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Bound by Borders: Voter Mobilization through Social Networks

Abstract

A vast and growing quantitative literature considers how social networks shape political mobilization but the degree to which turnout decisions are strategic remains ambiguous. Unlike previous studies, we establish personal links between voters and candidates and exploit discontinuous incentives to mobilize across district boundaries to estimate causal effects. Considering three types of network—families, co-workers, and immigrant communities—we show that a group member's candidacy acts as a mobilizational impulse that propagates through the group's network. In family networks, some of this impulse is non-strategic, surviving past district boundaries. However, the bulk of family mobilization is bound by the candidate's district boundary, as is the entirety of the mobilizational effects in the other networks.

JEL-Codes: D720, D850, C330.

Keywords: political participation, social networks, electoral geography.

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1. Introduction

Political parties can leverage social networks to boost voter turnout (Shachar and Nalebuff, 1999). They can, for example, make appeals through networks; orchestrate pressure to increase the social cost of *not* voting (Dellavigna et al., 2016; Gerber, Green and Larimer, 2008); and choose candidates with an eye to their ability to mobilize the voters with whom they are connected.

Existing studies focus on candidates' mobilizational incentives (would effort make the difference between winning and losing?) and the characteristics of the networks they seek to activate (how strong are the links?)—while limiting attention to networks embedded within single electoral districts. For example, experimental studies examine the propagation of mobilizational messages from spouse to spouse (Nickerson, 2008) and friend to friend (Bond et al., 2012); survey-based analyses explore propagation within villages (Cruz, 2019; Eubank et al., 2021); observational studies consider propagation through electoral districts (Cox, Rosenbluth and Thies, 1998); and studies based on administrative data examine propagation from spouse to spouse (Dahlgaard et al., 2022) and neighbor to neighbor (Finan, Seira and Simpser, 2021). Because these studies focus on single districts, they cannot examine how mobilization and turnout change when district boundaries are crossed—which is our focus here.[1]

Theories of turnout can be divided into those that emphasize strategic mobilization by candidates and parties; and those that stress individual voters' characteristics. Strategic mobilization theories naturally imply that mobilizers will target those who can vote in the specific election in which they are interested; and will thus be concerned with voters' geo-location inside or outside of electoral district boundaries. In contrast, prominent alternative theories downplay mobilization and focus instead on (a) consumption values such as "citizen duty" (Riker and Ordeshook, 1968), (b) individual resources and

[1]A related literature uses fine-grained geo-coded data to study the importance of geography in determining the location of local public goods and bads (Carozzi and Repetto, 2019; Folke et al., forthcoming; Harjunen, Saarimaa and Tukiainen, 2023). These papers also focus on single electoral districts and thus do not examine how mobilization in social networks changes when district boundaries are crossed.

expressive values (Brady, Verba and Schlozman, 1995), and (c) altruism (Fowler, 2006).[2] Under these theories, voting is a largely non-strategic act, and—as we explain below—electoral boundaries should play a much smaller role than they do in models of strategic mobilization.

Our aim in this paper is to empirically explore whether and how much turnout is shaped by electoral boundaries. In particular, we examine the effects of within-network candidacies on turnout in several different social networks; and the extent to which these effects change at district boundaries. Do effects decline sharply, consistent with mobilization being the dominant determinant of turnout; or do they decline gently or insignificantly, consistent with turnout being driven mostly by individual resources and decisions? The stronger the boundary effect, the more that parties should take into account the overlap between potential candidates' social networks and their electoral districts; and we explore this issue, too.

The empirical setting for our analysis is Norway, which affords panel data on the turnout of a large sample of urban Norwegians. Our unique data allow us to observe these voters' connections to the universe of local-level political candidates (approximately 60,000 per year) over two election periods. We consider three types of social networks—families, co-workers, and immigrant-occupation groups—and estimate the extent to which the candidacy of a group member acts like a mobilizational impulse which propagates through the group's network.[3] Our research design mitigates several problems noted in the literature on peer effects (Bramoullé, Djebbari and Fortin, 2020). For example, neither self-selection into networks nor endogenous change of network structures over time are significant problems for the static networks we study. We deal with common external causes of turnout via fine-grained local unit-time fixed effects.

[2]In a review of the literature, Smets and van Ham (2013, p.345) conclude that the "jury is still out on what the foundations of micro-level turnout are".

[3]Several scholars have used comparable administrative data from Norway to examine the empirical relevance of different types of social networks. For example, Dahl, Kostøl and Mogstad (2014) document the existence of 'family welfare cultures', where parents' involvement in disability insurance influences their children's future participation. Markussen and Røed (2015) document how social insurance claims spread among neighbors and former schoolmates. Additionally, Bratsberg et al. (2021) find that the initial neighborhood that refugees are placed is highly predictive of future electoral participation.

We find that the mobilizational boost from having a network member running for office is about two to four percentage points. The boost is stronger in narrow networks (e.g., close family members), falls moderately with increasing geographical distance, but falls sharply to zero when social networks cross district boundaries. This suggests that candidates seek to win seats and therefore mobilize only those in their network(s) who can actually vote for them.

We also provide two kinds of evidence that political parties select immigrant candidates for their mobilizational prowess. First, in Section 6 we document a "Jackie and Jill effect" (Anzia and Berry, 2011): immigrant candidates face voter bias and it appears that they can secure list spots only if they can mobilize enough new voters to compensate for the loss of biased voters. Consistent with this view, we find that immigrant candidates generate substantially larger turnout boosts among their social networks (here, we explore in particular their families) than do native candidates; and this effect is larger in parties whose members view immigrants less favorably. Second, in Section 7 we offer some correlational evidence that immigrants with more *electorally efficient* occupational networks—with higher percentages residing in the same electoral district as the potential candidate—are more likely to become candidates.

2. Mobilizing social networks across boundaries

If voters care only about which candidate wins, then equilibrium turnout will be near zero in large electorates, since the probability of a single vote being pivotal is negligible (Palfrey and Rosenthal, 1985). To explain why turnout is well above zero, scholars have sorted into two broad schools, one arguing that turnout results from individual decisions, another focusing on strategic mobilization.

These schools make differing predictions about how electoral boundaries shape turnout. Strategic mobilizers should naturally target voters who can actually vote for them. Thus, any turnout effects due to candidates mobilizing their social networks should stop at the border, where their mobilizational incentives discontinuously decline.

In contrast, theories of turnout that focus on individuals sometimes predict little or no border effects. For example, (1) instrumental voters would not generate a border drop-off because the difference between having literally zero chance of affecting the outcome (for out-of-district voters) and virtually zero chance (for in-district voters) is negligible; (2) citizen-duty voters would not generate a border drop-off because they vote based on a generalized sense of duty which should not vary discontinuously at any particular border; (3) genetic predispositions to participate (Fowler and Dawes, 2008) do not vary discontinuously at borders; and (4) individuals' resource endowments (Brady, Verba and Schlozman, 1995) do not vary discontinuously at borders (even if they do, our individual fixed effects adjust for these).

What if voters turn out simply because they enjoy voting for a candidate with whom they have social ties? This act-contingent utility would drop discontinuously at the candidate's electoral border.[4] Thus, if enough voters turn out as an act of consumption, then a border drop-off could arise in the absence of active candidate mobilization. As regards this possibility, we simply point out that candidates' optimal mobilizational effort is not zero. They know which of their network members will be likely to vote, if informed of their candidacy, and they choose the level of nagging appropriately. Thus, candidates should mobilize in order to complement voters' consumption utilities.

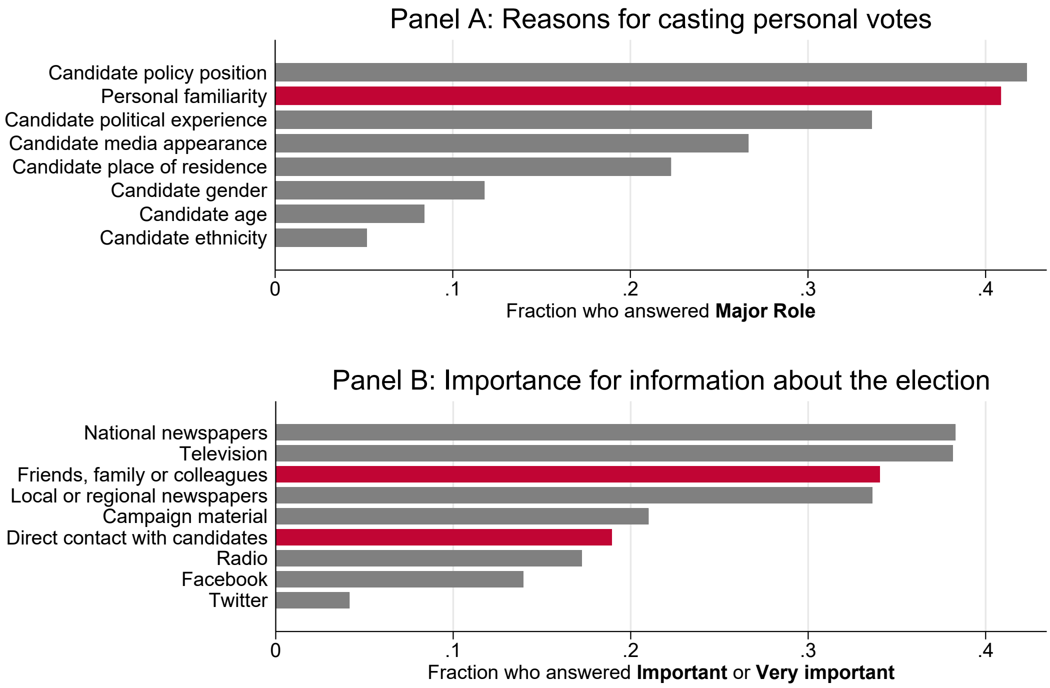
We also know from surveys that acquaintance with and direct contact by candidates are important mediators for voting decisions. In the 2015 Norwegian local elections, personal familiarity played a major role for 40% of respondents casting a personal vote (Panel A of Figure 1), suggesting candidates mobilized their "friends and neighbors."[5] A separate survey conducted by Statistics Norway in 2015 showed that 34% of respondents considered *"family, friends, and co-workers"* to be important or very important

[4]Of course, if voters enjoy voting for a within-network candidate's *team*, then again district boundaries will not matter as much.

[5]Several studies – from Norway (e.g., Fiva, Halse and Smith, 2021) and other countries (see Górecki, Bartnicki and Alimowski, 2022, for a recent review) – have documented that candidates tend to receive more votes in their hometowns. Key (1949) famously refers to this as "friends and neighbors" voting.

for getting information about the election, while 19% reported that direct contacts with candidates were important or very important (Panel B of Figure 1).

Figure 1: Survey evidence on voting decisions



Notes: Panel A presents survey evidence of voters' reasons for casting personal votes. Reported are the fraction of survey respondents answering that they cast a personal vote because the reason given in the legend played a 'major role'. Alternative responses are 'don't know', 'no role', and 'some role'. Data from the 2015 Local Election Survey (Lokalvalgsundersøkelsen) (n= 1,190). The analysis is restricted to the 619 respondents who report that they cast a personal vote. Panel B presents survey evidence showing the importance of various factors for getting information about the election. Reported are the fraction of survey respondents answering 'important' or 'very important'. The alternative responses are 'not important', 'of little importance', and 'of some importance'. Data from the 2015 Election Survey (Velgerundersøkelsen) (n= 6,275).

If strategic mobilization is a primary driver of turnout patterns (as we posit here), and candidates are most effective at mobilizing through their social networks (as much literature suggests), then parties should consider the overlap between potential candidates' social networks and the electoral districts in which they might run. We consider this possibility in Section 6 below.

3. Empirical case: Norway 2015–2019

3.1 *Elections and voter turnout*

Norway's unitary state has three governmental tiers: central, regional and local. The local governments, which employ about 17% of the Norwegian work force, are multipurpose authorities responsible for welfare services like child care, compulsory schooling, and primary health care. The regional governments have more limited tasks, such as regional transportation, and employ 2% of the Norwegian work force.

Local and regional elections are held concurrently every fourth year in September. Norwegian citizens aged 18 or older by the end of the election year, and non-citizens with three years of consecutive residency, are eligible to vote (see Appendix B). Voter registration is automatic, and individuals receive a letter in the mail about a month before the elections informing them of their rights and the closest polling place (Ferwerda, Finseraas and Bergh, 2020).

Local elections are decided by "flexible list systems" where both voters and parties affect candidate selection. Voters choose a party list and may opt to express preferences for individual candidates by casting personal votes. Parties affect candidate selection by granting some candidates, listed on the top of the ballot in bold face, a "head start". The advantage is so large that other candidates almost never receive enough personal votes to overtake a candidate with a head start (see Appendix C).

In Norway, local councilors typically hold other jobs concurrently. However, mayors (elected by the councilors) have full-time well-paid jobs that also serve as stepping stones to national politics (Cirone, Cox and Fiva, 2021).

3.2 *Candidate-level data combined with administrative voter turnout data*

Our candidate-level data set stem from Fiva, Sørensen and Vøllo (2021) and cover candidates running for local and regional office in the 2015 and 2019 elections. We restrict our analysis to those running for one of the nine main parties that dominate Norwegian politics.[6] 90% of these candidates run only for local office, 8% run for local and regional office, and 2% run for regional office only. We focus on candidates running for the local office only (92,767 candidate-year observations).

We use administrative registers to construct a balanced panel of 1,400,562 voters in the 2015 and 2019 elections, constituting about 34% of the Norwegian vote-eligible population (see Appendix B for details on sample construction). Our main outcome of interest, turnout, is collected from the *Electronic Election Administration System* adopted by 27 municipalities (out of 428) in 2015. We excluded two municipalities due to a reform which altered their borders between 2015 and 2019. While candidacies may well affect not just whether, but also for whom, people voted, we lack data on this and so cannot study it.

