How Social Networks Shape Our Beliefs: A Natural Experiment among Future French Politicians

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Very preliminary – Comments welcome

This paper shows how a public policy shapes convergence of beliefs through newly-formed social networks, with a focus on political opinion. We use a unique natural experiment that randomly assigns students into first-year groups at a French college that forms future top politicians. Pairs of students in the same group are much more likely to become friends. The randomized group membership serves as instrumental variable in a dyadic regression of differences in beliefs on friendship. We find that students' political opinions converge particularly strongly between friends, reaching 11% of a standard deviation only after 6 months. Convergence is strongest among pairs least likely to become friends without the randomized exposure, or friends whose characteristics are the most different. While there is evidence of homophily in network formation, it does not seem to affect the estimates of convergence, except among very similar friends. The same strategy shows that a longer network distance implies slower convergence.

JEL Classifications: C93, D72, Z13.

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I. INTRODUCTION

What do Francois Hollande, Nicolas Sarkozy, Jacques Chirac, Francois Mitterrand and Georges Pompidou, the last five French presidents, have in common?[1] What is the smallest common denominator between twelve of the previous Prime Ministers of the French Republic?[2] The short answer is Sciences Po: the elite French School of Public Affairs that has been training all the top French politicians since World War II. All the different generations of French political leaders have met for the first time on Sciences Po's benches, and most of them have formed their more solid friendship and network relationship by that time. This has led to harsh criticism against friendship connection and homophily among the leaders ruling the country.

This anecdotal example raises a broader research question on the role of friends and social networks in beliefs formation. How does social networks influence political opinions? What determines the speed of convergence or the persistence of disagreement among friends, and what are the mechanisms behind it? While there has been extensive research on how leaders and group of people may influence voting behavior,[3] or on the impact of media exposure and persuasion on turn-out and political opinions,[4] the role of social networks and friends on political opinion has received less attention. In a seminal theoretical paper, Golub and Jackson (2012) analyze how the speed of convergence of agents' beliefs depends

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[1] If your answer is womanizer, you got it wrong… Georges Pompidou was not.

[2] Dominique de Villepin, Lionel Jospin, Alain Juppé, Edouard Balladur, Michel Rocard, Laurent Fabius, Raymond Barre, Jacques Chaban-Delmas, Maurice Couve de Merville, and Michel Debré, in addition to Jacques Chirac and Georges Pompidou.

[3] See e.g. Della Vigna and Gentzkow (2010), Gabel and Scheve (2007), Carlsson et al. (2015).

[4] See e.g. Della Vigna and Kaplan (2007), Gentzkow (2006), Gentzkow, Shapiro and Sinkinson (2011), Kendall, Nannicini and Trebbi (2015), Gerber, Karlan and Bergan (2009).

on network structure in a model with homophily to explain the persistence of segregation and persistence in disagreement. But this study has not led to empirical identification, due to the lack of observational studies where the social network formation is exogenous and not plagued by sorting and reflection problem. In a seminal non-experimental study, Lazarfeld, Berelson and Gaudet (1944) found that US voters in the 1940 Presidential election were more influenced by friends than mass media. More recent empirical papers exploit online networks such as Facebook to measure social contagion of messages (Bond et al., 2012) on political mobilization and turn-out, but without identifying the impact of friends' political beliefs.

This paper addresses this issue by exploiting the near ideal natural experiment of Sciences Po to provide causal evidence of the role of friends in political opinion and behaviors. While most of the top political leaders meet each other and start their political enrollment at Sciences Po, an administrative curiosity has recently introduced a source of exogeneity in the building of their friendship relationships by randomly assigning students into tutorial classes for the first year courses. We exploit this random assignment policy by performing a survey for the first-year student who have entered Sciences Po in early September 2013, and ask incentive-compatible questions to elicit their social networks (as, for example, in Leider et al., 2009, 2010). Students were asked to provide a list of friends and were rewarded if friends provide cross-validated answers to a few questions. We also surveyed students' political opinions over time, and behaviors in latest national and local elections, and students' opinions on key policy issues such as immigration policy. We then examine the diffusion and convergence of political opinions within social networks by using the panel of all pairs of students and by estimating dyadic regression of differences in beliefs on friendship.

Naturally the main traditional concern in such regression is reverse causality and correlation in unobservables due to homophily: people have proclivities to link to others similar to themselves, both on observed and unobserved characteristics that could influence their behavior (Manski, 1993; McPherson, Smith-Lovin and Cook, 2001; Currarini, Jackson and Pin, 2009). As a result, the OLS estimate of the role of friendship in beliefs formation might be upward biased since people tend to be similar. They tend to form friendship relationships with individuals who originally share their political opinions. We address this concern by using an instrument for friendship formation based on the *initial exogenous allocation* of Sciences Po students into small tutorial groups at school entry. During the first year, students are asked to follow common introductory courses in economics, history, sociology, political science and law. Those core courses are constituted by one weekly lecture that groups the whole cohort (800 students) and by compulsory weekly tutorials that group together about twenty students each and where most of the social interactions across students take place. In order to enhance further social links among first-year students who come from all over France and from abroad, the administration has chosen few years ago to link tutorials together into packs. Students are assigned the same classmates across all the subjects with whom they have at least three meetings together each week during the tutorials, and common free time for homework and group projects.

