

## **Social Networks and Citizen Election Forecasting: The More Friends the Better**

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### **ABSTRACT**

Most forecasts by citizens as to which party will win a given election are correct, and such forecasts usually have a higher level of accuracy than voter intention polls. How do they do it? We argue that social networks are a big part of the answer: much of what we know as citizens comes from our interactions with others. Previous research has considered only indirect characteristics of social networks when analyzing why citizens are good forecasters. We use a unique German survey and consider direct measures of social networks in order to explore their role in election forecasting. We find that three network characteristics – size, political composition, and frequency of political discussion – are among the most important variables when predicting the accuracy of citizens' election forecasts.

**KEYWORDS** Social networks, election forecasting, citizen forecasting, public opinion, political interest, expectations, Germany

## **Social Networks and Citizen Election Forecasting: The More Friends the Better**

### **1. Introduction**

In most elections, the majority of citizens are able to predict the election winner correctly, regardless of who they plan to vote for (Lewis-Beck & Skalaban, 1989; Lewis-Beck & Tien, 1999; Miller, Wang, Kulkarni, Poor, & Osherson, 2012; Murr, 2011, 2015, 2016). Most US citizens typically predict correctly not only which presidential candidate will win their state, but also who will win the presidency (e.g., Graefe, 2014); and most British citizens are usually correct about both which party will win their constituency and which will garner a parliamentary majority (e.g., Lewis-Beck & Stegmaier, 2011; Murr, 2016). How do they do it?

A small body of work suggests that social networks are a big part of the answer. Since much of what we know as citizens comes from our social networks (e.g., Huckfeldt & Sprague 1995), we base our election predictions – like so many of our beliefs – on information from other people in our network (Uhlener & Grofman, 1986; Lewis-Beck & Tien, 1999; Meffert, Huber, Gschwend, & Pappi, 2011). However, previous studies on social networks and citizen forecasting accuracy have been hampered by the lack of direct measures of social network characteristics, relying instead on indirect or proxy measures. For example, Lewis-Beck and Tien (1999) find that people with higher levels of education are better able to predict who will win. This is probably because people with higher levels of education are more likely to develop skills in acquiring and processing information. They also intimate that a person's level of education tells us something about the size of their network, with more educated individuals possessing larger networks. Uhlener and Grofman (1986) and Meffert et al. (2011) use electoral differences between the citizen's electoral district and the national level to capture the network's partisan composition indirectly, because the surveys that they use do not collect measures of social network party leanings. However, these indirect measures may miss important aspects of the effect of social networks on citizen forecasting.

This study uses direct measures of citizens' network sizes and compositions, along with other network characteristics, in order to build a more complete model of citizen forecasting. Using a unique cross-sectional survey that collected both citizen election forecasts and direct measures of several social network characteristics in Germany in the autumn of 1990, we demonstrate that social networks have as much predictive power of citizen forecasting accuracy as the predictors identified as most important by previous research, namely vote intention and political interest. In addition, we show which social network characteristics have predictive power for influencing election forecasts (size, political composition, and frequency of discussion) and which do not (heterogeneity and level of expertise). In addition, we also provide guidance for future surveys as to what network measure to include in order to improve the accuracy of citizen election forecasts. Using a cross-validation exercise, we demonstrate that a single, abbreviated measure of the network size improves out-of-sample predictions.

## **2. Why citizen forecasts?**

As the field of election forecasting has grown, scholars have experimented with many different measures and methods in an attempt to find the most accurate predictors (for reviews, see Stegmaier & Norpoth, 2017; Lewis-Beck & Stegmaier, 2014). Such models often include vote intentions or government approval ratings a few months prior to the election as a gauge of the electorate's preferences.<sup>1</sup> Such variables can be found in models of elections in the US (Campbell, 2016; Erikson & Wlezien, 2016), Britain (Ford, Jennings, Pickup, & Wlezien, 2016; Stegmaier & Williams, 2016) and Germany (Norpoth & Gschwend, 2017; Jérôme, Jérôme-Speziari, & Lewis-Beck, 2017), among others. Both the approval and vote intention items reflect the respondent's personal assessment of the incumbent government or the candidates. However, a developing branch of the election forecasting literature has begun to utilize electoral expectations, measured by the question, "who do you think

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<sup>1</sup> In addition to voting intention polls or approval ratings, such models often include economic performance measures, the number of terms the party has held office, and previous election results.

will win the election?” This approach is referred to as “citizen forecasting”, and has been used for election prediction in both the US (Lewis-Beck & Skalaban, 1989; Lewis-Beck & Tien, 1999; Graefe, 2014; Murr, 2015) and Britain (Lewis-Beck & Stegmaier, 2011; Murr, 2011, 2016).

In such citizen forecasting models, the survey responses are aggregated to the level of prediction, whether the national level or the constituency level, and most often, citizens get it right. For instance, in their pioneering study, Lewis-Beck and Skalaban (1989) looked at citizen forecasts of eight US presidential elections between 1956 and 1984. They found that, on average, 69% of citizens forecast the election winner correctly, but that the majority of citizens forecasted 75% (six out of eight) of the elections correctly. In other words, moving from individual to aggregate forecasts improved the accuracy from 69% to 75% – an increase of six percentage points. Their two main findings – that most citizens forecast correctly most of the time, and that groups forecast better than individuals – have subsequently been replicated at two different levels (subnational and national) and in two countries (Britain and United States); see for example Graefe (2014), Lewis-Beck and Stegmaier (2011) and Murr (2011, 2015, 2016).

In addition to demonstrating that citizen forecasts are accurate, several studies have also shown that citizen forecasts are more accurate than any other forecasting approach, including voter intention polls. Using national-level data from the last 100 days before each of the seven US presidential elections between 1988 and 2012, Graefe (2014) compared the relative accuracies of citizen forecasts, voter intentions, prediction markets, expert surveys, and quantitative models. He found that citizen forecasts are better than any other approach at forecasting both election winners and vote shares. Similarly, Murr, Stegmaier, and Lewis-Beck (2016) used national-level data from the 48 months before each of the 18 British general elections between 1950 and 2015 to compare the relative accuracies of citizen forecasts and voter intentions, and found that citizen forecasts are better than voter intentions at forecasting both the winning party and its seat share.

As Murr (2015) has shown, the accuracy of citizen forecasts can even be increased by weighting and delegating the individual forecasts optimally

based on the citizens' competence (e.g., Grofman, 1975; Kazmann, 1973; Shapley & Grofman, 1984). The method involves two steps: first, predict the probability that each citizen will forecast correctly; then, delegate the forecasting to the most competent citizen and weight their forecasts according to their level of competence. Using data from eleven US presidential elections between 1952 and 2012, Murr (2015) showed that this increases the forecasting accuracy of both the candidates' vote shares in a state and which candidate will carry the state. Thus, being able to predict the chance of a citizen forecasting the election correctly is crucial for improving the forecasting accuracy.

### 3. Why can citizens forecast correctly?

The explanation as to why citizen forecasts are accurate has two parts (Murr, 2017). The first part explains why groups forecast better than individuals. This explanation rests on the assumption that individuals forecast better than chance on average, and the second part of the explanation rests on why individuals are able to do so.