Appendix Table A.1 shows that the 25 municipalities in our main sample – which includes the four largest cities in Norway – have a higher share of immigrants and somewhat lower voter turnout (about 58%).[7] The 2015 data have been previously used by Ferwerda, Finseraas and Bergh (2020), who study how immigrants' early access to political institutions affects turnout in subsequent elections, and Bratsberg et al. (2021), who study how refugees' initial neighborhood affects their future political participation. Geys and Sørensen (2022) use 2013-2019 panel data to study how public sector employment affects voter turnout.

Norway is divided into approximately 14,000 "basic statistical units" (BSU's) nested within electoral districts (municipalities). These units vary in size, from just a few city blocks to several square kilometers in rural areas. Each BSU is constructed to cover homogenous areas in terms of demography, nature and infrastructure. An illustrative map of BSU's in Oslo (the capital) is shown in Appendix Figure A.2. Our data document

[6]Ordered along the left-right dimensions, the nine main parties are: Red Party, Socialist Left Party, Labour Party, Center Party, Green Party, Liberal Party, Christian Democrats, Conservative Party, and Progress Party. The non-main parties include party-independent lists and minor parties that tend to get limited electoral support.

[7]Appendix Figure A.1 illustrates our sample using maps of Norway.

the BSU in which each voter and candidate resides, as well as their family relations, immigration status, employment, and occupation.

3.3 *Social networks*

We consider three types of social networks—families, co-workers, and immigrant communities. We face a trade-off in choosing how broad the network definitions should be; a broad definition is useful for statistical precision but the network ties are probably weaker. A narrow definition may have lower statistical precision but the network ties are probably stronger. For each of these three types of network, we therefore create one narrow and one broad category, with the latter subsuming the former. All social networks are assumed to be static and defined as they exist in 2015.[8] This section provides a brief description of each network (see Appendix B for details).

Families

Political candidates are matched to family members in *close family networks*, defined as any parent, sibling or child, or in *extended family networks*, which also include grandparents, aunts, uncles, cousins, nieces, nephews, grandsons, and granddaughters. We cannot accommodate spouses or co-habitants, as we are specifically looking for cases of geographic variation between voters and politicians.

On average, a close (extended) family network has five (fifteen) members (Appendix Table A.2; Appendix Figure A.3). Among voters and politicians who belong to the same close family network and live in the same municipality, 23% reside within the same BSU (Appendix Figure A.4) (presumably many belong to the same household).

Co-workers

As mentioned above, most candidates also hold regular jobs outside of politics. In a study using Swedish data, Aggeborn and Andersson (2022) find that workplace networks

[8]Violations of this assumption mean that some ties between candidates and people in their networks may no longer exist (e.g, a person switching jobs). In general, this should weaken any results we find.

matter for individuals' decision to run for office. We match candidates to their co-workers using payroll reports from Norwegian employers (*A-melding*), restricting our sample to small and medium establishments, thereby excluding "super" firms where social connections are likely to be weaker. Even with this restriction, we retain over 97% of registered establishments (63% of employees). Co-workers are defined at either the broader establishment or the narrower establishment-age group (younger than 35, 35-50, over 50) level. We believe the latter to be a plausible proxy for factions within workplaces but also consider splits by firm size in the appendix. Each co-worker network contains around three (six) voters on average at the establishment-age group (establishment) level (Appendix Table A.2).

Immigrants

We define first-generation immigrants as people born outside of Scandinavia to non-Scandinavian parents.[9] The five largest immigrant groups in our voters sample are from Poland (10.5%), Pakistan (6.0%), Somalia (5.2%), Iraq (5.2%) and Iran (3.9%). Among political candidates in 2015, the top five groups were from Germany (10.3%), Iran (5.6%), the Netherlands (4.8%), Poland (4.1%) and Bosnia-Herzegovina (4.0%). Because immigrants sharing the same occupation are more likely to be in the same social network, we match candidates and voters who were born in the same country and have the same profession (in 2015).

To classify occupations, we use the standard four-level classification of Norwegian occupations (*STYRK-08*). We use three-digit occupation codes (e.g., "231 University and higher education teachers") to define the narrow category, and two-digit codes (e.g., "23 Teaching professionals") to define the broad category.[10] The three most common three-digit occupations among immigrant voters are *Domestic, hotel and office cleaners*

[9] We disregard Swedish and Danish immigrants, who are culturally and historically similar to native Norwegians.

[10] The fraction of immigrants with politicians in their network is 40% and 53%, for three-digit or two-digit occupation codes, respectively. We do not define immigrant networks at the birthcountry level because then almost all immigrants (98.47%) have at least one politician in their network. We explore this further in Section 7.

and helpers (8.6%), *Personal care workers in health services* (8.2%) and *Shop salespersons* (5.2%). On average, there are 14 (29) voters per network using the three-digit (two-digit) definition (Appendix Table A.2; Appendix Figure A.3). Compared to politicians in the other network types, immigrant candidates tend to be more educated, but have less political experience and are less likely to be granted a "head start" by their party (Appendix Table A.3).

4. Empirical specification

4.1 *Baseline model*

To study voter mobilization in networks, we estimate the following linear probability model:

$$Turnout_{ibt} = \alpha_{ib} + \lambda_t + \beta AnyDistrict_{it} + \gamma SameDistrict_{it} + \varepsilon_{ibt}. \quad (1)$$

$Turnout_{ibt}$ is an indicator variable turned on if individual i, residing in BSU b, at time t turns out to vote. $AnyDistrict_{it}$ is an indicator variable turned on if i has a network member running for office at time t. $SameDistrict_{it}$ is an indicator variable turned on if i has a network member running for office in i's election district at time t.[11] β captures any network-wide effect on members' propensity to turn out (that does not depend on co-residence), while γ captures the additional effect of co-residence. We expect district boundaries to affect the propagation of mobilization within networks, i.e., $\gamma > 0$.

By including individual-BSU fixed effects (α_{ib}) in Equation (1), we ensure that inference is drawn from individuals who do not move across BSUs but do experience a change in their social network over time (i.e. a network member entering or exiting politics). We also include time fixed effect (λ_t) and allow for arbitrary correlation within BSUs ($n = 3,705$) by clustering the error term ε_{it} at this level. Clustering at the election

[11] Candidacy is coded as 1 regardless of the number of connected politicians. Among nation-wide networks with at least one candidate, 94% (close families), 87% (age-establishment co-workers) and 44% (3-digit immigrants) are single-candidate networks.

district level ($n = 25$) gives similar standard errors.

4.2 *The discontinuity at the district boundary*

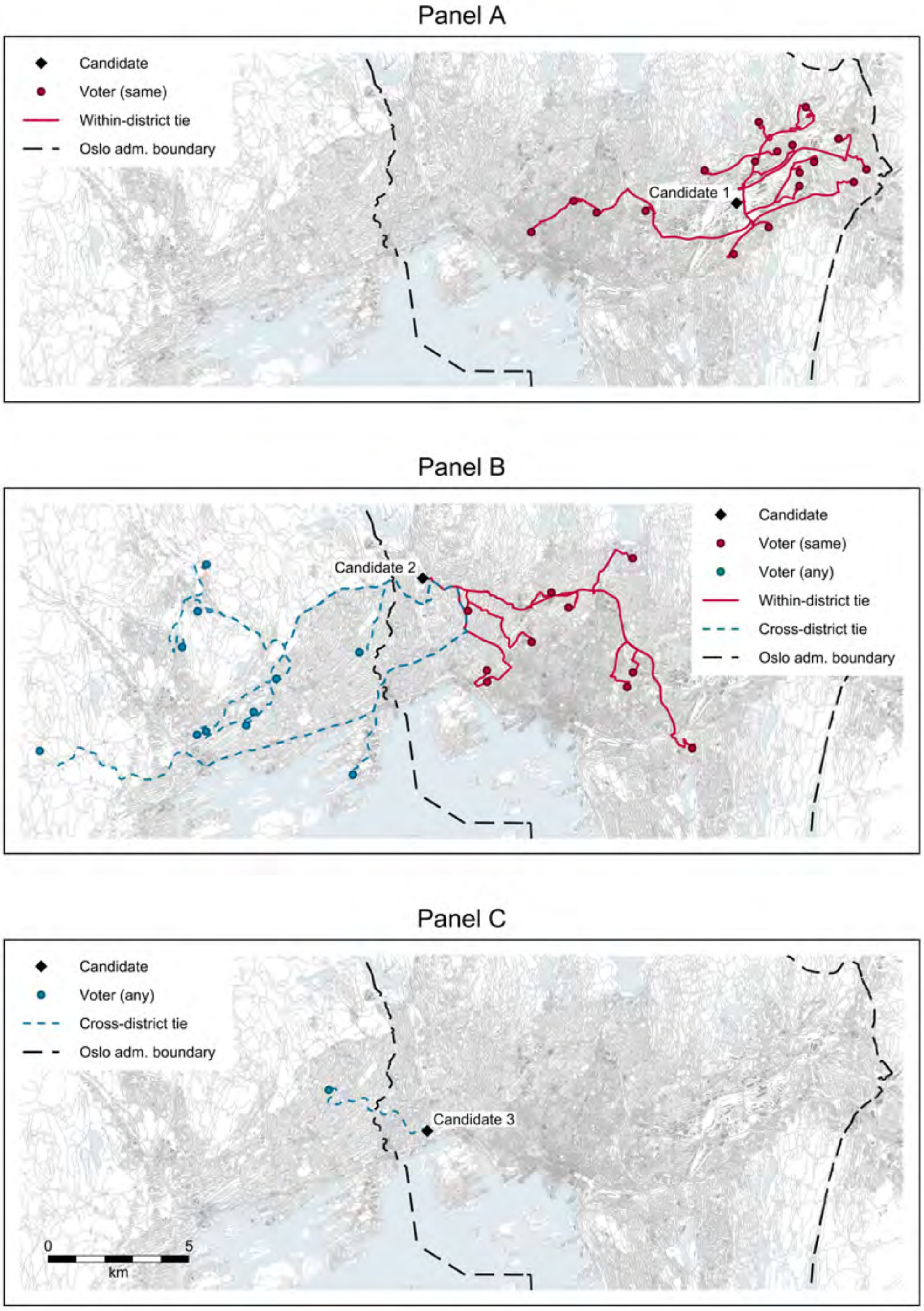
The baseline model (Equation (1)) distinguishes between candidates inside and outside the focal voter's district. A natural extension is to use the district boundary explicitly in our research design. Specifically, we measure the fastest driving distance in kilometers between the BSU of the candidate and the BSU of the network member (voter).[12] We expect the mobilizational impulse to fall in distance within districts and to exhibit a sharp drop-off when the network crosses the candidate's district boundary.

To fix ideas, consider the co-worker networks illustrated in Figure 2. At one extreme, candidate 1's co-workers all reside in the same municipality (Oslo). At another extreme, all of candidate 3's co-workers (in this case, just one person) reside outside the candidate's home district. In-between, about half of candidate 2's co-workers are in the same district. Our empirical design exploits this distributional feature by recognizing that politicians have discontinuous incentives to mobilize voters within and outside their own electoral districts. In Figure 2, candidates 1 and 2 may improve their election outcomes by mobilizing some or all of their connected voters. For candidate 3, however, we would expect the mobilization incentive to be negligible.

Our identification strategy is related to the geographic regression discontinuity design, where a geographic or administrative boundary splits units into treatment and control (Keele and Titiunik, 2015). Examples include Black (1999), who leveraged school district boundaries to estimate parents' willingness to pay for good schools, and Huber and Arceneaux (2007), who compared same-state voters in different media markets to study the effects of advertising. In geographic regression discontinuity designs, units *equally close to the boundary* but on opposite sides of it are taken as valid counterfactuals for each other. We consider voters who are *equally close to the politician network member*,

[12]If a voter has multiple network members running for office inside the district boundary, we use distance to the geographically closest within-network candidate. If a voter has no network members running for office inside the district boundary, we use distance to the geographically closest network member outside the district.

Figure 2: Network Appearance



Notes: The figure shows the geospatial distribution of voters and politicians in three co-worker networks in our data (estbl. level). Black diamonds indicate the geographic locations of politicians, while red (blue) circles indicate the locations of voters in the same (different) district(s). Solid (dashed) lines illustrate the fastest driving route between politicians and each connected voter when both reside in the same (different) district(s). In this illustrative example, the within-district locations of each politician is randomized to preserve their anonymity, while we use the actual basic statistical unit of connected voters. Underlying map data: ©OpenStreetMap contributors. Data available under the Open Database License.

but on opposite sides of district boundaries, as valid counterfactuals for each other (after netting out α_{ib} and λ_t).[13]

5. Results

5.1 *The mobilization boost*

Table 1 provides estimation results from the baseline model (Equation (1)) for different definitions of the family (columns 1-2), co-worker (columns 3-4) and immigrant networks (columns 5-6).[14]

Column (1) shows that voters with a close family member running in *another* district from the one they live in increase their turnout rate by about 0.6 percentage points (from a baseline turnout level of 66.6 percent). This effect, which is statistically significant, might be driven by increased civic pride, belief in the legitimacy of the political process, and feelings of efficacy that affect family members regardless of where they reside.

The mobilization effect is, however, about five times as large for family members co-residing in the municipality where the candidate runs for office. We estimate a mobilizational boost of an additional 2.6 percentage points. The cross-district drop-off in the mobilizational impact of having a family member as a candidate—from 3.2 to 0.6 percentage points— reflects the fact that the candidate has a larger incentive to lobby family members who can vote for them, as we hypothesized in Section 4.1 ($\gamma > 0$). We discuss challenges to this interpretation in Section 5.4.

When using the broader family network (column (2)), we find that both the out-of-district boost and the additional within-district boost are smaller. This is as expected

[13] Any time-invariant factors that potentially change at the border (such as the probability to belong to a particular network) are netted out by α_{ib}.

[14] Clustering at the election district level ($n = 25$) gives similar standard errors as in Table 1. As an alternative way to assess our statistical inference, we re-estimate our baseline model after randomizing who is running for office (keeping the social networks constant). This placebo exercise, which we repeat 100 times for each type of network, yields a distribution of point estimates which are centered at zero (Appendix Figure A.5). Importantly, the actual point estimates from Table 1 lie well outside the placebo distributions for all network types.

