Opinion Polls’ Effect on Political Attitudes -
Results from a time-series survey experiment in a general population web panel

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Paper to be presented at the ECPR General Conference 2015, Montreal, Canada, August 26-29.
Abstract
When people form their preferences on political issues, other people’s opinions matter to them. There is thus a potential self-reinforcing mechanism at play when individuals form their political preferences, where the aggregate level of support and opposition becomes a factor of its own in shaping public opinion. In this paper we present an experiment where we inform the treatment groups with a skewed distribution of opinions about a political issue, and then track the treatment effect over a sequence of polls with the aim of exploring the effect of the treatment over time. The research design of the presented experiment gauges to what extent knowledge of opinion polls as such have a lasting impact on people’s political preferences. Can polls themselves change the dynamics of public opinion formation among the citizens? To facilitate the implementation of the experimental design, we introduce a technical innovation which we label the *Dynamic Response Feedback*. This procedure automatically generates a pie chart with poll distributions from previous responses and uses it as information to respondents who are taking the survey in present time. By repeating this procedure several times a series of poll distributions are created within one survey wave. The survey experiment is conducted on 2500 respondents in The Norwegian Citizen Panel, which is a probability based web panel of Norwegian residents. The paper presents results from an experiment on the question of whether or not the respondents think that measles vaccination of children should be compulsory. We find that when respondents are presented with a poll that is slightly skewed in the sense that it displays a higher share of supporters for the issue than the true share (as found in the control group), the aggregate mean of the treated respondents also becomes higher. Moreover, the effect of the initial poll distribution has a diminishing effect over time which resembles a fading autoregressive (AR1) process.
Introduction
In contemporary democracies citizens are more or less constantly exposed to political opinions of other citizens, most often through opinion polls presented in different types of media and carried out by a wide array of political actors, such as political parties and interest organizations. The political consequences of the opinion poll explosion have been subject to debate, where both potentially positive and negative effects have been put forth. On the one hand, it could be argued that the frequent use and presentation of opinion polls may lead to increased opportunities for the public to learn about important political issues and collective public opinion. On the other hand, some have raised concerns about the fact that polls themselves may change individual-level attitudes since they may change citizens’ expectations, in the end leading to opinion polls being self-fulfilling prophecies (Rothschild and Malhotra 2014). There is widespread popular belief that expectation effects such as bandwagon and underdog effects exist. They have been used as explanations for erroneous poll projections (McAllister and Studlar 1991), resulting in pollsters being banned from publishing poll rates during the final days of election campaigns in countries such as France and Switzerland. The issue is most pressing in the run-up to elections, but also in settings beyond election campaigns there are popular worries that the publishing of polls is an act that entails potential political consequences in the sense that polls can move the public opinion on their own.

The theoretical underpinnings of these worries come both from rational choice theory and from established social psychological mechanisms at the individual level. From a rational choice perspective, citizens are in general cognitive misers. That is, when being asked about their opinion on an issue which they normally have not considered and where they do not have access to any apparent information they instead rely on social cues, i.e. what others think about this matter. In psychology, scholars have since Sherif (1936) observed that people tend to conform to opinions of others. Holding and expressing divergent attitudes is a social cost that people, all else equal, desire to avoid if they can (Noelle-Neumann 1993; Kuran 1997). Particularly in the political domain people learn about the views of the majority through frequent reporting of opinion polls. For instance, during electoral campaigns the media tends to focus on the “horse race” between the major candidates (Rothschild and Malhotra 2014). Such situations have been argued to create a bandwagon effect where pre-election polls tend to disfavor the losing side by influencing doubtful voters to side with the candidate leading according to the polls (cf. Gallup and Rae 1940). In political science, the bandwagon effect
has mostly been discussed within the field of electoral studies. However, today polls are used in many different ways and media often reports about the public opinion on a wide variety of political issues and policies.

The survey experiment reported in this paper aims at investigating the impact of polls on aggregated opinion distributions on a concrete issue. More specifically, it asks about a specific question that recently was up to debate in Norway, namely to what degree the respondents agree or disagree that measles vaccination of children should be compulsory. A novel contribution to the literature is the inclusion of the time dimension introduced in the experiment: If there is a poll effect on political attitudes, how long does it last? Does the effect prevail or does it die out as time goes by? In order to investigate these issues we use an innovative dynamic experimental design. By taking advantage of the Norwegian Citizen Panel, a national representative web panel, we are able to investigate the effect of opinion polls on the public opinion by instantly processing completed responses and form them into poll information for subsequent respondents. The data generating process and the experimental strategy are further outlined below, preceded by a discussion on the theoretical arguments for why polls have the potential to influence people’s opinions.

