Mobilizing young voters with short text messages in two nationwide field experiments

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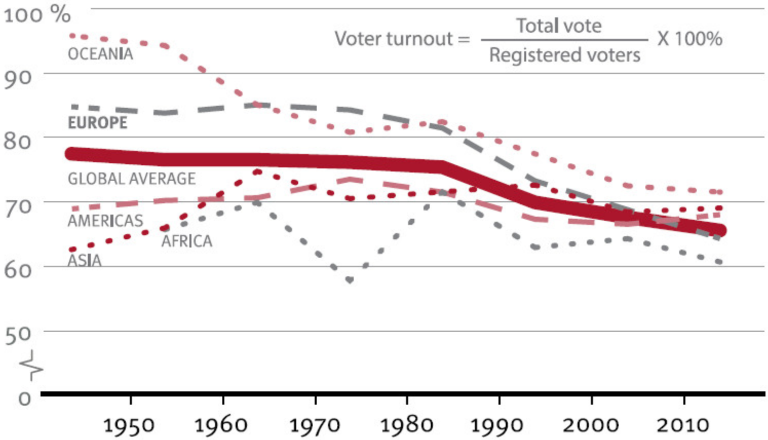
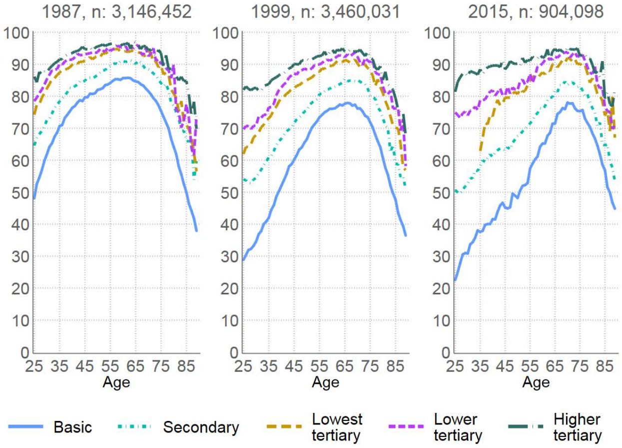
EEA 2024, Rotterdam

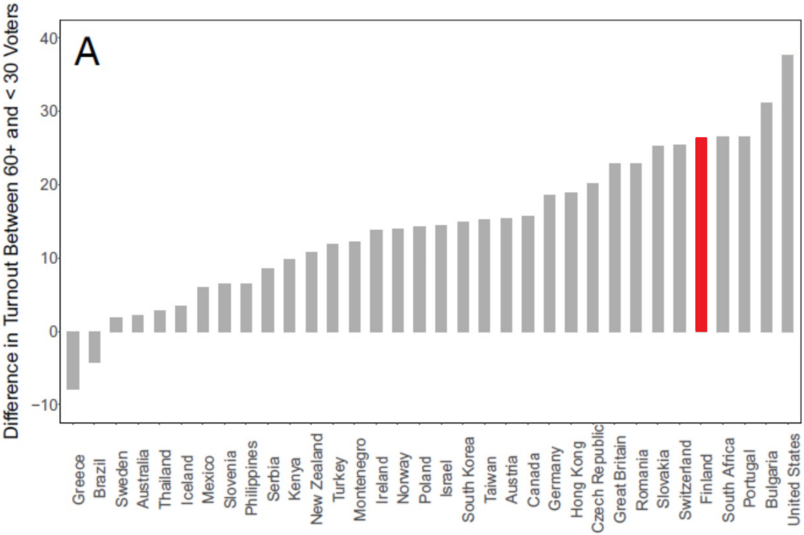
Turnout (Solijonov, 2016)



Turnout in Finland - Parliamentary Elections (Lahtinen, 2019)



Age-group Differences in Turnout (Mo et al., 2022)



Two SMS Experiments

- We evaluate the effectiveness of short text message (SMS) reminders as a tool to mobilize young voters (under 30 years old) and ameliorate the gap in political participation between younger and older citizens in the context of Finnish county (low salience) and parliamentary elections (higher salience).
- We are able to merge individual level turnout data to comprehensive administrative data including information on voters and their cohabitants.
- We study:
  - i) the direct effect of SMS reminders on turnout
  - ii) potential spillover effects within households
  - iii) the effect of SMS-based mobilization on the composition of the electorate both for the direct and spillover effects.
  - iv) persistence effect from SMS sent during previous year's county elections
  - v) dynamics effects i.e. receiving messages during both elections vs. only in 2023

Our Contribution

- Evidence from new electoral context – Finland uses an extreme form of open-lists: each voter gives exactly one vote to one candidate. Candidates are listed in alphabetical order in the party list. The absolute number of votes is used to rank the candidates within parties.