Murr (2011) explains the fact that groups predict better than individuals based on Condorcet's jury theorem and its generalizations (Condorcet, 1785). Condorcet demonstrates the conditions under which the group decisions reached by a plurality rule are better than, equal to, or worse than individual decisions. His proof assumes that (i) the group faces two alternatives, one correct and one incorrect, (ii) the  $k$  group members vote independently of one another, and (iii) each member has one vote and the same probability  $p$  of choosing the correct alternative. Then, the probability of a correct group decision by a majority vote is

$$P = \sum_{m=\lfloor k/2 \rfloor + 1}^k \binom{k}{m} p^m (1-p)^{k-m}.$$

He shows that if each member chooses the correct alternative with more than a 50% probability, the probability of a correct group decision approaches unity as the group size increases to infinity ("wisdom of crowds"). He also shows that if each member chooses the correct alternative with less than a 50% probability,

the probability of a correct group decision approaches zero as the group size increases to infinity (“folly of crowds”).

Although Condorcet’s jury theorem refers to group sizes approaching infinity, even small groups show the effect of aggregating individual choices. Consider a group of three independent members, each with an 0.6 probability of choosing the correct alternative. This group chooses the correct alternative using a majority vote if at least two of the three members vote correctly. Using the above formula, the probability of a correct group decision is  $P = 3 \times 0.6^2 \times 0.4 + 0.6^3 = 0.648$ , an increase in accuracy of about five percentage points. This probability increases as the group size increases: it is 0.6824 with five independent members, 0.7102 with seven members, 0.7334 with nine members, and so on. In other words, even though individually members may be only slightly better than chance in getting it right, collectively they may choose the correct alternative with almost certainty, if the group has enough members. Table 1 displays the probabilities of a correct group decision for different individual probabilities of getting it right ( $p = 0.6, 0.7, 0.8, \text{ and } 0.9$ ) as well as different group sizes ( $k = 3, 5, 7, \text{ and } 9$ ).

**Table 1. The probability of a correct majority vote from  $k$  members with an individual probability of getting it right of  $p$ .**

	$k = 3$	$k = 5$	$k = 7$	$k = 9$
$p = 0.6$	0.6480	0.6826	0.7102	0.7334
$p = 0.7$	0.7840	0.8369	0.8740	0.9012
$p = 0.8$	0.8960	0.9421	0.9667	0.9804
$p = 0.9$	0.9720	0.9914	0.9973	0.9991

In deriving his theorem, Condorcet made three assumptions: each member chooses between only two alternatives, votes independently of the others, and has the same probability of voting correctly. Since the publication of his theorem, several other authors have relaxed each of these assumptions in turn and generalized the theorem accordingly. The theorem still holds even with more than two alternatives (List & Goodin, 2001), which is important because many elections involve voters choosing between more than two parties. Further, Ladha (1992) generalizes the theorem to correlated votes.

This is important because citizens might share the same information, talk to each other, or tend to “groupthink” (e.g., Janis, 1982). Finally, Grofman, Owen, and Feld (1983) prove that the theorem still holds if members differ in their probability of getting it right as long as they are all better than chance on average. This is important because Lewis-Beck and Skalaban (1989) show that citizens vary in their probability of making a correct forecast. In summary, these generalizations make the theorem useful for explaining why groups of citizens predict better than individuals.

Since the explanation of why groups predict better than individuals rests on the fact that individuals predict better than chance on average, the next step is to explain why this is the case. Murr (2017) explains the fact that individuals predict better than chance based on Uhlaner and Grofman’s Contact Model (Uhlaner & Grofman, 1986). Echoing Condorcet’s jury theorem, the Contact Model proves the conditions under which a citizen’s forecast, reached by choosing the party that is supported by the plurality of information available to the citizen, will be better than, equal to or worse than chance. The proof assumes that the citizen is forecasting a two-party election, receives and accepts pieces of information from the environment independently of one another, and counts each piece of information equally.

The Contact Model implies that if a citizen receives and accepts only information that is consistent with her vote intention (“selective sampling”), citizen forecasts will always be better than chance on average, though always as informative as voter intentions. However, if a citizen receives and accepts information that is representative of the public’s voter intentions (“random sampling”), citizens will always be better than both chance and voter intentions on average. As the number of randomly sampled bits of information increases to infinity, the probability of a correct forecast approaches unity. In other words, citizens will do better than chance and voter intentions, as is indeed the case, as soon as they receive and accept at least some information that is representative of the public’s vote intention (e.g., Lewis-Beck & Skalaban, 1989; Graefe, 2014).

Because much of what we know as citizens comes from interpersonal communication, we argue both that citizens’ social networks predict their

election forecasts, and that these networks offer the representative information that is necessary to enable them to forecast better than chance.

#### **4. Social networks and citizen forecasts**

The study of social networks—the social context through which individuals are tied to others—has shed light on both the way and the extent to which friends, family, neighbors, and peers influence electoral belief formation and voting behavior. In addition to learning from previous cohorts and personal experience (Manski, 2004, Blais & Bodet, 2006) and the media (Entman, 1989), networks provide contextual information that both allows voters to form expectations about elections and influences their choices. Meffert et al. (2011), for example, analyze various factors that influence electoral expectations, such as political motivations (knowledge and interest), rational and strategic considerations (the perceived distance between parties), and social context (regional differences, as a proxy for personal networks), and how these expectations influence voting behavior. The authors find that voters can form reasonable expectations about the winning party and that these beliefs are used to cast “fairly sophisticated votes”, such as strategic coalition voting.

Complementarily, Pattie and Johnston (1999) showed that conversations with partisan discussants influence vote decisions, and can even lead citizens to switch their vote to another party. Similarly, Huckfeldt and Sprague (1991) showed that vote preferences are not determined only by voter characteristics, but also by their discussant partners’ characteristics and political preferences; while Nickerson (2008) provided evidence regarding the influence of couples on voting behaviors. Other studies have shown that variations in the composition and size of an individual’s network affect their political attitudes and the amount of political information they have, which in turn affect their behavior and their beliefs (Huckfeldt, 2007; Mutz, 1998; Huckfeldt & Mendez, 2008; Partheymüller & Schmitt-Beck, 2012; Pietryka, 2015).



But how do people form electoral expectations? Citizens may gather information and update their beliefs about electoral victories based on: (1) their network members' characteristics, by observing how other members act and think about political, social and economic matters; (2) direct information from their network, by discussing who they think will win the election and which party they support; (3) previous electoral experiences; and (4) the news and opinion polls.

The very nature of social networks makes this source of information more likely to influence citizen electoral expectations and behavior than other sources such as the news media or polls. For instance, Schmitt-Beck and Mackenrodt (2010) show that personal communication appears to be more influential regarding turnout in a German local election than mass communication. Despite the fact that the media and polls may provide more reliable and balanced information about the electoral environment than social networks, information from social networks may provide more personalized information by using language and terms that are closer to the local context and more familiar.

While the news media and polls are passive sources of information, social networks give citizens the chance to actively disagree with dissonant information and to learn from it by debating with network members. Hence, though all sources of information may be complementary, social networks provide citizens with the opportunity to engage in back-and-forth debate and to learn from disagreements. As was suggested by McClurg (2006), social networks can encourage higher levels of political involvement, as well as an increased openness to differing viewpoints. In other words, people can learn from their networks.