Political cues and public opinion
From an impressive stock of electoral research we know that the way people process information and form opinions about political issues have important implications for their choices in the voting booth. While an informed electorate is crucial for the functioning of representative democracies, studies show that most voters lack comprehensive information about politics (Kinder and Sears 1985; Kuklinski 2002). At the same time, recent empirical research suggests that voters are in fact capable of making complex decisions on the basis of very little information. By using informational shortcuts known as cues, heuristics and schemes, voters make their way through overwhelming and sometimes conflicting information (Slothuus 2008; Tomz and Sniderman 2004).

Scholars have investigated several potential cognitive cues, for example (left-right) ideology (Budge et al. 2001; van der Brug and van der Eijk 1999), social class (Oskarson 1994), and party identification (Campbell, Converse, Miller, and Stokes 1960; Fiorina 1981; Popkin 1991; Sniderman, Brody, and Tetlock 1991). Other types of cues can be for example economic or sociotropic evaluations (Kumlin 2004; Pattie 2001). It has also been argued that
people learn from the aggregate actions of others, as represented by histories (Fiorina 1981; Key 1966), or opinion polls (McKelvey and Ordeshook 1985). Early on, Lazarsfeld and colleagues discovered that many voters that were undecided half a year before the election but had anticipations about the winner later would decide to vote for the candidate they expected to win (Lazarsfeld, Berelson and Gaudet 1944). Since then several scholars have picked up on this phenomenon, exploring the existence of what has become known as the bandwagon and underdog effects. The former occurs in political elections when, ceteris paribus, voters favor a party or candidate that is perceived as a likely winner (i.e. doing well in the polls) before Election Day. The underdog effect, on the other hand, states that the perceived losing candidate receives increased support by the voters (Simon 1954).

Possible mechanisms behind a polling-effect

In a recent experimental study of the bandwagon-effect in public opinion polls, Rothschild and Malhotra (2014: 1) draw on social psychological research and outline three mechanisms by which opinion polls may lead to conformity with the majority opinion. The first concerns normative social influence. People like to believe that they are on the winning team and therefore they desire to adopt the majority position. The second concerns informational social influence, i.e. that people believe that others have more knowledge about the particular policy issue and that their interpretation of the situation is more accurate. This helps people to choose an (in their minds) “appropriate” view. The third mechanism is that people aim to resolve cognitive dissonance by jumping onto the side they think is going to win according to the poll (cf. van der Meer et al. 2015).

However, polling effects – and in particular the bandwagon effect – has been debated for decades, and the experimental literature on the subject reports mixed results. When it comes to studies of the effect of opinion polls on vote choice, which is the issue most often subject to investigation, some studies do observe a bandwagon effect (e.g. McAllister and Studlar 1991; Ansolabehere and Iyengar 1994; Mehrabian 1998; van der Meer et al. 2015; Fleitas 1971), while others report support for the null hypothesis or mixed results where the effect is found for certain groups of people but not for others (cf. Dizney and Roskens 1962; Navazio 1977; Tuchman and Coffin 1971). The relatively few studies approaching the issue from a perspective of shifts in the general public opinion on particular issues, such as abortion, as a result of polls are also demonstrating contradictory results (e.g. Ragozzino and Hartman 2014; Rothschild and Malhotra 2014; Sonck and Loosveldt 2010; Nadeau et al. 1993; Marsh 1985).
An experimental dynamic approach in studying poll effects

Taking into account the mixed support for poll effects on the public opinion in the existing literature, there is a need for more research on the topic to uncover under what circumstances there are poll effects and not. For example, there is reason to believe that the maturity of the topic in question matters with regards to how easily influenced people are to the opinions of others: If the political issue has been debated for a long time and the citizens know the positions of different social groups and political parties on the issue, there are already a number of cues out there that have assisted citizens in consolidating a position on the issue. When there is a new issue under deliberation, however, citizens might be more susceptible to influence from cues that come their way. For this reason, we seek to explore an issue, which by the time the survey was distributed to the respondents, was fairly new and where it could be anticipated that many citizens had yet to form their opinions. One of our aims is to examine whether being presented with an opinion poll at all has an impact on the aggregated opinion on the political issue. In the real world, using observational data, it is impossible to isolate opinion polls and their effects on public opinion. We therefore design a survey experiment in which the experimental treatment condition is data on the public opinion concerning a specific political issue. Thus, the treatment group is exposed to the actual distribution of the public opinion on a policy relevant issue. The control group receives no such information.