- We try to separate individual voting interest and social environment in effect heterogeneity.

- Only a few prior studies on spillovers (e.g., Bhatti et al., 2017). We are first to analyse how household spillovers affect inequalities in participation.

- We asses the existence of both persistence and dynamic effects.

Theory

- Noticeable Reminder Theory (Dale and Strauss, 2009) proposes that a reminder is enough to increase turnout for people who have voting intentions but might not follow their plans through without the message.
  ➔ High treatment effect among individuals who have voted in the past.

- The Receive-Accept-Sample theory (Zaller, 1993) proposes that individuals living in environments with low amount of cues will be most likely affected by a simple message.
  ➔ High treatment effect among predicted low propensity voters.

- Arceneaux and Nickerson (2009) suggests that (nearly) indifferent voters are the most easiest to mobilize.
  ➔ High treatment effect among predicted marginal propensity voters.

Experimental Design: Experiment I

- We conducted an RCT in the context of low salience Finnish nationwide county elections hold in 2022 in collaboration with the Prime Minister's Office and the Ministry of Justice (Finland).
- Target population of the experiment was 18 to 29 year-old eligible voters living in 118 municipalities where there is an electronic voting register available. These municipalities are well representative of the whole domestic population.
- We found a mobile phone number for total of 51,101 individuals, around 18%, of the target population.
- Reminders sent a day before the advance voting period and a day before the election day.

Messages: Experiment I

Neutral (N=10223)

Hi, please remember that regional elections will be held on January 23. More information at vaalit.fi. Regards, Ministry of Justice.

Expressive (N=10219)

Hi, please remember that regional elections will be held on January 23. Democracy needs your voice, please use your right to vote. More information at vaalit.fi. Regards, Ministry of Justice.

Rational (N=10219)

Hi, please remember regional elections on January 23. By voting, you can have a say on the organization of health and social care services, and fire and rescue care. More information at vaalit.fi. Regards, Ministry of Justice.

Control Group (N=20440)

Estimation I

- We use a Linear Probability Model with individual level controls to estimate the treatment effect:

$$Y_i = \beta_0 + \beta_1 \mathit{Treatment}_i + \boldsymbol{X}_i' \boldsymbol{\beta} + \epsilon_i$$

Estimation II

- Building upon the papers by Arceneaux and Nickerson (2009) and Enos et al. (2014), we explore heterogeneous treatment effects among young voters by their voting propensities.

- Heterogeneity by voting propensity not included in the PAP, but executed as in Hirvonen et al. (2023).

- 1. We estimate the following probability model for voting, using individuals in the control group as a sample:

$$Pr(Y_i = 1|\boldsymbol{X}_i) = \frac{exp(\boldsymbol{X}_b)}{1 + exp(\boldsymbol{X}_b)}$$

  where $Pr(Y_i = 1|\boldsymbol{X}_i)$ is a probability to vote conditional on individual covariates (gender, age, ethnicity, taxable income (mostly parents'), education (mostly parents'), SES background (mostly parents'), eligibility to vote for the first time and municipality fixed effects).

- 2. We use the estimated propensities to vote in the control group to compute predicted probabilities to vote in the whole sample.

Estimation II (continued)

- 3. Voters are divided into three groups according to their estimated voting probability: i) low propensity voters, ii) marginal voters, iii) high-propensity voters. $\rightarrow$ This practice allows us to detect possible non-linearities, while it retains statistical power for doing group comparisons compared to finer sample splittings.

- 4. We estimate treatment effect among the voting propensity groups by LPM.

- Robustness: We address the concern that the within-sample estimates of voting propensities may overfit the data, using machine learning techniques (Elastic Net, Causal forest) that separate the choice of covariates and fitting the prediction model.