Table 1: Results - Baseline Networks Analyses

	Family		Co-workers		Immigrants	
	(1) Close	(2) Extended	(3) Age-estbl.	(4) Estbl.	(5) 3-digit	(6) 2-digit
No candidate in network	ref.	ref.	ref.	ref.	ref.	ref.
Any District	0.006	0.002	-0.001	-0.003	-0.004	-0.004
	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Same District	0.026	0.015	0.014	0.010	0.045	0.036
	(0.005)	(0.004)	(0.005)	(0.004)	(0.012)	(0.010)
Observations	2,801,126	2,801,126	1,087,562	1,087,562	239,810	239,810
Clusters	3,733	3,733	3,702	3,702	3,535	3,535
Mean turnout (%)	66.56	66.56	66.50	66.50	41.19	41.19

Notes: Each column represents a separate regression based on Equation (1), where the dependent variable is turnout for voter i in BSU b at time t. The sample is trimmed in columns (3)-(4) and (5)-(6) to only consists of individuals who belong to a network under the indicated category. Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.

since ties between close family members are stronger than among extended family members.[15]

Columns (3)-(6) show that social networks are also important for turnout among co-workers and co-occupational immigrant populations. For both networks, our estimates are somewhat larger for the narrow (age-establishment) than the broad (establishment) definitions of the network. We estimate a mobilizational boost of 1.4 percentage points for co-workers from the same age group (from a baseline turnout of 66.5 percent).[16]

For co-occupational immigrants, we estimate the largest mobilizational boost (4.5 percentage points from a baseline of 41.2%); we comment on why this is larger than in other networks in Section 6.[17] There are no statistically significant effects of having network members outside the district boundary for co-workers or co-occupational immigrant

[15] Appendix Table A.4 show that the strongest mobilizational boost come from children and parents running for office. All family categories display positive point estimates, except cousins, where the estimate is negative but statistically indistinguishable from zero.

[16] The co-worker network effects decline with network size (Appendix Table A.5) suggesting that social ties are stronger in smaller workplaces.

[17] Appendix Table A.6 shows that the within-district mobilizational boost is primarily driven by co-occupational immigrant networks where members have ties to Africa and Asia.

networks.

In Appendix D, we estimate heterogenous mobilization effects depending on candidates' electoral viability. We find that having a network member running in *another* district boosts a voter's turnout negligibly, irrespective of candidate viability. The within-district mobilization effect is, however, increasing in candidate viability. For example, we estimate that a strong candidate in a co-worker-age-group increases network members' probability of voting by six percentage points, while a hopeless candidate in the same co-worker-age-group only increases network members' turnout rate by one percentage point. The relationships between candidate viability and voter mobilization are similar, albeit more muted, for family and co-occupational immigrant networks.

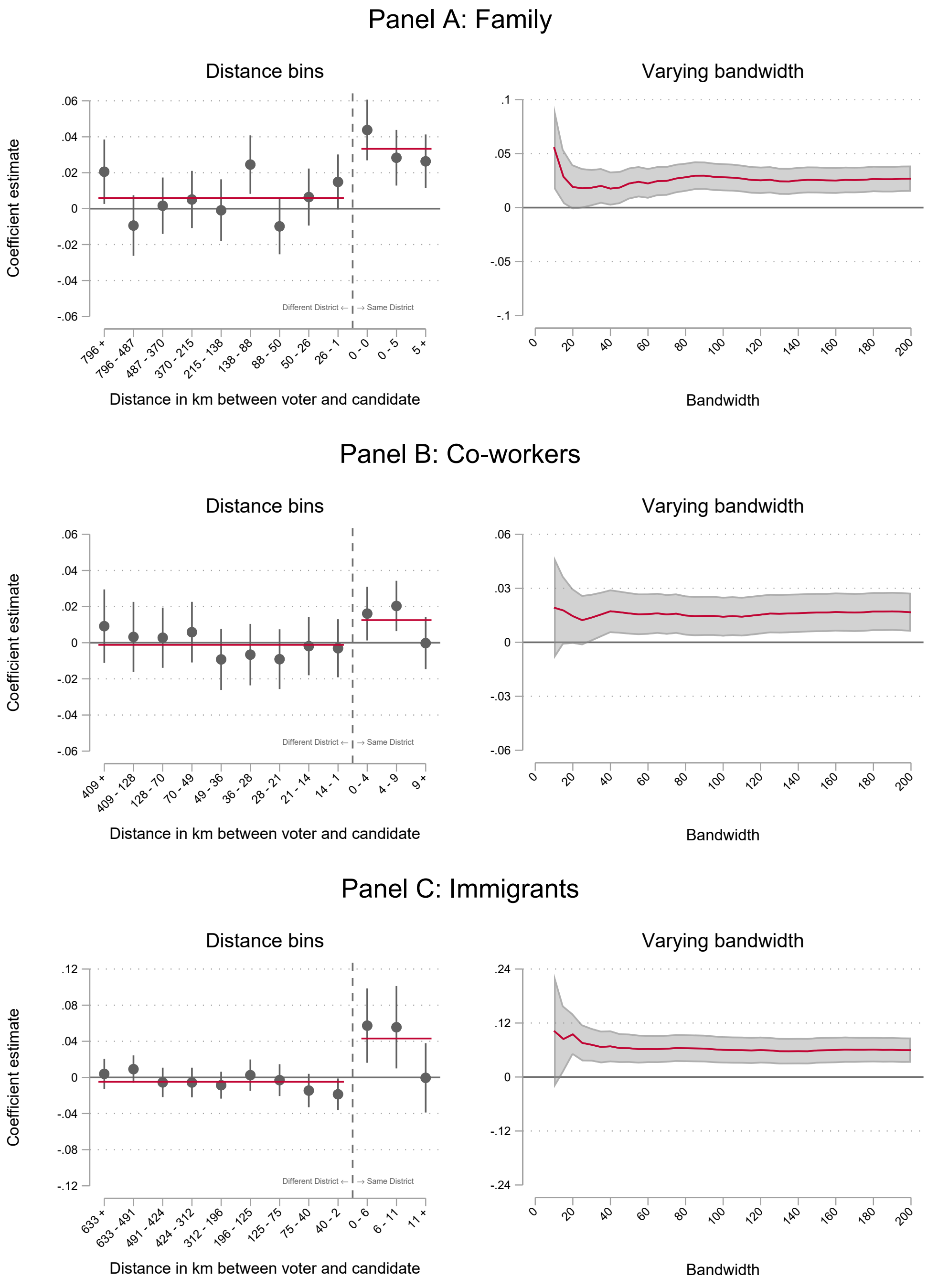
5.2 ***The border drop-off***

Panel A of Figure 3 shows how the mobilizational impact varies with distance between the voter and the candidate in his/her close family member network (the bins on each side include the same number of observations). Consider first the left side of the threshold in the plot to the left in Panel A, which captures effects for candidates living in a different district as the voter (and the horizontal red line correspond to the estimate of β reported in Column (1) of Panel A in Table 1). There is no indication that distance matters for turnout; even if network members reside within walking distance of each other (but in different districts) the confidence intervals overlap with zero.

Estimates to the right of the threshold capture effects for candidates living in the same district as the voter. We find that estimates are largest (above 4 percentage points) when network members reside in the same geographical unit but remain around 2.5 percentage points further away. The difference between the two horizontal red lines in Figure 3 corresponds to the estimated γ from Column (1) of Panel A in Table 1.

In the plot to the right in Panel A, we investigate how the average border effect (i.e., the difference between the red lines in the left-most plot) varies as we zoom closer to the threshold. As we move to the left, only individuals whose network distance is smaller

Figure 3: Effects over Distance and across District Boundaries



Notes: This figure displays how the mobilizational impact depends on distance in kilometers between voters' and candidates' basic statistical units (BSU). In each panel, the left plot reports coefficient estimates and 95 percent confidence intervals for observations belonging in each distance bin. The red lines denote the average mobilization impacts on the left and right side of the threshold. The number of observations per bin are constant on each side. The right plots in each panel reports our main coefficient estimates from Equation (1) but excludes from identification all observations whose distance falls outside the indicated bandwidth (i.e., the red line shows the difference between the lines in Panel A as we zoom closer to the threshold). If a person has multiple candidates in his/her network we use the geographically closest candidate to measure distance. For all networks, we use the narrow definition ('close', 'age-establishment', and '3-digit'). A small fraction of the sample is omitted from each analysis due to missing distance. Standard errors are clustered on the BSU level.

are used for identification. We find that the estimated γ is stable across bandwidths but increases slightly when the bandwidth becomes very small, in line with the results from the left-most plot. We believe this mitigates concerns about endogenous political entry; if candidates were chosen based on unobserved trends in the political engagement of their social networks, then we would have seen "mobilization" both inside and just outside district borders.

Panel B and C of Figure 3 performs an identical exercise for the narrow definition of co-worker and co-occupational immigrant networks. The results are similar to those for families but with less statistical precision to the right of the threshold (because of network and sample size).[18]

5.3 ***Two-step network effects***

In Table 2, we investigate whether mobilized voters in politicians' social networks go on to mobilize *additional* voters in their own social networks. Column (1) shows that turnout rates go up by 0.6 percentage points among the close family members of a person who has a close co-worker running for office when they all reside in the same district. Column (2) shows corresponding estimates when the mobilization impulse goes in the opposite direction, from family to co-worker networks. In this specification the two-step mobilization estimate is also positive (0.3 percentage points) but not statistically significant. In column (3), we pool the two-step mobilization effects to improve statistical precision. We find a statistically significant pooled effect of 0.5 percentage points. If the typical family member was connected to at least 25 persons as strongly as they were to their close co-workers, then the overall turnout boost via secondary mobilization would exceed the primary boost by a factor of four, in line with existing studies (e.g., Fowler, 2005; Bond et al., 2012).

Models 4-6 provide similar analyses of mobilization propagating from narrow immigrant-occupation to close family networks, vice versa, and pooling the two directions. As can

[18] Appendix Figure A.6 provides corresponding results using the broad network definitions.

Table 2: Mobilization Effects in Two-step Networks

	Co-workers and families			Immigrants and families		
	(1) Candidate → co-wkr.→ family	(2) Candidate → fam.→ co-worker	(3) Pooled	(4) Candidate → imm.→ family	(5) Candidate → fam.→ immigrant	(6) Pooled
No candidate in network	ref.	ref.	ref.	ref.	ref.	ref.
Any District	0.001	-0.003	-0.001	-0.002	0.006	0.003
	(0.002)	(0.002)	(0.001)	(0.006)	(0.004)	(0.004)
Same District	0.006	0.003	0.005	0.015	0.018	0.019
	(0.004)	(0.004)	(0.003)	(0.013)	(0.011)	(0.008)
Observations	2,801,126	2,801,126	2,801,126	2,801,126	2,801,126	2,801,126
Clusters	3,733	3,733	3,733	3,733	3,733	3,733
Mean turnout (%)	66.56	66.56	66.56	66.56	66.56	66.56

Notes: Each column represents a separate regression based on a variant of Equation (1) that estimates mobilization effects from multiple networks in the same model. The dependent variable is turnout for voter i in BSU b at time t. The variables of interest indicate if the voter is two steps *away from a candidate (e.g., the politician is a co-worker of a close family member, as in column (1)). All three network members (voter, mediator, candidate) must reside in the same district in order for* Same District *to indicate. First-order effects from the involved networks are also included in all models. Columns (3) and (6) consider pooled models where the mobilization impulse is allowed to be mediated by either of the networks in the preceding columns. All network categories use the* narrow *definitions (close, age-estbl., 3-digits). Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.*

be seen, we find a statistically significant pooled effect of 1.9 percentage points.

In both of these analyses, we again find a border dropoff. There is no evidence of two-step mobilization effects when the candidate resides in a different district from either their primary or secondary network member.

5.4 *Internal validity*

It is widely recognized that "in ... observational studies, the self-selection of people into peer groups can make the measurement of peer effects extremely difficult"(Sacerdote, 2014, p. 235). For example, Christakis and Fowler's (2007; 2008) finding that health outcomes (obesity, quitting smoking) propagate through networks of friends has been challenged by Cohen-Cole and Fletcher (2008), who show that even non-transmissible traits appear to propagate through friends' networks, using Christakis and Fowler's method.

Our research design mitigates such concerns. First, we study *static* networks. Thus, several threats arising from endogenous change in networks do not afflict our analysis. Second, individuals do not choose their families or immigrant groups; and their choice of workplace and occupation is more constrained than their choice of friends. Families do share nature (genes) and nurture (upbringing), and so do immigrant groups (genes, culture). But our individual-BSU fixed effects (α_{ib} in Equation (1)) control for the direct effect on turnout of these factors.

What about local variables that boost turnout among all network members residing in the same neighborhood? We can address that concern by replacing our year fixed effects (λ_t in Equation (1)) with BSU-year fixed effects (λ_{bt}).[19] Appendix Table A.7 shows that this leaves our results mostly unaltered.

Finally, the internal validity of our analysis could be compromised if parties allocate list positions to people whose networks are becoming more politically engaged over time. However, if candidates' networks were trending upward in political engagement, then we should see "mobilization" both inside and just outside district borders, contrary to what

[19] This follows the approach to controlling for environmental confounding via area fixed effects (Cohen-Cole and Fletcher, 2008).

we actually find.

5.5 *External validity*

Because candidates choose to seek list spots and parties choose to accept them, our results do not provide evidence that, were one to randomly assign list spots to the general population, similar mobilizational impacts could be expected. If parties award list spots to candidates they believe can mobilize more latent party supporters, then the within-network mobilizational boosts we identify will reflect the largest mobilizational boosts the party can discover among its supporters. Thus, our results may provide evidence on the upper tail of the mobilizational impacts that one could expect.

