Compliance Behavior in Networks: Evidence from a Field Experiment
Online Appendix

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April 2019

Appendix A: Online Survey

This Appendix reports details on the design and results of the survey described in Section II in the paper implemented in cooperation with a professional online survey provider.

The company maintains a sample that is representative for Austria's adult population (age > 20 years). Subjects from this sample are incentivized to regularly participate in surveys. From this pool we invited random subsamples – stagged over different days and stratified according to population size – to participate in our survey. To avoid that the sample would be dominated by participants from urban areas (and to cover a sufficiently high number of respondents from small municipalities), we set a quota for participants from large municipalities at $N = 500$ and an overall sample target of $N = 1,850$.[1]

The survey first asked participants about their housing situation and the population size of the municipality they live in. The main questions followed thereafter:[2] we asked about (a) the geographic distance to as well as (b) the communication frequency with their closest, their second-, and their third-closest neighbor (in terms of geographic distance, i.e., 'measured by the door-to-door distance'). In doing so, the survey randomly varied the sequence in which questions on the first-, second- or third-closest neighbor were asked.

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[1]The quota implied that, once 500 participants from large municipalities completed the survey, other subjects from such municipalities were no longer invited to participate.

[2]The specific wording of the key questions is presented at the end of this section.

To compare the responses to these questions with a benchmark, we also asked about the communication intensity with their best friend from work/school. The survey then turned to the content of communication. Here we asked how common certain topics are in the communication with neighbors and whether they are willing to pass on relevant information to neighbors (to 'warn' them). The survey concluded with questions on age, gender, highest education and occupational status.

Table A.1 - Summary Statistics

	mean	SD
Age	39.70	12.15
Female	0.58	0.49
Education High	0.19	0.39
Education Low	0.30	0.46
Occ Working	0.68	0.47
Occ School	0.08	0.27
Occ Retired	0.08	0.27
1-Family Housing	0.55	0.50
Small Municip	0.73	0.45

Notes: Summary statistics (mean and standard deviation) for the survey sample ($N = 1,841$).

Our data cover a total of $1,841$ completed questionnaires.[3] The summary statistics for background characteristics of the survey participants are provided in Table A.1. The respondents have an average age of almost 40 years, 58% are female, 19% have a high (university/college), 30% a low level of education. More than two-thirds of the respondents are working, 8% are still in education and another 8% are retired. 55% of the survey participants live in single family houses. Our sample weights (see above) are reflected in a share of 73% living in 'small municipality' (with less than 5,000 inhabitants).

Survey Results

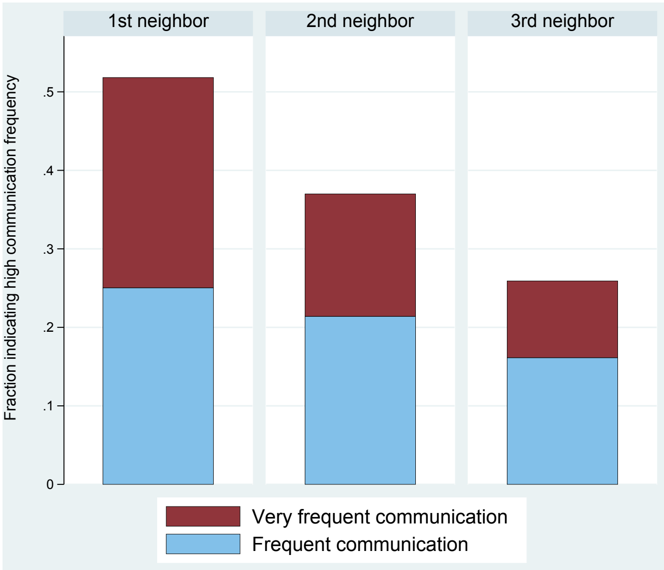
(1) Communication Frequencies. Figure A.1 (which is a re-scaled version of Panel (a) from Figure 1) presents a first key result from the survey. It shows how interaction frequencies decline from the first- to the second- and to the third-closest neighbor. While 52% indicate frequent or very frequent communication with their closest neighbor, the number drops to 37% for the second- and 26% for the third-closest neighbor. Note that this pattern is not an artifact of the sequence at which we asked these questions; it is equally observed for all (random) sequences.[4]

A different way to illustrate how communication intensities decline with distance is provided by Figure A.2 (which is a re-scaled version of Panel (b) from Figure 1).

[3]The completion rate – i.e., the fraction of individuals who completed all survey questions conditional on starting it – was 96.59%. This high percentage reflects the incentives for the survey companies panel participants, who are paid according to *completed* surveys.

[4]Details on this and all further results are available from the authors upon request.

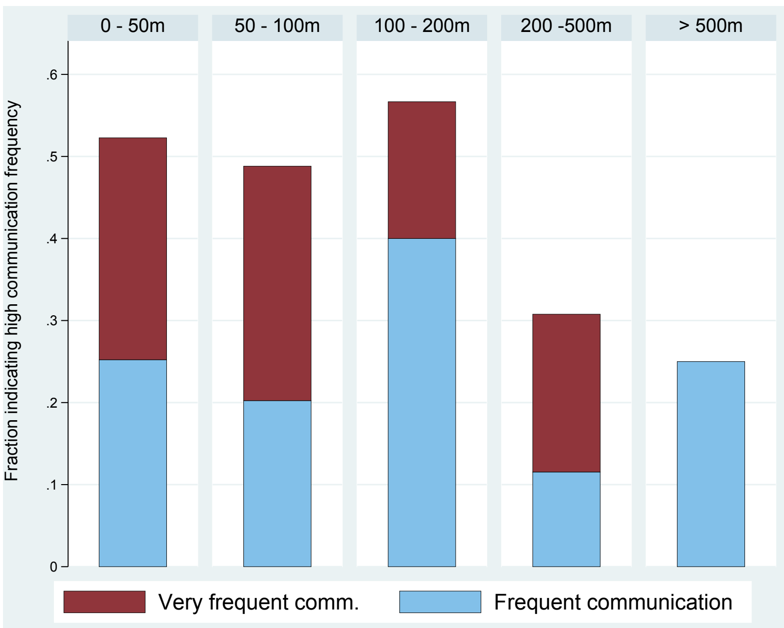
Figure A1 - Communication frequencies with neighbors



Notes: The figure presents the fraction of respondents indicating high communication frequencies with their first-, second- and third-closest neighbor (in geographical terms).

