SOCIAL INTERACTION AS CUES: A LOW-COST TOOL FOR CHANGING POLITICAL OPINION

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Abstract

Social science literature has long investigated the relationship between political behavior and social networks, however, it is usually hard to excavate a true causal relationship between political views and social affiliations. The common feature of political science literature related to a social network is that they mostly focus on whether the individuals' political views and their social networks co-evolve or not. According to the recent literature, social networks do not simply evolve but also stimulate our political behavior. Most of the literature finds that people seek individuals with similar political views to be friends with and individuals who often talk to each other tend to be more similar over time Although there is broad agreement on that while our social network is dynamically flourishing, it is also affecting our attitude, but the process of this impact is still not clear. This research aims to examine the channel between social affiliations to the changes of political behavior. The research uses network data collected from experiments to specify the social affiliation effects on the change of political views under a deliberation process. The results suggest that, on the one hand, political opinion significantly influences friendship network formation, which fosters social homophily. On the other hand, a significant spillover effect has found on the likelihood of political opinion change, where the spillover effect strongly depends on the peers' network centrality.

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1. Introduction

In political science literature, there has been a democratic dilemma long time ago. According to this dilemma, the electorate is unable to judge whether what the government is doing is good or bad (Campbell et al. 1960). So the people who have to make a choice may not be capable of evaluating the opportunities (Lupia and McCubbins 1998). Berelson and his fellows (1954 pp. 311.) are going further, they claim that "*if the democratic system depended solely on the qualification of the individual voter, then it seems remarkable that democracies have survived through the centuries*."

Since Downs (1957) we know that the electorate's ignorance towards politics is rational and inevitable. The individual feels that she has slight, almost zero weight in the election and therefore her vote is unnecessary. This leads to a collective action problem where nobody believes it is worth to collect knowledge - that has cost - to cast an informed vote. There is abundant evidence of this ignorance in the literature, mostly from the United States. One of the first evidence comes from Erikson, Luubeg, and Tedin (1980). They asked citizens about the international political situation, and they found that more than sixty percent of American considered Soviet Union a member of the NATO and the ally of the USA. McGuire (1985) run a survey about political attitude and knowledge, and he found that almost forty percent of the United States citizens believe that Isreal is an Arabic country. However, citizens are not only ignorant of international politics but also have a weak interest in domestic politics too. Popkin (1991) showed that in the United States one-third of the citizens could not name the Vice President. However, does this ignorance matter for the elections at all? According to the literature, there is no one clear answer. On the one hand, Lessen (2005) on election turnout, Feldman (1990) on attitude stability and Verba and Nie (1972) on civic participation, found that individual-level political information has a small but significant influence on the citizens' everyday life. One possible explanation from Bartels (1986) is saying that ignorance increases the uncertainty of the candidates' real positions. Therefore risk-averse voters sanction the candidate's cause of their unclear political positioning. Theose citizens who penalize tend to vote for the wrong candidate regarding the actual policy preferences. On the other hand, Lazarsfeld and Bereslson (1968) find that individual-level ignorance does not matter. Until the democratic system works satisfactorily, voters would not bother to collect information to overcome the collective action problem. Therefore one has to judge the election consequences at the country level, whether the policy outcomes are satisfactory or not. So the minuscule probability that the individual vote is pivotal makes participation and information gathering so costly that the individual tends not to vote or cast a "wrong" vote. This leaves room for some other open questions. Can we tell the citizens how far does she has to travel to cast a ballot? Can we even tell how she should have voted? It is very hard to determine what is the "right" vote for somebody. The "right" vote always depends on the individual preferences regardless of being uninformed it is almost impossible to discover it with scientific methods. There are three concepts on how to determine the "right" vote.

One of most frequently used voting behavior view is class-voting. This concept assumes that the high and middle class supports right-wing political parties because they control for inflation, while working-class favors left-wing parties to solve unemployment. The second theory comes from Robert Dahl and first used by Lau and Redlawsk (2001). They assign the right vote as the same vote that the individual would vote for if she would have perfect information. This idea has some underlying assumptions such as people voting instrumentally, they are rational and do not take the non-political outcomes into account. The problem is that we cannot observe instrumentally rational individuals' voting behavior. However, in laboratory experiments, we can create full information environment for the voters, but it is difficult to control for their cognitive abilities and motivations. Finally, the reductionist view used by Lupia (1994), where we can determine an 'ideal point' for the voters in a multidimensional political scale with taking into account the characteristics and policy preferences of the electorate that we can observe. This type of concept is widely used in experimental designs and formal models.

However there is no perfect solution to determine how an individual should vote, but we can see the devices uninformed people use to vote. Governments cannot make citizens informed, and sometimes the government has no interest in making the citizens informed (Downs 1957). Voters want to minimalize the cost of collecting information, therefore are using freely available information and shortcuts. There is some readily accessible information around people. Government unintentionally distributes information about its political preferences through for example tax rates. Furthermore, parties and interest groups scatter their propaganda by media. However, what is the most significant for this paper is the interpersonal communication with other people. These freely available information sources serve as cues for uninformed people to imitate fully informed behavior.

Cues are the most widely used concept about how ignorant individuals can cast a correct choice. The existence of cue-taking is long studied in the various field of political science literature. The first notable example comes from Lazersfeld and Berelson et al. (1954) on the relationship between partisanship and self-identification. Most recent studies (Popkin 1991, Lupia 1994, Lau and Redlawsk 2001) showed the existence of cues in the case of the campaign, consumption patterns, and polls. According to Lau and Redlawsk (2001), the most common cues is the appearance of the candidate. From the outfit voters derivate information about the candidate's honesty or intelligence. Poll results, ideology, and endorsements also very frequently used as a cue to the performance of the candidates and parties. There is no one precise definition for a cue, in fact, heuristics and shortcuts are usually used as synonyms for cue without any distinction. The easiest way to describe cue is as a low-cost tool for an uninformed individual to makes a choice from seemingly irrelevant but easily collectible information. If the cue is unbiased then counting on it would lead to a good choice, but cues are infrequently unbiased. A photo of the candidate may help the voter recall information thus serve as a cue, but almost every case it would carry a bias. Some people are more attractive than others, and a choice based on a photo instead of policy preferences could lead to the wrong choice. Furthermore, cues frequently produce an illusion of our knowledge. A cue can make us believe that we know something when we actually only have a probably misleading cue.

The part of the literature that based on psychological studies (Tversky and Kahneman 1974) using ‘heuristics’ as a very similar way to cues. Tversky and Kahneman (1974) define heuristics as spontaneously used cognitive shortcuts to substitute missing information with simple deduction based on the uncostly observable information. Lodge and Hamill (1985) use the concept of ‘schemata’ as a process describing how individuals provide categories to labeling people. They showed that people use guesses based on schemas to make choices in the incomplete information environment. The main difference is where we look for the causal mechanism behind information gathering: in cognitive mechanisms or stereotypical experiences. While the concept of cues emphasizing the content of the collection of information, Tversky and Kahneman with heuristics, focusing more on the cognitive functions and the concept of schemata may focuse on the existence of labeling. Heuristics and schemata are very similar to cues, and there is no clear distinction in the literature yet. The best way to think about them is as information shortcut tools to reduce uncertainty with a small cost.

In this paper, I would like to contribute to the literature of social cues by giving a theoretical and empirical explanation of political opinion change related to cues. In the next chapter, I present an alternative explanation on how cues may foster social homophily. Then I demonstrate my experiment and the data. Finally, I give an empirical analysis on the relationship between political opinion change and social peer effect.

2. Theoretical model

Lazarsfeld and Berelson (1968) emphasise political influence spreading via interpersonal communication at the micro level. They claim that social networks are homogeneous politically because most of their respondents said that their parents and grandparents voted for the same party as they do. Thus, interpersonal interactions play an essential role in the evolution of our mindset. Family, friends and every social connection may shape our opinion about people and society as a whole. We are using our peers as a hint to guide our opinion because collecting information from our friends and family is relatively easy and costs less. In other words, we are using our peers as cues. People using other people similar to them in age, gender, education and so on to collect information about the word, for instance, what is the new fashion, what music should I listen or which party should I vote for. The aim of this section is twofold. On the one hand, to present an explanation on how personal influence may serve as a social cue and a reason for emerging homophily. On the other hand, to present a social spillover model which shows how people build their peers' characteristics and opinion into their own behavior.

2.1 How social homophily emerges?

Homophily is important to understand why communication results in circulating within one group and not in another group or why an idea ends up hitting a part of the society as opposed to the whole population. So understanding the structures of homophily could have been important to understand several social phenomena. Such as, why do we see these patterns, why do we see this separation and segregation?

Homophily refers to the fact that if we track the characteristic of nodes, we tend to find that linked nodes are similar to each other. This phenomenon is recognized in human interactions around the beginning of the 17^{th} century by from Philemon Holland phrased "as commonly birds of a feather will flye together". The term homophily was coined by Lazarsfeld and Merton

(1954) and has been documented across many different studies. The relationship between social structure and homophily is conceptualized by Blau (1977), who argued that structure is determined by social positions, such as class, sex, and age.

Shrum et al. (1988) analyzed the development of racial and gender segregation among schoolchildren. Their results suggest that both racial and gender homophily remain stable over time, while the relationship between homophily and grade is curvilinear. Moody (2001) suggests that grades tightly bound to friendship formation, moreover friendship segregation persist and peaks in various schools. Inter-race friendships and marriages clearly illustrate homophily. Marsden (1987) looking at the national survey in the US finds that only 8% percent of people have named anybody of another race that they discuss important matters with. 8% is much lower than one would expect if people would be naming people without regards to race. A study by Fryer (2007) shows the surprisingly low ratio of interracial marriages in the US. Only 1% of whites marry outside of whites, 5% of the blacks and 14% of Asian marriages are interracial. Although the numbers differ on the base of the size of the subpopulation, basically, these numbers are less than what should be expected to happen at random. Shrum et al. (1988) show that less than 10% of the expected cross-race friendships exist in US middle schools. Although, this phenomenon is not unique to US high schools. A study by Baerveldt et al. (2004) used survey data from Dutch high schools show that however, Dutch students make up the 65% of the population 79% of their friendships occur with another Dutch. That is 5%-27% for Moroccan and 6%-59% for the Turkish subpopulation. Regarding gender homophily, Verbrugge (1977) found that only 10% of men name a woman and 32% of women name a man as their closest friend. Also again, these numbers are below the 50% reference point where would be no bias.

As literature shows, people have a higher tendency to be connected to their own type than different types. Many theory may occur to explain homophily. It could be opportunities, which refer to the phenomena when somehow the groups of people structured in a way that the possibilities for meeting people is biased by individual characteristics. So who do you contact depends on demographic features. It could be benefits and costs. Having a common set of understanding, shared culture and language could make a difference in how people interact with each other. In the following section, I show an alternative explanation for homophily considering social cues as a driving force of change in political opinion.