The magnitude of a network's influence on citizens' beliefs about who will win the election may depend on the network's size, frequency of political discussion, political expertise and composition (heterogeneity), along with additional sources of political information.<sup>2</sup> Citizens who are embedded in larger social networks may have an advantage in forecasting elections, as they

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<sup>2</sup> Similarly, Millner and Ollivier (2016) discuss three main factors that determine the public's beliefs in the context of environmental policies: individual inference (how the updating of beliefs takes place), social learning and media.

frequently have higher levels of political knowledge (Kwak, Williams, Wang, & Lee, 2005). In addition, the larger the social network, the more likely it is to reflect the vote intentions of the population, making the aforementioned indirect inference more accurate (Banerjee & Fudenberg, 2004).<sup>3</sup>

Citizens without a network (*isolated* citizens) are likely to form their beliefs about who will win the election based on media or poll information, as well as on their own electoral preferences. However, if these citizens are incorrect in their belief of who will win the election, they lack the social contextual pressure or ability to update their expectations. In contrast, citizens with initially wrong or uncertain beliefs who are embedded in networks may retrieve information from their network in order to revise their expectations using information about their network's voting preferences (Chandra, 2009).

Having large networks may influence beliefs and behavior, but the information that citizens obtain from them should be updated frequently. The more political discussions that citizens have with their network, the more information they collect from its members and the more they will be able to remember it. Additional information may also render the network's information more salient than the citizen's own information when it provides the citizen with new information. Moreover, the increased frequency of discussion encourages citizens to become more informed, thus improving their ability to forecast (Eveland, 2004; Eveland & Hively, 2009).

Both informed and uninformed citizens use networks to gather information about the political system and elections (Pietryka, 2015). They seek out political experts to help them evaluate an election, even if they do not share the same partisan affiliation. Citizens are more likely to be influenced by those who they perceive as having expertise (Huckfeldt & Mendez, 2008; Ryan, 2011; Ahn, Huckfeldt, & Ryan, 2014; Huckfeldt, Pietryka, & Reilly, 2014) than by non-experts. Thus, these experts within the network should help improve citizens' forecasting accuracy by providing accurate, if still biased, information. Political expertise can also help in recognizing dissonant information and rejecting it (McClurg 2006).

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<sup>3</sup> This is true only if the most important agent's influence diminishes as the number of network members increases (Golub & Jackson, 2010).

In general, social networks play a role in both the dissemination of information and the acquisition of information that reduces ambiguity (Manski 2004; Ahn et al., 2014; Eveland & Hively, 2009; Finkel & Smith, 2011). However, in some cases, the information acquired from social networks may actually decrease the likelihood of a correct election prediction. When a political network leans toward the losing parties, or a citizen is unsure of how other network members will vote, this will undermine the citizen's ability to offer an accurate election prediction. Those embedded in homogeneous networks may assume that there is a greater support for a political party than in fact exists, and such networks may also reinforce "wishful thinking"; thus, citizens belonging to these networks may overestimate the chances of victory of a party that actually has little chance of success.

While political disagreement in networks persists even in multiparty electorates (Huckfeldt, Ikeda, & Pappi, 2005; Huckfeldt & Johnson, 2004), individuals frequently find themselves in social networks with other like-minded individuals. The homogeneity (homophily) of the network may either increase or decrease the likelihood of a successful forecast. Individuals in heterogeneous networks tend to show higher levels of political knowledge, as they frequently seek out additional information when they interact with those who do not share their views, which should improve their electoral forecasts (Eveland & Hively 2009). However, to the extent that individuals rely on their networks to act as representative samples, more homogenous networks, particularly those which are allied with an unlikely winner, will decrease the likelihood of a correct forecast. Thus, in such cases, the inclusion of more people in a person's network will not add new information. As such, social networks may improve citizens' ability to make accurate electoral forecasts, but this depends on the size and composition of the networks.

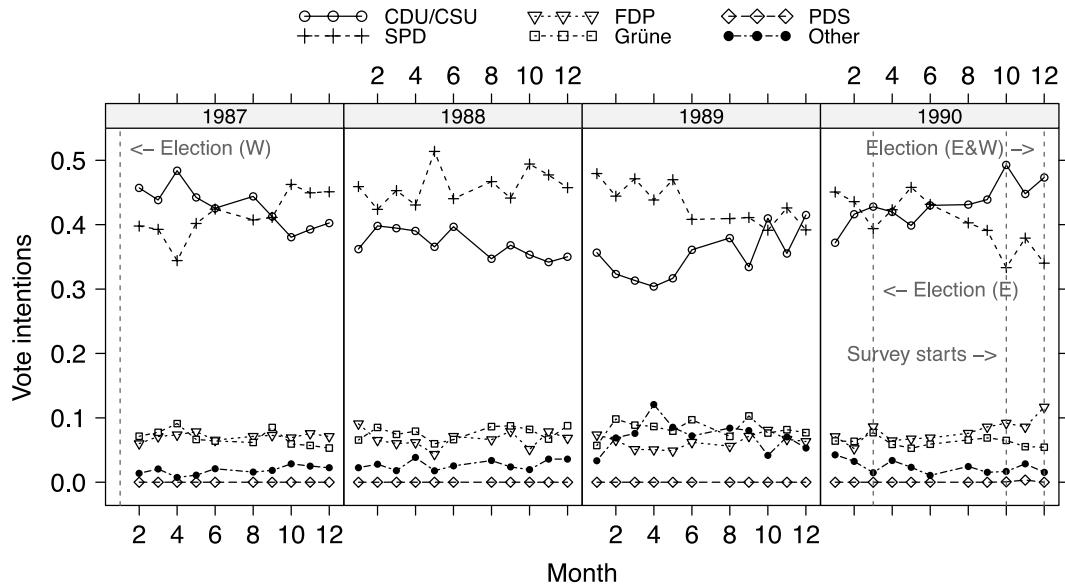
## **5. Data and measures**

The 1990 German federal election offers a unique electoral context in which to examine how social networks predict citizens' ability to forecast the election, as it provides a direct comparison between citizens with long-term

democratic experience (West Germans) and citizens who were new to democratic elections (East Germans), without varying the institutional or electoral context. West Germany held its first democratic election on 14 August 1949, whereas East Germany did not hold its first democratic election until 18 March 1990. The December 2, 1990, Bundestag federal election was the first Federal Republic of Germany election for East Germans, who had voted only four months earlier to unify with West Germany.

The governing Christian Democratic Union (CDU) had been losing support ever since its electoral victory in January 1987 (Figure 1). This loss benefited the main opposition party, the Social Democratic Party (SPD), which then led the polls from October 1987 to September 1989. However, the CDU started to recover midway through the electoral cycle, and led again for the first time in October 1989, beginning a period of uncertainty about whether the CDU or the SPD would win the subsequent election. From March 1990 onward, it looked increasingly likely that the CDU would be victorious in December. They won the East German general election in March, leading the SPD by 19 percentage points. In April, Oskar Lafontaine, the SPD candidate, fell victim to an assassination attempt and was unable to campaign for three months. From August onwards, opinion polls showed the CDU to be in the lead, due largely to the public perception that the CDU was the party best able to handle the economic consequences of unification (Pulzer, 1991). However, even though the outcome was fairly certain, as we discuss in the next section, not everyone correctly forecast a CDU win.

**Figure 1: Voting intentions, 1987–1990.**



Source: Forschungsgruppe Wahlen (2017).