Average Treatment Effect

Table: Average treatment effect

	Outcome: Voted			
	(1)	(2)	(3)	(4)
Treatments Pooled	0.009**	0.009*	0.009**	0.009**
	(0.003)	(0.003)	(0.003)	(0.003)
Controls	No	Basic	All	All
Municipality FE	No	No	No	Yes
Untreated $\bar{Y}$	0.307	0.308	0.308	0.308
Observations	50,140	49,679	49,679	49,679

- Effect size is around 3% vs. control group baseline or shrinks the gap around 6% vs. all voters (around 16% vs. 30-39 years old).

Effect of Different Messages - Neutral Seems to Work Best

Table: Different treatments

	Outcome: Voted			
Treatment:	Pooled (1)	"Neutral" (2)	"Expressive" (3)	"Rational" (4)
Treated	0.009** (0.003)	0.016*** (0.005)	0.009* (0.005)	0.002 (0.004)
Controls	Yes	Yes	Yes	Yes
Untreated $\bar{Y}$	0.308	0.308	0.308	0.308
Observations	49,679	29,799	29,806	29,832
		Neutral - Expressive	Expressive - Rational	Rational - Neutral
Differences		0.007 (0.007)	0.007 (0.006)	-0.015** (0.007)

Heterogeneous Effects by Voting Propensity

Table: Heterogeneity by voting propensity

	Outcome: Voted			
	All	"Low Propensity" Bottom 25%	"Marginal Voters" 25-75%	"High Propensity" Top 25%
	(1)	(2)	(3)	(4)
Treated	0.009*	0.020***	0.012**	-0.008
	(0.003)	(0.007)	(0.005)	(0.008)
Controls	Yes	Yes	Yes	Yes
Untreated $\bar{Y}$	0.309	0.151	0.299	0.485
Observations	49,458	12,363	24,727	12,368
		Marginal - Low	Marginal - High	High - Low
Differences		-0.008	0.020**	-0.028***
		(0.008)	(0.009)	(0.010)

A Puzzle ...

Table: Heterogeneous Effects by Voting in 2021 and Urbanity

	Voted			
	Voting in 2021		Urbanity	
	Voted	Not voted	Rural	Urban
	(1)	(2)	(3)	(4)
Treated	0.028***	0.006	0.005	0.012***
	(0.007)	(0.004)	(0.014)	(0.004)
Controls	Yes	Yes	Yes	Yes
Control group $\bar{Y}$	0.593	0.114	0.313	0.306
Observations	17.643	27.800	5.335	38.791
Differences	0.022***		-0.007	
	(0.008)		(0.014)	

… Resolved!

Table: Spillovers by Combination of Voting Propensity Groups and Voted in 2021

	Voted			
	All	"Low Propensity" Bottom 25%	"Marginal Voters" 25-75%	"High Propensity" Top 25%
	(1)	(2)	(3)	(4)
Panel A: Voted in 2021				
Treated	0.028***	$\boxed{0.062^{***}}$	0.030***	0.009
	(0.007)	$\boxed{(0.019)}$	(0.012)	(0.010)
Controls	Yes	Yes	Yes	Yes
Untreated $\bar{Y}$	0.594	0.431	0.579	0.692
Observations	17,594	2,871	8,769	5,954
		Marginal - Low	Marginal - High	High - Low
Differences		-0.031	0.021	-0.052**
		(0.022)	(0.015)	(0.021)
Panel B: Did Not Vote in 2021				
Treated	0.006	0.009*	0.012**	-0.016
	(0.004)	(0.005)	(0.006)	(0.010)
Controls	Yes	Yes	Yes	Yes
Untreated $\bar{Y}$	0.115	0.057	0.118	0.210
Observations	27,678	8,789	14,177	4,712
		Marginal - Low	Marginal - High	High - Low
Differences		0.003	0.028**	-0.025**
		(0.008)	(0.012)	(0.011)

Large Within Household Spillover Effects

Table: Heterogeneity by voting propensity

	Outcome: Voted			
	All	"Low Propensity" Bottom 25%	"Marginal Voters" 25-75%	"High Propensity" Top 25%
	(1)	(2)	(3)	(4)
Treated in HH	0.013**	0.021**	0.016**	-0.006
	(0.006)	(0.010)	(0.008)	(0.011)
Controls	Yes	Yes	Yes	Yes
Control group $\bar{Y}$	0.497	0.242	0.495	0.761
Observations	36.723	9.180	18.362	9.181
Differences		Marginal - Low	Marginal - High	High - Low
		-0.005	0.022*	-0.027*
		(0.013)	(0.013)	(0.015)

Experimental Design: Experiment II

- We conducted similar RCT in the context of parliamentary elections held in 2023 for the target population of 18 to 30 year-old eligible voters living in 128 municipalities where there is an electronic voting register available.