Arguably the most innovative part of our experiment, however, is that we measure the poll effect over time. Rather than limiting the study to the one-time effect of these information treatments, we track their potential effect over time by applying the so-called Dynamic Response Feedback during the survey data collection. As illustrated in Figure 1, the Dynamic Response Feedback fetches previous answers given by respondents who have already completed the survey, and presents in real-time the current distribution to the respondent who is about to answer the question. For every i-th response, the distribution of support for the issue is re-calculated, thus creating several “mini-polls” within the same survey wave. For each new treatment group, there is a complementary control group. The effect of the poll is measured as the difference of means between each treatment and control group at time t+k, ensuring that the only thing that varies between the treatment and control group is the poll information, and not for example external events that distort the level of support for the issue in question. In this way, we are able to investigate whether the effect of the initial treatment
conditions vanishes, ending up at the level of the control group, or if the initial treatment condition continues to have an impact on the aggregate distribution.

The experiment we present was designed as follows. A sub-group of 425 respondents were randomly distributed into one control group and one treatment group. In the control groups the respondents were asked about their opinion about whether measles vaccination for children should be compulsory or not.\(^1\) The treatment group was asked the same question but with the addition of being presented with the results from an earlier poll.

This initial poll had been automatically constructed by asking the first 15 respondents taking the survey about their opinions on the issue. From these responses a pie chart was automatically generated and displayed to the first treatment group at time t1.\(^2\) The intention with generating the initial poll from such a low number of respondents was that it increased the likelihood that the poll would be skewed in comparison with the “true” distribution. This way we avoid deceiving the respondents with a fake poll. Also, we argue it reflects a realistic situation where an opinion poll for some statistical reason does not reflect the “true” underlying distribution among the public. Thus, in terms of real world issues this study aims to investigate if public polls – today conducted and presented by a wide variety of actors, such as newspapers, political parties and interest organizations – by themselves play a role in shaping the actual public opinion.

The responses from the first mini poll replaced the initial poll and served as treatment condition for the treatment group at time t2 by showing the share of respondents at time t1 that agreed and disagreed with the statement. The response distribution from the mini poll at time t2 served as treatment condition for the treatment group at time t3, and so on.\(^3\) In all, six mini polls were generated within the general survey wave, each showing the responses from the previous poll. Each mini poll consists of 425 respondents randomized into one control and one treatment group. So, the respondents in the treatment group are presented with a pie chart

\(^1\) See Appendix A for full question wording.
\(^2\) A JAVA script was created in order to implement the Dynamic Response Feedback into the web survey. The script directed the number of respondents into each time observation, and randomized the respondents into treatment and control groups. When one mini poll was filled up, the script processed their responses and generated the pie chart which was displayed to the next treatment group. The responses from each group were stored as separate variables. Thanks to Øivind Skjervheim and Ideas 2 Evidence for assisting with the implementation process.
\(^3\) The responses did not accumulate, so the treatment group at time t was only shown the response distribution of the previous group at time t-1.
of the distribution of the initial condition (generated by the first 15 respondents in the survey wave). The respondents in the treatment group are then given the information about the distribution of the previous group, and so on until the end of the survey wave. By adding a control group to each specific mini poll, we are capturing potential time specific influences. The field work was conducted in the period of March 9th to March 31st, which on average produced a time frame of about three and a half days for each mini survey. The procedure is presented graphically in Figure 1.

Figure 1. Dynamic Response Feedback

Data generating infrastructure
The survey experiment was conducted in the spring of 2015 as part of the fourth wave of the Norwegian Citizen Panel (NCP) at University of Bergen, Norway. The NCP is a general representative population web panel established for academic purposes, where the participants have been recruited via random sampling from the Norwegian National Registry. The registry contains names and contact information about all residents in Norway, ensuring that all registered residents have an equal chance of being contacted. As of 2014, the panel consisted of about 8500 panelists, of which 2508 participated in the experiment presented in this paper. For an elaborate presentation of response rates and other methodological issues, we refer to
the methodology report for the NCP’s fourth survey wave. The full survey data set is freely available for scholars via the Norwegian Social Science Data Archive.