The group membership for the tutorials is thus by far the first place within the institution where first year students interact together. By exploiting our 2014 survey, we find a very strong relationship between common group membership and friendship: being in the same group increases the chance of a pair of students to become friends by 35 percentage points. Common group membership alone explains about 15% of the variation in pairwise undirected friendships across dyads, whereas alternative control variables could explain only 1.6% more. Importantly, the assignment to these tutorials is exogenous with respect to the students' characteristics. We describe at length in the paper the exogeneity of the assignment procedure: it takes place at school entry, when the overwhelming majority of students do not know each other, and the enrolment process does not provide neither time nor information for any coordination among students. We then give additional statistical tests by regressing dyadic model of group formation on the initial characteristics of the members of the dyad, and show the absence of any statistically significant characteristics. We then provide several additional tests to show that group membership to tutorials is thus a valid instrument for friendship formation.

We next estimate the causal impact of friends on beliefs formation by using group membership as an instrument. The IV strategy is based on local average treatment effect (LATE) among compliers, which is among those who become friend only due to the group assignment. We find very strong first stage estimates and check that the exclusion restriction, that common membership does not affect opinions through other channels, is respected. The second-stage estimates of the impact of undirected friendship imply an average convergence in political opinion among first-year friends. The magnitude of the convergence is quite substantial: around 0.16 points over a scale from 1 to 10 in political opinions, which accounts for 11% of the standard deviation. The magnitude is unchanged with the exclusion of pre-Sciences Po difference in political opinion, suggesting that the IV estimates properly address the previous issue of homophily.

Besides, we show that convergence in political opinion happens only among friends, while the effect would be insignificant if we were focusing on pairs of non-friends belonging to the same group. This finding is important with respect to the literature on peer effects since what really matters in social learning or imitation is not peers, but friends. Moreover, friends not only converge in political *beliefs*, but also in *behaviors:* pairs of friends significantly converge in their associative lives and among those who do enroll in a political party; a pair of friends becomes more likely to enroll in the same political party.

We next analyze potential heterogeneous effects to analyze the mechanisms and channels behind this convergence process. A first important finding is that convergence is higher among students with more initial differences in political attitudes. This is in line with DeGroot model of convergence (DeGroot, 1974; DeMarzo, Vayanos and Zwiebel, 2003; Golub, and Jackson, 2010, 2012). The second important finding is that the network structure plays a key role. Convergence mostly takes place among direct friends, while the convergence decays with second-order direct friends.

We also find that convergence works partly thanks to common friends: convergence is higher when more common friends hold opinion in between. Strikingly, people's beliefs converge towards the beliefs of *stars*, which are the students who have the highest network centrality (in terms of betweenness and eigenvector centrality). To put it differently, those who are the most likely to change their political opinions are those who are the least central. This finding suggests that imitation or leadership is the main driver in the formation of political attitudes, rather than acquisition of information or social learning. The third main heterogeneous effect is related to *extremists*: while there is a stronger convergence in beliefs among friends with opposite political priors, in contrast there is a divergence among students who share initially extreme left priors.

The rest of the paper unfolds as follows. Section 2 relates our paper to the literature on peers, social networks and social learning. Section 3 describes the data and analyzes the exogenous allocation process of students across groups at school entry. Section 4 details the empirical strategy. Section 5 presents the baseline results and Section 6 studies the heterogeneous effects. The role of the structure of the social network is analyzed in Section 7. Finally, Section 8 concludes.

II. Related Literature

Although our paper provides a novel analysis of the role of social networks on political belief formation, there has been an extensive literature on the impact of peers and social networks on other beliefs and behaviors. We discuss below the main identification issues raised in this literature and how we address them in this paper.

II.A. Peer Effects

There is an important literature on peer effects. This literature looks at the causal impact of peers on different outcomes and mainly uses field experiments (see e.g. Angrist and Lavy, 1999; Sacerdote, 2001; Zimmerman, 2003).[5]

For example, Boisjoly et al. (2006) show that the racial composition of freshman housing assignments can have a long run impact on student attitudes. They show that, if a student is randomly assigned to a black roommate, he/she is somewhat more likely to support Affirmative Action in admissions and societal income redistribution.

Other interesting peer-effect studies include that of Sacerdote (2001) and Carrell et al. (2009) who analyze specific contexts in which first-year roommates (or hallmates or squadron mates in the case of military academies) are randomly assigned by the housing office. This creates exogenous variation in one's peer group, which is then used to ask how much peers matter, which peers matter, and for what outcomes. They find strong peer effects in education. A recent paper by Carrell et al. (2013) examines squadron mates in the case of military academies. They manipulate the groups by putting together low-ability and high-ability incoming cadets at the US Air Force Academy. They show that performance for the

[5] For an overview of this literature, see Sacerdote (2011, 2014).

lower-ability students fell relative to lower-ability students in the randomly assigned control group.