Of course, most parties place many people in unwinnable positions on their lists, and many of these may be selected for their loyalty or past service to the party, rather than their mobilizational ability. Moreover, if we were able to directly observe network connections, the mobilization boosts in our co-worker and immigrant networks (which are both proxies that may contain some rather weak ties) might be larger.

6. Comparing immigrant and native candidates

We have seen, in Section 5, that the immigrant co-occupational boost is substantially larger than the family and workplace boosts. One plausible reason for this is that immigrants have less information and lower baseline turnout rates than natives. For example, in a canvassing experiment in France, Pons and Liegey (2018) find larger impacts of visits on immigrants than the native population, and present evidence suggesting that immigrants' lower baseline level of information about the elections drive the heterogeneous impact.

Another plausible reason for the large size of the immigrant co-occupational boost is a "Jackie and Jill effect" (Anzia and Berry, 2011). To explain, suppose that party gatekeepers accept immigrant candidates only if they believe those candidates can mobilize enough new immigrant voters to compensate for the expected vote loss among natives. In this case, immigrant candidates should generate larger turnout boosts in their social networks than native Norwegians; and that turnout gap should be larger in parties whose voters harbor greater anti-immigrant biases.

We explore this first by estimating family turnout effects separately for immigrant and native families. Columns (1) and (2) in Table 3 reproduce the results from the first two columns in Table 1, except that the sample is restricted to voters who were born in Norway. Columns (3) and (4) explicitly considers immigrant families. Immigrants generate much larger turnout increases among their family members than do native candidates.

Table 3: Native versus Immigrant Families

	Natives		Immigrants	
	(1) Close	(2) Extended	(3) Close	(4) Extended
No candidate in network	ref.	ref.	ref.	ref.
Any District	0.006**	0.002	0.023	0.027
	(0.003)	(0.002)	(0.028)	(0.026)
Same District	0.021***	0.012***	0.139***	0.127***
	(0.005)	(0.004)	(0.043)	(0.041)
Observations	2,301,710	2,301,710	408,566	408,566
Clusters	3,723	3,723	3,601	3,601
Mean turnout (%)	71.59	71.59	39.39	39.39

Notes: Each column represents a separate regression based on Equation (1), where the dependent variable is turnout for voter i in BSU b at time t. The sample in columns (1) and (2) consist of voters who were born in Norway, while the sample in columns (3) and (4) considers all first-generation immigrants (as defined in section 3.3). Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.

Moreover, Appendix Figure A.7 documents that immigrant candidates' mobilizational boost grows progressively stronger the less favorable party supporters are toward increased immigrant participation.[20] This aligns with the notion that party gatekeepers strategically allocate list spots to immigrants whom they believe will induce a compen-

[20] Appendix Figure A.8 shows that our measure of attitudes toward immigrants correlate with party bloc (left-right) and the proportion of immigrant candidates on party lists.

satory increase in voter turnout within the immigrant community (proxied here by family members).

7. The political consequences of border drop-offs

Many scholars have noted that groups whose members are distributed inefficiently across electoral districts may have difficulty converting their votes into seats (e.g., Rodden, 2019; Taylor and Johnston, 1979). Section 5.2 documented one mechanism that worsens votes-to-seats conversion: candidates' inability to use their social networks to mobilize people who can actually vote for them.

In Appendix Table A.8, we provide evidence on the average *electoral efficiency* of candidates' networks that is, the average share of network members who reside in the same district. We find that electoral efficiencies vary widely across different networks, suggesting that groups may have mobilization (dis)advantages based simply on the distribution of their members relative to district boundaries. In the rest of this section, we consider whether network efficiency helps to explain where immigrants become candidates.

In Table 4 we present regression results where the dependent variable is the share (in percent) of a group's total candidacies at time t (across all municipalities) that occurred in municipality m. We control for birthcountry fixed effects and either a linear, quadratic, cubic or quartic polynomial of the share of each group's population in each municipality. The regressor of interest is the maximum available birthcountry-occupation efficiency. In other words, in municipality m, we examine each occupation group from each immigrant group, compute the birthcountry-occupation electoral efficiency, and record the maximum (*maximum efficiency*).[21] Unlike in Section 5 (where we needed to observe turnout), these analyses use the full population of immigrants.

We focus on the maximum efficiency because only about 1% of birthcountry groups

[21] Appendix Table A.9 provide evidence that candidates were not systematically mobilizing their entire co-resident immigrant communities (as defined by birthcountry alone). They were, however, successfully mobilizing co-residents who shared both their birthcountry and occupation. This is why we focus our analyses on this level.

Table 4: Effect of Maximum Efficiency on Candidacy

	(1)	(2)	(3)	(4)	(5)
Maximum efficiency (std.)	0.365	0.191	0.174	0.123	0.119
	(0.056)	(0.052)	(0.043)	(0.042)	(0.042)
Population share polynomial	-	Linear	Quadratic	Cubic	Quartic
Observations	22,321	22,321	22,321	22,321	22,321
Clusters	47	47	47	47	47
Mean dependent variable	0.40 %	0.40 %	0.40 %	0.40 %	0.40 %

Notes: Each column represents a separate regression of the share (in percent) of a group's total candidacies (across all municipalities) that occurred in municipality m *on the maximum available birthcountry-occupation efficiency. The unit of observation is birthcountry-municipality-years. Occupations are defined at the 2-digit level. The sample is restricted to immigrant-occupation groups with ten or more individuals (per year) and countries with a (nationwide) population of more than 1000. Starting in column (2), we include a polynomial which controls for the share of each group's population in each municipality. Country of birth fixed effects are included in all specifications. Standard errors are clustered on the birthcountry level and reported in parenthesis.*

have more than one candidate running in a given municipality. Thus, one would expect the most efficient occupational subgroup in each municipality to be the most likely to secure a list spot. For interpretive convenience, we standardize maximum efficiency to have mean zero and standard deviation one.

Flexibly controlling for the percent of the group's population in each municipality and birthcountry fixed effects, we find that maximum efficiency is positively and significantly associated with candidacy. Substantively, increasing the maximum available efficiency by one standard deviation increases the expected share of candidacies by between 0.1 and 0.2 percentage points, when including population controls (columns (2)-(5)).[22] This corresponds to 25% – 50% of the mean of the dependent variable.

Our results resonate with Cruz, Labonne and Querubin's (2017) finding that candidates for public office in the Philippines are disproportionately drawn from families with higher network centrality. Possible mechanisms include immigrants with more efficient occupational networks being more likely to seek candidacies; and parties seeking

[22] We exclude from the sample immigrant-occupation groups with less than ten individuals and countries with a (nationwide) population of less than 1000. Appendix Figure A.9 shows that these results are robust to a range of population restrictions.

to list someone from a particular immigrant group preferring persons with more efficient birthcountry-occupation networks.

Of course, someone might make a good candidate by virtue of other networks they can mobilize—e.g., through their church or former university classmates. At this point, we have little ability to identify each candidate's full portfolio of networks. So, occupational network efficiency may correlate with other networks' efficiency. Future work will have to deal with this and other forms of omitted variable bias. That said, the correlation we report suggests that the first step toward converting a group's votes into seats—converting its votes into candidacies—depends in a plausible way on how its members are distributed across relevant electoral districts (in this case, municipalities).

8. Conclusion

In this paper, we exploit high-resolution administrative data from Norway to explore how electoral geography affects mobilization through social networks. For families, coworkers, and birthcountry-occupational groups, we show that the candidacy of a group member acts like a mobilizational impulse that propagates through the group's network. The effects are substantial, corresponding to a 2-4 percentage point increase in turnout. Effects increase as the strength of social ties increase—for example, they are larger in smaller business establishments than in bigger ones. Effects also increase when candidates' incentives to mobilize increase—in particular, viable candidates mobilize more voters than do hopeless ones.

The political parties appear to select immigrant candidates on the basis of their mobilizational ability. Immigrant candidates generate larger turnout boosts in their families than do natives; and this effect grows in proportion to anti-immigrant attitudes among the party's members. Moreover, parties are more likely to select immigrants whose co-occupational networks are electorally more efficient (with more members residing within the potential candidate's electoral district). While we cannot directly observe candidates' mobilizational efforts, our results, as well as survey data, are consistent with candidates actively mobilizing their social networks and being selected for that ability.

The electoral impact of social networks is likely larger than our estimates suggest. First, within-network candidacies will plausibly affect not just turnout but also vote choice. Second, there are many primary networks beyond the three we can observe with our data. Third, secondary mobilization will magnify primary-network turnout effects (as previous work and our two-step analysis show).

More novel than the results described above, our work also illuminates how electoral district boundaries shape mobilizational impulses. Previous research has focused on local networks (e.g., spouses, neighbors) contained within single districts. The networks we study often spread beyond individual districts, allowing us to show that mobilization is bound by borders. Within district borders, mobilizational impulses decline moderately with distance. However, the impulse falls off dramatically as soon as the social network crosses the candidate's district boundary. To our knowledge, our paper is the first to provide quantitative assessments of such border effects.

The sharpness of the border drop-off, combined with the general importance of mobilization through social networks, suggest that electoral geography has more complex effects than previously thought. For example, formal models of gerrymandering typically take the parties' objective to be sorting individuals with fixed partisan preferences (and turnout propensities) across districts to optimize how votes translate into seats from the party's perspective (e.g., Owen and Grofman, 1988). Yet, to the extent that elections hinge on mobilizing supporters, the gerrymanderer's objective should be to sort entire social networks efficiently across districts. More generally, the electoral success of any given group will depend not just on how its members are distributed geographically but also on the distribution of their social networks.

Our work also suggests a broader issue in network studies. Most businesses have "service areas," some with fairly sharp borders (e.g., TV stations), others with fuzzy borders defined by travel times and competition. Any ad campaign seeking to orchestrate word-of-mouth support for a business would need to consider the overlap between their primary contacts' social networks and their service area.

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Appendix A: Supplementary analyses

Table A.1: Municipality-level summary statistics

	Included municipalities		Excluded municipalities	
	Mean	SD	Mean	SD
Population	84,571	132,625	7,572	9,428
Vote-eligible population	66,784	106,118	5,975	7,409
Pre-school age (percent)	7.24	0.70	6.47	1.28
School age (percent)	12.28	0.98	12.15	1.43
66 years and older (percent)	15.03	2.48	18.35	3.58
Women (percent)	49.72	0.73	49.12	1.04
Unemployed (percent)	2.52	0.60	2.01	0.71
Immigrants (percent)	13.68	4.65	9.24	3.41
Turnout (percent)	58.36	4.01	63.12	6.07
N	25		403	

Notes: This table reports summary statistics for various outcomes in municipalities that are included ($N = 25$) versus not included ($N = 403$) in our sample. The data are from 2015 only. Supplementary data from Fiva, Halse and Natvik (2020). The included municipalities [nation-wide population rank] are Oslo [1], Bergen [2], Trondheim [3], Stavanger [4], Bærum [5], Fredrikstad [7], Sandnes [8], Drammen [10], Asker [11], Sarpsborg [12], Skien [13], Skedsmo [14], Bodø [15], Ålesund [16], Karmøy [20], Tønsberg [21], Haugesund [22], Porsgrunn [23], Mandal [75], Vefsn [87], Hammerfest [111], Våle [120], Tynset [188], Radøy [202], and Bremanger [238].

Table A.2: Networks summary statistics

Panel A: 2015	Family (N = 1,400,563)		Co-workers (N = 543,781)		Immigrants (N = 119,905)	
	Close	Extended	Age-estbl.	Estbl.	3-digit	2-digit
Number of unique networks	1,400,563	1,400,563	171,716	97,443	8,372	4,167
Voters with $AnyDistrict = 1$	40,656	115,058	36,357	77,072	47,190	64,092
Voters with $SameDistrict = 1$	9,664	18,533	12,154	26,463	3,049	4,899
Network size (average)	4.85	14.92	3.17	5.58	14.32	28.77
Distance (km) $\vert AnyDistrict = 1$	260.17	309.94	85.43	79.79	324.81	297.09
Distance (km) $\vert SameDistrict = 1$	4.59	6.14	8.28	7.97	9.13	9.12
Panel B: 2019	Family (N = 1,400,563)		Co-workers (N = 543,781)		Immigrants (N = 119,905)	
	Close	Extended	Age-estbl.	Estbl.	3-digit	2-digit
Number of unique networks	1,400,563	1,400,563	171,716	97,443	8,372	4,167
Voters with $AnyDistrict = 1$	36,961	111,096	36,563	79,485	48,917	64,676
Voters with $SameDistrict = 1$	8,914	17,768	11,522	25,680	2,173	3,619
Network size (average)	4.85	14.92	3.17	5.58	14.32	28.77
Distance (km) $\vert AnyDistrict = 1$	269.69	325.17	109.68	100.45	352.43	307.85
Distance (km) $\vert SameDistrict = 1$	4.95	6.40	8.38	8.04	8.96	9.09

Notes: The table shows summary statistics relating to the social networks of voters and politicians in our estimation sample. 'Number of unique networks' reports the total number of social networks within each category (this is identical to N for families since family connections are unique to each person). 'Voters with..' counts the number of individual voters for whom the indicated variables are equal to one. 'Network size' reports the average number of connected members in each social network. 'Distance..' reports the average distance in kilometers between voters and (the nearest, if multiple) politicians, conditional on an existing connection and co-residence, respectively. The full distributions of these variables are shown in Appendix Figures A.3 and A.4.