It displays the communication frequency with first-order neighbors (i.e., the closest neighbor) that live either more or less close. The figure suggests that there is more frequent communication with (first-order) neighbors who are more close rather than with the more distant ones. For a distance up to 200 meters, between 49 and 56% indicate

Figure A.2 - Communication frequencies and distance



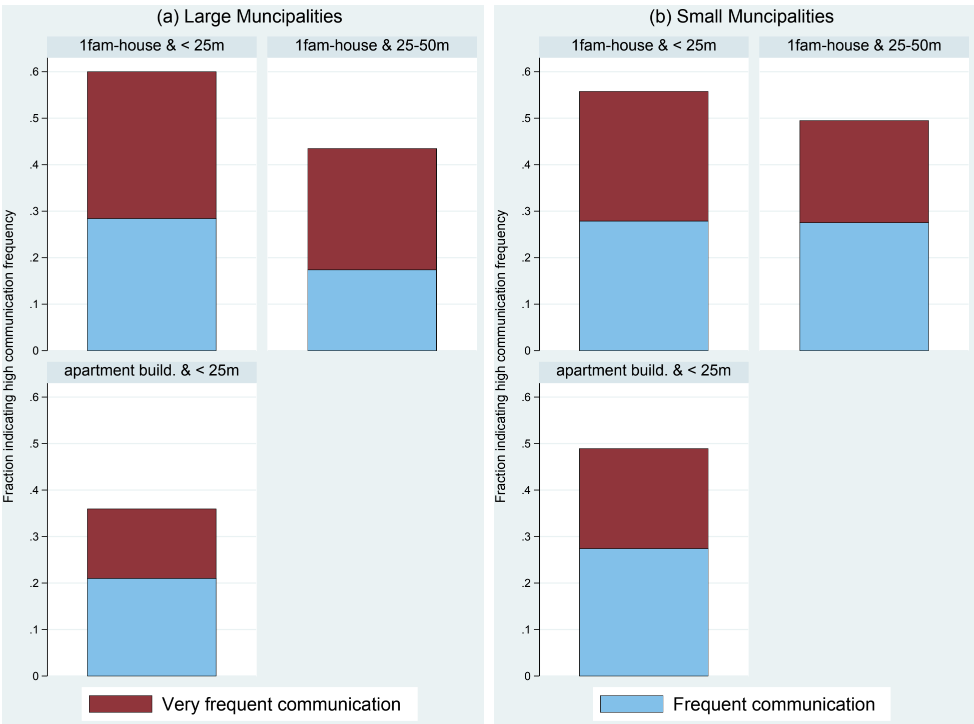
Notes: The figure presents the fraction of respondents indicating high communication frequencies with their first-closest neighbor as a function of the geographic distance to this neighbor.

frequent or very frequent communication with their FON. Beyond 200 [500] meters, this rate drops to 31% [25%]. Non-parametric as well as parametric tests (based on probit as well as ordered probit estimates) indicate that this drop in communication frequencies at 200 meters is statistically significant.

A similar decline in the communication intensity is observed if we focus on the share of respondents indicating very frequent communication (indicated by the dark red bars in Figure A.2). For a distance below 100 meters, this rate is between 27 and 29%. Beyond 100 meters it drops to 17–18% and then, for a distance beyond 500 meters, to zero.

Figures A.1 and A.2 document that communication frequencies among neighbors are declining with distance – both, for the distance to a given 'closest' neighbor as well as when we move from the first- to the second- and to the third-closest neighbor. While this finding is very robust, our data also reveal a systematic deviation from this negative link between distance and communication intensity that is related to the housing structure. The point is illustrated in Figure A.3, which again presents communication frequencies with first-order neighbors.

Figure A.3 - Housing structure and municipality size



Notes: The figure presents the fraction of respondents indicating high communication frequencies with their first-closest neighbor as a function of the geographic distance to this neighbor. Panel (a) presents the responses for 'large municipalities', panel (b) for 'smaller municipalities' (with more or less than 5,000 inhabitants, respectively). Both panels differentiate between the distance to the nearest neighbor as well as the housing structure (apartment building vs. single-family housing).

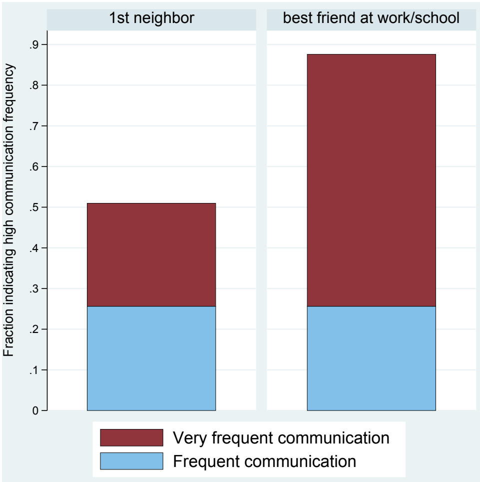
Panel (a) of Figure A.3 focuses on respondents from 'larger municipalities' (with more than 5,000 inhabitants). The two bar-charts on top of panel (a) show responses from individuals living in single-family houses ($N = 127$). In line with the result from above, it illustrates that communication frequencies decline with the distance to the neighbor. The bar-chart at the bottom of panel (a) considers individuals from multi-unit apartment buildings ($N = 376$). For this subset, *all* first-order neighbors live very close to them (i.e., within 25 meters). At the same time, however, they indicate *less frequent* communication as compared to those who have a first-order neighbor with a distance of more than 25 meters (which, naturally, are people not living in apartment blocks but in single-family houses): comparing the top right with the bottom left bar graph from panel (a), we observe that the share reporting frequent or very frequent communication with their FON declines from 44 to 36%. The fraction reporting very frequent communication (indicated by the dark-red bars) falls from 26 to 15%.

In this case, communication frequencies are therefore *not declining* but rather increasing in geographic distance. Intuitively speaking, this is driven by people in apartment buildings who, by definition, live very close to each other and, at the same time, communicate with their neighbors fairly infrequently. This pattern would cause a problem for the geographic network approach introduced in Section III, which computes networks based on geographic distance between neighbors. In large, urban municipalities, we would treat households from apartment buildings as one (very close) network while we would probably assign two more distant households living in single-family houses (e.g., in suburban areas) into two different networks. In both instances we would very likely make a mistake: in the former, the high geographic proximity is correlated with a lower communication intensity; in the latter, there might be frequent interaction among the neighbors (from single family houses), despite the higher distance. To wrap up, the survey data suggest that the application of our geographic network approach is problematic for urban areas.

In a next step, we explore whether apartment buildings from smaller, more rural municipalities – where multi-unit buildings are clearly less frequent but still present – also induce problems for the negative correlation between distance and communication frequencies. This point is addressed in panel (b) of Figure A.3. The two bar-charts on top of panel (b), which focus on respondents living in single-family houses ($N = 752$), show that – consistently with the results from above – communication frequencies are declining when we compare those with very close (< 25 meters) and close (25–50 meters) first-order neighbors. What is more interesting, however, is the fact that in small municipalities, the respondents living in apartment buildings ($N = 186$) report almost identical communication frequencies. This point is captured in the lower left part of panel (b): 49% state that they frequently or very frequently talk to their most proximate neighbor from their apartment building. The response pattern is almost identical which the ones observed for respondents who live in single-family houses with the closest neighbor in the 25-50 meters range.

For small Austrian municipalities, the 'closeness' of neighbors in apartment buildings is thus not aligned with a lower interaction frequency. As becomes clear from the comparison of the lower bar-graphs of panel (a) and panel (b), this is in stark contrast to

Figure A.4 - Communication frequencies for FON and best friend from school/work



Notes: For the subsample that is either employed or in education ($N = 1,393$), the figure compares the fraction of respondents indicating high communication frequency with their first-order neighbors as well as their 'best friend' from school/work.