We examine how social networks predict the ability of citizens to forecast by using the 1990 German section of the Comparative National Elections Project, a cross-national survey that collects both traditional individual-level data and information on the respondents' media, organizational, and (most importantly for this project) social network characteristics (Gunther, Beck, Magalhães, & Moreno, 2015; Gunther, Puhle, & Montero, 2007). The German section of this survey relies on face-to-face interviews in the pre-election period (October and November 1990), and includes a network battery that asked respondents to name up to five people with whom they discuss important matters. Our sample includes a total of 1547 respondents, of whom 487 are from East Germany. This survey uniquely (to the best of our knowledge) provides both information on the character and extensiveness of a respondent's social networks *and* the respondent's electoral forecast.

To measure the ability of citizens to forecast the winner of the election correctly, we rely on a survey item that asks respondents whether they believe that a CDU-led or an SPD-led government is likely to win the election, or they do not know.<sup>4</sup> Based on the previous literature, we code all respondents who predict a CDU victory as correct forecasters, and all other respondents as

<sup>4</sup> The question wordings can be found in the appendix.

incorrect. The majority of respondents forecast the winner correctly; however, approximately 25% of West Germans and 18% of East Germans made incorrect forecasts about the election. It is notable here that the East Germans were better forecasters than the West Germans, despite their limited experience with democratic elections.

We differentiate between uncertain and inaccurate answers by creating a categorical variable, where those who answer SPD are treated as inaccurate, those who respond with 'don't know' are uncertain, and correct CDU forecasts are treated as the reference category. While the proportions of inaccurate forecasts are similar between East and West Germans, with 9.9% and 9.5% respectively forecasting an SPD victory, more than 15.7% of West Germans were uncertain about the election outcome, compared to only 8.9% of East Germans.

We test how social networks predict the accuracy of election forecasts by examining four network characteristics: network size, frequency of political discussion in the network, political expertise in the network, and network ideology (heterogeneity). The network size ranges from 1 to 5,<sup>5</sup> and is based on the number of discussants that the respondent named in the network battery.<sup>6</sup> The frequency of political discussion measures how often, on average, the respondent discusses political matters with members of their network, based on the respondent evaluation, ranging from always to never (network discussion). Network expertise is based on the average evaluation of each network member's level of political knowledge. Network ideology is measured as both the proportion of the network that the respondent believes will vote for a left-leaning party (network left), and the proportion of the network for whom the respondent does not know the political party preference (network

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<sup>5</sup> We exclude respondents without a discussant because the other network characteristics cannot be calculated for them.

<sup>6</sup> Since the creation of this survey in 1990, there has been a growingly scholarly discussion about network size generators. Although Mardsen (2003) demonstrates that less than 10% of respondents generate more than five names, and Merluzzi and Bert (2013) provide evidence suggesting that five is a cost-effective number of network responses, Eveland, Hutchens, and Morey (2013) argue that the type of name generator used in this survey consistently underestimates the network size. However, given our theoretical expectation, we argue that this underestimation provides a conservative test for our hypotheses. In addition, summary network measures cannot measure network characteristics other than the size (Eveland et al., 2013).

unknown).<sup>7</sup> Finally, network heterogeneity is operationalized as one minus the absolute difference between the proportions of left- and right-leaning members in the respondent's network.<sup>8</sup> While increases in the network size, frequency of discussion, network expertise, and network heterogeneity may be expected to improve the ability of the respondent to forecast the outcome of the election correctly, the network ideology, particularly for left-leaning networks, may decrease the likelihood of a correct election forecast, as was suggested in the previous section. Table 2 displays summary statistics of the network variables.

**Table 2: Summary statistics of network variables.**

	West Germans				East Germans			
	Average	SD	Min	Max	Average	SD	Min	Max
Network size	2.46	1.21	1	5	2.67	1.24	1	5
Network discussion	1.64	0.80	0	3	2.39	0.63	0	3
Network expertise	1.08	0.54	0	2	1.27	0.50	0	2
Network left (proportion)	0.31	0.40	0	1	0.27	0.37	0	1
Network unknown (proportion)	0.29	0.41	0	1	0.28	0.40	0	1
Network heterogeneity	0.42	0.43	0	1	0.43	0.43	0	1

In addition to these network effects, we also consider other factors that previous studies have suggested might predict the accuracy of the forecasts (e.g., Lewis-Beck & Tien, 1999; Meffert et al., 2011): political, media, and demographic factors, as well as the number of days before the election that the survey interview took place. We capture individual partisanship and the effects of 'wishful thinking' by creating three dummy variables based on the respondent's reported vote intention on the second ballot, namely SPD voters, CDU voters, and voters who are uncertain about how they will vote, with minor

<sup>7</sup> While there could potentially be concerns regarding projection effects when using respondents' evaluations of their discussion partners' party preferences, previous research has demonstrated that voters are surprisingly accurate at identifying their discussion partners' political preferences (Huckfeldt & Sprague, 1995).

<sup>8</sup> The proportion of right-leaning members is one minus the proportions of left-leaning members and members for whom the respondent does not know the political party preference. Respondents with equal proportions of left- and right-leaning members in the network reach the highest value of one on the measure, indicating complete heterogeneity, while respondents with network members of only one ideological direction reach the lowest value of zero on this measure, indicating complete homogeneity. Respondents with ideologically mixed networks reach values between these two extremes.

party supporters being treated as the referent category.<sup>9</sup> We also control for self-reported levels of political interest, attention to television news, and attention to news in newspapers. The sociodemographic measures that we include are gender, age (transformed into four quartiles), and education (transformed into three categories). Finally, since the survey was conducted over a number of weeks, we account for the number of days before the election that the respondent was surveyed.

Because we argue that social networks provide citizens with information that helps them to forecast correctly, it is instructive to examine how our network measures differ from other measures related to information, such as formal education, political interest, and media attention (TV and print). We measure how network characteristics relate to these other informational measures by calculating Pearson’s correlation coefficient  $r$  (Table 3). While there is an association between network characteristics and political education, interest, and media attention, most of the time it is either very weak ( $|r| < 0.20$ ) or weak ( $0.20 \leq |r| < 0.40$ ). This means that while many people have personal characteristics (e.g., a low political interest) that might make accurate forecasts less likely, they nevertheless have social network characteristics (e.g., many discussants) that might make accurate forecasts more likely. In other words, for many citizens, their social network may potentially compensate for their lack of information from the media, while for others it may correct or complement the media information they receive. The weak correlation between network characteristics and political interest, education and media attention, together with our theoretical arguments, justify us in considering network characteristics as additional predictors of a citizen’s forecasting accuracy.

**Table 3: Correlation between network characteristics and education, political interest, and media attention.**

	Political interest	TV news attention	Print news attention
Education			

<sup>9</sup> Germany uses a mixed member proportional electoral system, which provides voters with the opportunity to cast both a candidate vote (first ballot) and a party vote (second ballot) for the Bundestag, with the party vote determining the overall share of seats in the legislature. This latter measure of vote intention forms the most comparable measure between East and West Germany, as partisanship was not asked of East German respondents.



Network size	0.20	0.18	0.12	0.12
Network frequency	0.33	0.46	0.43	0.31
Network expertise	0.22	0.34	0.28	0.24
Network left	0.01	0.09	0.03	0.04
Network unknown	-0.05	-0.13	-0.11	-0.10
Network heterogeneity	-0.01	-0.06	-0.06	-0.06

The regression analyses reported below weight the respondents by inverse sampling probability in East and West, because East Germans were oversampled relative to their proportion of the population, and cluster the standard errors by sampling point.