Table A.3: Descriptive Statistics of Politicians

	2015			2019		
	Family	Co-workers	Immigrants	Family	Co-workers	Immigrants
Political attributes						
First time (percent)	40.51	41.50	62.73	41.22	39.62	55.12
Party bonus (percent)	8.55	9.40	5.40	8.96	9.65	6.00
List rank (average)	14	13	15	15	14	16
Elected (percent)	16.42	18.85	10.29	15.66	17.75	8.88
Personal characteristics						
Age (average)	50	47	44	50	49	46
Female (percent)	42.40	43.31	49.75	43.24	43.52	51.44
Immigrant (percent)	2.43	3.31	100.00	2.65	3.80	100.00
Higher education (percent)	45.77	45.49	59.79	48.92	50.07	63.47
Income (average)	442,492	480,077	469,890	488,380	531,992	540,201
N	47,483	26,853	1,186	43,787	24,662	1,250

Notes: The table shows descriptive statistics for politicians in our sample across social networks and years. The top four statistics are computed from Fiva, Sørensen and Vøllo (2021); 'First time' reports the percent of network candidates who ran for the first time in the indicated year. 'Party bonus' reports the percent of network candidates selected by their party to receive a 25% boost in personal votes (see Appendix C). 'List rank' reports candidates' average rank on the ballots. 'Elected' reports the percent of candidates who won a seat in the indicated year. The remaining statistics are computed from matched administrative data. 'Immigrant' is defined (as in the paper) as a person born outside of Scandinavia to non-Norwegian parents. 'Higher edication' is defined as having completed the first stage of higher education (undergraduate level). 'Income' (reported in NOK) is defined as the sum of pre-tax market income from wages, self-employment and work-related cash transfers, including unemployment benefits, sick leave benefits, and parental leave benefits ("pensjonsgivende inntekt*"). The table does not distinguish between candidates in narrow and broad networks as these are essentially the same regardless of the definition used.*

Table A.4: Extended family analyses

	(1) Parents	(2) Siblings	(3) Children	(4) Grandpar.	(5) Grandch.	(6) Nieces & nephews	(7) Aunts & uncles	(8) Cousins
No network candidate	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Any District	0.006	0.007	0.002	-0.030	-0.009	0.004	-0.002	-0.000
	(0.005)	(0.004)	(0.006)	(0.019)	(0.011)	(0.003)	(0.004)	(0.003)
Same District	0.032	0.012	0.035	0.006	0.001	0.008	0.003	-0.003
	(0.012)	(0.008)	(0.009)	(0.044)	(0.019)	(0.009)	(0.013)	(0.010)
Observations	2,801,126	2,801,126	2,801,126	2,801,126	2,801,126	2,801,126	2,801,126	2,801,126
Clusters	3,733	3,733	3,733	3,733	3,733	3,733	3,733	3,733
Mean turnout (%)	66.56	66.56	66.56	66.56	66.56	66.56	66.56	66.56

Notes: Each column represents a separate regression based on Equation (1), where the dependent variable is turnout for voter i in BSU b at time t. The independent variables of interest in each specification are indicator for candidacy among the type of family members specified in the column headers. Voters with multiple family candidates figure in only one category (whoever is geographically closest). Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.

Table A.5: Extended co-worker analyses

	2-5 co-workers		6-15 co-workers		16+ co-workers	
	(1) Age-estbl.	(2) Estbl.	(3) Age-estbl.	(4) Estbl.	(5) Age-estbl.	(6) Estbl.
No network candidate	ref.	ref.	ref.	ref.	ref.	ref.
Any District	-0.003	-0.006	-0.001	-0.005	0.001	-0.002
	(0.007)	(0.008)	(0.005)	(0.005)	(0.005)	(0.003)
Same District	0.028	0.040	0.016	0.017	0.005	0.006
	(0.014)	(0.017)	(0.008)	(0.009)	(0.008)	(0.004)
Observations	478,054	245,446	422,968	352,094	186,540	490,022
Clusters	3,681	3,640	3,644	3,647	3,555	3,657
Mean turnout (%)	64.72	64.39	66.60	63.91	70.85	69.42

Notes: Each column represents a separate regression based on Equation (1), where the dependent variable is turnout for voter i in BSU b at time t. All models are estimated within (complete) subsamples of equally-sized co-worker networks (i.e., not equally-sized bins), as specified in the column headers. The reported coefficients for β and γ in columns (3)-(4) of Table 1 thus reflect a weighted average of these individual effects. Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.

Table A.6: Extended immigrants analyses

	Europe inc. Russia		Africa		Asia		North America		South America	
	(1) 3-digit	(2) 2-digit	(3) 3-digit	(4) 2-digit	(5) 3-digit	(6) 2-digit	(7) 3-digit	(8) 2-digit	(9) 3-digit	(10) 2-digit
No network candidate	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Any District	-0.007	-0.007	0.011	0.025	-0.007	-0.008	0.028	0.007	0.053	0.026
	(0.005)	(0.005)	(0.019)	(0.017)	(0.008)	(0.008)	(0.031)	(0.032)	(0.028)	(0.026)
Same District	0.040	0.008	0.079	0.057	0.039	0.056	-0.101	-0.033	-0.080	-0.047
	(0.021)	(0.015)	(0.025)	(0.022)	(0.018)	(0.015)	(0.355)	(0.124)	(0.058)	(0.039)
Observations	113,928	113,928	29,474	29,474	80,822	80,822	6,034	6,034	8,590	8,590
Clusters	3,453	3,453	2,479	2,479	3,134	3,134	1,710	1,710	1,880	1,880
Mean turnout (%)	33.92	33.92	48.55	48.55	46.76	46.76	54.52	54.52	49.44	49.44

Notes: Notes: Each column represents a separate regression based on Equation (1), where the dependent variable is turnout for voter i in BSU b at time t. All models are estimated within (complete) subsamples of immigrant networks originating from different continents, as specified in the column headers. The reported coefficients for β and γ in columns (5)-(6) of Table 1 thus reflect a weighted average of these individual effects. Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.

Table A.7: Results - Baseline networks analyses (geo-time fixed effects)

	Family		Co-workers		Immigrants	
	(1) Close	(2) Extended	(3) Age-estbl.	(4) Estbl.	(5) 3-digit	(6) 2-digit
No candidate in network	ref.	ref.	ref.	ref.	ref.	ref.
Any District	0.006	0.002	-0.000	-0.002	-0.004	-0.006
	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Same District	0.027	0.016	0.013	0.009	0.039	0.033
	(0.005)	(0.004)	(0.005)	(0.004)	(0.012)	(0.009)
Observations	2,029,996	2,029,996	752,908	752,908	150,494	150,494
Clusters	3,683	3,683	3,624	3,624	3,241	3,241
Mean turnout (%)	66.56	66.56	66.50	66.50	41.19	41.19

Notes: Each column represents a separate regression based on a variant of Equation (1) that also includes BSU-time fixed effects. The dependent variable is turnout for voter i in BSU b at time t. The model omits singleton-observations (i.e., people who move between periods). Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.

Table A.8: Summary of electoral efficiency, by network types

	Family		Co-workers		Immigrants	
	Close	Extended	Age-estbl.	Estbl.	3-digit	2-digit
Mean	55.7	43.3	79.1	73.5	47.6	38.8
Standard dev.	37.5	33.4	27.2	28.3	35.5	33.7
Minimum	0.0	0.0	2.4	2.2	0.9	1.0
Maximum	100.0	100.0	100.0	100.0	100.0	100.0
N	3,653,458	3,663,688	392,949	197,477	10,626	4,945

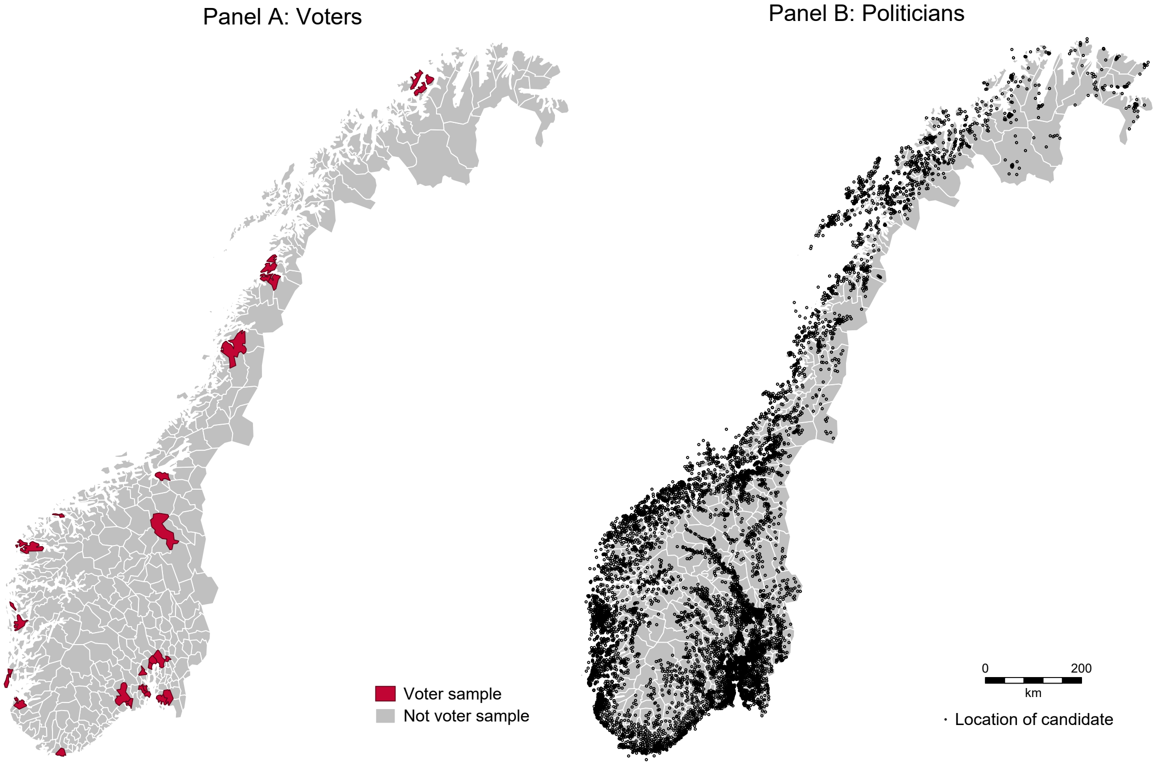
Notes: The table reports summary statistics on the electoral efficiency of each social network, using data from the entire Norwegian population (in 2015). Electoral efficiency is defined the average share of network members who reside in the same district. The unit of observation is at the level of the individual networks.

Table A.9: Alternate immigrant specifications

	(1)	(2)	(3)	(4)
Any District	ref.	ref.	ref.	ref.
Same District (Birthcountry)	0.008			0.005
	(0.007)			(0.008)
Same District (Occupation)		0.015		0.011
		(0.006)		(0.006)
Same District (Both)			0.036	0.029
			(0.014)	(0.015)
Observations	96,107	96,107	96,107	96,107
Clusters	3,419	3,419	3,419	3,419
Mean turnout (%)	44.22	44.22	44.22	44.22

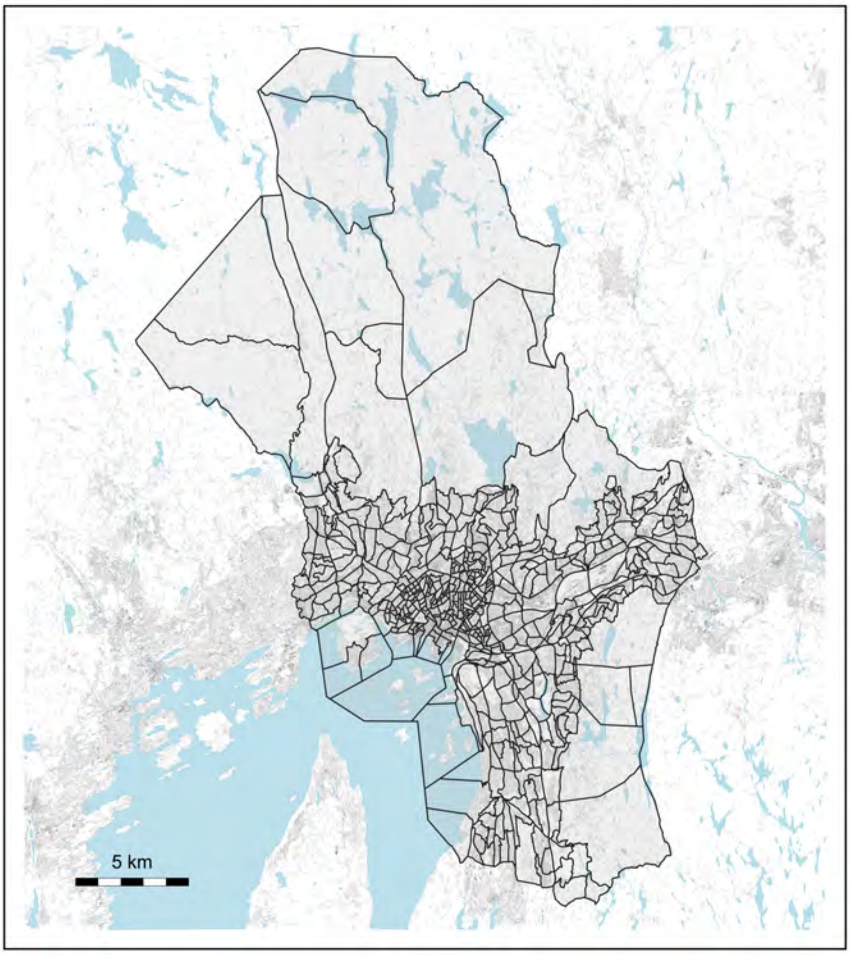
Notes: Each column represents a separate regression based on a modified Equation (1), where observations with $AnyDistrict$ = 1 constitutes the reference category (β in equation (1) is no longer identified). The dependent variable is turnout for voter i in BSU b at time t. The independent variables capture effects of having a politician in the network originating from the same country of birth, the same occupation, or both, respectively. Not reported, but also included in all models, are individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level and reported in parenthesis.