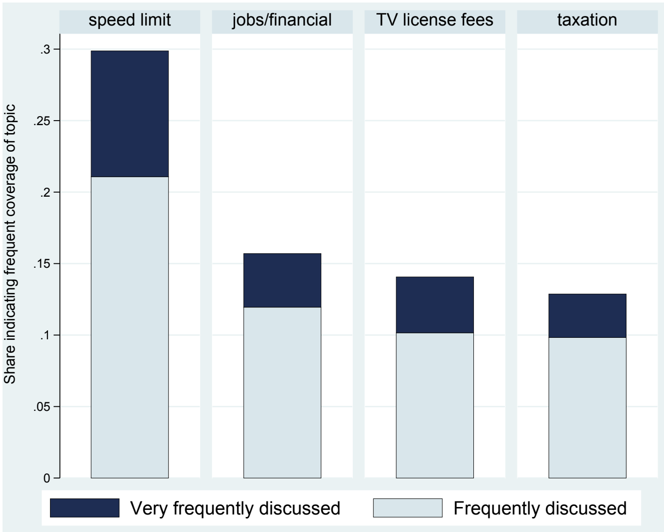
the outcome for large municipalities. In the latter type of municipalities, where apartment buildings tend to be larger and more anonymous, only 36% of respondents from apartment buildings report frequent or very frequent communication with their FONs. In small municipalities it is 49%.

We conclude our analysis of communication patterns by assessing whether the reported communication frequencies among neighbors are particularly high or low. To do so, we have a brief look at reported communication frequencies with the 'best friend' from school/work. Figure A.4 presents the results. Among the subsample that is either working or in education ($N = 1,393$), 51% report frequent or very frequent communication with their FON. Among the same sample, almost 88% say they frequently or very frequently talk to their best friend from school/work. Hence, the fraction indicating a high or very high communication frequency with FONs is roughly 60% lower as compared to the communication pattern among friends. The figure further reveals that it is mainly the fraction reporting very frequent communication which declines (from 62 to 25%) when we compare the best friend to the FON.

(2) Communication Content. Let us now turn to the content of the communication. The data from the survey indicate that TV license fees are, in general, a topic that is not too often addressed in the communication with neighbors. The responses presented in Figure A.5 suggest that license fees are an equally (un)common topic such as, for instance, discussions on financial opportunities and job offers or discussions related to taxation issues.

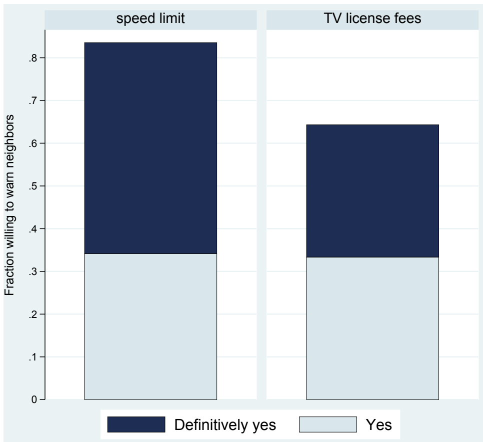
The survey further reveals, however, that people *are* willing to pass on information on TV license fee to their neighbors, once some relevant news arrives. This point is illustrated in Figure A.6, which indicates the fraction of respondents who would share

Figure A.5 - Communication topics



Notes: The figure presents the fraction of respondents indicating how frequently certain topics – (i) experiences with the enforcement of speed limits, (ii) financial opportunities or job offers, (iii) experiences with TV license fees or (iv) taxation – are discussed with neighbors.

Figure A.6 - Willingness to pass on information



Notes: The figure presents the fraction of respondents indicating that they are willing to share relevant information – on speed controls or TV license fee mailings – with their neighbors (to 'warn' them).

(i) information about a recent experience of a speed control or (ii) information about receiving a FIS mailing (which indicates a possible inspection) with their neighbors. More than 80% would warn their neighbors about speed controls and roughly two-thirds would communicate about the license fee inspection risk after receiving a FIS mailing. The evidence therefore suggests that, while license fees are not the most common topic of communication, neighbors are certainly willing to initiate communication after receiving a mailing.

Main Survey Questions

Think of your neighbors which live closest to you in geographical terms. Consider the neighboring household which {- measured by the door-to-door distance {- is the [most/second/third] closest to you.[5]

- How far is this neighbor's household from your house?

  < 50 meters / 50-100 meters / 100-200 meters / 200-500 meters / > 500 meters

- How often do you communicate with this neighbor?

  very frequently / frequently / sometimes / rarely / very rarely

- Now think of your best friend from work/school. How often do you communicate with this friend?

  very frequently / frequently / sometimes / rarely / very rarely

- When you talk with your neighbors, how often do you discuss...

  ... <u>financial opportunities or job offers</u>?

  ... experiences with <u>taxation</u> (filing, audits, etc.)?

  ... experiences with the <u>enforcement of speed limits</u> (e.g., speed camera controls)?

  ... experiences with <u>TV license fees</u> (FIS mailings, inspections, etc.)?

  very frequently / frequently / sometimes / rarely / very rarely

- Suppose you are stopped by the police for speeding somewhere in your region. Would you share this information with a neighbor ('warn him/her'), when you meet him/her afterwards?

  definitely yes / yes / no / definitely no

- Suppose you are not paying TV license fees and you receive a letter which indicates a possible inspection. Would you share this information with a neighbor ('warn him/her'), when you meet him/her afterwards?

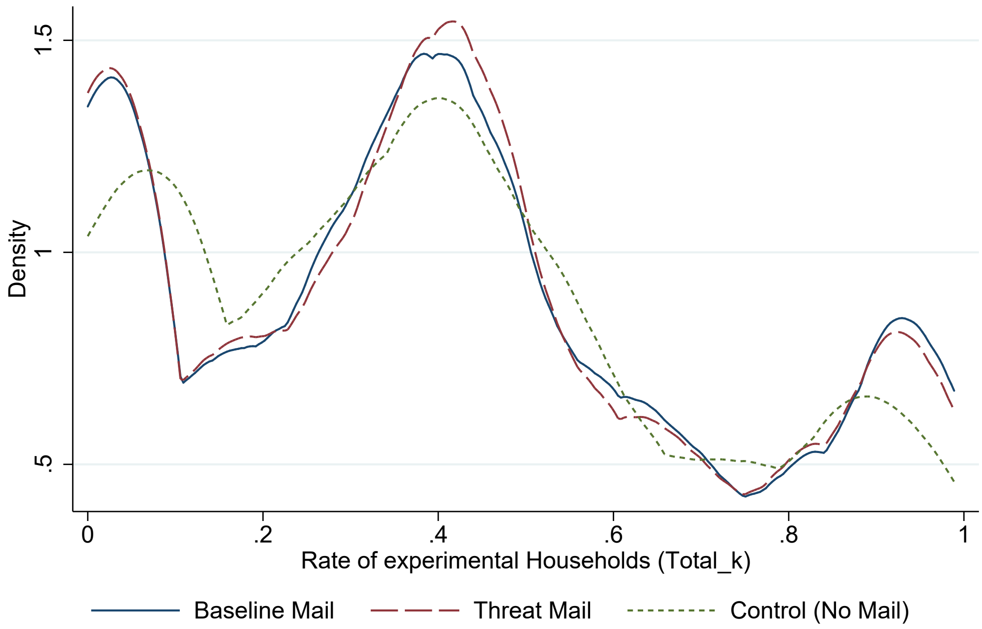
  definitely yes / yes / no / definitely no

[5]To produce random sequences, the part in squared brackets was randomly varied. Note further that for households living in apartment buildings, the survey questions were framed differently. In particular, we asked the following (again in random sequences): `Consider now the neighboring household` <u>`in your building`</u> `which {- measured by the door-to-door distance {- is the closest to you.` (Here we did not ask for the geographic door-to-door distance but only for the communication frequency.) `Consider now the neighboring household` <u>`not living in your apartment building`</u> `which {- measured by the door-to-door distance {- is the closest/second closest to you.`

Appendix B: Complementary Results

This Appendix reports additional tables and figures mentioned in the empirical analysis of the paper.