## 6. Results

### 6.1. Correct and incorrect forecasts

First, we examine the variables that predict the accuracy of Germans' election forecasts. The outcome in the logit model shown in Table 4 is whether the respondent forecasted the CDU victory correctly or not. In this analysis, incorrect forecasts include both responses that the SPD would win and "don't know" answers. While we are most interested in the differences in forecasting accuracy between respondents with different social network characteristics, looking at other variables that could predict the forecast accuracy enables us to compare these results to those of the handful of other studies that have looked at the characteristics of accurate forecasters.

The results of the binary logit model in Table 4 indicate that social networks predict the forecast accuracy in ways that are consistent with our expectations, even when controlling for a host of other political, media, and demographic characteristics.<sup>10</sup> We observe that both the number of people in the respondent's network and the frequency of political discussion have positive and statistically significant coefficients. This means that both having more people in the network and having more frequent discussions in the network

<sup>10</sup> These computations and those that follow were performed on a Mac OS X 10.11.6 with Stata/SE 12 using the logit, mlogit, margins, and lincom commands.

make a positive difference to the probability of a correct forecast. Conversely, we observe that the shares of the network with left or unknown political leanings have negative and statistically significant coefficients. This means that the larger the share of the network with left or unknown political leanings, the less likely the respondent's forecast is to be correct. The coefficients of both network expertise and network heterogeneity are in the expected positive direction, but miss conventional levels of statistical significance.

**Table 4: Correct forecast of CDU victory  
pooled binary logit estimates.**

	Log-odds	
	Estimate	(Std. error)
Constant	-0.89	(0.65)
East	-0.09	(0.19)
Age	0.09	(0.06)
Female	-0.01	(0.13)
Education	0.06	(0.13)
Political interest	0.29**	(0.09)
TV news attention	-0.03	(0.09)
Print news attention	0.03	(0.07)
SPD voter	0.03	(0.18)
CDU voter	2.10**	(0.27)
Undecided voter	0.53**	(0.25)
Days until election	-0.01	(0.01)
Network size	0.22**	(0.07)
Network discussion	0.19*	(0.11)
Network expertise	0.24	(0.16)
Network left	-0.77**	(0.24)
Network unknown	-0.59*	(0.35)
Network heterogeneity	0.15	(0.33)
<i>N</i>	1547	

Note: \*  $p < 0.10$ , \*\*  $p < 0.05$ . Standard errors are clustered by sampling points. The data are weighted by inverse sampling probabilities in East and West.

Of the other variables, only a few of the coefficients attain statistical significance. We corroborate the findings of earlier studies that respondents with higher levels of political interest are more likely to make accurate forecasts, and find evidence that CDU voters are more likely to forecast a CDU victory correctly than the excluded “minor party vote” category. We also observe that respondents who say that they don’t know for whom they will vote (undecided voters) are also more likely to forecast correctly than minor party voters, though the coefficient is smaller than for CDU voters. In contrast, SPD voters are just as likely to get it right or wrong as minor party voters.

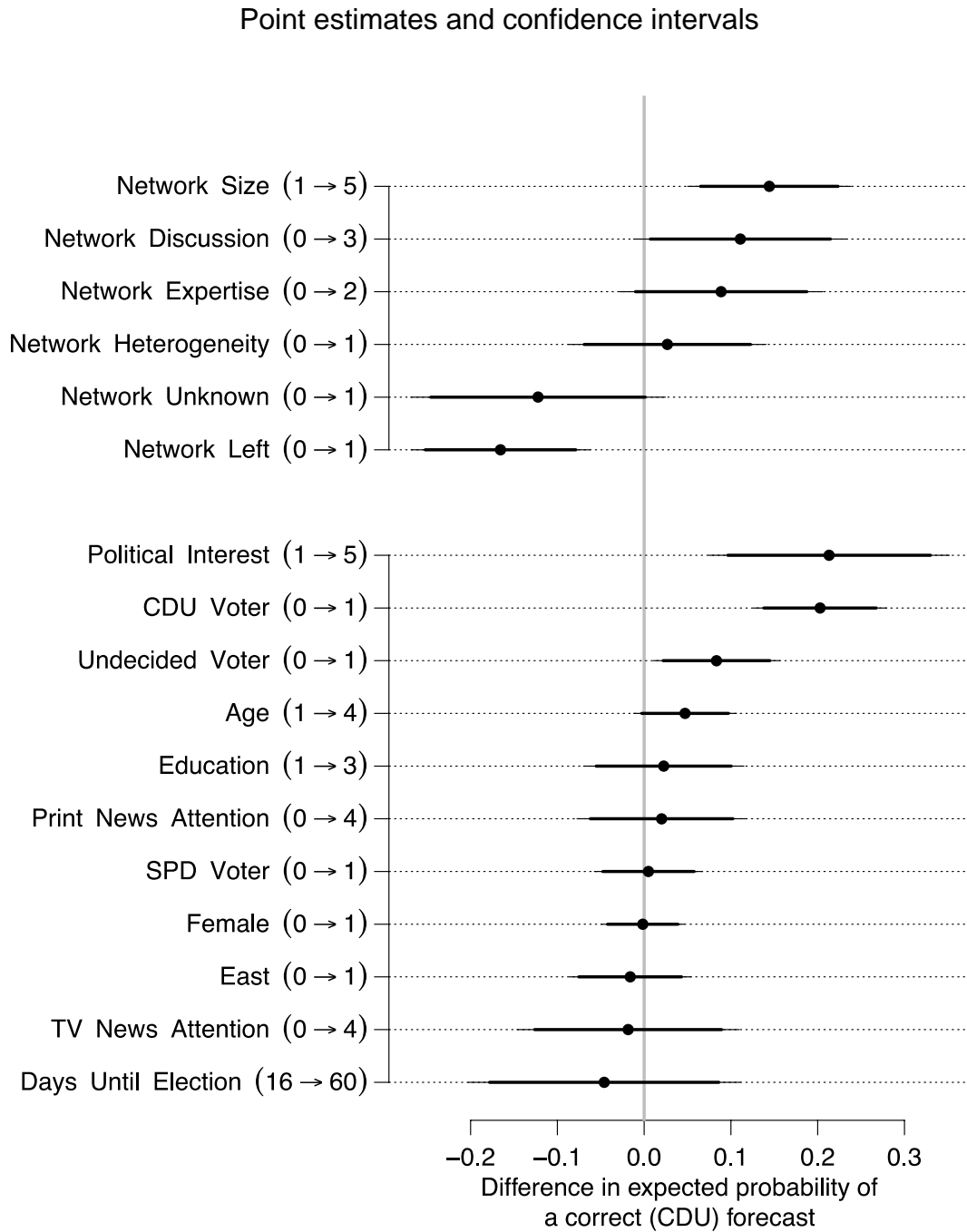
Notably, the coefficient of the “East” variable, which is designed to capture systemic differences between East and West Germans in this pooled analysis, is not statistically significant. Furthermore, the demographic variables, media exposure, and number of days before the election are not predictive of the forecasting accuracy.

We investigate the results of the full binary model and the subsequent multinomial logit models further by computing first differences (King, 1989, pp. 107f). First differences estimate how much the fitted values would differ on average when comparing two respondents who have different levels of a given predictor while being identical on all other variables. We compute first differences by subtracting the expected probability of an outcome given the maximum value of a predictor from the expected probability given its minimum value, holding all other variables at their median.