Figure A.1: Maps of Norway



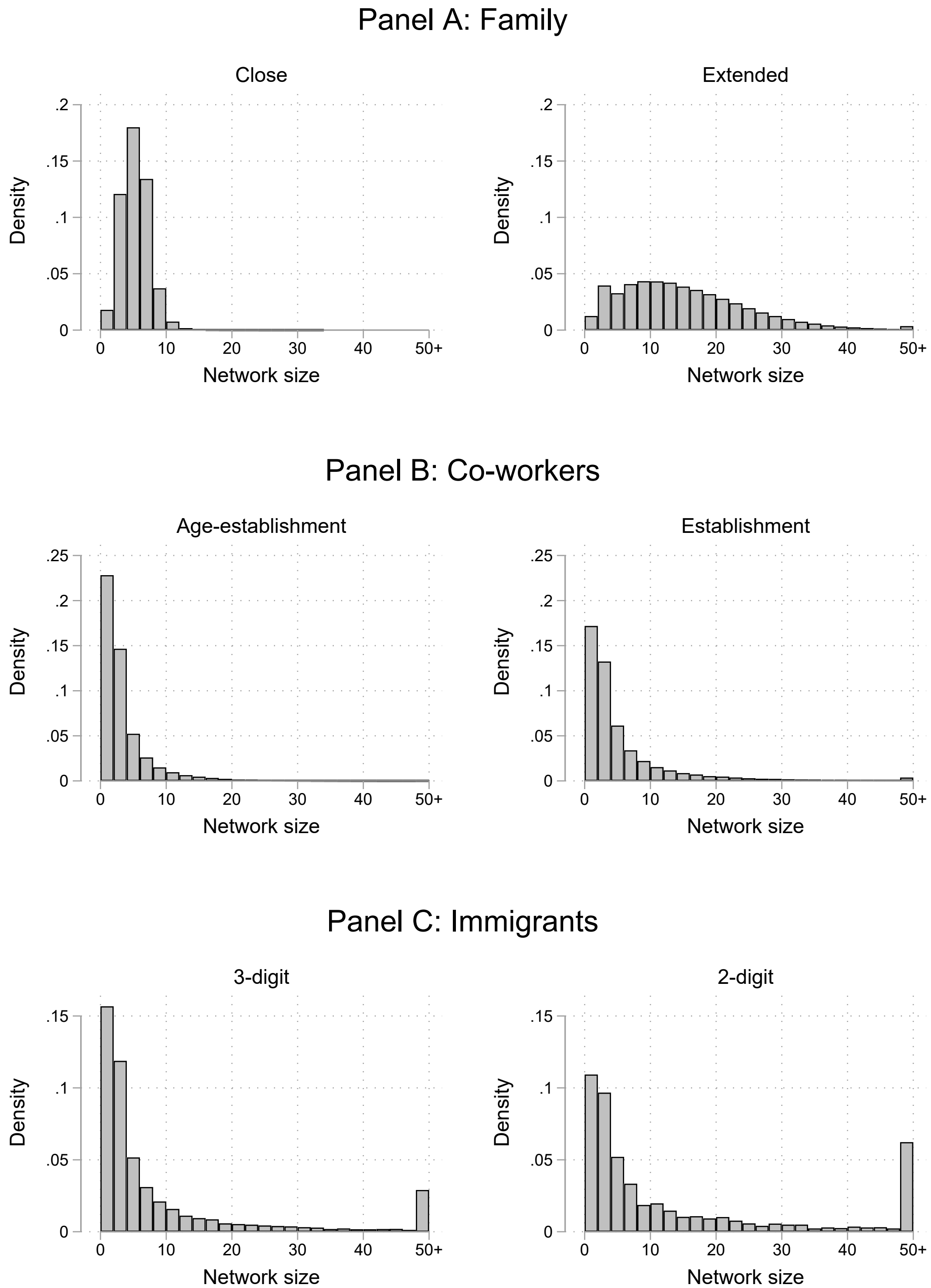
Notes: Panel A highlights the 25 municipalities for which our estimation sample covers the population of voters. This includes the four largest cities in Norway (Oslo, Bergen, Trondheim, and Stavanger). Panel B shows the locations of all political candidates (in 2015).

Figure A.2: Map of basic statistical units in Oslo municipality



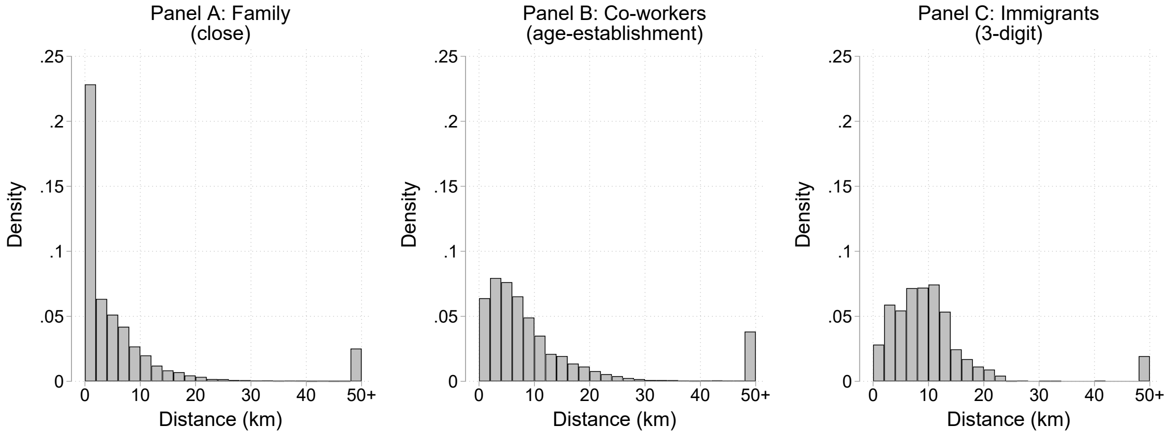
Notes: This map shows the basic statistical units (BSU's) of Oslo municipality. In total, there are 589 BSU's covering about 140 square kilometres. Like in the rest of Norway, each BSU is constructed to cover homogenous areas in terms of demography, nature and infrastructure. As a consequence, the size of each BSU vary dramatically from downtown Oslo to the forests in the north and east. On average, each BSU has a population of about 1,200 (the total population of Oslo is approximately 700,000). Underlying map data: ©OpenStreetMap contributors. Data available under the Open Database License.

Figure A.3: Distributions of network sizes



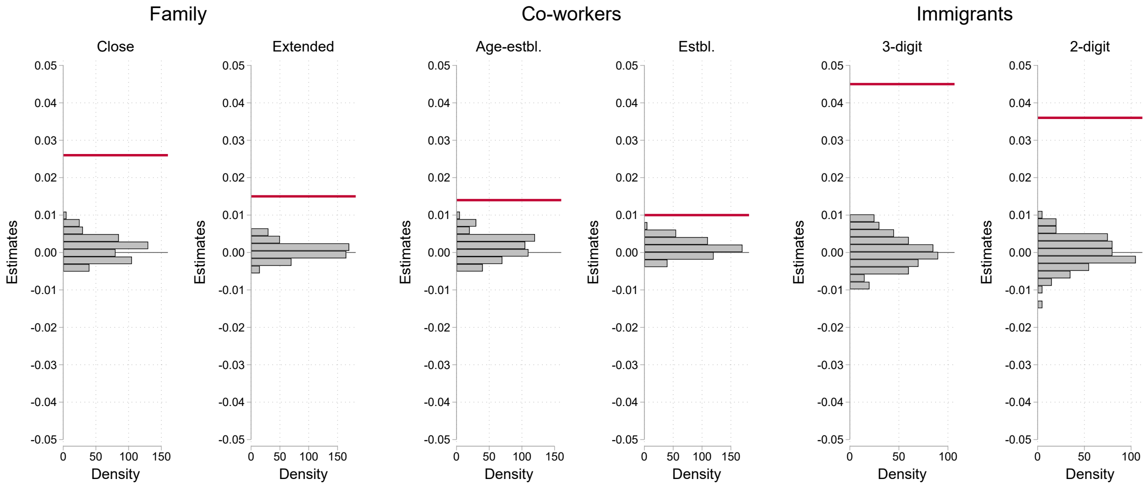
Notes: The figure shows the size distributions for each type of family network (Panel A), co-worker network (Panel B), and Immigrant network (Panel C) in our sample. We collapse all networks larger than 50 into "50+".

Figure A.4: Distance Between Voters and Politicians who Belong to the Same Network and Reside in the Same Municipality



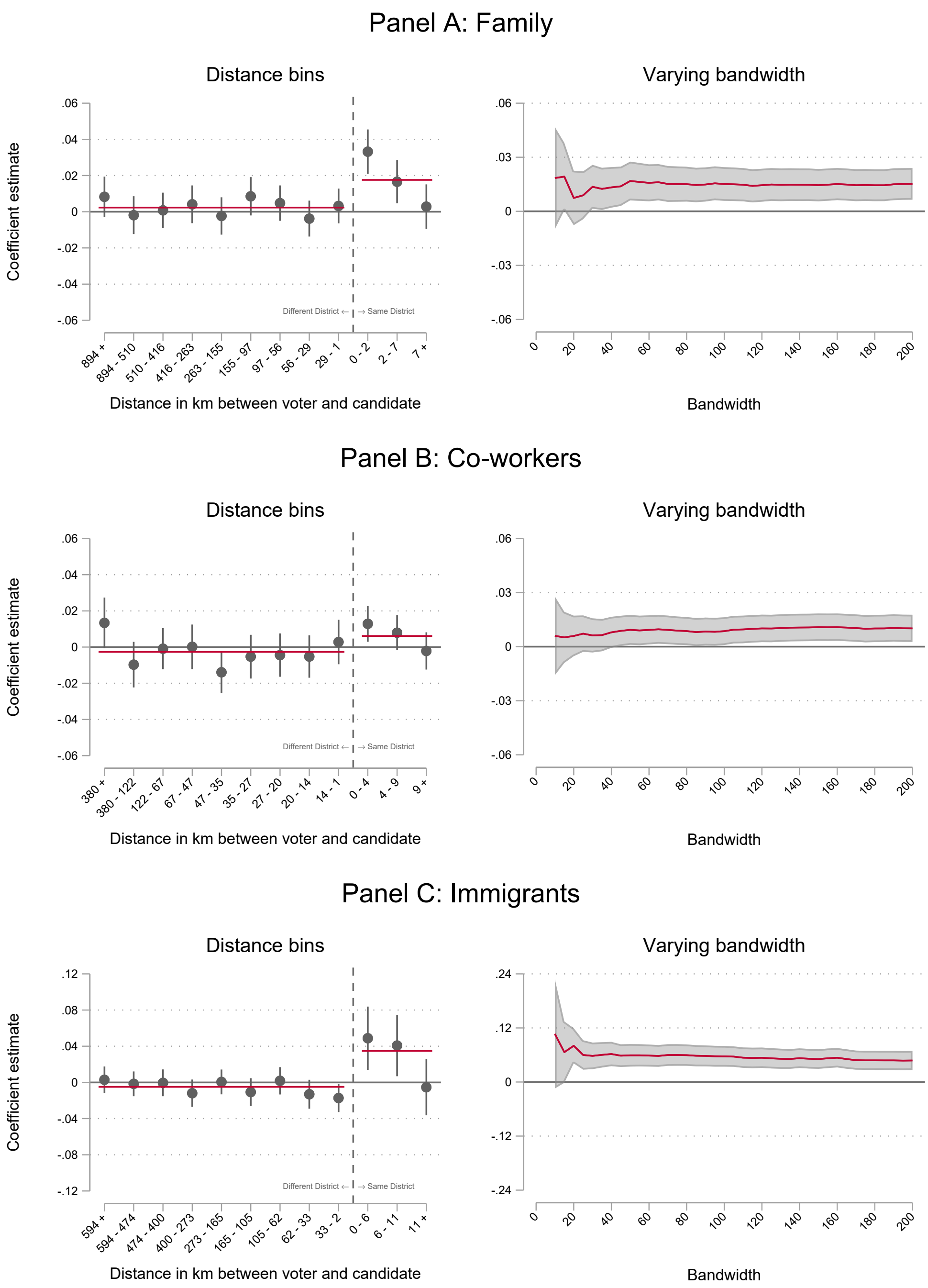
Notes: The figure shows the distributions of distance between voters and politicians in our sample, conditional on living in the same district (municipality). Only the narrow network categories are shown. We collapse all distances greater than 50 into "50+".

Figure A.5: Simulation results - randomized politicians



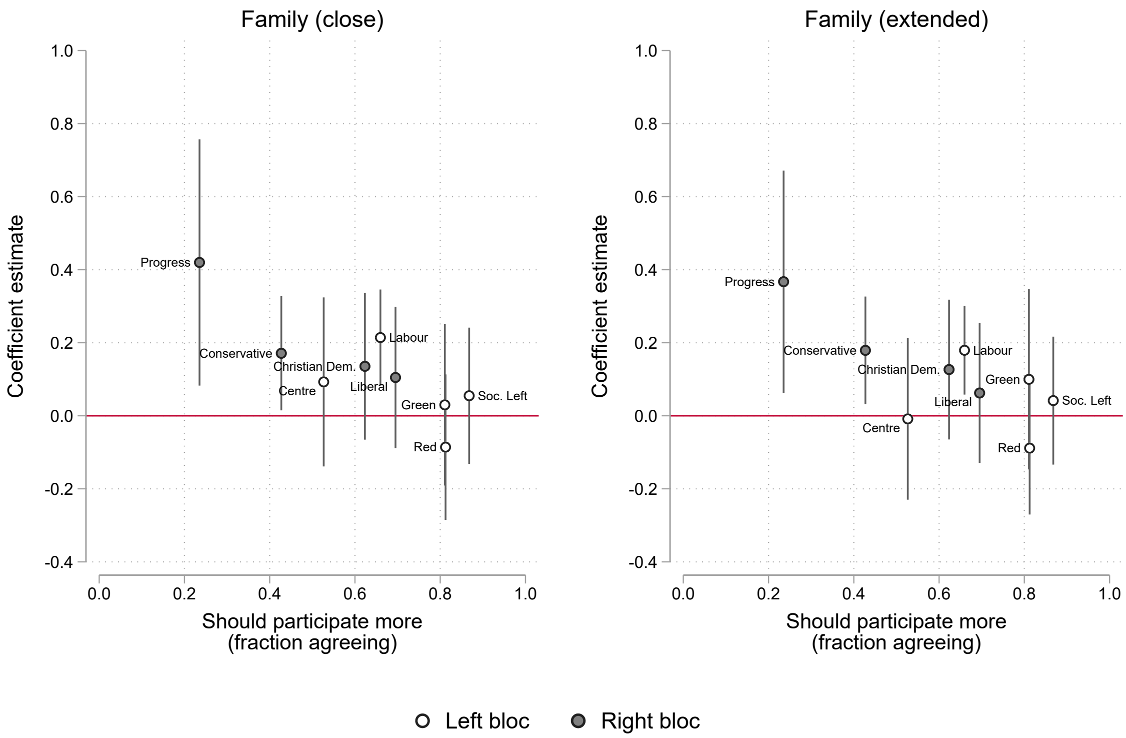
Notes: The figure shows the distribution of simulated effects for co-residence (γ in Equation (1)) after 100 iterations. In each iteration, we keep the actual network structures but assign randomly "politician status" to as many individuals in the vote-eligible population of Norway as there are true politicians in the sample (per year). The red line shows the actual estimates from Panel A in Table 1.