Compared to this literature, we study *network* rather than *peer effects*. Indeed, peer effects are usually conceived as an average intra-group externality that affects identically all the members of a given group. For example, in the example above, all cadets affected to the same squadron are considered as peers. This means that the group boundaries for such a homogeneous effect are often arbitrary, and at a quite aggregate level, in part due to the constraints imposed by the available disaggregated data. For instance, in standard peer effect papers (such as Angrist and Lavy, 1999), peer effects are measured at the school or the classroom level using average school achievements. In this paper, we focus on the smallest unit of analysis for peer effects, that is the *dyad*, a two-person group. The collection of active bilateral influences or dyads constitutes a social network. In our dataset, this means that the reference group (or peers) for each student is not the whole classroom but the friends that he/she has nominated. Contrary to the peer-effect literature, we can then study the impact of the network structure, in particular the centrality of each student and the distance in the network §between students, on the convergence of political beliefs.

II.B. Empirical aspects of networks

A growing empirical literature has documented the effects of social networks on behavior (see e.g. Jackson, 2008, 2011, 2014; Jackson et al., 2015; Jackson and Zenou, 2015; Blume et al., 2011; Ioannides, 2012; Advani and Malde, 2014; Topa and Zenou, 2015 for overviews). Since social networks are so prevalent in economic settings, modeling these networks is essential in order to understand how network structure affects behavior. However, it is very difficult to cleanly test theoretical predictions using data, since there are many confounding features in the environment.

The estimation of network effects is indeed complicated by several issues: reflection problem, common shocks and endogenous network formation.

It is well-known that when estimating peer effects using a linear-in-means model (i.e. when regressing individual activity level on the average activity level in the neighborhood/among the peers), the endogenous and contextual effects cannot be separately identified due to the *reflection problem*, first formulated by Manski (1993). With explicit social network data, as we have here, this problem is eluded (see, e.g. Bramoullé et al., 2009; Lee and Liu, 2010; Calvó-Armengol et al., 2009; Lin, 2010; Liu et al., 2014). Indeed, the reflection problem arises in linear-in-means models because individuals interact in groups - individuals are affected by all individuals belonging to their group and by nobody outside the group. In the case of social networks, instead, since the reference group is individual specific, this is not true because peer groups are overlapping. Formally, social effects are identified (i.e. no reflection problem) if at least two individuals in the same network have different links (Bramoullé et al., 2009) is generally satisfied in any real-world network.

Another concern is the fact that students might be exposed to *common shocks* that drive the convergence of beliefs, irrespective of their social interaction. One of the most plausible candidates is a teacher fixed effects. Students who have been randomly assigned to a group are also exposed to the same teachers. We run various placebo tests in this paper to rule out the direct impact of the group on beliefs formation. In particular, we show that the main driving force in the convergence process is the structure of the network within the group, and in particular direct paths between friends.

The other (and often most) important issue is the potential *endogeneity of the networks*. Indeed, as stated above, people have proclivities to link to others similar to themselves (homophily), both on observed characteristics and unobserved characteristics that could influence their behavior. By failing to account for similarities in (unobserved) characteristics, similar behaviors might be mistakenly attributed to interactive effects when they are actually due to underlying characteristics or exposure to common stimuli. As discussed by Goldsmith-Pinkham and Imbens (2013), Graham (2015), Jackson et al. (2015), there is no simple solution to this problem. One can explicitly model the network formation process and structurally estimate it (see, e.g. Mele, 2013; Goldsmith-Pinkham and Imbens, 2013; Chandrasekhar and Jackson, 2014; Graham, 2014; Badev, 2014), or use instrumental variables (Bifulco et al., 2011; Bramoullé et al., 2009; Calvó-Armengol et al., 2009; Patacchini and Zenou, 2014).

Another way out is to use controlled experiments. In the field of networks, this has been implemented by either (*i*) fully controlling the network of relationships in the laboratory (Choi et al., 2012; Kearns et al., 2009) or (ii) assigning subjects in the field positions in a network through which they must communicate (Centola, 2010, 2011; Goeree et al., 2010; Babcock and Hartman, 2010; Cai et al., 2015). In the latter papers, the network is still endogenous and not randomized. What is randomized is the intervention. For example, in Babcock and Hartman (2010), the network is self-reported and thus not random, but subjects (students at UC Santa Barbara) have different fractions of their friends who are being randomly treated (free access to exercise at the university gym).

In our paper, we use a natural experiment where agents are randomly allocated to the network. We believe this is one of the first papers that uses such a strategy in the context of networks. It gives a “clean” identification strategy that allows testing the effect of network position on educational outcomes.

II.C. Social learning

There is an interesting literature on learning in social settings.[6] From a theoretical viewpoint, two basic approaches have been considered. One is a Bayesian approach, where agents update their beliefs based on either communication or observation of other agents' actions over time. This approach provides a nice benchmark for what happens with full rationality (see e.g. Bala and Goyal, 1998, 2001; Acemoglu et al., 2011). Another approach is more mechanical, where agents repeatedly process the information from their neighbors according to fixed rules (see e.g. DeGroot, 1974; DeMarzo, Vayanos and Zwiebel, 2003; Golub, and Jackson, 2010, 2012).