Figure 2 provides a visual assessment of the differences between the expected probabilities of a CDU forecast when comparing two respondents who have the minimum and maximum levels of a given predictor, while holding all of the other variables at their medians. The bold lines depict the 90% confidence intervals around the point estimates of the differences in expected probabilities, while the thinner and slightly longer lines show the 95% confidence range. The predictive power of the social network variables is apparent here, reinforcing the importance of the network characteristics. The network size and ideological leanings show large differences in the expected probability of forecast accuracy, differences that are rivaled only by political interest and respondent vote intention for the CDU or not known. For instance,

if we compare a respondent who has five network members with someone who has only one network member (the maximum and minimum values for network size), we expect the respondent with the larger network to have a 15 percentage point higher chance of making a correct forecast on average. As another example, if we compare a respondent whose network consists of only left-leaning members with someone whose network consists of no left-leaning members, we expect the one with the more left-leaning network to have a 16 percentage point smaller chance of making a correct forecast on average. (Table A1 in the online appendix provides the differences in expected probabilities and their confidence intervals that correspond to this figure.)

**Figure 2: Difference in expected probabilities for pooled binary logit model.**



Note: Difference in expected probabilities between two respondents with maximum and minimum values of the indicated predictor while holding the remaining predictors constant at their median value. The predictors are sorted by increasing effect, for network characteristics and controls separately. Bold segments indicate 90% confidence intervals and thin segments indicate 95% confidence intervals.

## 6.2. Correct and incorrect forecasts and the “don’t knows”

Next, we recognize that not all “wrong” forecasts are the same. A respondent could either provide an incorrect forecast of an SPD victory, or report not knowing who will win, and the covariates that predict these results are likely to be different. We assess this by estimating multinomial logit models where those who offer incorrect (SPD) or uncertain (don’t know) responses are assessed separately relative to those who forecasted correctly. We estimate this both for the pooled survey and in the form of an interactive model where we assess whether differences exist between East and West Germans when it comes to the coefficients of the various predictors.

Again, we explore the results of the multinomial logit model further by computing first differences.<sup>11</sup> Figure 3 presents the differences in expected probabilities and the corresponding confidence intervals for each predictor and each forecast (CDU, SPD, don’t know), based on the estimates of the pooled multinomial logit model (full results are reported in Table A2 in the online appendix). We observe that the social network variables differ in their predictive power across the three distinct forecasts. In general, we observe that respondents whose networks displayed a higher share of left or unknown leanings or lower levels of expertise were more likely to provide an incorrect SPD forecast. In contrast, respondents who had less frequent discussions with those in their network were more likely to give “don’t know” responses. Specifically, if we compare a respondent whose network has five members to someone whose network has one member, we expect that the respondent with the larger network will be 14 percentage points more likely to make a correct CDU forecast, 11 percentage points less likely to give a “don’t know” response, and 2 percentage points less likely to make an incorrect SPD forecast. In other words, we expect that respondents with varying network sizes will differ in their chances of giving a CDU forecast or a “don’t know” response, but that they will be similar in their chances of giving a SPD forecast on average. In summary, the larger the network, the more accurate and certain citizen forecasts are.

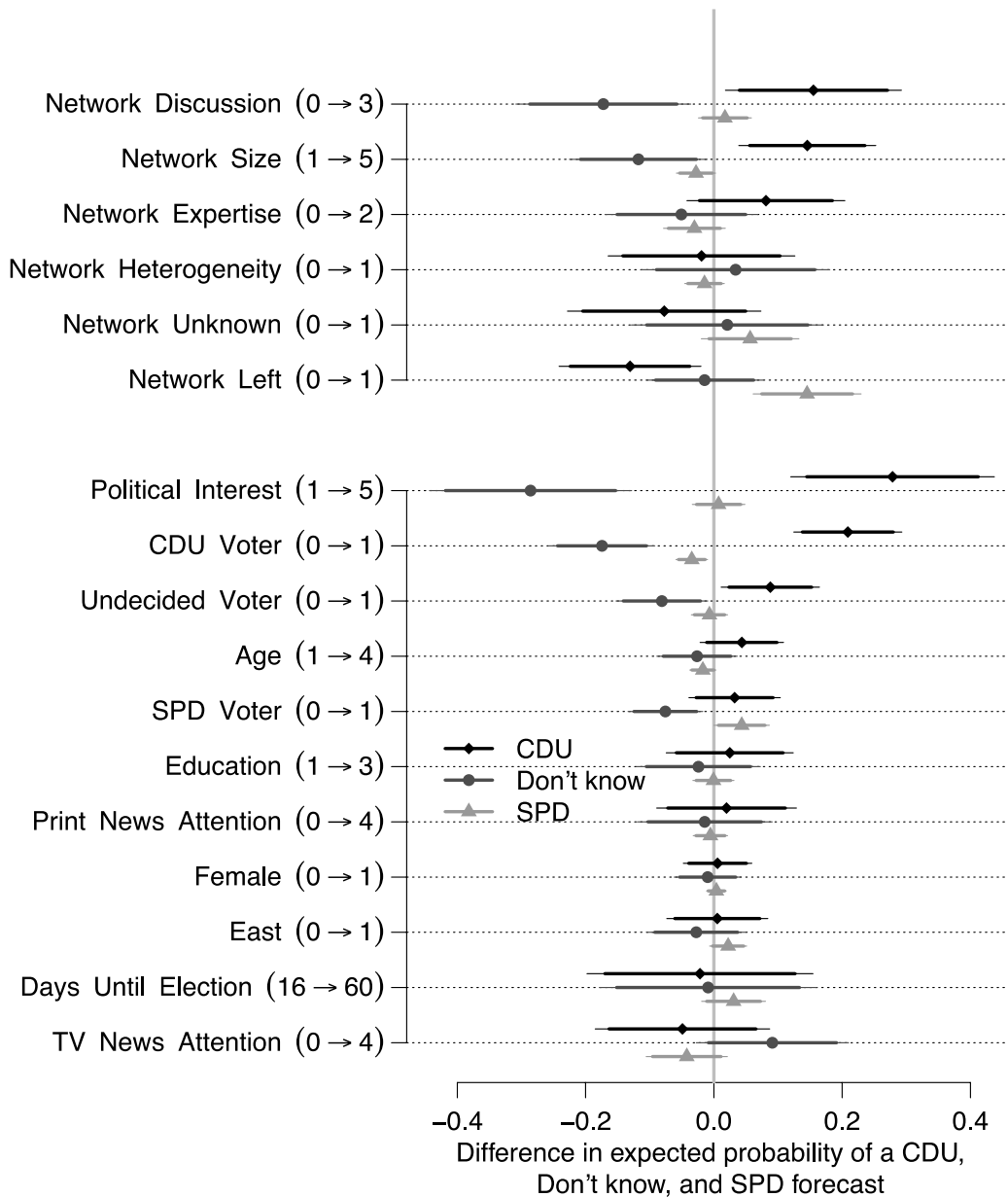
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<sup>11</sup> Online Appendix Table A2 reports the full results of our pooled and interactive multinomial logit models.

(Table A3 in the online appendix reports the differences in probabilities and the values of the 95% confidence intervals.)