Figure A.6: Effects over distance and across district boundaries (broad)



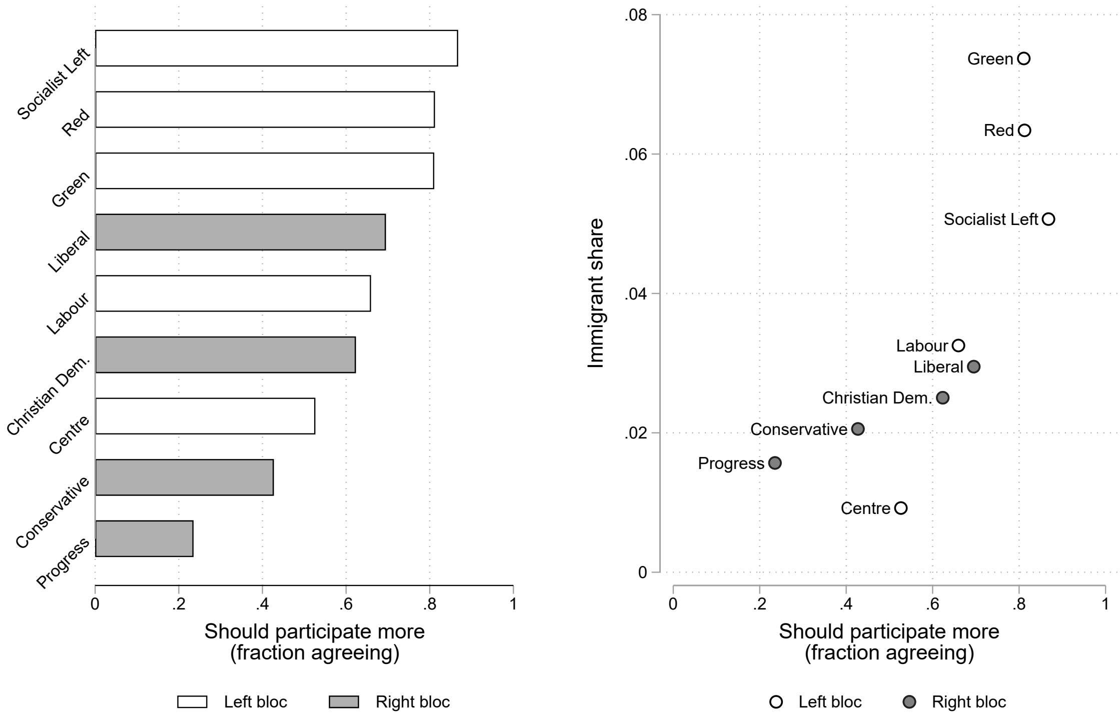
Notes: This figure displays how the mobilizational impact depends on distance in kilometers between voters' and candidates' basic statistical units (BSU). In each panel, the left plot reports coefficient estimates and 95 percent confidence intervals for observations belonging in each distance bin. The red lines denote the average mobilization impacts on the left and right side of the threshold. The number of observations per bin are constant on each side. The right plots in each panel reports our main coefficient estimates from Equation (1) but excludes from identification all observations whose distance falls outside the indicated bandwidth (i.e., the red line shows the difference between the lines in Panel A as we zoom closer to the threshold). If a person has multiple candidates in his/her network we use the geographically closest candidate to measure distance. For all networks, we use the broad definition ('extended', 'establishment', and '2-digit'). A small fraction of the sample is omitted from each analysis due to missing distance. Standard errors are clustered on the BSU level.

Figure A.7: Within-family mobilization boost for immigrants, by party



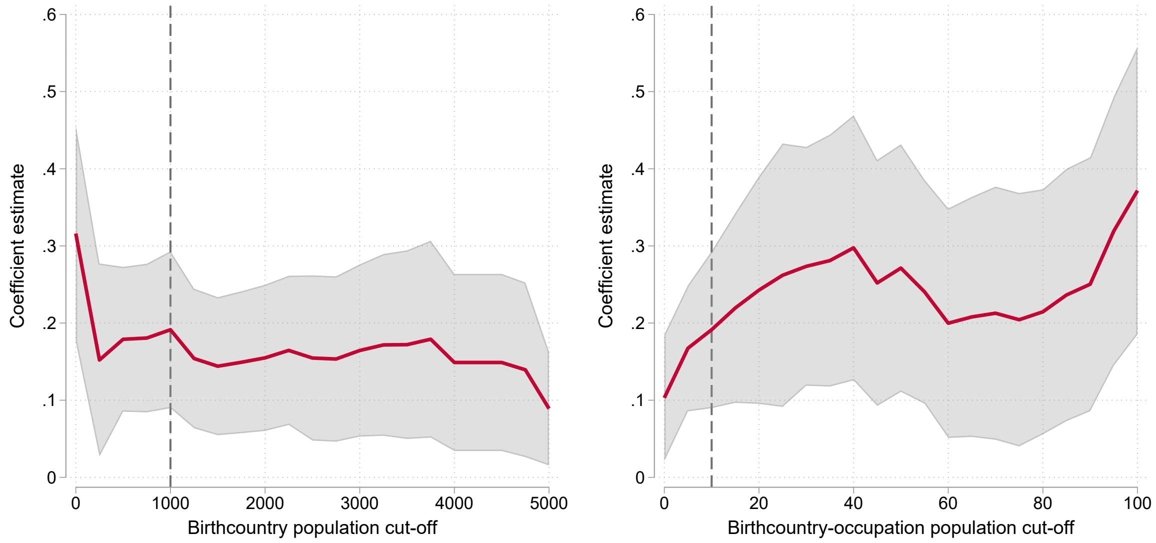
Notes: This figure shows estimates of γ in equation (1), split by political party. Coefficients are sorted by the fraction of respondents to the 2015 Local Election Survey (n= 1,190) who answered that 'immigrants should participate more in politics' (see Figure A.8). The β coefficient in equation (1) is treated as constant (an f-test of differential effects rejects that β varies by party (p = 0.41)). Models include individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level.

Figure A.8: Survey evidence on attitudes toward immigrants, by party



Notes: The left plot shows voters' attitudes to immigrants by party for which they reported to have voted. Reported are the fraction of survey respondents answering that 'immigrants should participate more in politics'. Alternative responses are 'conditions are good as they are', 'should participate less', and 'don't know'. The right plot graphs responses against the proportion of immigrant candidates on party lists. Both plots distinguish between 'left bloc' and 'right bloc' parties. Data from the 2015 Local Election Survey (Lokalvalgsundersøkelsen) (n= 1,190)

Figure A.9: Sensitivity of maximum efficiency estimates to sample restrictions



Notes: The figure shows how estimates of the parameter of interest in Table 4 varies over the cut-offs used for the nationwide population of birthcountry groups (left) and the birthcountry-occupation population (right). Both plots use the specification presented in column (2) of Table 4, i.e., with linear population controls. The restrictions used in the baseline analysis is indicated with dashed gray lines. In the left plot, we vary the birthcountry population cut-off while keeping the birthcountry-occupation population cut-off constant at ten individuals (per year). In the right plot, we vary the birthcountry-occupation population cut-off, while keeping the birthcountry population cut-off constant at thousand (per year). Standard errors are clustered on the birthcountry level.

Appendix B: Sample construction

Voters

Our sample of voters covers the vote-eligible population[23] as of September 2015 in the 25 municipalities described in Table A.1.[24] We drop from this sample anyone who were not eligible to vote in both periods, those who moved in/out of the sample region between periods, and people who, in either of the two periods, ran for office themselves (including candidates from other than the nine major parties used in this paper). Turnout is observed for 98.5 percent of these individuals. The remainder is likely an artefact of the timing discrepancy between observations of turnout (measured in September) and residency (measured in January), and are dropped from the sample.

Politicians

While voter outcomes is only observed for a subset of Norway, our politicians sample covers the universe of political candidates running for local office in both years (approximately 60,000 candidates per year).[25] We focus on candidates running for the nine major Norwegian parties. Candidates who ran simultaneously for local and regional office are dropped. We also lose a small fraction of candidates who were not successfully matched with administrative registers (< 0.1 percent).

Social Networks

Close family members (parents, siblings and children) are directly linked in Statistics Norway's administrative registers, and politicians are matched to voters using their individual id's.[26] We match politicians to voters directly using their individual id's. For co-workers and immigrants, we first construct network id's using population registers and then match politicians and voters belonging to the same groups. All social networks are assumed to be static and defined as they exist in 2015.

[23]Norwegian citizens aged 18 or older by the end of the election year, Nordic citizens registered as residing in Norway by June 30 in the year of the election, and non-citizens with three years of consecutive residency, are eligible to vote (`https://www.ssb.no/en/valg/stortingsvalg/statistikk/personer-med-stemmerett`). In 2015, 20 municipalities participated in a trial in which the voting age was lowered to 16 years (three of these municipalities are part of our estimation sample). Our analysis only includes individuals who have reached the age of majority (18 years).

[24]The voting records are collected from the *Electronic Election Administration System*, which was gradually rolled out across Norway, and, in 2015 adopted by 27 municipalities. In 2019, all municipalities had adopted this system. We consider a balanced sample of 25 municipalities that were unaffected by an amalgamation reform implemented during our sample period (reducing the number of municipalities from 428 to 356).

[25]These data originate from the *Local Candidate Dataset* (Fiva, Sørensen and Vøllo, 2021).

[26]We identify extended members by iterating forward/backward through generations.

To classify places of work, we use compiled registers of payroll reports from Norwegian employers (*A-melding*).[27] Every person in our sample who were either part-time and full-time employed in September 2015 is included. If a person had multiple jobs, we keep the position with the highest average full-time equivalent percentage. If this is not reported, an implied percentage is computed based on the salary paid. We define "place of work" at the establishment level (as opposed to the higher-tiered enterprise level) and drop all establishments with more than 100 employees to conform with the Confederation of Norwegian Enterprises' definition of small and medium firms. From this sample we let age groups (18-34, 35-49, and 50+) proxy factions within firms, and distinguish between co-worker networks that are of approximately the same age (narrow) and all-encompassing (broad).

To classify occupations, we use the Norwegian standard classification of occupations (*STYRK-08*, based on *ISCO-08*).[28] The system has a four-level hierarchical structure, from which we use the second and third levels to distinguish between broad and narrow categories. All individuals in our sample with a registered occupation in 2015 are included. We then group each of these occupations by country of birth to form our immigrant networks.

Some voters are connected to more than one politician in their social networks. In analyses where we condition on candidates' attributes, we always use the politician residing in the same electoral district (if any), and then, secondarily, the candidate with the shortest distance.

Distance

Norway is divided into approximately 14,000 "basic statistical units" (BSUs) which are nested within electoral districts (see Appendix Figure A.2). This level constitutes the smallest geographic unit we observe in our data.[29] For each voter who is connected to a political candidate, we determine the *fastest* driving distance in kilometers between the geographic centers of the voter's BSU and the politician's BSU.[30] There are some locations between which the shortest route cannot be computed. In such cases the observation is dropped from the sample, unless there are other politicians in the network to whom a distance is successfully computed.

[27] The *A-melding* is a monthly report from Norwegian employers (who have employees or pay salary, pension or other benefits) to the Tax Administration containing information about the employment and income of each individual employee. In our data, each employer is assigned a unique ID.

[28] `https://www.ssb.no/en/klass/klassifikasjoner/7`

[29] To ensure consistency across time, we create synthetic BSUs for 50 units in the greater Oslo region that were partitioned between 2015 and 2019. A handful of BSUs where this is not practical (due to more complicated border reforms) are dropped.

[30] These data are provided to us by Bjørn Gjerde Johansen (*Institute of Transport Economics*).

Appendix C: Candidate selection

Both voters and parties affect candidate selection

Local council elections in Norway are decided by a "flexible list system" where both voters and parties affect candidate selection. Voters choose a party list and may opt to express preferences for individual candidates by casting personal votes (for as many candidates as they like). Parties affect candidate selection by granting some candidates, listed on the top of the ballot in bold face, a "head start" (amounting to 25 % of the total number of list votes received by the party).[31] The advantage is so large that other candidates almost never receive enough personal votes to overtake a candidate with a head start. The initial ranking on the ballot, also decided by parties, only matters for the election outcome if there is a tie between candidates.

Example of candidate selection process

To illustrate the candidate selection process, consider the Labour Party in *Bodø* municipality in 2019. This list received 6922 out of 25309 of the party list votes (27%) and won 11 out of 39 seats in the local council (28%).[32] Table C.1 illustrates how the 11 candidates were selected among the 45 candidates the party had on their list. The top six candidates, including the party's popular mayoral candidate listed on the top of the list, received a head start. This corresponded to a boost of 1730.5 extra personal votes ($6922 \cdot 0.25 = 1730.5$). All the "head start" candidates was elected in addition to five "non head start" candidates originally listed in position 7, 8, 13, 14, and 16.