From an empirical viewpoint, the social learning literature has provided several major insights. First, careful observational studies, natural experiments, and field experiments have established the importance of social learning in many domains, such as in the introduction of new technologies and innovations (e.g. Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Henkel and Maurer, 2010; Conley and Udry; 2010) and labor markets (Granovetter, 1974; Munshi, 2003; Topa, 2001; Bayer, Ross and Topa, 2008; Damm, 2009; Beaman, 2012). Second, some studies carefully measure social networks and estimate the relative effect of geographic neighbors, direct friends, and second-order friends. The evidence on this question is mixed, with some papers finding an almost equal influence of second-order neighbors (Kremer and Miguel, 2007) and others finding no

[6] For overviews, see Goyal (2011) and Mobius and Rosenblat (2014).

effect (Rao, Mobius and Rosenblat, 2007)[7] or significant decay (Patacchini and Zenou, 2012; Mobius, Szeidl and Phan, 2015).

However, most of these studies focus on outcomes, with the adoption of new technologies or product, or employment outcomes. But they do not distinguish outcomes from beliefs, whether the process goes through the transmission of information or just imitation. This is what we do in our paper.

III. Background, Data Description and Exogenous Allocation

This section provides a description of the context of the natural experiment at Sciences Po. We first present the organization of the curriculum and the exogenous rules of allocation of first-year students across different classes. We then provide a description of our data and social links among Sciences Po students.

III.A. Sciences Po background and organization

Since its foundation, Sciences Po has always been strongly involved in the training of politician and high level civil servants. The university (called *"Ecole libre des Sciences Politiques"* at that time) was founded in 1872, after the defeat of France against Prussia, and its explicit aim was to provide a modern training to the French elite, akin to the one received in Germany. Although being a fully private institution until 1945, it soon gained a *de facto* monopoly for the preparation of examinations enabling to enter the highest level of the French administration. In particular, 80 to 90% of the students entering *Ecole Nationale d'Administration*

[7] They find that there is important positive social learning from direct friends but *not* second-order friends about the benefits of flu vaccination in a study of undergraduate students at a private university.

(the most prestigious public exam) each year have been trained originally at Sciences Po (Rouban, 2014a). The university has also strong links with French politicians. Between 12 to 15% of French MPs elected in the last decades graduated from Sciences Po (Rouban, 2011), as well as more than fifteen percent of the mayors of cities above 30,000 inhabitants (Rouban, 2014b). Sciences Po students are also extremely present in the executive branch, with many ministries coming from Sciences Po.

While not all Sciences Po students want to become politician or civil servant, politics is much more important for them than for students from other universities or *Grandes écoles*. One tenth of the students are member of a political party, a very large proportion compared to their age group. About one quarter of the students choose a master in public affair, which is the traditional path of access to French administration. Therefore, Sciences Po plays the central role in the training of the French political and administrative elite.

As most *Grandes écoles* students, Sciences Po students are very different from the students enrolled in public universities. They are academically stronger, and come from a much more wealthy background.

To change its reputation of an elite school nurturing networking and homophily, Sciences Po has implemented various innovative pedagogical reforms in the recent years, such as quotas for students from poor suburbs and a widening of recruitment outside Paris from different French regions and abroad. One of the most important innovations implemented in 2007 by the former dean, Richard Descoings, was to force first-year students from different socio-economic background to mix with up each other. To achieve this goal, students are exogenously allocated to different classes at school entry.

The first year of Sciences Po bachelor is made of a large curriculum core, with six introductory courses in microeconomics, macroeconomics, history, sociology, political science, and constitutional law. Each of these courses consists in one weekly lecture, and compulsory weekly tutorials. The tutorials last two hours, gather about twenty students each, and enable to review the materials seen in the lecture and to do exercises (such as oral presentation, for instance). It involves a lot of work in small groups in order to do collective assignments. Since the number of students enrolled in the lectures is large (about 800), the tutorials are where most social interactions across students take place.

In order to foster interactions, the administration chose few years ago to link tutorials together into packs. Therefore, students are assigned the same classmates across all the subjects. This was implemented because the administration felt that many students were isolated because of the large size of the program. It further reinforced the role of tutorial as creating social links.

Other sources of social interactions are associations (close to one hundred, including political parties and student unions), sports, and the monthly parties organized by the student office. However, the interactions in the tutorials are much stronger, with at least three meetings a week, and many opportunities of working together through group work. As we show in the next section, tutorials are responsible for the majority of friendship link formation.

III.B. Data and Survey description

Our analysis is based on first-year students who entered Sciences Po Paris the academic year 2013 (starting in September). In March 2014, we performed a survey/game for all the first-year students (800 students), and ask incentive-compatible questions to elicit social networks (as in Leider et al., 2009 and 2010). We surveyed their cultural values and political opinions, as well as their network of friends, through an Internet platform. To maximize the participation rate, which is critical in empirical studies on networks, since a large rate of non-response can create bias in the estimates (Chandrasekhar and Lewis 2011), we incentivize the survey. We offered material incentives taking the form of a lottery for twenty-five iPads, each iPad having a monetary value of approximately 300 Euros. Given the number of participants, each student had an average probability of about 6% to win. We choose to give them gifts in order to avoid crowding their intrinsic motivations, and frame the participation to the survey as an altruistic act leading to a reciprocal reward, with a guarantee of full confidentiality. Eventually, 68.4% (547 out of 800) of the students answered to at least some question in the survey, and 65.6% (526 out of 800) completed the whole survey.

