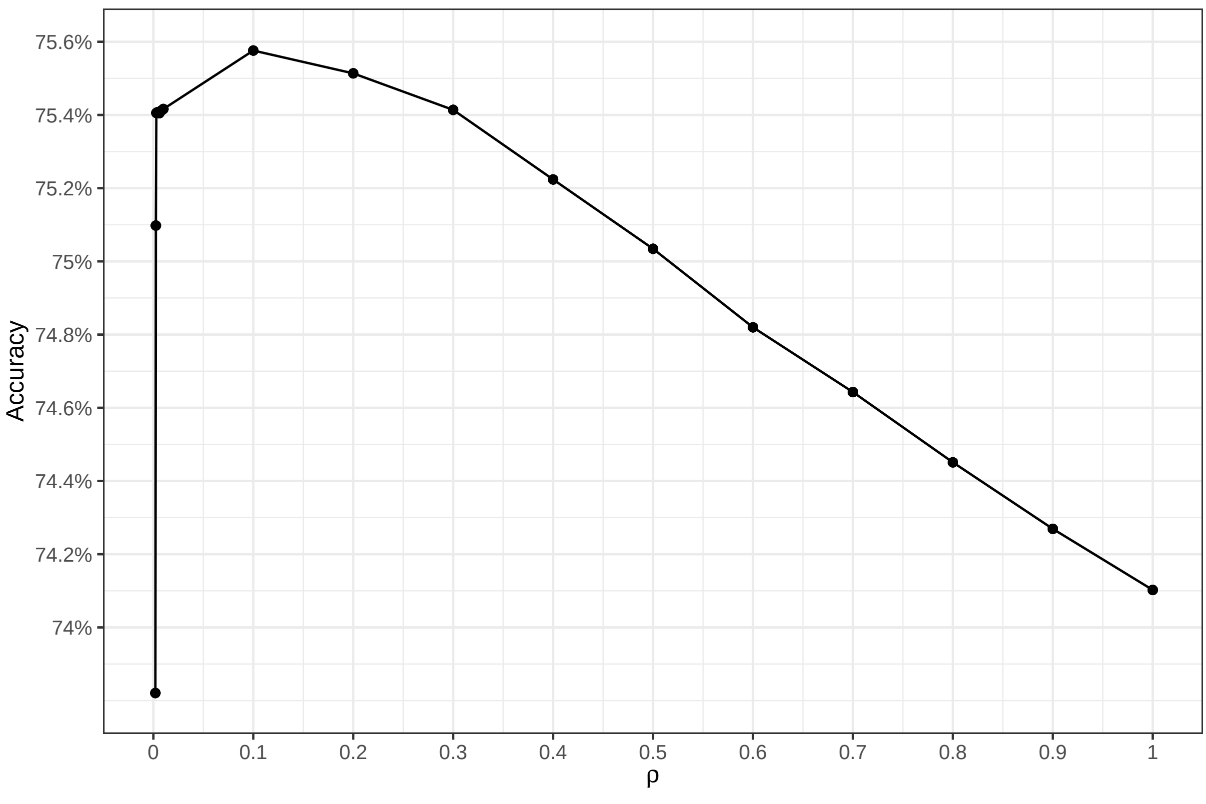
Table B.6: Marginal Effect of Ordered Net Benefits on Turnout

	Dependent variable: Turnout					
	(1)	(2)	(3)	(4)	(5)	(6)
U^{1st}	3.403***	2.384***	2.465***	1.945***	2.892***	3.581**
	(0.182)	(0.164)	(0.160)	(0.308)	(0.341)	(0.202)
U^{2nd}		1.220***	1.278***	1.002*	0.988**	−2.163
		(0.170)	(0.183)	(0.414)	(0.395)	(0.581)
U^{3rd}			0.565***	0.142	−0.003	1.202
			(0.171)	(0.405)	(0.350)	(3.364)
U^{4th}				1.025**	0.999**	−0.521
				(0.378)	(0.394)	(3.698)
U^{5th}					0.774**	−0.365
					(0.333)	(0.561)
U^{6th}						1.626
						(0.729)
# of propositions	1	2	3	4	5	6
# of voting days	11	22	26	7	11	2
Observations	9,816	16,801	21,211	6,079	7,966	1,161

Note: The dependent variable is individual self-reported turnout, re-scaled from 0 to 100. The table presents the average marginal effects of logistic regressions in percentage points. All regressions include canton and year fixed effects, and control variables for gender, marital status, age, education, political knowledge, political ideology, and the legal form of the propositions. The robust standard errors in parentheses in columns (1)-(5) are two-way clustered by canton and voting day, and in column (6) they are one-way clustered by canton because the analysis includes only two voting days. *** p<0.01, ** p<0.05, * p<0.1.