Figure B.1 - Density of the total rate of experimental participants



Notes: The figure presents kernel density estimates of the total rate of experimental participants ($Total_k$) for experimental households in the baseline, threat and control treatment (Epanechnikov kernel with optimal bandwidth).

Table B.1 - Network properties of relevant networks for different distance thresholds z.

Network threshold $z =$	25	50	75	100	250	500	1000	1500	2000
Networks	3,243	3,764	3,319	2,990	2,113	1,554	1,169	1,073	1,020
Mean Network Size	5.90	17.98	32.93	45.13	90.40	151.95	232.91	261.66	279.54
Type I HHs	7,056	14,028	17,144	18,705	21,612	22,956	23,473	23,550	23,575
Type II HHs	5,337	14,987	23,673	29,212	41,547	50,688	58,498	60,520	61,551
Type III HHs	6,761	38,673	68,481	87,009	127,846	162,487	190,306	196,691	200,004
All HHs	19,154	67,688	109,298	134,926	191,005	236,131	272,277	280,761	285,130

Notes: The table reports the distribution of household types and the mean network size for relevant networks obtained for different thresholds z. A network becomes relevant for studying spillovers if there is at least one type I and at least one type II household.

Table B.2 - Balancing tests

	(1) Base_k	(2) Base_k	(3) Threat_k	(4) Threat_k
(a) Network-level characteristics				
Network Size	0.0000		-0.0001	
	(0.0001)		(0.0001)	
Clustering	-0.0026		-0.0025	
	(0.0148)		(0.0145)	
Degree	0.0004		-0.0005	
	(0.0005)		(0.0006)	
Eigenvector Centrality	0.0309		-0.0261	
	(0.0315)		(0.0314)	
Enforcement Rate	-0.0400		0.0359	
	(0.0490)		(0.0502)	
(b) Experimental HHs characteristics				
Diffusion Centrality ($T = 1$)	-0.0032		-0.0010	
	(0.0107)		(0.0105)	
Diffusion Centrality ($T = 10$)	-0.0004		-0.0007	
	(0.0088)		(0.0087)	
Eigenvector Centrality	0.0095		-0.0074	
	(0.0278)		(0.0275)	
IH Index	-0.0198		0.0075	
	(0.0242)		(0.0239)	
IH^+ Dummy	-0.0017		0.0018	
	(0.0108)		(0.0110)	
(c) Municipal variables				
Population		-0.0000		0.0000
		(0.0000)		(0.0000)
Labor Income		-0.0000		0.0000
		(0.0000)		(0.0000)
Average Age		0.0073		-0.0161
		(0.0160)		(0.0162)
Catholic		0.1858		-0.1905
		(0.2289)		(0.2244)
Non-Austrian Citizens		-0.3394		0.4487
		(0.8703)		(0.8657)
1- or 2-family dwellings		0.1464		-0.2451
		(0.2587)		(0.2581)
Voter Turnout		-0.1665		0.1188
		(0.5156)		(0.5174)
Observations	3,764	771	3,764	771

Notes: The table reports estimates from the balancing tests from equation (4) at the network level (columns 1 and 3) and at the municipal level (columns 2 and 4), respectively. Among the former, we distinguish among network-level characteristics for *all households* in a network (panel a) and network-level averages among *all experiment (type I) households* (panel b). Each entry in the table presents the estimated coefficient from a separate regression based on 3,764 (network-level) or 771 observations (municipality-level) of the baseline treatment rate (column 1 and 2) and of the threat treatment rate (column 3 and 4) on each observable variable. Each regression controls for the total experimental rate (Total_k) non-parametrically by including Total_k fixed effects (see equation (4)). Robust standard errors are in parentheses. None of the coefficients is significant at conventional levels.

Table B.3 - Interactions with municipality characteristics

Variable M =	(1) Income	(2) Catholic	(3) Population	(4) Age	(5) Non-Austrians	(6) Turnout	(7) Dwellings
Base_k	0.2194	0.6901**	0.2376***	1.6643**	0.2421***	-0.3015	0.0448
	(0.2184)	(0.2959)	(0.0518)	(0.7529)	(0.3719)	(0.2380)	(0.1189)
Threat_k	0.4018	0.5332**	0.3380***	0.4034	0.3875***	-0.0198	0.0541
	(0.2184)	(0.2660)	(0.0564)	(0.7824)	(0.3444)	(0.2584)	(0.1351)
$\text{Base}_k \times M$	0.0000	-0.4963	0.0000	-0.0297*	0.0182	0.7614**	0.2583*
	(0.0000)	(0.3247)	(0.0000)	(0.0157)	(0.3990)	(0.3318)	(0.1491)
$\text{Threat}_k \times M$	-0.0000	-0.2033	0.0000	-0.0011	-0.5560	0.5172	0.3868**
	(0.0000)	(0.2921)	(0.0000)	(0.0163)	(0.3692)	(0.3581)	(0.1710)
M	0.0000	0.0026	-0.0000	0.0018	-0.1174	0.0672	-0.0104
	(0.0000)	(0.0482)	(0.0000)	(0.0029)	(0.0822)	(0.0722)	(0.0276)
R^2	0.0907	0.0953	0.0971	0.0952	0.0956	0.0973	0.0964

Notes: The table reports results from LPM estimates of extension of equation (1) where the treatment rates are interacted with a municipality variable M (see Panel (C) in Table (2)). All estimates are based on 14,987 observations from 3,764 networks. A constant term is included but estimates are not reported. Standard errors, clustered at the network level, are reported in parentheses. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table B.4 - Spillover effects within the experiment

	(1)	(2)	(3)	(4)
Base_i	0.0591***	0.0609***	0.0594***	0.0621***
	(0.0037)	(0.0039)	(0.0052)	(0.0056)
Threat_i	0.0656***	0.0658***	0.0661***	0.0656***
	(0.0038)	(0.0040)	(0.0053)	(0.0058)
Base_k	-	0.0119	-	-0.0045
		(0.0262)		(0.0726)
Threat_k	-	0.0132	-	-0.0145
		(0.0255)		(0.0702)
Constant	0.0109***	-	0.0137***	-
	(0.0028)		(0.0041)	
Observations	23,626	23,626	14,028	14,028
Networks	–	10,535	–	3,764
R^2	0.0034	0.0331	0.0033	0.0606

Notes: The table reports LPM estimates for the *direct treatment effects* in the experimental sample (type I households). Base_i and Threat_i indicate a dummy equal to 1 if type I household i was in the baseline or threat treatment, respectively. In columns (1) and (2) we run regressions on all type I households included in our raw data, in column (3) and (4) we focus on type I households from relevant networks with $z = 50$ (as defined in Section III.B). Columns (2) and (4) add controls for the treatment rates at the network level and include $Total_k$ fixed effects. In columns (1) and (3) robust standard errors are in parentheses, in columns (2) and (4) standard errors are clustered at the network level. *** indicates significance at the 1%-level.