**Expected results**

The general hypothesis we derive from the theoretical discussion is that when the public is exposed to a poll on a certain political issue, this information is carried over and, all else equal, influences the distribution of opinions on the same issue. More specifically, if an opinion poll is different from the “true” distribution, it will skew the public opinion in the direction of the presented poll. The respondents see the polls and are influenced by it when they give their own responses. Not all change their answers, and some perhaps react by going in the opposite direction of the general public. On average, though, we expect the aggregate distribution to settle closer to the poll than the control group who responds at the same time point but has not seen the poll. Given that the polls displayed to the treatment groups on average are different from the true distribution, we therefore expect the mean support of the treatment groups to be different from that of the control groups:

$$H_1: \bar{x}_{t+k}^T - \bar{x}_{t+k}^C \mid [P \neq \mu] \neq 0,$$

where $\bar{x}_{t+k}^T$ is the treatment group mean, $\bar{x}_{t+k}^C$ is the control group mean, $P$ is the poll distribution, and $\mu$ is the population mean. We estimate this by pooling the treatment groups and the control groups to measure whether there was an overall effect of the treatment condition.

Normally, a poll reflects the opinions of the population of which the respondents were sampled. The distribution of support in the sample should be similar to that of the population, albeit with some level of estimation error because the estimate is based on a random sample of the population. Hence, in our experiment, the mean score for the vaccination issue in the control group can be written as

$$\bar{x}_t^C = \mu + \epsilon_t^C,$$

where $\bar{x}_t^C$ represents the mean of the poll for the control group C at time $t$, $\mu$ is the population mean, and $\epsilon_t^C$ is the error term, assumed to be gaussian white noise.

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4 http://tjinfo.uib.no/Vedlegg?id=1c587c7c73964822f67a03d738fbf7

5 http://www.nsd.uib.no/nsddata/serier/norsk_medborgerpanel_eng.html
When the respondents are exposed to the previous poll distribution, however, we expect some of the information to be carried over to the following group of respondents, breaching the assumption of temporal independence between the units of analysis. We hypothesize that the poll serves as a link between the time points, creating serial correlation between the mini surveys. To account for this we must add an autoregressive component in the model, where the mean score is also influenced by the mean score in the previous poll:

\[ \bar{x}_t = \mu + \bar{x}_{t-1}^C + \epsilon_t^T, \]

where \( \bar{x}_{t-1}^C > 0 \).

\( \bar{x}_t^C \) represents the mean of the poll for the control group C at time t, \( \mu \) is the population mean, and \( \epsilon_t^T \) is the error term assumed to be gaussian white noise. The extra component \( \bar{x}_{t-1}^T \) represents the hypothesized influence of the poll at time t-1. Its value is expected to be non-zero and positive, i.e. the component skews the mean of the current poll in the direction of the previous poll mean. In plain words, we expect the distribution in the treatment groups to be “sticky” in the sense that they are more similar to the previous distribution than are the control groups.

When the time dimension becomes part of the model, there are several potential variations of the \( H_1 \) hypothesis. One is that the poll has a spiraling effect on the distribution and thus over time increases the difference in support between those who are exposed to the polls and those who are not. When the respondents for instance see a poll that shows higher support for an issue than there really is, even more respondents support the issue, creating an even more skewed distribution which then is presented to the next group of respondents, and so on. One could imagine a scenario where this development is plausible, for example concerning a contentious issue where a large number of citizens have not yet formed an opinion and/or fear to speak out their true opinion. The resulting time series would reflect this trend such that the difference of means between the treatment groups and control groups would increase over time:

\[ H_1 \alpha: \Delta \bar{x}_t = c + \rho (\Delta \bar{x}_{t-1}^T) + \epsilon_t^T, \]

where \( \rho \geq 1 \).
\( \Delta x_t \) represents the difference of \( \bar{x}^T_t \) and \( \bar{x}^C_t \). This model represents a non-stationary process. Though such a model is conceivable for certain issues and in certain situations, we argue that such a development is not the most likely one for our issue on compulsory measles vaccination. On the contrary, we argue for a more modest poll influence, where the poll effect from the initial distribution diminishes over time rather than increases. Assuming that most respondents do not change opinion even though they are shown an opinion poll, we should see that the effect of the skewed distribution fades over time:

\[
H_1 b: \Delta \bar{x}_t = c + \rho(\Delta \bar{x}_{t-1}) + \epsilon_t,
\]

where \( 0 < \rho 1 < 1 \).