2.2 Social interaction as a cue

One of the essential roles of social networks is in affecting the flow of information as well as the diffusion of opinions, knowledge, and behaviors. On the most basic level, the question is that a representative individual's decisions are based on how much that influences his or her social interactions. The problem is we usually cannot proxy for all of the attributes that may affect the people's preferences. If we observe two friends, and they both vote for the same party, should we conclude that the one influenced the other to vote for the same party? There are too many other things that may affect their individual preferences, such as their social class, education, religiosity or urban-rural residence and so forth. If somehow we would be able to control for all other factors then we could test for the network influence by checking whether a friend's vote for a party leads to an increase or a decrease in their own, personal willingness to vote for the same party. Furthermore, to prove that people are affected by their connections due to using them as cues, the primary purpose of my research is to give an empirical explanation of how this influence depends on the individuals' social network capital.

The description of the effect of cues begins with a model of how an agent is affected by another in her reference network. The reference network or reference group is merely a set of other individuals whose characteristics, actions and social affilitation can change the agent behavior. To clarify a formal definition of peer effect I present a linear model of social interaction with two agents. I use a linear model of social interaction to give an explanation of what are the underlying effects of social interaction that result in two types of peer effect: social spillovers in one case and social multipliers in the other. Social spillovers come to light when a policy directed at an individual affects the activity of others in her social network via her peer connection. In particular cases, social interaction also involves a feedback loop in a way that the modified activity of the reference group gives feedback to confirm the agent's behavior. This impact in turn also affects the behavior of the group, until an equilibrium arrives.

I use a linear model of social interaction from Hartmann et al. (2008) with a simultaneous equations framework with two agents i and j.[1] Both agents want to maximize her payoff function. To clarify let $y_i(.)$ and $y_j(.)$ denote as the action of agents and denote $U_i(y_i)$ and $U_j(\,y_j)$ the agents' payoff from action y_i and y_j. The following functional forms represent a linear relation between *i* and *j* characteristics and actions for every $i \neq j$:

$$U_i(y_i) = \alpha_i x_i + \omega_i(N_j)y_j + \mu_i z_j + u_i \tag{2.1}$$

$$U_j(y_j) = \alpha_j x_j + \omega_j(N_i)y_i + \mu_j z_i + u_j \tag{2.2}$$

where x_i are the characteristics of i and z_j is the characteristics of agent *j* that affects *i* player action and u_i represents the unobservable that may affect the behavior of i or the errors (accordingly same for j). Agent specific α and μ measure the effects of these characteristics on behavior. While μ measures on agent's characteristics on another, ω measuring the causal effect of on agent's behavior on another, which depends on N_j the social reputation of *j*. Following Manski (2000) I will refer to μ as an exogenous and ω as an endogenous social effect. Note, without social interaction the action of y_i only depends on her own agent specific characteristics and unobservable features $y_i = \alpha_i x_i + u_i$.

[1] For simplicity in this part of the model I will leave aside the group index, since only two agents form the network.

Let’s say that agents have imperfect information about their policy preferences. Their preliminary political attitude coded into their initial characteristic x_i . Under a deliberation process they would use other agents to position themselves. So my first hypothesis is the following:

H1: People during a deliberation process with their peers are more likely to change their behavior than people who are not directly affected by peers.

However, agents have different demographic and social capital characteristics. Particular agents have a higher impact on their peers than others. Additionally, agents tend to trust in on other individuals who are similar to them. So:

H2: People tend to use other individuals more likely as cues who are more similar to them to change their political opinion.

Additionally, a social multiplier arises from the equations above if $\omega_i \neq 0$ and $\omega_j \neq 0$, and both have the same sign. In this situation there is a feedback effect, since action of i affects j’s action through ω_j and j’s action also affects the action of i via ω_i. A minor shift of y_j rises y_i via ω_i, that in turn rises y_j even forth via ω_j, and so on until an equilibrium comes. The key concept of social multiplier is that actions of agents have an immediate analogous effect on each other.

In the other case, social interactions generate spillover effects in place of multipliers. Social spillover can be symmetric or asymmetric. In case of asymmetric spillover, one of the agents’ action does not affect the other, e.g. $\omega_i \neq 0$ but $\omega_j = 0$. Therefore, a shift in x_j will lead change in y_j through α_j and also change y_i via ω_i. There is no multiplier effect, since $\omega_j = 0$ and the action of i has no feedback effect on y_j. On the other hand, in case of $\omega_i = \omega_j = 0$ but $\mu_i \neq 0$ or $\mu_j \neq 0$ the spillover effect is symmetric. Change in characteristics results in a spillover effect, since in in a change in z_j will affects y_i, but there is no feedback back to y_j, so there is no multiplier effect.

H3: People generate asymmetric social spillovers, which depend on their social capital. They tend to adopt to individuals more likely as cues who have a higher level of social capital to change their political opinion.

It is important to note that, in the linear social interaction model outcome actions y_i and y_j will correlate with each other. The key concept of these models is to use the perceived connection between the actions of the agents, in order to determine the causal effects of ω and μ. Note that correlation may also come into being if the unobservable (or errors) u_i and u_j are correlated. In the next sections I provide my research method that intended to measure peer effect, while take all the possible experimental and statistical difficulties into account.

3. Research Design and Data

Social interactions and peer effects are hard to measure outside of abstract models. Therefore, I designed an experiment that grants me the possibility to attach real numbers to the formal mathematical model. In this following section, I present the details of the experiment and the variables used in the empirical analyses.

3.1 Experiments in Social Sciences

An essential question is whether using students as experimental participants creates problems for causal interference or not. The typical experiment implies assigning participants randomly under some manipulation. This means that researchers have to recruit volunteers for the research who agree to be manipulated in a laboratory environment. To overcome practical and ethical troubles of the recruitment process the researcher is usually forced to use a sample of college students. Using students as participatants of the experiment usually get criticized, mostly in the field of a political scientist who put high emphasizes on generalization (Druckman and Kam 2009).

However, internal validity is necessary for experiments, still, most researchers use experiments to draw a generalized conclusion (Shadish et al. 2002). The typical example is when a researcher wants to judge whether a media story about a certain policy program causes the citizens to become more supportive of the policy. In this case, the aim the experiment is to separate the effect of the media story from other factors that may affect the supportiveness for the policy. Experiments are differentiated from a descriptive inquiry by focusing on the causal relationship. An essential element for making a causal relationship is security of internal validity. Shadish (2002 pp. 53.) defines internal validity as the *"inferences about whether observed covariation between A and B reflects a causal relationship from A to B […]."* Internal validity is a necessary condition to demonstrate the causal relationship between the response and the independent variables, without internal validity there is nothing to generalize (Anderson and Bushman 1997).

Many political science scholars use students in their experiments, for instance, Kam et al. (2007) recorded that more than twenty percent of articles with experiments from 1990 to 2006 used students subjects. Druckman et al. (2006) report an even higher proportion: more than seventy percent of the literature related to psychological experiment used students.

Do the results of these studies have debatable validity? To answer this question first, we should see what external validity demands. According to Liyanarachchi (2007 pp. 55.) "*true external validity of findings can only be obtained by converging the results of many studies in an area. Reiterating this point in social sciences, McGrath et al. (1982) suggested: No one 'finding' is evidence, and no one study yield[s] knowledge; empirical information can Gain credence only by accumulation of convergent results.*" So, to judge the validity of any single study regardless its subject, it must be done in the context of the larger research paradigm which it tries to contribute to. In this sense, external validity refers to generalization as not merely generalization on the dimension of individuals but also across multiple dimensions like across time, institutions, frameworks and measurements. Arceneaux and Johnson (2008) demonstrated that if the participants can choose whether to receive the treatment, then the effects highly change. This case does not take into account that the contextual framework would constitute a greater threat to external validity than students as the subject of the experiment. To sum up, external validity not merely refers to that phenomenon when re-running the estimation on a different sample would provide the same results, but refers to a more complex relationship that can detect across other dimensions not just people but time and context (Anderson and Bushman 1997).

Druckman and Kam (2009) contrasted different sample of students with simulations to investigate the extent of using students as participants for an experiment creates causal problems. They used simulation data to recognize the circumstances when student subject are likely to limit experimental deduction. Surprisingly, they show that those cases are limited. They conclude that students as subjects are not an inherent problem for experimental investigation. To conclude, the problem is not whom we study but how we study them.

3.2 Experimental design

The general issue of this topic is the problem of measuring cues. The novelty of this research is its research methodology which allows measuring individuals' accurate social influence. In order to specify the true magnitude of this influence, I conduct an experiment with measuring both political behavior and social affiliation. 120 students were involved in the experiment from a closed group with broad social connections. The experiment has two parts:

In the first part, the students have to answer two types of questions. 1) The first type asks about their friendships, co-studding habits, their knowledge and basic demographic control questions. From this type of questions, I am able to conduct the students' social network and control for their undelaying characteristics. 2) The second type asks about their political views on different social and economic policies. From these answers, I could define every individual's opinion about certain political statements.

After the first part, the students were randomly separated into three groups. One group is the control group and there are two treatment groups. Students in the control group got almost the same type of questions as in the first part just paraphrased. According to my theory, their answers perfectly correlate with their previous answers. In the first treatment group, the students are form pairs by random. The individuals in the treatment group also have to answer the same question like in the control group; the difference is that they had to discuss the questions in pairs. In the second treatment group, they also discuss the questions in pairs, but the students were told that they are paired because they are matched to each other in the light of their previous answers.

According to my assumption, the control group will have the same political preferences on both tests. So the political view changes in the treatment group attributable to the social influence from the joint work on the test because they are using their pairs as a cue.

The participants of the experiment were last year's high school students from four classes from the same high school in Budapest. The language of the experiment was Hungarian and all the participants were native Hungarians. On average the experiment took 49 minutes with minimal deviation across classes. 120 students were involved in the experiment from closed groups with broad social connections. We collected 118 fully completed surveys, from 37 male and 81 female students. After the data cleaning 103 unique student ID-s remained.

I asked the permission of the students' parents for revealing background information about the family and their habits. The parents received a small letter to inform them about the nature of the research. In the letter, there was contact information if they had any questions or concerns about the experiment or they wanted to exclude their children from the experiment. The answers of the students are anonymized according to standard experimental policies; students' identity is untraceable and only randomly generated ID codes and nicknames were used in the analyses.

3.3 Dependent variable

The dependent variable is derived from questions of the last part of the experiment where students were asked about their political opinion. Participants had to state whether they strongly disagree, disagree, agree or strongly agree with 50 political statements. The first 25 and the second 25 statements asked about the same political or economic phenomena but were paraphrased. For instance, statement (I) was formulated in the following way: *"Refugees should be welcomed in our society."* than it was paraphrased for statement (II) as*:" International migration is a threat to our country."*. I assume that if a student agrees with the statement (I) then she should disagree with the statement (II).

Thus, the dependent variable $y_{iq} \in [0,1]$ can form zero or one, where 1 represents when student i changed her opinion at statement q from (strongly)agree to (strongly)disagree or vice versa and 0 otherwise. Table 13 in the appendix shows the percentage of students by class who changed their opinion at the given statement. The table suggest that on average students in class A and C changed their opinion for more than half of the statements and students in class B and D changed their opinion more than two out of three times for the statements. This observation is important to understand the nature of the treatment in the next section, to choose the right statistical methodology and for the interpretation of the results. For the questions on students' political opinion see the Appendix.