Another critical aspect of such surveys is to get truthful answers, since some students could fill the survey at random in order to do it more quickly. We thus designed the survey as a coordination game. Not only we asked students who their friends were, but we also asked them how they met them, how much time they spent together, which activities they did together, and how strong was their relationships. We announced in the survey that their answers would be cross-checked with those of the other students, and that if their answers matched those of their friends, they would gain points, later converted into an additional probability of winning the gift. We did not disclose the exact mechanism, in order to avoid that some students engaged into strategic behavior and try to actively coordinate with other people. The survey was done during a vacation week, which limited the possibility for the students to interact with each other and to fulfill the survey together. We also required that they complete the whole questionnaire in order to be included in the lottery. We present in Appendix the details of the questions and procedures, as well as the algorithm to allocate the prizes. We also report robustness tests showing that students indeed answered honestly to the survey.

Table 1 – Panel A reports the main statistics on the number of friends and the social network structure among the first-year students. The average and maximum number of nominations per student is 8.8 and 21, respectively, with a very high variance. Moreover, there seems to be some small world properties with a

very small average path length (3.7) and a relatively small diameter (9). The clustering is also relatively high, which means that roughly 25 percent of students have friends of friends who are friends. Even though it is not reported in the table, there are around 50 percent as many *reciprocal* friends as *reported* friend. We also look at the percentage of answers that are correct for each of the four surveyed characteristics of friendships among the reciprocal links. The rate of agreement is quite high, particularly for the way of meeting, which is less arbitrary and subject to disagreement. Note that a disagreement does not imply a lie and can be an honest mistake. This confirms that students mostly answered truthfully to the survey. Another important result of the survey is the fact that 44% of the friendship links were formed thanks to the tutorials, so belonging to a same group is likely to be a powerful instrument for friendship formation.

The second part of the survey was devoted to questions about political opinion and values. We asked them their political opinion today, and the summer before admission, by using a Likert scale from 1 to 10, and if they were a member of political party (today, or in the past). We also asked questions on related political opinions such as attitudes toward immigrants, by using question taken from the world value survey.

Table 1 – Panel B shows the descriptive statistics about the political opinion and values of Sciences Po students. The political opinion of Sciences Po students are close to the center. Even though the mean of the political opinion hardly changes before and after the entry in Sciences Po, there is a reduction of the variance of about 15 percent. And the entrance in Sciences Po is associated with a large increase in the enrolment in a political party.

[Insert Table 1 here]

Figure 1 shows the distribution of political opinion. We can see at a first glance that there is some change in the distribution of belief after few months of studying with new classmates. If the average does not change very much, the shape of the distribution changes, with a reduction in its dispersion.

[Insert Figure 1 here]

Table A2 in the Appendix reports the main descriptive statistics of our sample. Sciences Po students come massively from a privileged background, more than two third of them coming from a family with a very high social status. The median total gross income of the students who reported it is very high, above 80,000 Euros. There is a large majority of women, which is not surprising since it is a university specialized in social science. While foreigners are not very numerous (only seven percent of the sample), students having a dual nationality represent a sizable part of the sample (13.3 percent). This is due in part to the fact that a non-trivial share of the students has an immigrant background following the implementation of an Affirmative Action program targeting students coming from deprived high schools. While this program is not based on ethnicity, it stills concerns many students belonging to ethnic minorities, since these students are over-represented in under-performing high schools. Almost 20 percent of the sample is coming from this Affirmative Action program. Finally, one quarter of the students are enrolled into several subprograms, corresponding to dual majors.

III.C. Exogenous allocation of students across groups

This section documents the exogenous allocation of students across the different groups of tutorials at school entry. We first describe the allocation process and then provide formal statistical tests on exogeneity.

As discussed above, a crucial part of the curriculum is the enrolment in tutorials, which are grouped in pack. Since we will use them later on as an instrument for friendship link formation, it is crucial that allocation to tutorial is *random*. Several features of the enrolment process make extremely unlikely that students choose tutorial in purpose, for instance for schedule reason, for being assigned a given instructor, or to be with their friends.

First of all, it is impossible to have simultaneously access to the schedules of all tutorials in a same pack during the enrolment procedure, which is done online. Students can only choose a given tutorial in a given subject (and have access to the schedule and the professor's name in this subject only), and then are automatically enrolled in the corresponding tutorials in the other subjects. Reconstructing the schedules in all subjects for each pack means to spend a lot of time across different screens, while at the same time the enrolment procedure is ongoing, and lasts about half an hour. As a result, comparing the value of each pack in term of schedule is very difficult.

Moreover, students do not have information about teachers' quality and grading policy. Indeed, there is a large turnover of instructors, and the enrolment is done before the beginning of the academic year, as in Hoffmann and Oreopoulos (2009). Therefore, students have little possibility to acquire information about teachers by interacting with past first year students, and they cannot select into tutorials based on their expected difficulties.