**Figure 3: Difference in expected probabilities for the pooled multinomial logit model.**

Point estimates and confidence intervals



Note: Difference in expected probabilities of a CDU, don't know, or SPD forecast between two respondents with maximum and minimum values of the indicated predictor, while holding the other variables constant at their median value. Predictors are sorted by increasing effect on giving a CDU response, separately for network characteristics and controls. Bold segments indicate 90% confidence intervals and thin segments indicate 95% confidence intervals.

Figure 3 also shows large differences in expected probabilities for respondents who differ in their vote intentions and levels of political interest. Comparing two respondents with high and low levels of political interest, we expect that the one who is more interested in politics will have a 27 percentage points higher chance of correctly forecasting the CDU to win and a 27 percentage points lower chance of a “don’t know” response, but will not differ in the probability of an incorrect SPD forecast on average.<sup>12</sup>

So far, the binary and multinomial logit models and the difference in expected probability figures have demonstrated that social network characteristics are highly predictive of the accuracy of an election forecast, and can help us to distinguish between incorrect forecasts and respondent uncertainty. These network measures, in addition to political interest and vote intentions, by far outperform demographics and media variables. The number of days before the election that the interview took place is not predictive of the type of prediction given by the respondent.

### *6.3. Allowing the coefficients to vary between East and West Germans*

German reunification ended 40 years of political division between East and West Germany. It has been of general interest to describe the similarities and differences in public opinion and behavior between East and West Germans in order to understand the extent to which the country has developed a unified political culture (e.g., Gabriel, 1997; van Deth, Rattinger, & Roller, 2000; Fuchs, Roller, & Wessels, 2002; Gabriel, Falter, & Rattinger, 2005; Falter, Gabriel, Rattinger, & Schoen, 2006). In our context, we expect East Germans to rely more on social network information than West Germans, given the challenges that new democracies are likely to face, such as weak partisan cues, low levels of partisan identification, and volatile voters (Baker, Ames & Renno, 2006). Hence, we now examine whether the coefficients of our predictors differ between the East and West.

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<sup>12</sup> While we cannot reject the null hypothesis that the first difference for political interest is the same for network size related to a CDU response ( $b = 0.13$ ; Std. Err. = 0.09;  $z = 1.54$ ) or a SPD response ( $b = 0.04$ , Std. Err. = 0.03;  $z = 1.34$ ), we can reject the null hypothesis for a “don’t know” response ( $b = -0.17$ ; Std. Err. = 0.08;  $z = -1.98$ ).



We examine possible heterogeneous coefficients between East and West by following the recommendations of Tsai and Gill (2013) on interactions in generalized linear models. We first add product terms between each of the predictors and the East dummy variable to the pooled multinomial logit regression equation (the last two columns of Table A2 display the estimates of this interacted multinomial logit model), then calculate first differences of the predictors, separately for East and West. Finally, we compare the first differences of a predictor between East and West to assess the statistical significance and magnitude of the interaction (Figure A1 and Table A4 in the online appendix show all of these first differences).

By following this procedure, we found statistically significant interactions for only two network variables (the size of the network and the share of the network with left political leanings) on just one outcome (“don't know”). In other words, of the 18 possible interactions – six network variables multiplied by three outcomes – 16 are statistically insignificant. Since we would expect one to be statistically significant by chance out of 20 such comparisons, we do not want to emphasize the differences that we found. Thus, the results of the interacted model suggest that there are no major differences in how network characteristics predict forecast accuracy between East and West Germans: social networks predict the forecast accuracy in the same way for both groups.<sup>13</sup>

## **7. A simple network measure for improving accuracy of out-of-sample predictions**

The analysis above described which citizens were most likely to forecast the election correctly. Next, we would like to provide guidance for people who want to use citizen forecasts to forecast future election outcomes. As has been

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<sup>13</sup> We also considered possible interactions between the most important predictors (Gelman & Hill, 2007, p. 69): network size, network discussion, and network left, as well as political interest and vote intention. We tested whether the network variables interact with each other or with the other predictors, again following the procedure recommended by Tsai and Gill (2013). (In the online appendix, Tables A5, A6 and A8 show the estimated regression models, while Tables A7 and A9 and Figures A2 to A6 show the first differences.) We found one statistically significant interaction: the importance of the frequency of discussion decreases with higher levels of political interest for the outcomes CDU and don't know.

mentioned, aggregated citizen forecasts are most accurate when individual forecasters are weighted by their forecasting competence. The analysis above improves the researcher's ability to identify which individuals to weight more heavily: because social network characteristics predict forecasting competence, future aggregated citizen forecasts can be made more accurate by using these network characteristics to calculate the individual weights.

However, network batteries take a great deal of space on a questionnaire. The survey that we used in our analysis included five questions identifying network members, as well as follow-up items for each member thus identified, measuring their political preference, expertise, frequency of discussion, etc. Is including network batteries in new surveys worthwhile in terms of improving the election forecasting accuracy? Below, we show that even a single, abbreviated measure of the network size – asking citizens how many people they discussed an important personal matter with – improves out-of-sample predictions.

We compared the out-of-sample predictive accuracies of all possible subsets of the predictors considered above, with three modifications. First, as the response variable, we chose whether the citizen correctly forecasted the winner (0 = “no”; 1 = “yes”), excluding the response “don't know” because only actual forecasts can be weighted. Second, we considered the network size (0 = “no discussants” to 5 = “five discussants”) as the only network characteristic. We do this because the above descriptive analysis found the size to be correlated strongly with the forecasting accuracy, and because this predictor also applies to citizens without a discussant, while the other network characteristics apply only to citizens with at least one discussant. (Excluding “don't knows” and including citizens without networks changes the number of observations to 1,592.) Finally, we replaced the three vote intention predictors with a single dummy variable indicating whether a citizen forecasted the same party to win as the one they intended to vote for (0 = “no”; 1 = “yes”). We do this because this predictor can be used without the researcher knowing in advance which party will win (Murr, 2015). This leaves us with ten predictors: east, age, female, education, political interest, TV news attention, print news attention, forecast intention, days until election, and network size.

We used  $k$ -fold cross-validation (e.g., Ward, 2010, Murr, 2015) to compare the out-of-sample predictive accuracies of all  $2^{10} = 1,024$  possible subsets of predictors. Cross-validation splits the data randomly into  $k$  folds. It first fits the models to the  $k - 1$  folds and then tests them on the  $k$ th one, iterating these two steps from 1 to  $k$  to get a distribution of the predictive accuracy. We set  $k = 10$ , which is the typical value in the literature, and repeated  $k$ -fold cross-validation with ten different splits. We measured the predictive accuracy based on the area under the receiver operator characteristic curve (AUROC), which is a common measure of accuracy in the forecasting literature for binary classification tasks (e.g., Ward, 2010, Murr, 2015). An AUROC value of 50% indicates a random classifier and a value of 100% indicates an optimal classifier. The AUROC can be interpreted as the probability that a randomly chosen correct citizen forecaster will be ranked as more likely to be correct than a randomly chosen incorrect citizen forecaster (Fawcett, 2006).