- We found a mobile phone number for total of 49,866 individuals, around 16.5%, of the target population.

- Due to our results from the 2022 experiment, we use only the neutral message in order to increase precision and impact.

- We use 60/40 split instead of 50/50 split to increase power to detect the possible dynamic effects.

- Estimation procedure is same as in experiment I.

Findings: Experiment II

- The effect is coming from predicted low propensity voters.
- We find again a spillover, which is relatively larger than the direct effect.

Persistence

Table: Average treatment effect - Persistence

	Outcome: Voted in 2023			
	(1)	(2)	(3)	(4)
Treated in 2022	-0.004	-0.004	-0.004	-0.004
	(0.005)	(0.005)	(0.004)	(0.004)
Controls	No	Basic	All	All
Municipality FE	No	No	No	Yes
Untreated $\bar{Y}$	0.613	0.614	0.615	0.614
Observations	50,099	49,618	49,618	49,618

Dynamic Effects

Table: Average treatment effect - Dynamic Effects

	Outcome: Voted in 2023			
	(1)	(2)	(3)	(4)
Treated Twice vs Once	-0.005	-0.006	-0.007	-0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Controls	No	Basic	All	All
Municipality FE	No	No	No	Yes
Treated Once $\bar{Y}$	0.631	0.633	0.633	0.633
Observations	18,702	18,513	18,513	18,513

Conclusion

- RCTs with a limited focus on the analysis of individuals in the treatment and control groups alone may substantially underestimate the net effect of interventions.
- New evidence on compositional effects: results suggests that text message reminders decreased inequality in both low and high salience elections.
- The effect is the largest among individuals with covariates predicting a low voting probability but with high personal intentions to vote, giving support for Receive-Accept-Sample and Noticeable Reminder theories.
- No evidence for persistence nor dynamic effects $\Rightarrow$ reminders have to be repeated in order for them to be effective.

Thank You For Listening!

Direct Effect for Household Sample

Table: Direct effect - Household Sample

	Outcome: Voted in 2023			
	(1)	(2)	(3)	(4)
Treated	0.006	0.006	0.006	0.005
	(0.005)	(0.005)	(0.005)	(0.005)
Controls	No	Basic	All	All
Municipality FE	No	No	No	Yes
Treated Once $\bar{Y}$	0.320	0.321	0.321	0.321
Observations	28,564	28,302	28,302	28,302

Heterogeneity

Table: Heterogeneity by Vote Propensity

	Voted			
	All	Low Propensity 25%	Marginal Voters 25-75%	High Propensity 25%
	(1)	(2)	(3)	(4)
Treated	0.004	0.021**	0.004	-0.012
	(0.004)	(0.009)	(0.005)	(0.008)
Controls	✓	✓	✓	✓
Control group $\bar{Y}$	0.628	0.442	0.635	0.801
Observations	49.190	12.297	24.595	12.298
Differences		Marginal - Low	Marginal - High	High - Low
		-0.017	0.016	-0.033***
		(0.011)	(0.010)	(0.012)

Spillovers

Table: Heterogeneity by Vote Propensity

	Voted			
	All	Low Propensity 25%	Marginal Voters 25-75%	High Propensity 25%
	(1)	(2)	(3)	(4)
Treated in HH	0.007	0.035***	0.001	-0.013*
	(0.004)	(0.013)	(0.006)	(0.006)
Controls	✓	✓	✓	✓
Control group $\bar{Y}$	0.773	0.585	0.792	0.926
Observations	35.723	8.930	17.862	8.931
Differences		Marginal - Low	Marginal - High	High - Low
		-0.034**	0.014	-0.048***
		(0.014)	(0.009)	(0.014)