\( \Delta x_t \) represents the difference of \( \bar{x}^T_t \) and \( \bar{x}^C_t \). This hypothesis assumes that the poll has an effect on the aggregate mean, but that it is less than 1 and therefore has no spiraling effect. This development over time could be modeled as an autoregressive process, where the effect of the initial poll decreases exponentially but does not entirely fade out.

It takes a large amount of respondents to create the number of mini surveys needed to perform a proper statistical analysis of the effects over time and estimate a model. The number of respondents in our study (n=2508) is a comparatively large size by normal standards, nevertheless the six mini surveys we got out of those respondents are nevertheless too few to perform statistical analyses on at the aggregate level. Hence, in the results section we will settle with a visual inspection of the time trend of the mini surveys, and discuss whether there are signs of any autocorrelation in the average treatment effects.
Results
The initial poll seen by the first treatment group showed an overwhelming support for compulsory vaccination of children in Norway:

Comparing the distribution that the first treatment group receives and the “true” distribution below – which we here operationalize as the pooled distribution of all the control groups – we see that they were presented with a skewed distribution in favor of compulsory vaccination, albeit with only 3 percentage points difference from the control distribution. Quite surprisingly, nine out of ten residents in Norway support compulsory measles vaccination of children.

Knowing that the treatment condition was different from the distribution of the control groups, do we find as we expect that the support for vaccination is different between the treatment groups and control groups? Indeed, when pooling together all the treated groups and
comparing their means with all the control groups, there is a difference of means of 0.13, where the groups exposed to the polls have an average score of 5.91 on the scale which ranges from 1 to 7 compared to 5.78 for the control groups. The difference of means for the pooled treatment and control groups is

$$\overline{x}_{t+k}^T - \overline{x}_{t+k}^C = 0.13.$$ 

Considering that the initial treatment condition was only slightly skewed from the control group distribution, this is a sizable difference in the expected direction. The t-value of the t-test is 2.26, and the p-value is 0.024.\(^6\) Hence, despite the small difference between the initial poll and the “true” distribution, the treatment groups who see the polls are consistently responding more positively to the question on compulsory vaccination.

Examining the development over time, we see that the treatment groups overall maintain a higher support on average for vaccination than the control groups (Figure 2). The first four observation points clearly show a pattern of diminishing effect of the initial treatment condition as time progresses. The corresponding pie charts – which show the share of supporters versus opponents – follow the same pattern of a declining difference between the poll and the true share. Visually, this deteriorating impact of the initial poll does resemble an autoregressive process at first lag (AR1).\(^7\)

\(^6\) See Appendix B for more statistics.

\(^7\) We should keep in mind that the time of participation in the survey wave is not randomized for the respondent, which may introduce bias into the aggregate time series. It cannot be ruled out that differences in group compositions over time cause the differences in treatment effects (see Dahlberg et al. 2010). An overview of the group compositions with regards to social background characteristics is presented in appendix B.
However, the fifth observation complicates the picture as it seems that the treatment effect “bounces back” from zero, i.e. there is an effect of the poll when this poll reflects the true distribution in the population. The sixth observations again resembles the pattern of a declining treatment effect from the previous poll, though, so the fifth poll is the only one of the six observations that differ from our expectations as laid out in hypothesis H\textsubscript{1b}. It shall be noted that although the differences between the pooled treatment groups and control groups are statistically significant, the differences on each time series observation are statistically insignificant due to a lower number of respondents. Taken together, the time dimension results are intriguing and give some indication that initially skewed polls, all else equal, have a lasting effect on the public opinion. However, more experiments and data points are needed in order to robustly model the temporal dynamics of poll effects.