Not only the registration is completed in a short time, but it is also done in a gradual way. Every five or six minutes, the administration opens new slots in each pack, in order to avoid over-burdening the system. Since all the students are connected at that time, and try to enroll into tutorials, it means that each slot if fulfilled very quickly, sometimes in few seconds. As a result, coordinating in order to register into the same tutorial is difficult, and success is quite unlikely.

The registration is anyway organized before the beginning of the academic year, and for the two semesters, which means that students have little opportunity to know each other before the enrolment process. They only meet for a three day orientation week few days before the registration procedure, which is unlikely to create links strong enough to induce students to try to coordinate each other.

In order to test that students are indeed randomly allocated to group, we estimate a dyadic model of group formation. We regress a dummy variable taking the value of one if the two members of a dyad are enrolled in the same group on a set of dyadic controls, which capture the distance between the characteristics of the two members of the dyad. We use variables determined before the beginning of the year, and run the test only on the students who answered to the survey, since we want to test if pre-entrance political opinions have an impact on group formation.

Table 2 reports the results of this test. The explanatory power of the model is very low, with an adjusted R-square equal to zero. Most coefficients are insignificant (while the sample is very large, since we are using dyadic variables). The coefficient of the admission procedure (i.e. the way students entered into Sciences Po) is only marginally significant, and its magnitude is very low. Only the coefficient on program is significant, which is to be expected since students from different programs do not mix across tutorials. This confirms that allocation to group is random.

[Insert Table 2 here]

IV. EMPIRICAL STRATEGY

Our empirical design focuses on the following dyadic specification:

$$DY_{ij} = \alpha + \rho DY_{ij}^{0} + \beta L_{ij} + \gamma X_{ij} + \epsilon_{ij}. \tag{1}$$

The unit of observation is a pair of students i and j. DY_{ij}, the differences in an outcome variable Y between i and j, is related to the binary variable L_{ij} of undirected friendship between the two ($L_{ij} = 1$ iff at least one of the two names the other as friend). The coefficient of interest β addresses how much the difference in outcome Y between two individuals is affected by their friendship link. A negative β corresponds to a *convergence* effect, and a positive β a *divergence* effect. Convergence (or divergence) is about the difference between what would happen with and without a friendship link, over the period of 6 months between the entrance to Sciences Po and the survey. If friendship L_{ij} is assigned randomly to different pairs of students, a simple OLS would identify the convergence effect β.

We further control for other pairwise variables: the pre-Sciences Po difference in political opinions DY_{ij}^{0} (based on a retrospective question), and a vector of the pairwise commonness and differences in other predetermined variables X_{ij}. They include dummies for common Gender, common Nationality, common Admission type (essentially regular admission or affirmative action admission), common Honour Graduation from high school, common District of high school, common parental professions, common current residence's ZIP code, and the difference in in Tuition fees that proxies for the difference in parents' income. Their omission would likely produce a homophily bias, because they are likely correlated with both the friendship link L_{ij} and the outcome differences DY_{ij}. Indeed, if a control variable X_{ij}^{om} is omitted, the potential bias is $\gamma_{om}\mathrm{Corr}(L_{ij}, X_{ij}^{om})$, which pushes the OLS estimate away from zero (making the estimated coefficient stronger than it really is.) The difference between OLS estimates with and without control variables tells us the magnitude of the homophily bias due to observables. In reference to Altonji, Elder and Taber's (2005) argument that selection based on observables is usually stronger than selection based on unobservables, we may gauge the order of magnitude of the homophily bias due to unobservables.

To address the homophily bias caused by unobserved dyadic characteristics that correlate with both friendship and outcome, we instrument L_{ij} by the indicator CG_{ij} whether i and j are in the same group. As discussed earlier, CG_{ij} is arguably exogeneous and uncorrelated with any observable and unobservable pairwise variables regarding i and j, while it is also a strong predictor of L_{ij}. Given the exogeneity of CG_{ij}, the inclusion of control variables only helps improve estimation efficiency, and is no longer needed to treat potential homophily bias. In particular, there should not be a homophily bias due to observables, so the IV results with and without control variables are expected to be similar.

The difference between IV and OLS estimates is not only due to homophily bias, but also the heterogeneity of the convergence effect. The IV strategy would identify the Local Average Treatment Effect (Angrist and Imbens 1994) of a friendship link on outcome differences,[8] averaged among the compliers, i.e. the pairs who have become friends if and only if they are put together in a group. In this case, the compliers are the group affected by the policy, arguably the most important group.

Some concerns of the overall empirical design may arise. First, we consider convergence on the differences in contemporaneous opinions and attitudes DY_{ij}. One may opt to use the differences in the change of opinions $DY_{ij} - DY_{ij}^0$ as an outcome variable in our framework, but in presence of the control variable DY_{ij}^0, it does not matter to β whether the outcome variable is DY_{ij} or $DY_{ij} - DY_{ij}^0$. Even when the variable DY_{ij}^0 comes from retrospective questions and is potentially biased towards contemporaneous opinions, such that $DY_{ij}^0 = \rho DY_{ij} + (1 -$

[8] The last condition for the LATE interpretation is monotonicity: there are no defiers, i.e. pairs who would not become friends if and only if they are *not* in the same group. In our context, monotonicity is likely satisfied.