Table B.5 - Spillover effects and ex-ante compliance rate of experimental households

	(1) Comp= 1	(2) Comp< 1	(3) Full Sample
Base_k	0.1614***	0.2571***	0.2793***
	(0.0421)	(0.0463)	(0.0412)
Threat_k	0.3280***	0.3531***	0.3655***
	(0.0484)	(0.0473)	(0.0421)
Ex-ante Comp Rate_k			0.0007
			(0.0115)
$\text{Base}_k \times$ Ex-ante Comp_k			-0.1614***
			(0.0495)
$\text{Threat}_k \times$ Ex-ante Comp_k			-0.0620
			(0.0557)
Observations	1,625	13,362	14,987
Networks	583	3,181	3,764
R^2	0.1047	0.1000	0.0967

Notes: This table explores variation in the average ex-ante compliance rate among experimental (type I) households of network k. The first two columns report the results from LPM estimations of equation (1) for the restricted sample of networks with an average ex-ante compliance equal to one (column 1) and less than one (column 2), respectively. In column (3) we include a variable measuring the ex-ante compliance rate and its interactions with the two mailing treatment rates. Standard errors, clustered at the network level, are in parentheses. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table B.6 - Interactions with experimental households' centrality

Centrality measure c:	(1) $DC^{T=1}$	(2)	(3) $DC^{T=10}$	(4)	(5) $DC^{T_k}_{q_k}$	(6)	(7) EC	(8)
$Base_k$	0.0517	0.1090	0.1649***	0.2035***	0.1194*	0.1769**	0.0910	0.2073*
	(0.0798)	(0.0949)	(0.0511)	(0.0611)	(0.0642)	(0.0758)	(0.0899)	(0.1179)
$Threat_k$	0.2636***	0.3221***	0.2664***	0.3047***	0.2700***	0.3266***	0.2706***	0.3881***
	(0.0887)	(0.1022)	(0.0554)	(0.0638)	(0.0708)	(0.0807)	(0.0983)	(0.1246)
$Base_k \times c_k^{base}$	0.2163**	0.1688*	0.1203*	0.0952	0.1420*	0.1011	0.2263	0.0866
	(0.0867)	(0.0960)	(0.0619)	(0.0645)	(0.0734)	(0.0777)	(0.1397)	(0.1671)
$Threat_k \times c_k^{threat}$	0.1420	0.0935	0.1425**	0.1191*	0.1305	0.0912	0.1831	0.0398
	(0.0953)	(0.1035)	(0.0662)	(0.0677)	(0.0797)	(0.0830)	(0.1493)	(0.1765)
c_k^{base}	-0.0053	-0.0145	-0.0180	-0.0342	-0.0016	-0.0174	0.0172	-0.0194
	(0.0164)	(0.0187)	(0.0214)	(0.0256)	(0.0186)	(0.0222)	(0.0328)	(0.0418)
c_k^{threat}	-0.0322**	-0.0415**	-0.0303	-0.0474*	-0.0281	-0.0444**	-0.0378	-0.0727*
	(0.0162)	(0.0184)	(0.0207)	(0.0253)	(0.0179)	(0.0217)	(0.0343)	(0.0419)
c_k^{all}	-	0.0301	-	0.0326	-	0.0373	-	0.0955*
		(0.0232)		(0.0254)		(0.0236)		(0.0537)
F-Tests: Joint significance of interaction terms								
$Base_k \times c_k^{base} = Threat_k \times c_k^{threat} = 0$	3.956	1.675	3.466	2.103	2.689	1.148	1.729	0.134
	[0.019]	[0.187]	[0.031]	[0.122]	[0.068]	[0.317]	[0.178]	[0.874]

Notes: The table presents LPM estimates for the equation $y_{ik} = \boldsymbol{\delta}^{Total_k} + \beta_1 Base_k + \beta_2 Threat_k + \gamma_1^c\, c_k^{base} + \gamma_2^c\, c_k^{threat} + \gamma_3^c \left(c_k^{base} \times \text{Base}_k\right) + \gamma_4^c \left(c_k^{threat} \times \text{Threat}_k\right) + \epsilon_{ik}$ as well as for an augmented model that also controls for c_k^{all}. The variable c_k^j captures the mean centrality for centrality measure c among experimental households from network k in treatment condition j = baseline mailing or threat mailing, respectively. c_k^{all} indicates the mean centrality among *all* experimental households (independently of their treatment). The augmented models thus exploit variation in the randomly treated households' centrality, conditional on the centrality of all possible injection points in a network k. Note that we set c_k^{base} or c_k^{threat} equal to zero if, in a given network k, there are no households in either the one or the other treatment. (As any relevant network includes, by definition, at least one experimental household, c_k^{all} is always defined.) The basic and the augmented interaction model are estimated for four centrality measures c: diffusion centrality for one ($DC^{T=1}$, columns 1–2) and ten rounds of communication ($DC^{T=10}$, columns 3–4), the network specific diffusion centrality measure proposed by Banerjee et al. (2019), i.e., with network specific parameters T_k and q_k, where T_k is set to the diameter of network k and q_k equal to the inverse of the first eigenvalue of the network's adjacency matrix ($DC^{T_k}_{q_k}$, columns 5–6); and, finally, the eigenvector centrality (*EC*, columns 7–8). The lower part of the table presents F-statistics [with p-values in brackets] testing the joint significance of the two interaction terms (i.e., $\gamma_3^c = \gamma_4^c = 0$). Number of observations: 14,987; number of networks: 3,764. Standard errors, clustered at the network level, are in parentheses. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table B.7 - Impact by centrality of injection points: robustness check

Centrality measure c:	(1) $DC^{T=1}$	(2)	(3) $DC^{T=10}$	(4)	(5) DC_q^T	(6)	(7) EC	(8)
$\text{Base}_k^{c\text{-L}}$	0.1080*	0.1744	0.2375***	0.1937	0.2205***	0.2742*	0.3851***	0.4280*
	[0.0611]	[0.1158]	[0.0681]	[0.1492]	[0.0745]	[0.1453]	[0.1355]	[0.2299]
$\text{Base}_k^{c\text{-H}}$	0.2585***	0.2603***	0.2445***	0.2551***	0.2453***	0.2489***	0.2416***	0.2436***
	[0.0390]	[0.0402]	[0.0386]	[0.0395]	[0.0384]	[0.0394]	[0.0379]	[0.0381]
$\text{Threat}_k^{c\text{-L}}$	0.2456***	0.2799**	0.2994***	0.2265	0.3415***	0.3438**	0.6475***	0.6318***
	[0.0657]	[0.1174]	[0.0719]	[0.1483]	[0.0807]	[0.1461]	[0.1326]	[0.2381]
$\text{Threat}_k^{c\text{-H}}$	0.3612***	0.3640***	0.3535***	0.3652***	0.3513***	0.3564***	0.3454***	0.3471***
	[0.0398]	[0.0409]	[0.0394]	[0.0403]	[0.0394]	[0.0401]	[0.0388]	[0.0389]
$\text{Total}_k^{c\text{-L}}$		-0.0934		-0.0567		-0.1484		-0.3580*
		[0.1052]		[0.1347]		[0.1314]		[0.2107]
$\text{Total}_k^{c\text{-H}}$		-0.0662*		-0.0704*		-0.0728*		-0.1028***
		[0.0370]		[0.0365]		[0.0372]		[0.0362]
$(c)_k^{\text{all}}$	-0.0115	0.0178*	0.0169	0.0179	0.0238	0.0242**	0.1523***	0.0999***
	[0.0168]	[0.0107]	[0.0129]	[0.0114]	[0.0154]	[0.0117]	[0.0397]	[0.0217]
Total_k FEs	Yes	No	Yes	No	Yes	No	Yes	No
F-Tests: (See Table Notes)								
Base: High vs. Low	7.024	7.208	0.0129	0.956	0.130	0.965	1.169	0.868
Threat: High vs. Low	3.513	5.720	0.665	5.824	0.0162	2.554	5.485	0.118
R-squared	0.096	0.060	0.095	0.058	0.095	0.059	0.096	0.060