3.4 Treatment

The purpose of the research is to identify social affiliation as a cue for social homophily. To capture the direct effect of social pressure, I introduced a treatment into the experiment. Namely, in class B and D students paired randomly to discuss the second 25 statements. Even though, they were allowed to report their own opinion, they were also able to see and comment on their pairs' opinion. Class A and C serve as control groups. I assume that students in the control group do not change their opinion since they get the same question just paraphrased. Even if someone has changed her mind in the control group, for instance, she both agrees with: "*Refugees should be welcomed in our society."* and*" International migration is a threat to our country."*, then I assume that there is an inconstancy in the question, for which I can control with comparing the control and the treatment groups' response. In class D an additional treatment was introduced. In class D students were told they were not paired randomly but according to some common characteristics. I have two expectation: 1) first, students in the treatment groups are more likely to change their opinion than students in the control groups. 2) Students in class D are even more likely to change their opinions.

3.5 Social network centrality as explanatory variables

3.5.1 Friendship network composition

The students' social network is constructed from a student-student matrix. In the matrix student *i* and *j* are connected if both of them state that they are often spending their free time together after school. The friendship network stands for the weighted number of connections for every student. Formally, let $A \in \mathbb{R}^{n \times n}$ be an adjacency matrix for student-student network:

$$F_{ij} = \begin{cases} 1 \text{ if } A_i^k \times A_j^k = 1 \\ 0 \quad \text{otherwise} \end{cases} \tag{3.1}$$

Then,

$$w_{ij} = \frac{1}{\sqrt{d_i d_j}} F_{ij} \tag{3.2}$$

, where w_{ij} stands for the strength of the tie between student *i* and *j* in class *k*. $A \in \mathbb{R}^{n \times n}$ is an adjacency matrix for the class *k*, therefore $A_i^k \times A_j^k$ is 1 if student *i* and *j* indicated that they are often spending time together after school and zero otherwise, and d_i, d_j refer to the total number of friends of *i* and *j*. If student *i* and *j* only friends to each other than $w_{ij} = 1$. To maintain a friendship has its cost, therefore if student *i* or *j* have more than one friend, then the weight equals to the geometric average of the number of *i* and *j* connections.

The way in which a network is connected plays a large part in how to analyze and interpret it. When analyzing a network we are asking how integrated of fractured the overall network system is. Network descriptions help us understand the underlying social networks in the four different classes. Clustering coefficient is trying to capture how cliquishness is the network, how likely is it that two nodes are connected or are part of a larger highly connected group of nodes. The typical way of defining average clustering coefficient is to estimate the coefficient for every node and estimate their average. Therefore, the clustering coefficient for class k:

$$\text{Clustering Coefficient}_k = \sum_{i=1}^{n} \frac{\frac{2V_i}{d_i(d_i-1)}}{n} \tag{3.3}$$

, where d_i refers to the number of connection of student i, and V_i represents the number of links between neighbors of i. Clusters in a network have common characteristics or somehow the nodes relate to each other in a particular way. In a friendship network it asks how many of your friends know your other friends, the more friends know each other the more clustered your social network is. Clustering usually correlates with homophily.

Another important feature of a network is its size. Size network is important not solely because of the quantity of the nodes, but because it shows the context of how close are the two nodes in the network from each other. Average path length and network diameter show us how quickly can an information spread through the community. The further an information should travel along the network the more it costs and less likely it is to happen. The diameter of the network captures merely the longest of the shortest paths between every node in the network. While average path length is estimated by the finding the shortest path for all the pairs of nodes, summing them up, and then dividing by $n(n-1)$. Thus, network diameter and average path lengths give us an idea of how far an information might spread to get all across the network.

Table 1. Structural network characteristics of the four classes and the overall network

	Class A	Class B	Class C	Class D	Overall
Avg. Clustering	0.324	0.273	0.389	0.279	0.315
Avg. Path Length	2.124	2.135	2.43	2.52	2.301
Diameter	4	6	5	6	6
Nodes	29.13%	22.33%	24.27%	24.27%	100%
Edges	37.10%	17.06%	21.96%	23.88%	100%

Source: author's own data from field experiment.

Table 1 shows the structural network characteristics of the four classes and the overall network. The table above shows the average clustering coefficients are around 0.3 except for class C where the clustering coefficient is 0.38. It means that in class C students are more likely to form smaller groups inside the class. The average path length and the network diameter are similar in every class. Even though, the proportion of nodes, which basically represents the number of students in each class, are not significantly different across classes, the proportion of edges vary across classes. 37.1% of the edges occur in class A, while class B has the 17% of the overall connections. Although there are no high differences in the structural network characteristics of the classes and the individual level network centralities control for the different level of network density, a class level dummy variable may be justified later.

3.5.2 Network centrality indicators

In the analyses, I use network centralities as important explanatory variables. Network centrality tells us how influential a node is in the overall network. Centrality measures are asking the question what characterizes an important node, who is the most crucial position in the given network? Scott Adams, economitst mentined in one of his public talk, there is an inverse relationship between the power a person holds in an organization and the number of keys on his keyring. A janitor has all the keys to every office but no power, however, the CEO does not need any key since all the doors are open for him. Freeman (1979 137. pp.) pointed out "[T]here is certainly no unanimity on exactly what centrality is or on its conceptual foundations, and there is a little agreement on the proper procedure for its measurement." Evidently Freeman is still right today, for better understanding in the following I describe the popular centrality measures.

From a degree of the node's connectivity, we can get some idea about the node's importance in the overall network. The degree of the node's connectivity is probably the most straightforward and the most basic measure of centrality. We can measure the degree centrality of a node by looking at the total number of other nodes it is connected to and compared to the total it could possibly be connected with. This measurement of centrality only captures what is happening locally around the node. It does not tell us where the node lies in the network, which is needed to properly understand the overall influence. Centrality often depends on the context and trying to capture the significance of every given node in the network. The importance of the node can be thought of in two ways. First, how much of the network "resources" flow through this node. Secondly, how critical is this node to the flow, as in can it be replaced. Like a bridge in the national transportation network may be very significant because it carries a large proportion of the traffic as the only bridge between two important locations.

To quantify this intuition, I present four different centrality metrics. First, degree connectivity, which refers to the simple idea that a node with higher number of degree is more central. To formalize degree centrality let $A \in \mathbb{R}^{n \times n}$ be an adjacency matrix for a network, let $d \in \mathbb{R}^n$ be the degree vector and let $e \in \mathbb{R}^n$ be the all-one vector of the matrix. Then, we can define degree centrality as $d_i = Ae$.

In order to compare networks, I use the standardized degree by dividing by $n - 1$, where n is the number of nodes in the given network. In this measure, the degreeis simply the number of connections in one distance from the given node. Degree is often an effective way to measure infulence or the importance due to its simplicity. In social sciences, it is proved people with more peers tend to have more infulence on the overall network (Kempe 2003, Kwak 2010, Lewis 2010). Despite its effectiveness, degree connectivity disregards the complexity of the overall network by focusing merely on the local connections of the node.

Secondly, closeness centrality measure tries to capture how close a node is to any other node in the network. That is how quickly or how easily can the node reach other nodes in the network.

Closeness can be defined as the reciprocal of farness. Where the fareness of a given node is defined as the sum of the distance to all other nodes:

$$\text{Closeness } (i) = \frac{1}{\sum_{i \neq j} d_{ij}} \tag{3.4}$$

For comparison, I standardized the closeness value by dividing by the maximum number of possible links between two nodes $1/(n-1)$. Thus, the most central node is the lowest total distance to all other nodes. In case there is no path between node *i* and *j* than the path length replaced by the total number of nodes in the network. Closeness can be regarded as a measure of how long it would take to spread something from *i*, such as information or a virus from the node of interest to all other nodes sequently. Therefore, it measures the node's capacity to effect all other parts of the nework.

Betweenness is a third metric to use, which is trying to capture the node's role as a bridge between other groups of nodes. Betweenes is about how critical a node is to the network functioning as a bridging point between other parts of the network. Linton Freeman (Freeman 1977, Freeman et al. 1991) introduced this measure to quantify the communication between people in social networks. The betweeness of a node *i* in a graph G with V nodes can be computed in the following. 1) First, for each pair of the nodes *(j,k)* estimate the shortest path, 2) then, for these *(j,k)* pairs determine the proportion of the shortest path that pass through the node given node *i*, 3) finally, sum up the proportion for all pairs of nodes. Formally,

$$\text{Betweenness}(i) = \sum_{i \neq j \neq k \in V} \frac{\rho_{jk}(i)}{\rho_{jk}} \tag{3.5}$$

,where ρ_{jk} denotes the total number of shortest path between node j and node k and $\rho_{jk}(i)$ shows the number of those paths that go through node i. For normalization it divided by $(n-1)(n-2)/2$. Thus, betweeness quantifies the number of times the node acts as a part of the shortest path between two other nodes. Nodes that have high probability of occuring on a randomly chosen shortest path between two nodes have a higher betweenes value.

Lastly, I use prestige measurement, that is trying to describe how significant you are, based on the significance of the nodes you are connected to. Prestige measures try to capture how connected the nodes that the given node is connected to are. So instead of looking for the amounts of connections you have it is more interested the value of these connections. One particularly way to capture prestige is called Eigenvector centrality. Let *E* be the eigenvalue of a non-negative adjacency matrix *A*. Considering a particular node *i* with connected nodes *N(i)* we can formulate Eigenvector as:

$$E_i = \sum_{j \in N(i)} \sum_{j} A_{ij} E_j \tag{3.6}$$

Eigenvector centrality allocastes scores to all nodes in the graph based on the concept that connections to highly connected nodes are worth more than links to nodes with small degree of connectivity. Therefore, Eigenvector centrality depends not just on the number of connections $|N(i)|$ but also on the quality of the connections $E_j, j \in N(i)$. This is one measure used by web-search enginess trying to rank the relative importance of a website by looking at the importance of the website's link into it.

Table 2. Descriptive statistics and correlation for network centrality indicators on the overall sample

	Variable	Obs.	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)
(1)	Degree norm.	103	.2845	.1737	.03125	1	1			
(2)	Closeness	103	.4502	.1738	0	1	.4113*	1		
(3)	Betweenness	103	.0025	.0046	0	.03165	.7336*	.2249	1	
(4)	Eigenvector	103	.1914	.2242	0	1	.6719*	.0207	.5043*	1

Source: author's own data from field experiment. Note: * p<0.01.

To decide which one of these works best is context dependent. Even though, all of the four centrality index measure the importance of the node, yet they catch a slightly different nature of centrality. While degree merely catches the number of connections in the ego network the other three indicators take the complexity of the overall network into account. Even if someone has a high degree, it does not necessary mean high centrality in terms of closeness, betweenness and in eigenventor scores.

Individuals with high closeness and betweenness values have the ability to spread something through the network easily. In a classroom environment, it is useful to think about closeness as who has the highest capacity to spread a rumor. While about betweenness it is useful to think as someone who has a “bridge” position between cliques of the class.