$\rho)DY_{ij}^{0*}$, where the true pre-Sciences Po variable is DY_{ij}^{0*}, it would at best bias the convergence coefficient towards zero, i.e. against our finding significant convergence effects.

Second, the dyadic specification repeats each student in her relationship with all others. We account for this feature in the statistical inference by using *common group double clustering*: the error terms from any two observations are allowed to correlate, if they share a common group.

Third, the instrumental variable needs to satisfy the exclusion restriction that common-group membership does not affect differences in opinions via channels other than the friendship links. We will later relax this assumption to explore how indirect links affect convergence in different outcomes.

Fourth, the dyadic specification separates each pair of students from their relationships to other individuals. For instance, there is no constraint on the total number of friendship links for each individual. This is a cost to our "reduced form" dyadic approach. While we gain in clarifying the role of the IV in our setting, we may not stay close to a specific theoretical model that could produce predictions in the form of structural models.

V. BASELINE RESULTS

We first establish the causal effect of friendship on convergence of political opinions, using the empirical strategy described in section IV.

Table 3 shows the first stage relationships between common group membership and undirected friendship links in the sample of dyads for which control variables are available. The relationship between common group membership and friendship is particularly strong, as being in the same group increases the chance of a pair of students to become friends by 35 percentage points.[9] This is several orders of magnitude above the coefficients of any other common characteristics, including those that have a statistically significant effect on friendship such as common gender, common admission type, common department of high school, common high school graduation honors, common residence zip code, and the differences in political opinion before entrance to Sciences Po (the maximum is 10), and the differences in tuition fees (the maximum is 10,000). Common group membership alone explains for about 15% of the variation in pairwise undirected friendships across dyads, whereas the other control variables could explain only 1.6% more. Compared to any other observables, it is by far the best predictor of friendships. Thus, common exposure to first-year group studies has significantly caused friendships among Sciences Po's students.

[Insert Table 3 here]

Table 4 shows second stage results for differences in answers on political opinions in March 2014, and compares them to OLS results without IVs. Column (1) shows the results OLS without control variables, and columns (2) and (3) exhibit OLS results with and without the benchmark set of control variables while controlling for the differences in political opinion before entering Sciences Po. In columns (2) and (3), the coefficient of undirected friendship is around 0.13, predicting a gap of 0.13 points on a scale of 1 to 10 for friends versus non-friends. This gap is highly persistent over time, as 53% of its variation could be explained by the pre-Sciences Po difference in political opinion. When we do not control for

9 We use a linear probability model in the first stage for clarity of interpretation, following Angrist and Pischke's 2009 suggestion. Results are very similar, and available upon request, when we first run a logit model of friendship over common group and other characteristics, and then use the predicted probability as IV for actual friendship in the second stage (as described in Angrist and Pischke 2009, Section 4.6).

the pre-Sciences Po difference, the coefficient of friendship jumps to 0.22 (column (1)), consistent with the observation that the pre-Sciences Po difference is a significant predictor of both friendships and the gap in outcome, thus its inclusion as a control could address an important homophily bias. On the other hand, the other control variables do not seem to induce a strong homophily bias, likely because they are much less correlated with the gap in outcome.

Columns (5) and (6) show the IV results of around 0.16, respectively without and with control variables, but controlling for the pre-Sciences Po difference in political opinions. The coefficient's magnitude implies a convergence among first-year friends of 0.16 points over a scale from 1 to 10 in political opinions, over a period of 6 months. The effect accounts to 8% of the mean (1.92) and 11% of the standard deviation (1.47). By extrapolation, it is equivalent to a "half-life" of the average differences in political opinion of 6 months / $\log_{0.5}0.92$ = 50 months, or roughly 4 years.

[Insert Table 4 here]

Even when we exclude the control of pre-Sciences Po difference in political opinion, as shown in column (4), the IV estimate increases slightly to 0.19, suggesting that the previous issue of homophily bias due to pre-Sciences Po differences has been properly addressed by the IV strategy. The stability of the IV estimates with respect to the inclusion of observables strengthens our claim that it appropriately deals with homophily biases induced by observables and also unobservables, as discussed in section IV.

The differences between the IV and OLS estimates can be explained by two reasons. First, the IV strategy corrects for homophily bias. Homophily, if unaccounted for, would likely induce a bias towards more convergence, hence a larger OLS coefficient in absolute value, compared with the IV coefficient. It is consistent with an OLS estimate of 0.22 and an IV estimate of only 0.19 (columns (1) versus (4)), when we do not control for pre-Sciences Po difference in political opinion.[10] However, the existence of a homophily bias does not explain why IV estimates could be larger in absolute value than OLS estimates (columns (2) and (3) versus columns (5) and (6)). The other reason for this discrepancy is that the IV strategy estimates a local average treatment effect (LATE) among compliers to the group mixing policy. The higher value of IV indicates stronger convergence effects among pairs of students that become friends precisely because they end up in the same group. We will detail the heterogeneity of convergence effects in the next subsection.