Notes: The table replicates LPM estimations of equations (7) and (8) presented in Table 6 in the paper, now controlling for the median centrality $(c)_k^{\text{all}}$ of all experimental households in a network k. As in Table 6 we differentiate treatment rates according to the injection points' having above or below media measures of centrality c for: diffusion centrality for one ($DC^{T=1}$, columns 1 and 2) and 10 rounds of communication ($DC^{T=10}$, columns 3 and 4), diffusion centrality with T equal to the network's diameter and communication probability q equal to the inverse of the first eigenvalue of the network's adjacency matrix (DC_q^T, columns 5 and 6), and finally eigenvector centrality (EC, columns 7 and 8). The F-tests reported in columns (1), (3), (5) and (7) are based on equation (7) and test the H0: $\beta_j^{\text{L}} = \beta_j^{\text{H}}$ for $j = 1$ (Base) and $j = 2$ (Threat), respectively. The tests from columns (2), (4), (6) and (8) are based on the augmented equation (8) and test H0: $\alpha^{\text{L}} + \beta_j^{\text{L}} = \alpha^{\text{H}} + \beta_j^{\text{H}}$ for $j = 1$ (Base) and $j = 2$ (Threat), respectively. Adding up coefficients here accounts for the fact that $\text{Total}^{c\text{-L}}$ differs from $\text{Total}^{c\text{-H}}$. Number of observations: 14,987; number of networks: 3,764. Standard errors, clustered at the network level, are in parentheses. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table B.8 - Impact by injection points' diffusion centrality: different T and q parameters

(A) $q = 1$	$T = 1$	2	3	4	5	6	7	8	9	10
Base$_k^{c\text{-L}}$	0.1777	0.3026**	0.2540*	0.2576*	0.2624*	0.2621*	0.2349	0.2339	0.2057	0.1937
	(0.1160)	(0.1366)	(0.1406)	(0.1444)	(0.1446)	(0.1448)	(0.1454)	(0.1447)	(0.1467)	(0.1491)
Base$_k^{c\text{-H}}$	0.2601***	0.2462***	0.2503***	0.2500***	0.2496***	0.2496***	0.2518***	0.2520***	0.2540***	0.2552***
	(0.0401)	(0.0393)	(0.0393)	(0.0393)	(0.0393)	(0.0393)	(0.0394)	(0.0394)	(0.0394)	(0.0394)
Threat$_k^{c\text{-L}}$	0.2813**	0.3880***	0.3344**	0.3165**	0.3066**	0.3054**	0.2745*	0.2793*	0.2607*	0.2261
	(0.1177)	(0.1387)	(0.1415)	(0.1448)	(0.1448)	(0.1454)	(0.1459)	(0.1457)	(0.1467)	(0.1482)
Threat$_k^{c\text{-H}}$	0.3632***	0.3523***	0.3568***	0.3576***	0.3584***	0.3585***	0.3609***	0.3607***	0.3620***	0.3651***
	(0.0408)	(0.0401)	(0.0401)	(0.0401)	(0.0401)	(0.0401)	(0.0401)	(0.0401)	(0.0401)	(0.0402)
Total$_k^{c\text{-L}}$	-0.0970	-0.1916	-0.1449	-0.1362	-0.1326	-0.1311	-0.1039	-0.1056	-0.0823	-0.0604
	(0.1055)	(0.1223)	(0.1266)	(0.1299)	(0.1302)	(0.1305)	(0.1314)	(0.1308)	(0.1324)	(0.1346)
Total$_k^{c\text{-H}}$	-0.0463	-0.0414	-0.0449	-0.0456	-0.0460	-0.0462	-0.0483	-0.0483	-0.0501	-0.0520
	(0.0342)	(0.0337)	(0.0336)	(0.0336)	(0.0336)	(0.0336)	(0.0336)	(0.0336)	(0.0336)	(0.0337)
Base: H vs. L	10.92	3.821	4.218	3.123	2.549	2.442	2.491	2.691	3.015	2.255
Threat: H vs. L	9.051	4.860	5.866	6.793	7.788	7.615	8.253	7.775	7.119	8.871

(B) $q = 0.75$	$T = 1$	2	3	4	5	6	7	8	9	10
Base$_k^{c\text{-L}}$	0.1777	0.3018**	0.2593*	0.2574*	0.2612*	0.2944*	0.2682*	0.2147	0.2168	0.1959
	(0.1160)	(0.1368)	(0.1406)	(0.1450)	(0.1447)	(0.1618)	(0.1618)	(0.1461)	(0.1465)	(0.1487)
Base$_k^{c\text{-H}}$	0.2601***	0.2462***	0.2497***	0.2499***	0.2496***	0.2474***	0.2490***	0.2533***	0.2532***	0.2548***
	(0.0401)	(0.0393)	(0.0393)	(0.0393)	(0.0393)	(0.0390)	(0.0390)	(0.0394)	(0.0394)	(0.0394)
Threat$_k^{c\text{-L}}$	0.2813**	0.3896***	0.3453**	0.3085**	0.3103**	0.3164*	0.2909*	0.2674*	0.2681*	0.2400
	(0.1177)	(0.1386)	(0.1418)	(0.1456)	(0.1450)	(0.1620)	(0.1625)	(0.1460)	(0.1463)	(0.1484)
Threat$_k^{c\text{-H}}$	0.3632***	0.3522***	0.3558***	0.3581***	0.3579***	0.3578***	0.3592***	0.3615***	0.3615***	0.3636***
	(0.0408)	(0.0401)	(0.0401)	(0.0401)	(0.0401)	(0.0398)	(0.0398)	(0.0401)	(0.0401)	(0.0402)
Total$_k^{c\text{-L}}$	-0.0970	-0.1923	-0.1514	-0.1328	-0.1334	-0.1489	-0.1246	-0.0901	-0.0908	-0.0679
	(0.1055)	(0.1222)	(0.1266)	(0.1307)	(0.1302)	(0.1469)	(0.1470)	(0.1317)	(0.1321)	(0.1343)
Total$_k^{c\text{-H}}$	-0.0463	-0.0412	-0.0445	-0.0458	-0.0459	-0.0458	-0.0471	-0.0493	-0.0495	-0.0512
	(0.0342)	(0.0337)	(0.0336)	(0.0336)	(0.0336)	(0.0333)	(0.0334)	(0.0336)	(0.0336)	(0.0337)
Base: H vs. L	10.92	3.898	4.252	2.885	2.693	1.405	1.506	2.949	2.816	2.667
Threat: H vs. L	9.051	4.761	5.301	7.336	7.376	8.062	8.145	7.272	7.263	7.917