Finally, eigenvector centrality is a bit different from the previous measures. It considers the relative weight of every connection of the individual. In this environment, we can think that students with high eigenvector centrality have the most popular friends in the class.

As the descriptive statistics show, we can notice a significant correlation between the different centrality measures. In the analyses, I test these four measures to see how social network affiliation affects the power of the treatment. I expect that if student i has a weak or j an infulental centrality position in the social network, then i is more likely to change her opinion.

Table 3. Descriptive statistics and correlation for network centrality indicator by class

Class A	Variable	Obs.	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)
(1)	Degree norm.	30	.3625	.20787	.0937	1	1			
(2)	Closeness	30	.4629	.1675	0	.8055	.5978*	1		
(3)	Betweenness	30	.0029	.0059	0	.0316	.7449*	.3627	1	
(4)	Eigenvector	30	.4253	.2513	.1089	1	.6307*	-.0225	.6189*	1
Class B							(1)	(2)	(3)	(4)
(1)	Degree norm.	23	.2173	.1003	.0937	.4375	1			
(2)	Closeness	23	.5364	.2415	0	1	.3905	1		
(3)	Betweenness	23	.0010	.0011	0	.0038	.6064*	.1761	1	
(4)	Eigenvector	23	.0291	.0372	0	.1278	.6323*	.3163	.4424	1
Class C							(1)	(2)	(3)	(4)
(1)	Degree norm.	25	.2575	.1842	.0625	.7812	1			
(2)	Closeness	25	.4233	.0805	.3333	.6896	.4537	1		
(3)	Betweenness	25	.0027	.0058	0	.0249	.8031*	.6500*	1	
(4)	Eigenvector	25	.1292	.1477	0	.5571	.8856*	.2022	.6505*	1
Class D							(1)	(2)	(3)	(4)
(1)	Degree norm.	25	.2800	.1419	.0312	.5625	1			
(2)	Closeness	25	.3824	.1472	0	.6571	.7391*	1		
(3)	Betweenness	25	.0031	.0036	0	.0124	.7405	.4487	1	
(4)	Eigenvector	25	.1222	.1081	0	.4124	.6410*	.1644	.6998*	1

Source: author's own data from field experiment. Note: * p<0.01.

3.6 Demographic control variables

I introduced control questions to identify the socioeconomic background of the students without directly asking about their parents' income and education. Table 4 shows the overall, and the class means for the control variables, and Table 5 shows the descriptive statistics.

Table 4. Overall and the class means for the control variables

	A	B	C	D	Overall
Holiday	3,36	2,86	3,23	3,12	3,14
News	1,3	1,08	0,88	1,2	1,11
Grades	3,96	4,04	4,00	4,17	4,04
Knowledge	3	2,62	2,96	3,25	2,95
University application	93%	100%	84%	96%	93%
Female	21	14	18	15	68
Average time (minutes)	47	49	51	48	48,75
N	30	23	25	25	103

Source: author's own data from field experiment.

To indirectly measure family income I used the number of times the students have been abroad for a holiday in the last four years. Mergoupis and Steuer (2003) demonstrated that holiday participation could be explained by differences in income and demographic factors. Families with higher income are more likely to go abroad for a holiday compared to low-income families. The scales starts from zero and goes by one to the highest category which is 'six times or more'.

The second control question measures the extent of news consumption of the students. Namely, on an average week, how many times does the student read the news about politics or the economy. This question helps to identify students who are aware of news related to politics. The answers are decoded into a scale variable, where zero represents the students who never read political news and three denotes a student who reads the news every day. The average student reads news related to politics once per week. However the literature is divided on the relationship between media and political knowledge, several articles argue that reading the news at least once per week significantly influences political knowledge (De Vreese and

Boomgaarden 2006). Moreover, people who are reading the news are more likely to become more knowledgeable compared to people who prefer political entertainment (Prior 2005).

To measure the factual political knowledge, I introduced a variable that measures the student's specific knowledge on Hungarian politics. This variable is a combination of answers from six questions related to Hungarian political and party system, where all the questions have three possible answers. It is a scale variable from zero to six, where zero represents a student who had no correct answer, and six represents students with six correct answers.

The next control variable is the overall grade of the student from last semester. An early study from Dembo and McAuliffe (1987) investigated how grades affect group behavior. The results of their experiment suggest that differences in social interaction are significantly influenced by the perceived status of the students measured by their grades. However, I have to emphasize the fact that student self-reported their grades and people tend to have a self-assessment bias (for more in-depth psychological investigation see Walfish et al. 2012 or Dunning et al. 2003).

The grade variable is also a scale variable from 1 to 5, where 5 is the best available grade. University application is a binary variable, where 1 represents if the student applied to university and zero if did not. As Table 5 shows most of the students applied to university. Note that in class B all the students applied to university, which is a possible source of issues during the statistical analyses.

Table 5. Descriptive statistics of control variables by class

	Mean	Std. Dev.	Min	Max
Class A				
Holiday	3,36	1,9	0	6
News	1,3	1,2	0	3
Knowledge	3	1,11	1	5
Grades	3,96	0,39	3,2	5
University application	0,93	0,25	0	1
Class B				
Holiday	2,86	2,02	0	6
News	1,08	0,94	0	3
Knowledge	2,62	1,69	0	5
Grades	4,04	0,55	3	5
University application	1	0	1	1
Class C				
Holiday	3,23	1,94	0	6
News	0,88	0,95	0	3
Knowledge	2,96	2,03	0	6
Grades	4	0,41	3,4	5
University application	0,84	0,36	0	1
Class D				
Holiday	3,12	1,9	0	6
News	1,2	0,95	0	3
Knowledge	3,25	1,6	0	5
Grades	4,17	0,57	2,8	5
University application	0,96	0,2	0	1

Source: author's own data from a field experiment.

4. Methodology

So according to my hypotheses, the treated individuals will tend to change their political views in order to become more similar to their pair or to the median. I expect the likelihood of the changes to depend on their own and their partners' characteristics and social affiliation. According to the social capital theory personal contacts have value because individuals affect their neighbors (Bourdieu and Wacquant 1992, Coleman 1988). Putnam (1995) argues social capital can be measured by the amount of trust and "reciprocity" in a community of individuals. The contention comes from what "better connected" means (Burt 2002). Therefore I chose these four possible explanatory network indicator variables to derive from the data from the quasi-experiment survey:

The easiest method to measure an individual's impression on the network is by their degrees. The degree of individuals in the network is defined as the number of connections that an individual has. Although, the degree itself cannot capture all the social capital and knowledge-access characteristics of individuals, which are attributed to the structure of the ego-networks. Therefore, I use the well-known centrality indicators suggested by network science literature (Gest et al. 2001, Marsden 2002, Valente 2008), which measure the importance of an individual in her overall social network.

So my response variable is a binary variable which indicates whether the individual has changed her opinion at the given statement. The main explanatory variables would be the treatment and the network indicators, further explanatory variable would be how similar the two actors are to each other. However, there is a typical endogeneity issue in the data because as I mentioned before, there is a reciprocal relationship between our social affiliation and our political views due to social homophily.

4.1 Testing network endogeneity

The structural things like homophily are important in understanding how political opinion is formed, however the way of causality is often unclear. Social network and political opinion usually coevolve together.

In order to better understand the role of political opinion in the formulation of the social network in a class, I use exponential random graph models. Exponential random graph models are frequently used in biosciences (Saul and Filkov 2007, Fowler et al. 2009) to understand genetic variation in cell networks. However, these models are also often used in social sciences, for instance, used by Lubbers and Snidjers (2007) to analyze the formation of friendship networks or Cranmer and Desmarais (201) to understand cosponsorship networks in the US Senate. Exponential random graph models aim to recognize the features of the individuals that maximize the probability of the birth of a network with similar attributes as the observed network (Broekel et al. 2014). In my particular case, the exponential random graph model can identify the factors that determine the structure of the social network of the class and point out the reciprocal relationship between network homophily and political opinion. To formalize the general equation of exponential random graph models I follow Snijders et al. (2006):

$$\Pr(X = x) = \left(\frac{1}{k}\right) \exp\left\{\sum_{A} \eta_A g_A(x)\right\} \tag{4.1}$$

, where $\Pr(X = x)$ is the probability of network x created by a random graph process is identical with the observed graph (x). g_A is the network statistics of the graph A, such as clustering or average path length, and η_A represents the network structural configurations, such as node or dyad level properties of nodes. The coefficient of η_A shows the effect of the configuration property on the log-odds of the presence of a connection between two nodes. k is a normalizing parameter that ensures that the probability stays in 0 to 1 range.

In an efficient estimation the coefficients of exponential random graph model could be interpreted as the non-standardized betas acquired by logistic regressions. The exponential random graph setting allows me to catch which dyad level characteristic foster the given network structure. In my particular networks, I would like to test whether distance in political opinion significantly influences the graph appearance. Political attitudes significantly influence the students' social network reflects the problem of endogeneity, which I have to take into account during the statistical analyses.

4.2 Regression design

4.2.1 Treatment evaluation methods

Treatment evaluation is the measurement of the average effects of a program or treatment on the outcome of interest. Comparison of outcomes between treated and control observations. In my case treatment "program" is the peer effects on the students and in turn outcome is the political position of the student before and after the treatment. I assign the observations into two groups: the treated group that received the treatment that is paired with a student from class and the control group that did not. Treatment T is a binary variable that determines if the observation has the treatment or not. T=1 for treated observations and T=0 for control observations.

One obvious method is propensity score matching. The goal of matching is to compare the outcome of the treated and the control group by matching particular observations to each other. The propensity score model is a probit model with T as the dependent variable and x as independent variables and this model is the conditional (predicted) probability of receiving treatment given pre-treatment characteristics x. Estimate a probit model for the propensity of observations to be assigned to the treated group. Use x variables that may affect the likelihood of being assigned to the treated group.

$$\Pr(x) = \mathrm{P}(T = 1|x) = E(T|x) \tag{4.2}$$

Calculate the treatment effects: compare the outcomes y between the treated and control observations, after matching:

$$y = \begin{cases} y_T \; if \; T = 1 \\ y_C \; if \; T = 0 \end{cases} \tag{4.3}$$

To estimate the impact of the treatment we have to calculate the average treatment effect, which is the difference between the outcomes of treated and control observations $\Delta = y_1 - y_0$ by estimating:

$$y_1 - y_0 = E(y_T|x, T = 1) - E(y_C|x, T = 0) \tag{4.4}$$

However, this is just like a simple t-test between the outcomes for the treated and control groups. The average treatment effect is fine for perfect data but not in real life situations, it may be biased if treated and control observations are not similar. Therefore, I estimate the average treatment effect on the treated, which is the differences between the outcomes of the treated and the outcomes of the treated observations if they had not been treated:

$$E(\Delta|T = 1) = E(y_T|x, T = 1) - E(y_C|x, T = 1) \tag{4.5}$$

The second term is a counterfactual, so it is not observable and needs to be estimated. After matching on propensity scores we can compare the outcomes of treated and control observations.

$$E(\Delta|p(x), T = 1) = E(y_T|p(x), T = 1) - E(y_C|p(x), T = 1) \tag{4.6}$$

Obviously there is a counterfactual situation, we would like to compare the outcome of the treated observations with the outcome of the treated observations if they were not treated.