**Opinionating polls**

While our focus has been on the mean score on the response scale, in our analysis we encountered some other results among the treated respondents that we find worthy of mentioning. Operating with a seven point, bipolar agree/disagree answer scale, the midpoint of the scale is “neither agree nor disagree”. In the treatment groups the share of respondents that ticked off this alternative was 29 per cent lower than in the control groups. Assuming that there is a substantive reason for this difference, we speculate that being presented with a poll which shows that other citizens have an opinion triggers other respondents to also express a
position. This explanation is backed up by a follow-up question posed in the survey after the experiment. Asking the respondents how strong their views are on the issue on compulsory vaccination, the treated respondents report to have statistically significant stronger views on the topic than those in the control group (Table 1). It was not the aim of the experiment to explore these kinds of effects from opinion polls but the results could pave the way for future research on polling effects.

Table 1: Debriefing questions after survey experiment. (t)=treatment group, (c)=control group

<table>
<thead>
<tr>
<th>Question (group)</th>
<th>mean</th>
<th>std.dev.</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strength of opinion (t)</td>
<td>3.68</td>
<td>1.03</td>
<td>1195</td>
</tr>
<tr>
<td>Strength of opinion (c)</td>
<td>3.59</td>
<td>1.09</td>
<td>1292</td>
</tr>
<tr>
<td>Knowledge of issue (t)</td>
<td>3.46</td>
<td>0.84</td>
<td>1178</td>
</tr>
<tr>
<td>Knowledge of issue (c)</td>
<td>3.44</td>
<td>0.89</td>
<td>1286</td>
</tr>
<tr>
<td>Perception of public opinion (t)</td>
<td>4.08</td>
<td>0.89</td>
<td>1191</td>
</tr>
<tr>
<td>Perception of public opinion (c)</td>
<td>3.80</td>
<td>0.94</td>
<td>1296</td>
</tr>
</tbody>
</table>

Following the survey experiment, we also introduced in the questionnaire a manipulation check in order to measure whether the information about the distribution of preferences changed the respondents’ perceptions of what the Norwegian population thought about compulsory vaccination. Hence, we asked them to guess the number of Norwegians supporting compulsory vaccination. The respondents were asked to answer on a five point scale where 5 = “almost everyone” and 1 = “almost none”. For the respondents in the control groups, the average response was 3.8, that is, somewhere between “around half” and “around 2 out of 3”. Knowing that as many as nine out of ten support this issue it shows that the respondents misperceive the public opinion somewhat. The respondents in the treatment groups who see the poll are also misguided, but exposure to the poll pushes the average up to 4.1. The manipulation check thus shows that there is a fairly large and significant effect of showing the poll. We thus interpret the results as an indication of the fact that the manipulation has been noticed and absorbed into the minds of the respondents.
Discussion and conclusion

In this paper we aim to investigate if publication of opinion polls shapes the public opinion. Thus, the research design of the presented experiment aims to gauge to what extent exposure to opinion polls as such have a lasting impact on people’s political preferences. We therefore design a survey experiment in which the experimental treatment condition is data on the public opinion concerning a specific political issue, in this case whether measles vaccination of children should be made compulsory or not. In order to investigate this, we apply a process of so-called Dynamic Response Feedback during the survey data collection in order to measure poll effects over time. Put simply, a sub-group of 425 respondents were randomly selected into a control group and a treatment group. In the control group the respondents were asked about their opinion on compulsory measles vaccination. The treatment group was asked the same question but with the addition of being presented with the results from an earlier poll. This earlier poll was constructed by asking the first 15 respondents taking the survey about their opinions on the issue. The answers were then automatically transformed to a pie chart showing the share of respondents who support and oppose compulsory vaccination. The low number of respondents increased the likelihood that the poll would be skewed in comparison with the “true” distribution. This way of generating the initial poll lets us avoid deceiving the respondents with a fake poll.

The results displayed a small and statistically significant difference in opinions between treatment groups and control groups. More specifically, the treatment groups (having been exposed to the poll) were more positively skewed towards a positive opinion compared to the control group. We also found the effect to be decreasing over time.

Additionally, we also found that the treatment groups were not only affected in their opinions by receiving information about what the “others” think of the question at hand but also that they were more likely to actually form an opinion on the question, i.e. a substantially smaller portion of respondents opted out in the treatment group compared to the control group.