Changes to our Central Parameter ρ — The reduced-form results suggest that turnout on a voting day is affected by both the maximum and the sum of proposition net benefits and that propositions with a higher net benefit are more important determinants of the turnout decision. This lends support to our theoretical model. We complement these findings with a more structural approach. Based on the model described in Section 3, we predict the individual turnout decision for different values of ρ and then compare the predicted turnout with the actually observed turnout. The resulting prediction accuracy is the share of correctly predicted turnout decisions which is depicted in Figure B.5 for different values of ρ. These results show a limit value of $\rho = 1$, which is equivalent to taking the sum over all proposition net benefits per voting day, leading to the lowest prediction accuracy. At the other end of the spectrum, a model calibration with $\rho \rightarrow 0$ puts a lot of weight on the proposition with the highest net benefit and is slightly more accurate than the model with $\rho = 1$. However, a parameterized model with $\rho = 0.1$, which puts more weight on the higher proposition net benefits, gives us the highest prediction accuracy. The concave function in Figure B.5 indicates that not every proposition has the same importance for an individual's turnout decision, but neither does the proposition with the highest net benefit alone.

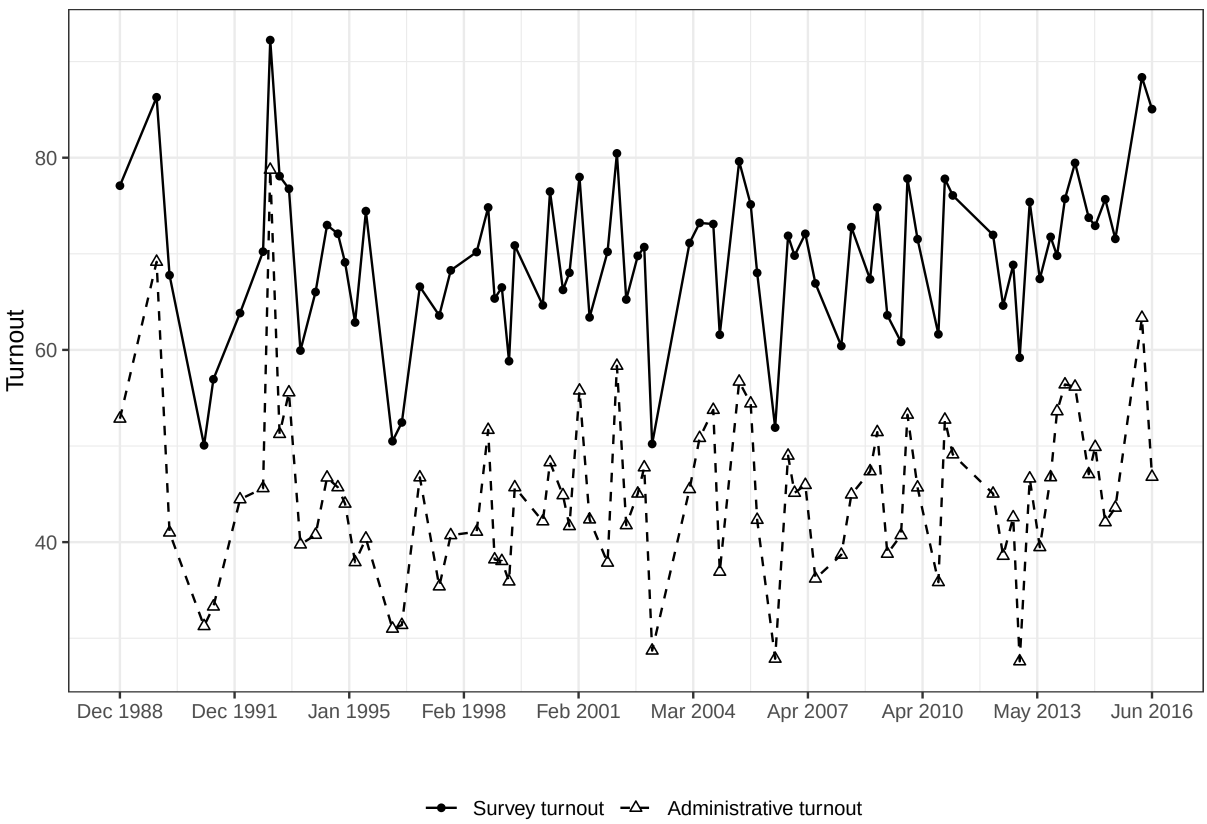
Figure B.5: Accuracy for Different Values of ρ



Note: The graph shows the accuracy of the predicted individual turnout based on equation (2) with different values for ρ. When $\rho = 1$, the model simply takes the sum over all proposition net benefits per voting day. When $\rho \rightarrow 0$, the model puts a lot of weight on the proposition with the highest net benefit per voting day.

Survey and Administrative Turnout — Table B.6 presents the average turnout per voting day for survey and administrative turnout data. Both turnout rates are running parallel to each other but with an average gap of 21.8 percentage points.

Figure B.6: Survey and Administrative Turnout



Note: The graph shows average turnout in the post-referendum survey (solid line) and in the administrative data (dashed line) for each voting day in our analysis.