Therefore, we would like to find a close match using as the control observations and use their outcome, in other words for each treated observation i, we need to find matches of control observation(s) j with similar characteristics. The two most frequently used matching method is nearest neighbor matching and Kernel matching. In Nearest neighbor matching treated individual i matched with the closest control observation j, formally minimalizing the distance between the two propensity score: $\min \left\| p_i - p_j \right\|$.

In Kernel matching each treated observation i is matched with several control observations, with weights inversely proportional to the distance between treated and control observations. The weights are defined where h is the bandwidth parameter:

$$w(i,j) = \frac{K\left(\frac{p_j - p_i}{h}\right)}{\sum_{j=1}^{n_0} K\left(\frac{p_j - p_i}{h}\right)} \tag{4.7}$$

In empirical estimation, each treated observation i has matched j control observations and their outcomes y are weighted by w:

$$E(\Delta | p(x), T = 1) = \frac{1}{n_1} \sum_{i \in (T=1)} \left[y_T^i - \sum_j w(i,j) y_C^j \right] \tag{4.8}$$

However, propensity score matching cannot overcome the typical endogeneity problem of homophily, moreover there are some other serious limitations (King 2016). The difference-in-differences approach is a simple solution for the above problems. These models are applied when the independent variable is available in the data before and after the specific action that the researchers are interested in (Albouy 2004), which are often called treatment or experiment. The advantage of the diff-in-diff method is that it can avoid many of the emerging endogeneity problems while comparing heterogeneous individuals (Meyer 1995). With this method I will be able to measure the true effect of social network on political views. In my particular case, the outcome is the individual's change in his or her political position. The model gives an estimation on the effect of the pair's social influence on political views by comparing the opinions before and after the treatment and also comparing the outcome of the treated individuals with the outcome of the non-treated individuals.

The difference-in-differences model is an improvement over the one-time period model and applied when data on outcomes are available before (pre) and after (post) the treatment occurs. The trend in control group approximates what would have happened to the treatment group in the absence of the treatment. In a diff-in-diff model the outcome Y_i is estimated by the following equation:

$$Y_i = \alpha + \beta_i T_i + (\gamma_1 - \gamma_0) t_i + \delta(T_i) + \varepsilon_i \tag{4.9}$$

,where Y_i denoted the political opinion of student i; β_i is the difference between the control and the treatment group which comes from the constant differences between the students; $T_i \in \{0,1\}$ equals 1 if the student is treated and 0 otherwise and ε_i is the error term. The δ term denotes the impact of the peer effect. This latter impact is calculated by assuming parallel trends of the outcome variable in the treatment and the control group. Making this assumption, we can approximate the value of the outcome in the treatment group that would occur in the absence of the treatment itself. The comparison of outcomes between the treated and control observations is formulated by:

$$\bar{\delta} = \left(E\left[\overline{Y^1_{T=1}}\right] - E\left[\overline{Y^1_{T=0}}\right]\right) - \left(E\left[\overline{Y^0_{T=1}}\right] - E\left[\overline{Y^0_{T=0}}\right]\right) \tag{4.10}$$

, and Table 6 summarizes the notations of the equation 4.10 according to equation 4.9.

Table 6. Supporting table for the difference-in-differences equation

	Pre Treatment	Post Treatment
$T = 0$	$E[Y^0_{T=0}] = \alpha$	$E[Y^1_{T=0}] = \alpha + \beta$
$T = 1$	$E[Y^0_{T=1}] = \alpha + \gamma$	$E[Y^1_{T=1}] = \alpha + \beta + \gamma + \delta$

Source: Albouy, D. (2004). Program evaluation and the difference in difference estimator. Economics, 131.

In equation 4.10 the first term refers to the differences in outcomes before and after the treatment for the treated group. This term may be biased if there are time trends. The second term uses the differences in outcomes for the control group to eliminate this bias. So by simple mathematical transformation, I can use this equation[2] to identify the expected values of the average outcome of the treatment δ:

$$\bar{\delta} = \alpha + \beta + \gamma + \delta - (\alpha + \beta) - (\alpha + \gamma - \alpha) = (\gamma + \delta) - \gamma = \delta \qquad (4.11)$$

However, taking these equations of the estimators, we can see that is unbiased, difference-in-differences method has some limitations. The main limiting assumption of the difference-in-differences approach is that the accomplishment of the control group should reflect what would happen to the treated group with the lack of treatment. The parallel trend assumption cannot be directly tested because I want to compare two world states of one individual, but this is obviously counterfactual, one cannot observe the evolution of the treatment group absent the treatment. In the parallel trends assumption assigned as $(\gamma_1 - \gamma_0)t_i$ we want to compare two world states of one firm, but this is not possible. One cannot observe the dynamics of the treatment group without the treatment; students are either treated or they are not.

Another problem is that it is often very hard or impossible to check the suppositions that are made about the unobservable entities and there is a possibility that despite the result of the

[2] For an easier understanding of the estimation I made a visualization of the equation, see Figure 2 in the appendix

treatment effect the bias may be so major that we get wrong estimates. Accordingly there is a debate about the validity of difference-in-differences method. Abadie (2005) had discussed about group comparisons in non-experimental studies, Athey and Imbens (2002) concern the interference in difference-in differences because of the linearity assumption, Besley and Case (1994) critique whether this method really can detangle the possibility of endogeneity and Bertland, Duflo and Mullainathan (2002) focus on issues related to the standard error of the estimates.

So difference-in-differences method provide an unbiased treatment effect if the time trend before the treatment would be the same for both on the treated and the control group. But in most of the cases the time trend before the treatment is unobservable. Propensity score matching is commonly used to handle the effective comparison between two groups (for example: Werner et al. 2009 or Song et al. 2012). Therefore, I used propensity scores as a weight inside the difference-in-differences model for the observed control variables. However this method is still under consideration the *"*[propensity score] *weighting approach can accurately recover treatment effects, and in an applied example it successfully balanced the four groups with respect to observed baseline characteristics."* (Stuart et. al 2014 181. pp.).

4.2.2 Regression models

There is a debate in the statistical literature on which probability model is better for regression with binary dependent variable (Aldrich et at 1984, Caudill 1988, Horrace 2006). On the one hand, social science researchers almost universally use logistic (or probit) regression instead of linear probability model when the outcome variable is dichotomous. On the other hand, although economists are aware of logistic regressions they frequently use a linear probability model. To decide which model to use is context dependent, there are situations where the linear probability model has some serious limitations, but there are situations where the linear model has a clear advantage due its simplicity.

If the outcome variable Y is dichotomous with values of 0 and 1, then the predicted probability of the event occurs in the linear probability model:

$$y = \alpha + \beta_1 x_1 + \varepsilon \tag{4.12}$$

, and the estimating equation is

$$\hat{P}(y = 1|x) = \hat{y} = \alpha + \widehat{\beta_1} x_1 \tag{4.13}$$

, where $\hat{y}$ is the predicted probability of $y = 1$ with the given values of x_1. This model assumes that the probability of $y = 1$ is a linear function of x explanatory variables. The biggest advantage of this model is its simplicity and interpretability. For instance if $\widehat{\beta_1}$ equals to 0.01, that means that one unit increase in x_1 leads to 1 percentage point increase in the probability of $y = 1$.

Although linear probability model has its obvious advantage due its simplicity it has some serious problems. One problem is heteroscedasticity in ε_i. We can write down the two particular values of ε_i can take: $\varepsilon_i = \begin{cases} -\beta x_i & \text{if } y_i = 0 \\ 1 - \beta x_i & \text{if } y_i = 1 \end{cases}$. First, the value of ε_i if $y_i = 0$ and the value if $y_i = 1$. If we consider the conditional variance of the error term it equals the expectation of the square of the error term at given regressors, which is equals to the weighted sum of the probabilities:

$$\mathrm{Var}(\varepsilon_i|x_i) = E(\varepsilon_i{}^2|x_i) = \sum_j P(y_i = y_j)\ \varepsilon_i{}^2 \tag{4.14}$$

, where y_j equals to either $-\beta x_i$ or $1 - \beta x_i$. Expressing equation 4.14 for each different cases we can reformulate it into a straightforward way:

$$= P(y_i = 0 \mid x_i)(-\beta x_i)^2 + P(y_i = 1 \mid x_i)(1 - \beta x_i)^2 \quad (4.15)$$

, and after factorizing equation 4.15 it equals to

$$= (1 - \beta x_i)\, \beta x_i(\beta x_i + 1 - \beta x_i) \quad (4.16)$$

In the equation 4.16 βx_i and $-\beta x_i$ cancels out, so the variance is given by $(1 - \beta x_i)\, \beta x_i$. Note that this variance is very much a function of x_i. Therefore, we have heteroscedasticity, because in case of homoscedasticity the variance is a constant. Thus, by applying the standard Gauss-Markov assumptions we know that the linear probability model does not provide the most efficient unbiased estimate for the parameter $\widehat{\beta_1}$ due to $\mathrm{Var}(\varepsilon_i|x_i) \neq \sigma^2$. Another problem with linear probability model is the non-normality of the errors. Which is a serious problem in case of small sample size. The last, but probably the most obvious problem is the fact that it allows probabilities to be outside the normal $0 < \hat{y} < 1$ range, which makes no sense, since there is no probability below zero or above one.

However, the logistic regression is less interpretable it provides a solution for problems of linear probability model. Logistic regression is specially made for binary dependent variable and always provides probabilities inside the normal $0 < \hat{y} < 1$ range. Logit model assumes that change in political opinion is a latent continuous unobserved y^* variable, which is connected to the observed y_i variable. The observed dependent variable takes two forms, 0 when the event has not occurred and 1 when the event has come about. I defined the connection between the unobserved continuous variable y^* and the observed binary variable y_i in the following way: $y_i = \begin{cases} 1 & \text{if} \quad y_i^* > 0 \\ 0 & \text{if} \quad y_i^* \leq 0 \end{cases}$.

The assumption of the latent variable model is based on the underlying propensity to change opinion result in the observed outcome. However, I cannot directly observe the underlying association, at a given point a change in y^* variable results in a change in y that I can observe, namely, whether the student changes her political opinion or not. The binary dependent variable for positive values of opinion change represented by $y_{iq} = 1$ if the student changed her answer at the given question, otherwise zero. The structural model for given values of single independent variable x demonstrate, how the distribution of the error term ε affect the probability of event $y_i = 1$ occurs, where the error term ε assumed to have mean of 0 with $\text{Var}(\varepsilon) = \pi^2/3$:

$$\Pr(y = 1|x) = \Pr(\varepsilon > -[\alpha + \beta x]|x) \tag{4.16}$$

, which is leading to estimate the logistic function of x in equation (4.17).

$$\Pr(y = 1|x) = \frac{\exp(\alpha + \beta x)}{1 + \exp(\alpha + \beta x)} \tag{4.17}$$

Thus, I implement the difference-in-differences method in two specifications. First, I use linear probability model to catch an easily interpretable difference-in-differences coefficient, which is sometimes problematic in nonlinear models (Ai and Norton 2003). Then I run logit models to control for the best unbiased estimation. I use clustered standard errors on student level that allow for repeated observations of the individuals. Besides that, in the logit models I use class dummy variables as a fixed effect to control for variety in the classroom environments.