Thus, we find evidence for the fact that exposure to polls on social issues in fact have an effect on the public opinion. This is the case even when the public opinion on the issue is heavily skewed, as in the case of compulsory measles vaccination for children. This is
interesting since earlier research has found the bandwagon effect to be issue-dependent and strongest on issues where pre-treatment attitudes have been weak (Rothshild and Malhotra 2014). Although more research is needed to further explore the effects of polls on the public’s opinion on social and political issues, we believe that the tendency shown in this experiment and related research have some interesting implications. The fact that polls seem to affect the general opinion – both in terms of support for an issue and the fact that people that are exposed to polls seem to use the information in order to decide where they stand on the issue – indicate that polls may be an effective instrument for different societal groups to shape the public opinion in direction with their interest. This is of course particularly important if interest groups use inferior, or even fake, polls in order to advance their own agenda.

However, our results also indicate that the timing of polls is important, since the poll effect seems to fade out over time. This means that in order to have a desirable effect on the public opinion, the poll should be presented at the right time.

References


Appendix A: Survey questions

*First treatment group:*

Q: “The vaccination of children has been heavily debated by the media recently. Some people think that it should be compulsory for all children to have measles vaccinations. To what extent do you agree or disagree with this?”

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Disagree
- Strongly disagree

![Pie chart showing 93% agree and 7% disagree.]

*First control group:*

Q: “The vaccination of children has been heavily debated by the media recently. Some people think that it should be compulsory for all children to have measles vaccinations. To what extent do you agree or disagree with this?”

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Disagree
- Strongly disagree

Q: “How strong are your views about this question?”
• Very strong
• Strong
• Fairly strong
• Weak
• I do not have an opinion about this

Q: “How good do you feel that your knowledge about this subject is?”

• Very good
• Good
• Some knowledge
• Not much knowledge
• No knowledge at all

Q: “If you had to make a guess, how many citizens in Norway do you think would agree that it should be compulsory for all children to be vaccinated against measles?”

• Almost everyone
• Around 2 out of 3
• Around half
• Around 1 out of 3
• Almost none
Appendix B: Extra material from analysis

Table B.1. Welch Two Sample t-test for difference of means between pooled treatment groups and pooled control groups on vaccination question

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{x}_{t+k}^T$</td>
<td>5.91</td>
</tr>
<tr>
<td>$\bar{x}_{t+k}^C$</td>
<td>5.78</td>
</tr>
<tr>
<td>$\bar{x}<em>{t+k}^T - \bar{x}</em>{t+k}^C$</td>
<td>0.13</td>
</tr>
<tr>
<td>t</td>
<td>2.26</td>
</tr>
<tr>
<td>df</td>
<td>2507.54</td>
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<tr>
<td>p-value</td>
<td>0.023</td>
</tr>
<tr>
<td>Lower confidence interval (95%)</td>
<td>0.017</td>
</tr>
<tr>
<td>Upper confidence interval (95%)</td>
<td>0.243</td>
</tr>
</tbody>
</table>

Table B.2. Group balance of randomized treatment and control groups

<table>
<thead>
<tr>
<th>Group</th>
<th>n</th>
<th>Female</th>
<th>Age 30-59</th>
<th>Higher ed.</th>
<th>Pol.int.(x)</th>
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<tr>
<td>Treatment $t_1$</td>
<td>190</td>
<td>42%</td>
<td>46%</td>
<td>61%</td>
<td>3.79</td>
</tr>
<tr>
<td>Control $t_1$</td>
<td>235</td>
<td>43%</td>
<td>47%</td>
<td>56%</td>
<td>3.70</td>
</tr>
<tr>
<td>Treatment $t_2$</td>
<td>216</td>
<td>48%</td>
<td>51%</td>
<td>59%</td>
<td>3.70</td>
</tr>
<tr>
<td>Control $t_2$</td>
<td>205</td>
<td>48%</td>
<td>49%</td>
<td>57%</td>
<td>3.68</td>
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<tr>
<td>Treatment $t_3$</td>
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<td>50%</td>
<td>60%</td>
<td>52%</td>
<td>3.61</td>
</tr>
<tr>
<td>Control $t_3$</td>
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<td>39%</td>
<td>54%</td>
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</tr>
<tr>
<td>Treatment $t_4$</td>
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<td>Control $t_4$</td>
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<td>59%</td>
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<tr>
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<td>Control $t_5$</td>
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<tr>
<td>Treatment $t_6$</td>
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</tr>
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<td>Control $t_6$</td>
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