(C) $q = 0.5$	$T = 1$	2	3	4	5	6	7	8	9	10
Base$_k^{c\text{-L}}$	0.1777	0.2893**	0.3068**	0.2867*	0.2416	0.2564	0.2681	0.2362	0.1839	0.1843
	(0.1160)	(0.1299)	(0.1374)	(0.1625)	(0.1713)	(0.1720)	(0.1728)	(0.1734)	(0.1739)	(0.1744)
Base$_k^{c\text{-H}}$	0.2601***	0.2474***	0.2457***	0.2478***	0.2506***	0.2497***	0.2487***	0.2509***	0.2544***	0.2543***
	(0.0401)	(0.0395)	(0.0393)	(0.0389)	(0.0389)	(0.0389)	(0.0389)	(0.0389)	(0.0390)	(0.0390)
Threat$_k^{c\text{-L}}$	0.2813**	0.3827***	0.4018***	0.3437**	0.2825	0.3014*	0.3066*	0.2708	0.2304	0.2262
	(0.1177)	(0.1325)	(0.1395)	(0.1640)	(0.1719)	(0.1728)	(0.1737)	(0.1744)	(0.1740)	(0.1745)
Threat$_k^{c\text{-H}}$	0.3632***	0.3526***	0.3512***	0.3555***	0.3595***	0.3583***	0.3576***	0.3601***	0.3627***	0.3631***
	(0.0408)	(0.0403)	(0.0401)	(0.0398)	(0.0397)	(0.0397)	(0.0397)	(0.0397)	(0.0398)	(0.0398)
Total$_k^{c\text{-L}}$	-0.0970	-0.1860	-0.1982	-0.1591	-0.1069	-0.1196	-0.1271	-0.0953	-0.0500	-0.0481
	(0.1055)	(0.1161)	(0.1236)	(0.1484)	(0.1568)	(0.1574)	(0.1580)	(0.1589)	(0.1591)	(0.1596)
Total$_k^{c\text{-H}}$	-0.0463	-0.0410	-0.0412	-0.0449	-0.0484	-0.0481	-0.0473	-0.0495	-0.0526	-0.0528
	(0.0342)	(0.0338)	(0.0336)	(0.0333)	(0.0332)	(0.0332)	(0.0332)	(0.0332)	(0.0333)	(0.0333)
Base: H vs. L	10.92	4.817	4.009	2.419	1.893	1.793	1.542	1.569	1.947	1.813
Threat: H vs. L	9.051	5.050	4.172	5.703	6.584	6.021	6.215	6.674	6.089	6.324

(D) $q = 0.25$	$T = 1$	2	3	4	5	6	7	8	9	10
Base$_k^{c\text{-L}}$	0.1777	0.2446*	0.2889**	0.3838**	0.3829**	0.3899**	0.3924**	0.3588**	0.2432	0.2122
	(0.1160)	(0.1397)	(0.1446)	(0.1588)	(0.1642)	(0.1688)	(0.1704)	(0.1759)	(0.1930)	(0.1929)
Base$_k^{c\text{-H}}$	0.2601***	0.2505***	0.2467***	0.2418***	0.2423***	0.2417***	0.2417***	0.2437***	0.2497***	0.2514***
	(0.0401)	(0.0393)	(0.0392)	(0.0389)	(0.0388)	(0.0388)	(0.0388)	(0.0388)	(0.0386)	(0.0387)
Threat$_k^{c\text{-L}}$	0.2813**	0.3385**	0.3952***	0.4476***	0.4600***	0.4869***	0.4881***	0.4683***	0.3640*	0.3470*
	(0.1177)	(0.1372)	(0.1412)	(0.1597)	(0.1656)	(0.1708)	(0.1727)	(0.1771)	(0.1883)	(0.1883)
Threat$_k^{c\text{-H}}$	0.3632***	0.3557***	0.3514***	0.3490***	0.3486***	0.3467***	0.3469***	0.3482***	0.3538***	0.3548***
	(0.0408)	(0.0402)	(0.0402)	(0.0398)	(0.0397)	(0.0397)	(0.0397)	(0.0396)	(0.0396)	(0.0396)
Total$_k^{c\text{-L}}$	-0.0970	-0.1415	-0.1844	-0.2533*	-0.2596*	-0.2687*	-0.2700*	-0.2425	-0.1358	-0.1123
	(0.1055)	(0.1246)	(0.1281)	(0.1429)	(0.1482)	(0.1523)	(0.1542)	(0.1590)	(0.1739)	(0.1738)
Total$_k^{c\text{-H}}$	-0.0463	-0.0446	-0.0423	-0.0395	-0.0396	-0.0400	-0.0402	-0.0421	-0.0480	-0.0494
	(0.0342)	(0.0336)	(0.0335)	(0.0333)	(0.0332)	(0.0332)	(0.0332)	(0.0332)	(0.0331)	(0.0331)
Base: H vs. L	10.92	4.708	4.132	2.008	2.411	2.444	2.374	2.688	3.121	3.609
Threat: H vs. L	9.051	4.971	3.407	4.346	3.744	2.413	2.447	1.955	1.782	1.465

Notes: The table presents the results from LPM estimations of equation (8) for diffusion centrality measures with $T \in \{1, ..., 10\}$ (columns 1–10) and $q \in \{1, 0.75, 0.5, 0.25\}$ (Panels A–D). (Compare the results from columns (2) and (4) from Table 6.) Within each panel, the last two lines report the F-Statistics testing the H0: $\alpha^{\mathrm{L}} + \beta_j^{\mathrm{L}} = \alpha^{\mathrm{H}} + \beta_j^{\mathrm{H}}$ for $j = 1$ (Base) and $j = 2$ (Threat), respectively. All estimates are based on 14,987 observations from 3,764 networks. Standard errors, clustered at the network level, are in parentheses. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Table B.9 - Local treatment concentration – Pooled mailing treatments

	IH – Index		IH^+ – Dummy	
	(1)	(2)	(3)	(4)
$Mailing_k$	0.3070***	0.2853***	0.3140***	0.2992***
	(0.0371)	(0.0386)	(0.0410)	(0.0427)
$Mailing_k \times IH_k^{mail}$	-0.0234	-0.0229		
	(0.1046)	(0.1047)		
IH_k^{mail}	-0.0460	0.0577		
	(0.0643)	(0.0849)		
IH_k^{exp}		-0.1070*		
		(0.0634)		
$Mailing_k \times IHD_k^{mail}$			-0.1463***	-0.1641***
			(0.0507)	(0.0540)
IHD_k^{mail}			0.0109	-0.0007
			(0.0126)	(0.0147)
IHD_k^{exp}				0.0216
				(0.0170)
R^2	0.0926	0.0928	0.0933	0.0934

Notes: The table replicates the estimates from Table 7 when we pool the two mailing treatment rates into one ($Mailing_k$ = $Base_k$+ $Threat_k$). All estimates are based on 14,987 observations from 3,764 networks and account for $Total_k$ fixed effects. Standard errors, clustered at the network level, are in parentheses. ***/**/* indicates significance at the 1%/5%/10%-level, respectively.

Appendix C

This Appendix offers further details on the network characteristics explored in Section V.

Network Characteristics

Recall that we refer to $\mathbf{A} = [\mathbf{a_{ij}}]$ as the adjacency matrix of a network, where $a_{ij} = 1$ if there is a link between households i and j (i.e., if $(i, j) \in \Xi$) and zero otherwise.

Degree. The degree of household i is given by the number of its first-order neighbors (FONs), i.e., by the cardinality of the set $\mathcal{N}_i$.

Clustering. The clustering coefficient is the fraction of neighbors of i who are neighbors themselves. The clustering coefficient c_i of household i is defined as follows: $c_i = \frac{\sum_{j<k} a_{ij}a_{ik}a_{jk}}{\sum_{j<k} a_{ij}a_{ik}}$.