Thus, my first models are linear probability difference-in-differences models with built in propensity score matching:

$$\Pr(\mathrm{y}_{iq} = 1 | T_i) = \alpha + \beta_1 (T_i = 1 | Z_i, Z_j, N_i, N_j) + \varepsilon_i \tag{4.18}$$

,where $\mathrm{y}_{iq} = 1$ if the student *i* changed her opinion at given question q, T_i denotes the treatment, which is conditional on the demographic characteristics of Z_i, Z_j, such as, gender, knowledge on politics, grades or news consumption and social capital N_i, N_j. ε_i is the error term. In this model treated individuals compared with individuals from the control group with similar propensity of receiving the treatment. The first model is without matching, in the second nearest neighbor matching, in the third model kernel matching were used.

However, propensity score matching helps us identify the treatment effect, it takes away the possibility to see the direct effect of the covariates. Therefore, the fourth to seventh models are using demographic characteristics Z_i as direct explanatory variables on y_{iq}, without propensity score matching. To control for the possible bias that comes from the linear probability specification from the following logistic model are used, and C_k is a fixed effect variable for class *k*.

$$\Pr(\mathrm{y}_{iq} = 1 | T_i, Z_i, N_i) = \alpha + \beta_1 T_i + \beta_2 Z_i + \beta_3 N_i + \mathrm{C}_k + \varepsilon_i \tag{4.19}$$

Additionally, to the previous specifications, regression models from (9)-(12) include the network characteristics (N_j) of the peers'. I expect that higher values of network centrality of peer N_j associated with higher likelihood of changes in y_{iq}, while higher values of centrality of student N_i leads to smaller likelihood of change in in y_{iq}.

$$\Pr(\mathrm{y}_{iq} = 1 | T_i, Z_i, N_i, N_j) = \alpha + \beta_1 Z_i + \beta_2 N_i + \delta_1 T(N_j) + \mathrm{C}_k + \varepsilon_i \tag{4.20}$$

I introduce the differences in student i and j, namely, the differences in demographic characteristic, $(Z_i - Z_j)$ and the political opinion distance between them regarding their distance in the original opinion at question q, $(\tau_{jq} - \tau_{jq})$.

$$\Pr\left(\mathrm{y}_{iq} = 1 \middle| Z_i, Z_j, \tau_j, \tau_j\right) = \alpha + \theta_1(Z_i - Z_j) + \theta_2(\tau_{jq} - \tau_{jq}) + \mathrm{C}_k + \varepsilon_i \tag{4.21}$$

I expect that higher distance between students i and j in terms of demographic characteristics associated with smaller likelihood of changes in y_{iq}. The expected way of the difference in political opinion is not straightforward, one can argue in both direction, therefore in this framework I leave $(\tau_{jq} - \tau_{jq})$ as a control variable.

The aim for the last three regression models is to identify how treatment effect diversified between the two treatment groups:

$$\Pr\left(\mathrm{y}_{iq} = 1 \middle| T_i, Z_i, N_i, Z_j, N_j\right) = \alpha + \beta_1 T_i^B + \beta_2 Z_i + \beta_3 N_i + \delta_1 Z_j + \delta_2 N_j + \varepsilon_i \tag{4.22}$$

$$\Pr\left(\mathrm{y}_{iq} = 1 \middle| T_i, Z_i, N_i, Z_j, N_j\right) = \alpha + \beta_1 T_i^D + \beta_2 Z_i + \beta_3 N_i + \delta_1 Z_j + \delta_2 N_j + \varepsilon_i \tag{4.23}$$

, where T_i^B refers to the treatment received by class B and T_i^D for the treatment received by class D, and all the other explanatory variables included in the regressions. Therefore, if $\beta_1 T_i^B$ and $\beta_1 T_i^D$ differ from each other, the magnitude of the difference $\omega = \beta_1 T_i^B - \beta_1 T_i^D$ should reflect the pure effect that comes from the different treatment.

5. Results

5.1 Exponential Random Graph models

Table 7 presents the results of the exponential random graph model on the four classes. On the one hand, Gender and GPA turned out to be positive and significant for all the four classes. It means students with the same gender and similar GPA score tend to form significantly more ties. This is in line with theory that gender and cognitive skills foster homophily. On the other hand, political Knowledge, Holiday as a proxy variable for family financial background and News consumption do not directly determine students' ability to form friendships. For the further analyses the most important dyad level feature is the Political Opinion variable. Political closeness is positively significant, which suggest that proximity of political opinion shape the formation of the friendship networks in Class A, B and D.

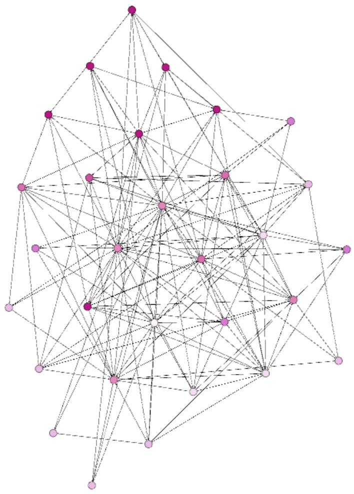
Table 7. Exponential Random Graph Models on friendship formation

	Variables	Class A	Class B	Class C	Class D
Dyad level similarity	Gender$_{ij}$	1.751***	1.591***	1.663***	1.102***
		(0.247)	(0.284)	(0.273)	(0.195)
	Knowledge$_{ij}$	0.369	0.399	0.323	0.298
		(0.247)	(0.251)	(0.177)	(0.190)
	GPA$_{ij}$	0.589***	0.617***	0.410***	0.413**
		(0.142)	(0.171)	(0.159)	(0.208)
	Holiday$_{ij}$	0.084	0.101	0.121***	0.119
		(0.057)	(0.097)	(0.048)	(0.102)
	News$_{ij}$	0.028	0.031	0.037	0.027
		(0.042)	(0.027)	(0.031)	(0.041)
	Political Opinion$_{ij}$	0.103***	0.113**	0.005	(0.095)***
		(0.035)	(0.056)	(0.004)	(0.017)
Structural level characteristics	Clustering	1.162***	1.321***	1.490***	1.268***
		(0.285)	(0.297)	(0.309)	(0.289)
	Average Path Length	-0.147***	-0.188***	-0.165***	-0.201***
		(0.041)	(0.039)	(0.042)	(0.739)
	N	30	23	25	25
	BIC	698.3	684.7	703.9	696.4

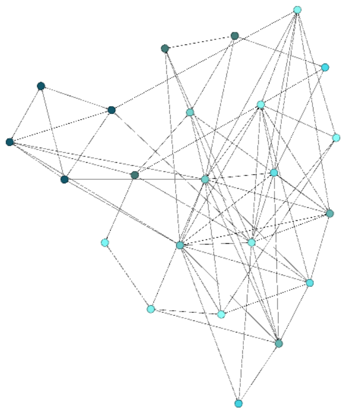
Source: author's own calculation used R. Note: Standard errors in parentheses. * p<0.10. **p<0.05. *** p<0.01. Further node level control variables that are not reported in the table include Gender, Knowledge, GPA, Holiday, and News.

Figure 1. Network visualization of friendships and political clusters

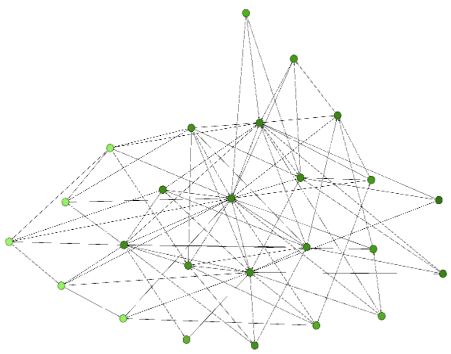
Class A



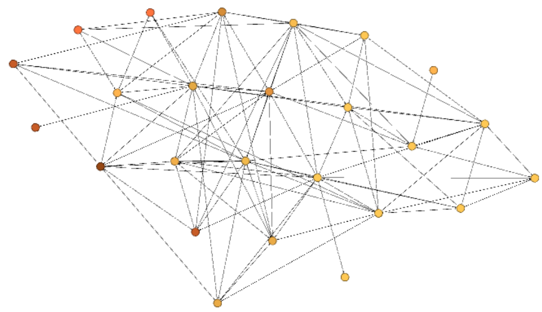
Class B



Class C



Class D



Source: author’s own visualization used Gephi. Darker color of nodes represent a more conservative answer on the statements during the experiment. Lighter color of the nodes represent a more liberal answer on the statements during the experiment. The shade of the nodes associated with their positions and clustering in the social network.

On the structural level Clustering is positive and significant, which shows that compared to a random network, students tend to form more triangles in their friendship network. The negative coefficient of Average Path Length indicates that the average distance between two students are smaller than in a random graph. The positive coefficient of Clustering and the negative coefficient of Average Path Length suggest that these graphs are more "small-worldlier" than random graphs, which is normal in a case of friendship networks (Watts, D. J. 1999, Catanese, S. A. et al. 2011.)

Figure 1 shows the network visualization of friendships in four classes with recolored nodes corresponding their political opinion. Darker color of nodes represent a more conservative answer on the statements during the experiment. Lighter shade of the node means that the given student answered the questions with a more liberal mind. For example, a student got a liberal answer if for the following question she answered agree or strongly agree *"Same sex couples in a stable relationship should have the opportunity to adopt a child."*, while the student got a conservative answer if her answer was disagree or strongly disagree.

The location of the nodes strengthens the results of the formal exponential random graph models. The graphs suggest that friendship formation and political opinion are related to each other. Students who have similar political opinion tend to more likely be friends, therefore there is political homophily in the friendship network. However, it is also possible that students had became friends first and then adopted to each other's political position. In summary, both the models and the graphs suggest that controlling for node level, dyad level and structural level characteristics, similar political attitudes enhance friendship formation.

5.2 Regression results

Table 8 shows the results from three lineal probability models. The first specification of the linear probability difference-in-differences model shows no significant result of the treatment on the probability of opinion change. The second and the third model uses propensity scores to match treated and control observations according to their demographic and network characteristics. Both the second and third model suggest that treated students are more likely to change their opinion than students in the control group. These models show that treated students are approximately 6% more likely to change their opinion on average.

The R^2 values show adequate model fit, to be specific the second and the third models can explain thirty-six percent of the variance in the dependent variable, however, one should not forget about the limitations of linear probability models, like biased standard errors due to heteroscedasticity.

Table 8. Difference-in-Differences estimation with Linear Probability Models

		(1) Linear probability without matching	(2) Linear probability (Kernel)	(3) Linear probability (Nearest Neighbor)
Difference-in-Differences estimation	Treatment x After	0.017	0.062**	0.057*
		(0.015)	(0.027)	(0.028)
	Cons.	0.001	0.000	0.000
		(0.002)	(0.050)	(0.050)
	R^2	0.11	0.36	0.36
	N	5150	5150	5150

Source: author's own calculation using STATA. Note: Standard errors in parentheses. * p<0.10. **p<0.05. *** p<0.01. Standard errors are clustered by students.