[31] The maximum number of candidates that party can give an advantage to depends on the size of the local council. In councils with fewer than 23 members, parties can give an advantage to a maximum of 4 candidates. For councils with 23 to 53 members, the maximum is 6, and for councils with more than 53 members, 10 is the limit.

[32] Seats are allocated *across* parties based on the modified Sainte-Laguë method. This method gives a proportional election outcome with a small advantage for large parties.

Table C.1: Illustration of candidate selection: the 2019 election in *Bodø* municipality

Rank	Candidate name	Head start	Votes	Incl. bonus	Elected
1	**Ida Maria Pinnerød**	1	2286	4016.5	1
2	**Morten Melå**	1	264	1994.5	1
3	**Ann Kristin Moldjord**	1	208	1938.5	1
4	**Fredric Martinsen Persson**	1	139	1869.5	1
5	**Anne Mari Haugen**	1	113	1843.5	1
6	**Håkon A. Magnussen**	1	121	1851.5	1
7	Salamatu Winningah	0	217	217	1
8	Sigurd Andreas Myrvoll	0	147	147	1
9	Rina Susanne Nicolaisen	0	134	134	0
10	Jorulf Haugen	0	52	52	0
11	Aida Barinan Knutsen	0	80	80	0
12	Terje Krutådal	0	27	27	0
13	Kristin Schjenken Navjord	0	166	166	1
14	Thor Arne Angelsen	0	170	170	1
15	Line Andresen Abelsen	0	103	103	0
16	Ali Horori	0	284	284	1
17	Aileen Sogn	0	80	80	0
18	Arild Nohr	0	93	93	0
19	Kristin Hunstad	0	77	77	0
20	Sander Delp Horn	0	37	37	0
21	Ingrid Torstensen	0	39	39	0
22	Jimmy Israelsen	0	47	47	0
23	Vibeke Nikolaisen	0	79	79	0
24	Hans Torger Austad	0	35	35	0
25	Henny Ovedie Aune	0	44	44	0
26	Lars Børre Vangen	0	31	31	0
27	Maya Sol Sørgård	0	75	75	0
28	Arild Ørjar Mentzoni	0	19	19	0
29	Rowena Daliva Ryvold	0	57	57	0
30	Mikael Ronnberg	0	54	54	0
31	Merete Silåmo	0	26	26	0
32	Arnstein Bård Brekke	0	18	18	0
33	Elsa Lovise Erichsen Øverland	0	35	35	0
34	Tor Erikstad	0	22	22	0
35	Lisbet Herring	0	19	19	0
36	Einar Lier Madsen	0	21	21	0
37	Judith Olafsen	0	21	21	0
38	Magnus Fjelldal Korsaksel	0	41	41	0
39	Amina Louise Persen	0	44	44	0
40	Øivind Jean Mathisen	0	34	34	0
41	Cecilie Haugseth	0	79	79	0
42	Odd Andreas Lund	0	93	93	0
43	Ingunn Fjelldal Korsaksel	0	43	43	0
44	Per Christian Størkersen	0	57	57	0
45	Selma Sørensen Bodøgaard	0	65	65	0

Appendix D: Heterogenous mobilization effects by candidates' electoral viability

Estimating candidates' likelihood of winning a seat in the council

To classify candidates chance of winning a seat in the council, we estimate a fully saturated linear probability model where we include the full interactions between year fixed effects, party fixed effects, list position fixed effects, and a "head start" dummy. We leave out the focal candidate from the estimation when obtaining the predicted probability for that candidate. In other words, we estimate the prediction model as many times as there are candidates in our data set. The likelihood that candidate j wins a seat corresponds then to the fraction of candidates in j's cell that win a seat, excluding j. The cell is defined by defined by year, party, list position and head start status.

The linear probability model strongly predicts candidates' election outcomes. The likelihood of winning a seat is strongly increasing in candidates' list position for all political parties. Candidates outside the top-ten have, on average, slim chances of winning a seat. However, for the largest parties, such as the Labour Party (a) and Center Party (sp), lower ranked candidates have non-trivial chances of winning a seat even outside the top-ten. The R^2 of the prediction model is 0.57.

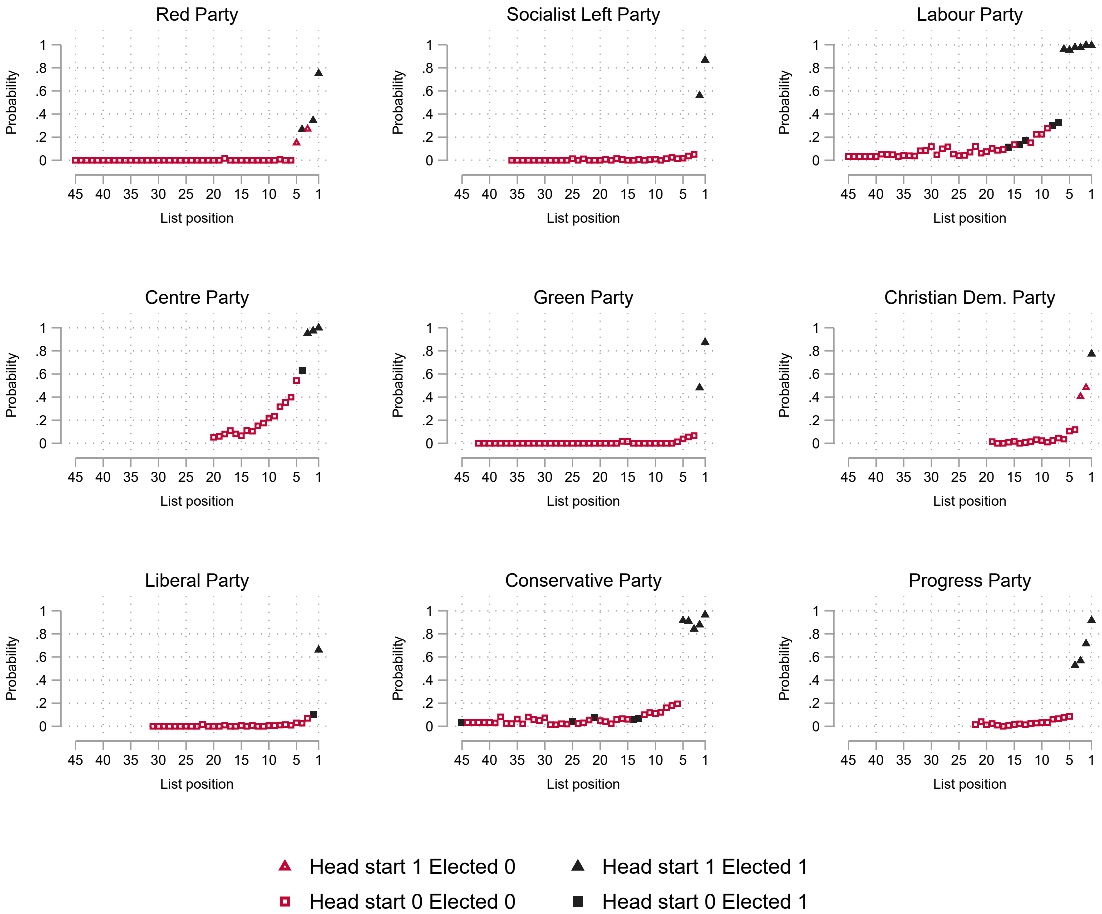
Illustrative example

To illustrate the results from the prediction model, we consider the case of *Bodø* municipality, one of the 25 municipalities included in our main estimation sample. Figure D.1 plots individual candidates' estimated probability of winning a seat for the nine main parties running in the 2019 election.

The Labour Party list, used as an example in Table C.1, is in the top-right panel of Figure D.1. Our prediction model gives the "head start" candidates from the Labour Party almost a hundred percent chance of winning a seat in the council. Among the "non head start" candidates the chances of winning are fairly low, but increasing in list rank. For smaller parties, such as the Red Party (middle-left), the chance of winning a seat is essentially zero for "non head start" candidates.

The plot for the largest party of the right-wing bloc, the Conservatives (bottom-middle), resembles the plot for the Labour Party. Here the lowest ranked candidate on the list, which the prediction model gives a zero chance of winning, ultimately got elected. This candidate was a former mayor of the Conservative party who ran in the top-ranked position in the three preceding elections. The final position on a list is sometimes used as an honorary position.

Figure D.1: Illustration of prediction model: The 2019 election in *Bodø* municipality



Notes: The figure plots individual candidates' estimated probability of winning a seat for the nine main parties in the 2019 election in *Bodø* municipality.

Results

Figure D.2 estimates heterogenous mobilization effects depending on candidates' electoral viability. We separate between candidates of four types:

- Hopeless candidates (likelihood below 1%; 22.0% of sample)
- Weak candidates (likelihood between 1% and 10%; 37.1% of sample)
- Viable candidates (likelihood between 10% and 50%; 28.2% of sample)
- Safe candidate (likelihood 50% and above; 12.8% of sample)

To interpret Figure D.2, we begin by noting that—because Norwegian parties run seniority systems (Cirone, Cox and Fiva, 2021)—candidates in all viability categories can have strong incentives to mobilize their networks. Candidates in hopeless and weak spots mobilize because they expect to be rewarded in future with advancement to a better spot. Candidates in viable spots mobilize both to earn future advancement and to win their current election. Candidates in strong spots mobilize because they will be in line to enter the municipal executive board (and other important posts) if their party wins.[33]

That said, some candidates who run in hopeless spots are non-careerists. They enter their party's list once, in order to help fill out the list, without any serious intention of seeking future advancement on the list. While these once-off candidates may exert mobilizational effort in order to help their party, we expect that they will not exert as much effort as other candidates, who will share the desire to help their party and also have the personal incentives discussed above.

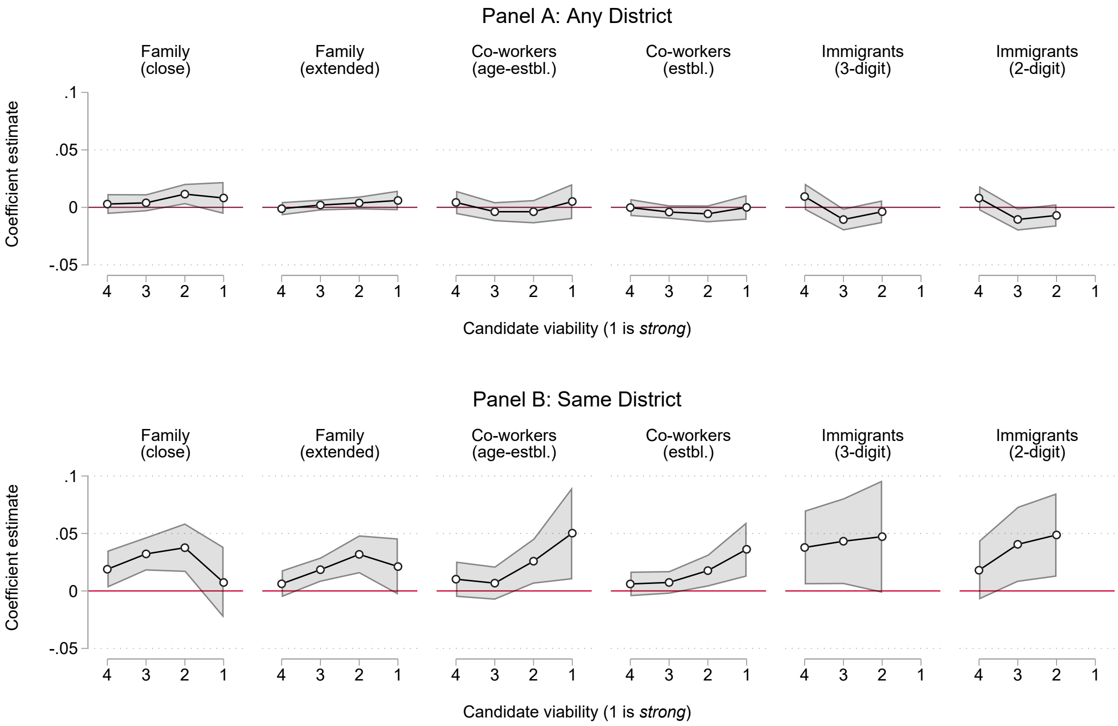
In line with our baseline results, Panel A shows that the effects of having a network member running in *another* district from the voter live is small or non-existent irrespective of candidate viability. Panel B indicates that the additional within-district mobilization effect is increasing in candidate viability.[34] For example, we estimate that a strong co-worker candidate in the same age group increases network members probability of voting with six percentage points, while a hopeless co-worker candidate in the same age group only increases network members probability to vote with one percentage point. The relationships between candidate viability and voter mobilization are similar, but more muted for family and co-occupational immigrant networks. The confidence intervals surrounding the point estimates in Figure D.2 are however quite broad, which makes it hard to draw firm conclusions.[35]

[33]Parties put their mayoral candidate on the top of the party list. Ideally, we would like to differentiate between candidates that are almost certain to win a seat in the council and other strong candidates, but we do not have statistical power to do so. Among immigrants, safe candidates are particularly rare.

[34]Because there are almost no immigrant candidates in strong spots, this category is merged with the viable group in the figure.

[35]The p-values from a test of equal effects among all four 'same district' categories are $p = 0.19$, $p = 0.08$, $p = 0.10$, $p = 0.08$, $p = 0.94$, and $p = 0.33$, respectively.

Figure D.2: Results - Split by electoral viability



Notes: This figure shows regression estimates based on equation (1), split by candidates' electoral viability (4=Hopeless, 3=Weak, 2=Viable, 1=Strong). Panel A reports network-wide effect on members' propensity to turn out (β), while Panel B reports the additional effect of co-residence (γ). The top two categories in the immigrant models are merged due to few observations. All estimated models include individual-BSU fixed effects and year fixed effects. Standard errors are clustered on the basic statistical unit level.