Eigenvector Centrality. Eigenvector centrality (EC) is one of several measures that determine the relative importance of a node within a network. The measure assigns relative scores to all nodes in the network, assuming that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Eigenvector centrality is defined as

$$EC_i = \frac{1}{\lambda} \sum_{j \in N_i} EC_j = \frac{1}{\lambda} \sum_{j \in \mathcal{N}} a_{ij} EC_j.$$

The equality can be rewritten as the eigenvector equation $\mathbf{A}\, EC = \lambda EC$. Newman (2006) shows that only the highest λ satisfies the requirement of entirely positive entries of the vector EC and thus, eigenvector centrality of agent i is uniquely determined as the i^{th} entry of the respective eigenvector EC.

Diffusion Centrality. Banerjee et al. (2019) have shown that in a simple model, where treated households ℓ initiate the spread of information I^1_ℓ, which is then passed on 'truthfully' by network neighbors in subsequent periods, the expected total number of times I_ℓ is heard by any other household in the network after T rounds of communication is given by

$$DC^T_\ell := \sum_{t=1}^{T} (q\mathbf{A})^t \vec{e}_\ell, \tag{1}$$

where $\vec{e}_\ell$ is the ℓ-th unit vector (i.e. the vector with all entries zero and the ℓ-th entry 1). DC_ℓ is referred to as household ℓ's 'diffusion centrality' (DC) and q is the probability with which information is passed on among neighbors, as defined in Section IV.A.

Local Concentration of Intervention

Let us denote with τ an agent's treatment within the experiment, i.e., $\tau \in \{\text{base}, \text{threat}, \text{control}\}$. Define by in^τ_k the average number of neighbors of type-τ agents in network k, who are also of type τ. Define by out^τ_k the average number of neighbors of type-τ agents in network k, who are *not* of type τ. Obviously, $in^\tau_k + out^\tau_k$ coincides with the average degree of type-τ households in network k, i.e., with their average number of FONs.

We can then define the index $H^\tau_k = \frac{in^\tau_k}{in^\tau_k + out^\tau_k}$ (compare Currarini, Jackson and Pin, 2009). Based on this, we can now introduce:

(i) **IH-Index**: The inbreeding homophily index for type τ is given by $IHI^\tau_k = \frac{H^\tau_k - \frac{N-1}{N}(\tau - rate_k)}{1 - \frac{N-1}{N}(\tau - rate_k)}$.

(ii) **IH Dummy**: $IHD^\tau_k = 1 \leftrightarrow IHI^\tau_k \geq 0$.

The IH-index is positive if there is homophily and negative if there is heterophily. Note that in small networks the IH-index is slightly biased downwards in the sense that in the case of purely random linking, the expected value of the index would be $\frac{-1}{N-1}$. This expression converges to zero as N becomes large, but it is clearly different from zero (and negative) for small network sizes. The latter fact motivates us to consider the IH Dummy, which indicates simply whether there is homophily in the network or not.

Appendix D

Baseline Mailing (FIS' Standard Cover Letter)

Dear Mr. X,

You listen to radio, you watch TV? Then you are aware of the program variety offered by Austrian Public Broadcasting. The provision of these services, however, requires funding. Therefore, everybody who owns a radio or a TV has to pay license fees. It is the task of FIS Fee Information Service GmbH to ensure that all TV and radio consumers pay these fees.

Our data base does not show a registration of TV or radio equipment at your address. *This can have several reasons:*

- *We may have made a mistake in our data base and you are already registered at FIS.* ***In this case, we apologize in advance.***
- *Your registration data may have changed, e.g., due to a move or a name change (marriage), and our computer system cannot match the data with your registration.*
- *You may not hold a radio or a TV at this address and therefore do not have to register anything.*
- *Maybe you have just forgotten to register your TV or radio.*

We are legally obliged to clarify this issue and kindly ask you to answer our questions – even if you have already registered at FIS. On the back of this letter you find a response form. ***Please fill in this form and send it back within the next 14 days.***

[1]

We thank you for your cooperation. If you require further information, please call our service hotline at 0810 00 10 80 (Monday to Friday, 8.00 am to 9.00 pm, Saturday from 9.00 am to 5.00 pm) or visit our web page at www.orf-gis.at. Kind regards, your FIS–Team.

Threat Mailing

The threat treatment includes the following paragraph at position [1] of the cover letter:

If you do not respond to this letter, a staff member of FIS will contact you in order to request information from you personally. *If you refuse to provide information or if there is a well-founded suspicion that you provide disinformation, FIS is obligated to order an inquiry by the responsible federal authorities. Please keep in mind that in this case you may face legal consequences and considerable costs.*

Original Copy of Threat Mailing

GEBÜHREN INFO SERVICE

GIS GMBH, 1051 Wien, Postfach 1999, DMMD210 60084178

Herrn
[redacted]

60084178
DMMD210

Wien, 27. September 2005

SIE HÖREN RADIO, SIE SEHEN FERN?

Sehr geehrter Herr [redacted],

Sie hören Radio, Sie sehen fern? Dann kennen Sie die vielfältigen Programme, die Ihnen der ORF täglich bietet. Diese Leistungen kosten Geld. Aufgabe der GIS Gebühren Info Service GmbH ist es, dafür zu sorgen, dass alle Konsumenten von Radio und Fernsehen Gebühren zahlen. Denn sobald man ein Rundfunkempfangsgerät besitzt, sind Gebühren zu bezahlen.

Unter Ihrer Anschrift finden wir keine Meldung von Rundfunkempfangsgeräten in unserer Datenbank. Das kann verschiedene Gründe haben:

- Vielleicht ist uns ein Fehler in der Datenverwaltung unterlaufen und wir dürfen Sie bereits zu unseren Kunden zählen. **In diesem Fall bitten wir schon jetzt um Entschuldigung!**
- Vielleicht haben sich Ihre Kundendaten geändert, etwa durch Übersiedlung oder Namensänderung (Heirat), und unsere EDV kann Ihre Daten nicht zuordnen.
- Vielleicht haben Sie keine Rundfunkempfangseinrichtungen unter dieser Adresse und sind daher auch nicht meldepflichtig.
- Vielleicht haben Sie aber einfach nur vergessen, Ihre Geräte anzumelden.

Wir sind von Gesetz wegen verpflichtet nachzufragen und bitten Sie deshalb, unsere Fragen zu beantworten - in jedem Fall, auch wenn Sie bereits Kunde sind. Eine Rückantwort ist auf der Rückseite dieses Schreibens vorbereitet. **Bitte füllen Sie diese aus und schicken Sie den Bogen innerhalb von 14 Tagen im Antwortkuvert an uns zurück.**

Sollten Sie auf dieses Schreiben nicht reagieren, wird Sie demnächst ein Mitarbeiter der GIS kontaktieren, um eine persönliche Auskunft zu erhalten. Verweigern Sie diese oder besteht der begründete Verdacht, dass Sie eine falsche Auskunft erteilt haben, hat die GIS eine Überprüfung der Gebührenpflicht seitens der zuständigen Bundesverwaltungsbehörde zu veranlassen. Bedenken Sie bitte, dass Ihnen in diesem Fall rechtliche Konsequenzen sowie erhebliche finanzielle Kosten entstehen können.

Wir danken Ihnen für Ihre Mithilfe. Wenn Sie weitere Informationen wünschen, können Sie uns unter der Service-Hotline **0810 00 10 80** (Montag bis Freitag von 8.00 bis 21.00 Uhr, Samstag von 9.00 bis 17.00 Uhr) anrufen oder uns im Internet besuchen: www.orf-gis.at.

Mit freundlichen Grüßen

Ihr
GIS Team

GIS GEBÜHREN INFO SERVICE GMBH
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