The results from the first three models suggest that without matching the treatment has no effect on the dependent variable in the linear probability specification. Nevertheless, including matching makes the treatment variable positive and weakly significant.

Table 9 shows the results from four logit difference-in-differences models using the demographic characteristics as direct control variables on the probability of opinion change, furthermore, network variables are introduced in the model as well. All of the four centrality measures are significantly negative, which means that students with more social capital are less likely to change their opinion.

Gender, GPA and Holiday variables turned out to be negatively significant, which means that male students with higher GPA and better financial family background are less likely to change their opinion. Knowledge, News and University Application have no significant effect on the dependent variable in these specifications. Based on pseudo R^2 one could conclude that model five has the best model prediction, however in case of probability models pseudo R^2 is usually misleading. Based on the Bayesian Information Criteria (BIC) I found that model seven has a significant improvement compared to the other models.

Table 9. Difference-in-Differences estimation with Logit Models I.

	Variables	(4) Logit model	(5) Logit model	(6) Logit model	(7) Logit model
Difference-in-Differences estimation (T)	Treatment x After	1.016***	1.005***	1.018***	1.009***
		(0.357)	(0.384)	(0.304)	(0.282)
Network centralities (N_i)	Degree $_i$	-1.753***			
		(0.357)			
	Closeness $_i$		-1.041***		
			(0.204)		
	Betweeness $_i$			-1.862***	
				(0.363)	
	Eigenvector $_i$				-2.024***
					(0.568)
Demographic control variables (Z_i)	Gender $_i$	-2.417**	-2.582**	-2.395**	-2.267**
	(ref. female)	(1.122)	(1.265)	(1.114)	(1.103)
	Knowledge $_i$	0.075	0.074	0.078	0.081
		(0.096)	(0.123)	(0.182)	(0.113)
	GPA $_i$	-0.203**	-0.196**	-0.212**	-0.201**
		(0.089)	(0.097)	(0.105)	(0.092)
	Holiday $_i$	-0.036***	-0.037***	-0.041***	-0.032***
		(0.009)	(0.008)	(0.008)	(0.009)
	News $_i$	-0.304	-0.231	-0.256	-0.252
		(0.196)	(0.149)	(0.156)	(0.189)
	University Appl. $_i$	-0.412	-0.422	-0.404	-0.561
	(ref. no apply)	(0.688)	(0.675)	(0.695)	(0.676)
	Cons.	-0.362	-0.361	-0.364	-0.362
		(1.366)	(1.362)	(1.365)	(1.379)
	Class FE	Yes	Yes	Yes	Yes
	McFadden R^2	0.28	0.36	0.29	0.35
	BIC	247.683	245.584	244.751	232.450
	N	5150	5150	5150	5150

Source: author's own calculation using STATA. Note: Standard errors in parentheses. * p<0.10. **p<0.05. *** p<0.01. Standard errors are clustered by students.

The results on the treatment variable from table 8 and 9 strengthen my first hypothesis, people are affected by their peers and more likely to change compared to other individuals who are not directly affected by their peers during a deliberation process, while controlling for their own characteristics.

Table 10. Difference-in-Differences estimation with Logit Models II.

	Variables	(8) Logit model
Difference-in-Differences estimation (T)	Treatment x After	1.357***
		(0.358)
Differences in political opinion	Political Opinion	0.557***
$(\tau_{jp\neq q} - \tau_{jp\neq q})$	(ref. different opinion)	(0.127)
	Gender	-2.416**
	(ref. same gender)	(1.124)
	Knowledge i-j	0.064***
		(0.011)
	GPA i-j	-0.448***
Differences in demographic variables		(0.136)
$(Z_i - Z_j)$	Holiday i-j	-0.105***
		(0.044)
	News i-j	0.048
		(0.142)
	University Appl.	0.041
	(ref. same appln.)	(0.574)
	Cons.	-0.362
		(1.366)
	McFadden R^2	0.34
	BIC	235.574
	N	5150

Source: author's own calculation using STATA. Note: Standard errors in parentheses. * p<0.10. **p<0.05. *** p<0.01. Standard errors are clustered by students.

Table 10 shows how the differences in *i* and *j* affect the likelihood of opinion change. Political Opinion is significantly positive, which means that if student *i* and *j* have similar answers on questions $p \neq q$ than student *i* is more likely to change her opinion at question q. That is a proof of an endogenous social spillover effect, which means that people who are similar to each other tend to become more similar in terms of political opinion during a deliberation process while controlling for their characteristics.

Gender, GPA and Holiday variables turned out to be negative and significant. Gender variable means that if the two students have different sexes then they are less likely to adopt to each other's political opinion. Furthermore, if the students are far from each other in terms of their grades or financial background they are less likely to adopt to each other's behavior. However, Knowledge turned out to be positive and significant, which means that if there is a higher distance between students i and j then student i is more likely to change. One possible explanation could be that a student with higher political knowledge can alter the opinion of a student with smaller political knowledge. News and University Application variables are positive but not significant, therefore the differences in news consumption and application to university do not directly affect the likelihood of change.

Model (8) confirmed my second hypothesis about how people tend to use those individuals more likely as cues, who are more similar to them to change their political opinion.

The next table 11 shows social spillover models, how the network characteristics of the peer influence the treatment while controlling for other covariates from models above. All of the four models show that students with higher network centrality, therefore higher social capital, influence peers to change their opinion during the treatment. The coefficients show that Eigenvector centrality has the highest impact, which means that students with important friends have the highest impact on their peers. In terms of goodness of model fit both pseudo R^2 and BIC statistics suggest model eleven as the best model.

Table 11. Difference-in-Differences estimation with Logit Models III.

	Variables	(9) Logit model	(10) Logit model	(11) Logit model	(12) Logit model
	Treatment x Degree $_j$	1.824***			
		(0.357)			
Difference-in-Difference estimation with network centralities as treatment 'dose' $T(N_i)$	Treatment x Closeness $_j$		2.155***		
			(0.357)		
	Treatment x Betweeness $_j$			2.396***	
				(0.357)	
	Treatment x Eigenvector $_j$				2.454***
					(0.368)
	Cons.	-0.051	-0.047	-0.052	-0.054
		(1.154)	(1.004)	(1.366)	(1.106)
	Class FE	Yes	Yes	Yes	Yes
	pseudo R-sq	0.36	0.41	0.34	0.52
	BIC	238.328	239.41	234.581	231.157
	N	5150	5150	5150	5150

Source: author's own calculation using STATA. Note: Standard errors in parentheses. * p<0.10. **p<0.05. *** p<0.01. Further control variables that are not reported in the table include Gender, Knowledge, GPA, Holiday, News, University Appl. Standard errors are clustered by students.

The results of table 11 strengthen my third hypothesis about social capital. It turned out that not only demographic proximity matters but social capital is also a crucial factor in the explanation of cues. In line with my hypothesis, people tend to use other individuals more likely as cues, who have higher level of social capital to change their political opinion.

Table 12. Difference-in-Differences estimation with Logit Models IV.

	(13) Logit model (Full sample)	(14) Logit model (Treatment = Class B)	(15) Logit model (Treatment = Class D)
Treatment x After	1.865***	1.605***	2.275***
	(0.357)	(0.525)	(0.758)
Cons.	-0.362	-0.252	-0.278
	(1.366)	(0.542)	(0.651)
McFadden R^2	0.61	0.59	0.62
BIC	227.931	231.517	235.528
N	5150	3900	4000

Source: author's own calculation using STATA. Note: Standard errors in parentheses. * p<0.10. **p<0.05. *** p<0.01. Further control variables that are not reported in the table include Gender, Knowledge, GPA, Holiday, News, University Appl. Standard errors are clustered by students.

The last table shows three models to identify how treatment diversified between the two treatment groups. Note, opposed to class B, students in class D were told that they were matched according to their characteristics because “they are good match to each other”, while in class B students were not told anything about the pairing. In case of model (14) the sample was restricted to the control groups and treatment class B, while for model (15) the sample was restricted to the control groups and treatment class D, but using the same covariates as explanatory and control variables. Therefore, the difference on the coefficients of treatments shows the pure effect of that students considering each other a good match, or in other words a good and costless cue. Thus, the difference of $e^{2.275}$ - $e^{1.605}$ $=\omega$ is the direct effect that came solely from the fact that students view each other as a low cost cue.

6. Conclusion

In this thesis, I investigated the effect of social peer effect on students' behavior related to political opinion change and what consequences different demographic and social network characteristics have on social cues. I conducted an experiment to collect data about political opinion and friendship formation from four classes. Due to the experimental design, the thesis has many hypothesis and thus has many results. A combination of difference-in-differences and a variety of linear probability models and logistic regressions models have been used.

I argue that voters in order to minimalize the cost of collecting information are using freely available shortcuts. These costless, available information serve as cues for people to form their political opinion. One of the most significant source of cues is interpersonal communication. However, there is no one precise definition for cue. I presented the concept and I gave an overview of the related literature; in short, the best way to think about cues as information shortcut tools to reduce uncertainty with a small cost. In this paper, I belive, I contributed to the literature of voting behavior by giving a theoretical and empirical explanation of political opinion change related to cues. I presented an alternative explanation how cues may foster social homophily and demographic and network characteristics behave like social spillovers.

Finally, I gave an empirical analysis on the relationship between political opinion change and social peer effect. My first finding from exponential random graph models suggest that friendship formation and political opinion are related to each other. People who have similar political opinion tend to be friends. Further regression analyses show many results. Among them the most important are that: 1) people are affected by their peers and a deliberation process increase the likelihood of opinion change; 2) people tend to use other individuals more likely as cues who are more similar to them to adopt their political behavior; and 3) turned out besides demographic similarity, social capital is a crucial factor in the explanation of the peer effect; and 4) a final model proves the existence of pure cue effect.

I can envisage a list of questions and concerns that my thesis can be extended to. First, further research is needed to show the dynamics of the opinion change during the deliberation process with a peer. However, I have some preliminary results on the dynamic I have no real answer to argue. The preliminary results show an S-shape curve with the number of the question on the horizontal and the predicted probability of opinion change on the vertical axes. A further research may uncover this relationship. Second, one may analyze the question with a better design and bigger sample. There is always a hidden issue in most of experimental design, and I am confident mine is not perfect either. Therefore, an improvement in the experimental design and data collection should be vital for better results. Third, 'difference-in-differences linear probability models with in-built propensity score matching' look "fuzzy". Simpler is sometimes better. An easier way should be to analyze the data without merging different estimation methods. Fourth, further dimension of social relations, like co-studding network should be analyzed to shed more light on how social capital enhance social peer effect.

However, the analyses is unique due to its experimental design and data, I encourage everybody to start to collect their own data which fit best for their research question. In case, someone would like to replicate my study or use my questioners and experimental design, please do not hesitate to contact me Toth_Gergo@alumni.ceu.edu address.