Including the network size as a predictor improved the predictive accuracy (Table 5). Overall, the model with the largest AUROC of 62.57% included only five of the nine predictors: age, TV news attention, forecast intention, days until election, and network size. In contrast, the best model excluding the network size achieved an AUROC of 61.40% – 1.17 percentage points lower than the best model including the network size. Averaging across all 1,024 models, the AUROC of models including the network size was 1.4 percentage points higher than that of models excluding the network size. In comparison, only forecast intention and age had larger increases, of 3.98 and 3.22 percentage points, respectively. Including some predictors even decreased the predictive accuracy on average. For instance, the AUROC of models including print news attention was an average of 0.17 percentage points lower than that of models excluding print news attention. This all demonstrates that it is worthwhile to include the network size as a measure on new surveys because it does a better job of predicting forecasting competence than many commonly available measures (e.g., print news attention). As elections grow increasingly competitive and election results grow tighter, even minor improvements in forecasting measurements may be critical in increasing the forecast accuracy.

**Table 5: Out-of-sample accuracy of all 1,024 possible subsets of variables for predicting correct forecasts (0 = “no”; 1 = “yes”) by 1,592 citizens before the German Bundestag election in 1990 using binary logistic regression.**

Rank	Predictors (0 = “excluded”; 1 = “included”)										AUROC
	Eas t	Age	Fem .	Educ .	Pol .	T V	Prin t	Forec .	Day s	Net .	
1	0	1	0	0	0	1	0	1	1	1	62.57
2	0	1	0	0	1	0	0	1	1	1	62.48
3	0	1	0	0	0	0	0	1	1	1	62.36
4	0	1	0	0	1	0	0	1	0	1	62.32
5	0	1	0	0	0	1	0	1	0	1	62.28
6	0	1	0	0	1	1	0	1	1	1	62.27
7	0	1	0	0	0	1	1	1	1	1	62.21
8	0	1	0	0	0	0	1	1	1	1	62.19
9	0	1	0	1	0	1	0	1	1	1	62.18
10	0	1	0	1	0	0	0	1	1	1	62.18
...											
91	0	1	0	0	0	1	0	1	1	0	61.40
...											

Note: Entries are sorted by decreasing average area under the receiver operator characteristic curve (AUROC) in 10-fold cross-validation across ten repetitions and by decreasing the number of predictors. Due to space constraints, only the ten best models are presented, along with the best model without the network size as a predictor.

## 8. Conclusion

This study has examined how social networks predict the ability of citizens to forecast the election winner correctly when controlling for other variables such as political interest, gender, education, media attention, and vote intention. Specifically, we have found that citizens who have larger social networks and engage in more frequent political discussions are better at forecasting the winner than people who do not share these network characteristics. Our analysis also shows that the political leanings of the network matter too. Those whose networks contained a higher proportion of left-wing party supporters were less likely to forecast (correctly) that the right-wing CDU would win. Furthermore, respondents who were unsure of their friends’ party preferences were less likely to provide correct forecasts. Essentially, voters with extensive, communicative, and varied groups of friends

– and, of course, neighbors, colleagues, family members, and peers – are best able to forecast the election winner accurately.

Finding such robust results for social network characteristics might be a surprise in this particular election, given that public opinion polls at the time of the survey in autumn 1990 pointed to a decisive CDU victory. We view this particular election as a conservative test of our social networks theory. With the election all but a foregone conclusion, one might expect the predictive power of social networks for the respondents' forecasts to be limited. However, even in this context, networks demonstrably predicted citizens' forecasts. In more competitive elections, where there is a greater degree of uncertainty about the likely winner, social networks and their characteristics would probably play an even more important role in predicting voters' election forecasts.

In addition to examining the predictive power of social network characteristics for election forecasts, we have also considered how experience with democratic elections might predict citizens' abilities to give an accurate forecast, based on whether a respondent resided in East or West Germany. Perhaps surprisingly, East Germans were more likely to forecast the victor correctly than West Germans. Also, while we might have expected that having had less democratic experience would mean that networks were more important for East Germans than for West Germans in predicting their expectations – given the challenges faced by new democracies (e.g., weak partisan cues, low levels of partisan identification and volatile voters, as was discussed by Baker et al., 2006), our analysis indicates that no such differences exist.

The robustness of our findings in both East and West Germany suggests that the predictive power of social networks should be present in both new and established democracies. However, since the institutional and political contexts of the 1990 German election are the same for both regions, future research should examine whether social networks predict citizen forecasts similarly in countries with different party systems and electoral rules.

Future research could study how the internet and the emergence of online social networks have influenced citizens' forecasting abilities. Some studies have shown that the internet has neither increased nor decreased

social capital, but instead supplemented it (e.g., Wellmann, Haase, Witte, & Hampton, 2001). Hence, citizens still seem to bond (form closer connections with others) and bridge (form ties across social groups) to the same extent as before. Other studies have shown a large overlap between offline and online social networks (e.g., Subrahmanyam, Reich, Waechter, & Espinoza, 2008), meaning that the networks elicited using electoral surveys are likely to be a subset of those captured in online social networks. Online platforms are likely to increase citizens' abilities to forecast because they provide a wider access to information without additional cost. They enable citizens to be updated about their networks' electoral preferences without face-to-face discussions, and allow citizens to be informed about all of their network members, even those who are distant from the most influential people in their network.

A final lesson of our analysis is that social network characteristics, and questions on citizen forecasting, are important elements in electoral surveys, and that their exclusion may inhibit our understanding of political learning and decision making. The size and composition of social networks are associated with citizens' ability forecast elections correctly, and understanding how and why citizens estimate the winners of elections correctly will be critical as the demand for political forecasting continues. In the absence of measures of social network characteristics, we cannot predict or utilize these forecasts fully. In addition, understanding citizen forecasting also reveals something important about how social networks predict political learning. The size and ideological make-up of networks compete with other factors in predicting whether citizens can make correct inferences about not just local, but also national, political trends. In summary, just as social networks help us to understand citizen forecasting, citizen forecasting informs us about how social networks predict contextual learning and political knowledge.

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## **QUESTION WORDING APPENDIX**

### **DEPENDENT VARIABLE**

#### FORECASTING:

From the present point of view: who would you say will win the next general election: The CDU/CSU or a coalition government led by CDU/CSU, or the SPD or a coalition government led by the SPD?

### **NETWORK VARIABLES**

#### NETWORK SIZE

From time to time, most people discuss important personal matters with other people. Looking back over the last six months, who are the people with whom you discussed an important personal matter?

#### NETWORK FREQUENCY

When you talk with these persons, how often do you discuss political questions? Would you say almost always, sometimes, seldom, or never?

#### NETWORK EXPERTISE

How much do these persons, in your opinion, know about politics: much or very much, average, less much? Would you say: much/very much, average, or less much?

#### NETWORK IDEOLOGY

Which party do you think would these persons vote for in the general election of 2 December this year?

### **INDIVIDUAL LEVEL**

#### VOTE CHOICE:

Second Vote: Which party will you vote for with your second vote?

#### POLITICAL INTEREST

Generally Speaking: How much are you interested in politics? Would you say:

very much, much, so-so, somewhat, or not at all?

#### TV NEWS ATTENTION

How attentively do you follow [television] news reports on political events in Germany and other countries? Would you say: very attentively, attentively, less attentively, or not attentively at all?

#### PRINT NEWS ATTENTION

Regardless of how often you read your daily newspaper: How attentively do you read the reports on the political events in Germany and other countries? Would you say: very attentively, attentively, less attentively, or not attentively at all?

#### EDUCATION

What education level do you have?

#### AGE

Please tell me what month and year you were born

#### GENDER

Sex of Respondent: Man or Woman.