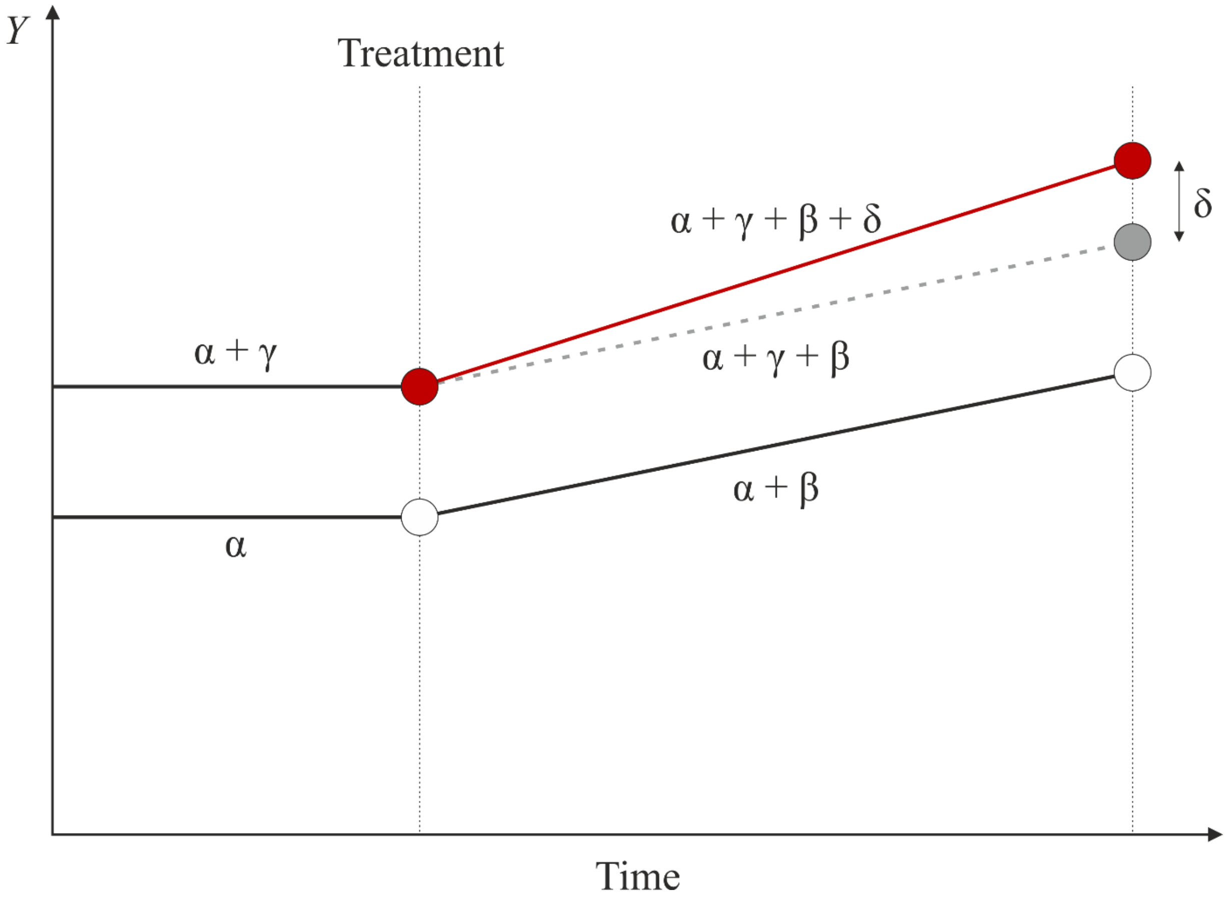
Appendix

Table 13. Percentage of students by class who changed their opinion at the given statement

Question Number	Class A (n=30)	Class B (n=23)	Class C (n=25)	Class D (n=25)
1	0.33	0.58	0.56	0.56
2	0.73	0.84	0.68	0.69
3	0.63	0.79	0.71	0.64
4	0.66	0.60	0.54	0.84
5	0.42	0.81	0.71	0.93
6	0.54	0.80	0.77	0.86
7	0.60	0.71	0.70	0.75
8	0.51	0.59	0.51	0.66
9	0.50	0.61	0.58	0.66
10	0.54	0.55	0.55	0.58
11	0.62	0.61	0.59	0.65
12	0.68	0.70	0.68	0.75
13	0.71	0.78	0.71	0.88
14	0.38	0.42	0.36	0.47
15	0.48	0.58	0.54	0.63
16	0.64	0.70	0.69	0.74
17	0.64	0.72	0.68	0.79
18	0.71	0.78	0.77	0.82
19	0.65	0.77	0.52	0.69
20	0.55	0.34	0.54	0.39
21	0.30	0.45	0.39	0.50
22	0.41	0.42	0.34	0.48
23	0.66	0.80	0.77	0.86
24	0.51	0.38	0.49	0.41
25	0.52	0.56	0.49	0.63
Total	13.92	15.89	14.80	17.11
Average	0.56	0.64	0.59	0.68

Source: author’s own data from field experiment.

Figure 2. Difference-in-Differences supporting visualization.



Source: author’s own visualization.

Economic

Question A ENG	Question B ENG
Riches are too little taxed.	More progressive tax system is required
Multinational firms are overregulated.	State should works harder to get international firms to invest into the country
Controlling unemployment is more important than keep inflation in hands.	Controlling the price level is the most important economic goal
Corporations have only one interest: to sell more	Making profit is the only aim of the company
Corporations do harm to the environment, so they should be taxed to compensate it	The state should make the corporations pay for the pollution they cause
Financial speculation should not be the foundation of economic culture	It is regrettable that many personal fortunes are made by people who simply manipulate money and contribute nothing to their society
The only social responsibility of a company should be to deliver a profit to its shareholders	It is very important that every company has CSR program.
Those with the ability to pay should have the right to higher standards of medical care.	High standard of medical care is an universal human right
Social justice is more important than free market.	Freer market makes freer people
I have more in common with other Hungarian people than with people on the same social status.	People are ultimately divided more by class than by nationality.

Gazdasági

Kérdés A HUN	Kérdés B HUN
A gazdagok nincsenek eléggé adóztatva	Egy progresszívabban, sávos adórendszerre lenne szükség
A multinacionális cégek túl vannak szabályozva	Az államnak jobban kellene igyekeznie, hogy multinacionális cégeket vonzón az országba
A munkanélküliség megfékezése fontosabb, mint az infláció kordában tartása	Az árszínvonal kontrolálása a legfontosabb gazdasági cél
Cégek egyetlen érdeke, hogy minél több terméket adjanak el	Nagyobb profit a vállalatok egyetlen célja
Cégek károsítják a környezetett, ezt kompenzálva adóztatni kellene őket	Az államnak kényszeríteni kellene a cégeket, hogy fizessenek a környezet szennyezését.
A pénzügyi spekulációnak nem szabadna részese lennie a gazdasági kultúránknak	Sajnálatos, hogy sok ember csupán pénzügyi manipulációk útján gazdagszik meg és valójában nem járul hozzá a társadalom fejlődéséhez.
A vállalat egyetlen felelőssége, hogy profitot termeljen a részvényeseinek	Nagyon fontos, hogy minden cégnek legyen valamilyen társadalmi felségvállalási programja
Akik ki tudnak fizetni, jobb orvosi ellátást azoknak legyen joga azt igénybe venni	Magas minőségű orvosi ellátást általános emberi jog
Társadalmi igazságosasság fontosabb, mint a szabad piac	Szabad piac nélkül nincs igazi szabadság
Több közös van bennem más magyarokkal, mint a velem egy társadalmi osztályba tartozókkal	Az emberek végső soron társadalmi osztályok szerint vannak megosztva nem nemzetiségük alapján

Social

Question A ENG	Question B ENG
In criminal justice, punishment should be more important than rehabilitation.	I would not want to work with an ex-convicted person
Good citizens should always support national interest	I had always support my country whether it was right or wrong
Military action that defies international law is sometimes justified.	Even the biggest nation should respect the international law during military intervention.
There should be compulsory military service.	It was a good decision to abolish compulsory military service.
Abortion should always be legal.	A mother's life is equal to her foetus
Parents sometimes should slap their child.	Domestic violence is always wrong
Marijuana should be legal to use with the same conditions like alcohol	Marijuana always should be illegal, except medical using.
Death penalty should be an option.	State has no right to justice over life and death
No one chooses his or her country of birth, so its' foolish to be proud of it.	People are tend to be too proud for their country nowadays.
Refugees should be welcomed in our society.	International migration is a threat to our country
Mothers' biggest carrier is to give birth to her child.	Both parents should take part in rising the child
One cannot be moral without being religious.	Atheism and religiousness should be treated on the same level

Társadalmi

Kérdés A HUN	Kérdés B HUN
Bűnügyi igazságszolgáltatásban a büntetés fontosabb, mint a rehabilitáció	Nem szívesen dolgoznék együtt börtönt megjárt emberrel
A jó állampolgár mindig a hazájáért dolgozik	Mindig segítem a hazám a céltól függetlenül
Az olyan katonai beavatkozás, ami szembemegy a nemzetközi joggal néha szükségszerű	A legnagyobb nemzetnek is tisztelnie kell a nemzetközi egyezményeket
Be kellene vezetni a kötelező honvédelmi szolgálatot	A sorkatonaság eltörlése egy jó döntés volt
Abortusznak minden esetben legálisnak kellene lennie	Az anya élete egyenrangú a magzatéval
Bizonyos körülmények között a szülői pofon jó is lehet	Családon belüli erőszak minden körülmények között rossz
A marijuana az alkoholhoz hasonló feltételek mellett legálisnak kellene lennie	Orvosi célokat kivéve a marijuanának illegálisnak kell maradnia
Be kellene vezetni a halálbüntetés lehetőségét	Az államnak nincs joga döntenie életről vagy halálról
Senki sem választja meg melyik országba születik ezért butaság büszkének lenne rá	Manapság az emberek hajlamosak túl büszkének lenni az országukra
A menekülteket be kellene fogadni az országba	A nemzetközi migráció veszély az országunkra
Az anyák legnagyobb karrierje, hogy gyermeket szülhetnek	Mindkét szülőnek egyenlő szerepet kell vállalnia a gyereknevelésben
Csak vallásosként élhetsz erkölcsös életet	Az ateistákat és a hívőket ugyanúgy kell kezelni

Only heterosexual couples should able to adopt child.	Same sex couples in a stable relationship should have the opportunity to adopt a child.	Csak heteroszexuális párok fogadhassanak örökbe gyereket	Stabil kapcsolatban lévő azonos nemű párok fogadhasson örökbe gyereket
Sex before marriage is immoral.	Sex is not exclusively about conceiving a child	Házasság előtti szex erkölcstelen	A szex nem csak gyereknemzésről szól
Universities should be free for everybody	Tuition fees, regardless its magnitude, is required for higher education	Az egyetemi oktatásnak ingyenesnek kellene lennie mindenki számára	Tandíj annak mértékétől függetlenül valamilyen formában szükségszerű az egyetemen

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