The IV estimates can be compared with the reduced form estimate of 0.05 in column (7), obtained from OLS regressions of the outcome gap in political opinion on common group membership. Let us consider four different types of pairs of students, based on two characteristics: friendship and common group. The reduced form coefficient correctly identifies same group convergence as the average effect on the outcome gap of same group versus different group pairs, where the average is taken among pairs of friends and non-friends within the group (versus different-group pairs). The contribution of the effects of pairs of friends can be approximated by the IV estimate of 0.16 times the average share of pairs of "compliers" among same-group pairs, indicated by the effect of same group membership on friendship link of 0.35 from Table 3. By multiplying 0.16 by 0.35, we obtain very close results to the reduced form coefficient of 0.05. It means that pairs of non-friends contribute practically nothing to the reduced form effect. Same-group convergence in political opinion thus happens only among direct friends.

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[10] In this case we cannot reject the exogeneity of the endogenous regressor of undirected friendship, controlling for all observables.

Next, Table 5 – Panel A shows some results of convergence in participation in political and associative activities, consistent with the expressed opinions. Columns (1) and (2) show that pairs of friends significantly converge in their associative lives. They tend to follow their friends in joining some associations, and also tend to join the same associations more often. While column (3) shows that the convergence is not significant for active participation in political parties, which remains rare among first-year students, column (4) indicates that, among those who do enroll in a party, a pair of friends becomes more likely to enroll in the same party. Thus, students' political actions follow their words.

[Insert Table 5 here]

Table 5 –Panel B then shows some convergence in students' views on the importance of different factors in their future: friends become more similar in their assessments of the role of family networks. However, we fail to detect convergence in their views of the social networks built via Sciences Po, or in their views about the importance of individual efforts, individual networks, or their degree.

In sum, we find consistent evidence of convergence of political opinions and beliefs on politics, and of participation in political parties and associations. The evidence is consistent in different ways with the claim that our IV strategy has appropriately addressed a potential homophily bias. The result also hints that the homophily bias on convergence, induced by either observable or unobservable characteristics, tends to be relatively small, which could be seen as good news for other studies in similar contexts that do not properly control for it.

VI. HETEROGENEOUS EFFECTS AND MECHANISMS

VI.A. Convergence among dissimilar pairs

The theoretical and empirical literatures on learning in networks typically assume homogenous effects of direct links on a node's beliefs. Examples include theories using average-based belief updating processes (the term coined by Golub and Jackson, 2012, for a generalized definition of the DeGroot's belief updating), or empirical estimations of peer effect in networks (such as Calvó-Armengol Patacchini, and Zenou, 2009, or Bramoullé, Djebari and Fortin, 2009). These theoretical and empirical models assume that each individual is influenced in the same way among her friends. Our framework allows a natural exploration how pairwise convergence varies based on the pairwise individual and network characteristics, with a focus on political opinion.

Under simple average-based belief updating processes, homophily has been shown to slow down information transmission in networks (Golub and Jackson 2012). We now want to understand whether the variation of the convergence effect across different pairs reinforces or dampens this phenomenon. If convergence is stronger among pairs of similar students (that are more likely to be friends), Golub and Jackson's effect should be mitigated. In contrast, if convergence is emphasized among pairs of dissimilar students (that are less likely to be friends), in this heterogeneous effect framework Golub and Jackson's effect would be strengthened.

Table 6 shows that the convergence coefficient varies substantially depending on predetermined differences. Each column includes an interaction term between undirected friendship and one of the three variables, which are: differences in pre-Sciences Po political opinion, common gender, and common admission type. The corresponding instruments include common group membership and its interactions with those three variables. The coefficients of the interaction terms in column (1) indicate that convergence in political opinion is significantly higher among pairs with more different opinions before entering Sciences Po. There is some hint that among students with identical initial opinions, friendship may have brought divergence, not convergence, although the positive coefficient of 0.05 is not statistically significant. We will return to the possibility of divergence in the next section. Similarly, we find that convergence is stronger for pairs of different genders and different admission types (the type being overwhelmingly either general admission process or admission by “prioritized education convention”, a form of Affirmative Action towards students in disadvantaged areas). While only the interaction of friendship and common gender is statistically significant at 5%, the coefficients of those interactions are very large compared to the baseline coefficient of undirected friendship. They suggest that convergence comes mostly from pairs of very different compliers.

[Insert Table 6 here]

By homophily, those pairs of very different students are less likely to become friends. We now explore the variation of the convergence coefficient by the propensity to become friends between pairs, excluding the effect of same group membership. We run probit regressions of undirected friendship on predetermined variables previously used as controls, and then predict the propensity to become friends between any pairs of students. The probit regression includes the same group dummy variable as a regressor, but the propensity score prediction excludes that variable.

Column (4) in Table 6 shows how the convergence coefficient varies with prior propensity to become friends. We interact friendship with the propensity to become friends, and instrument them with same group membership and its interaction with the same propensity. The coefficient of the interaction between friendship and propensity to become friends is positive, and statistically significant and sizeable.

We visualize the heterogeneity of the convergence coefficient by the pairwise propensity to become friends by a semi-parametric estimation of . For each grid point that separates the 10 deciles of (), we weight the observations by a Gaussian kernel (with bandwidth equal to 20% of the range of) around , so that pairs with farther away from receive less weights, and then run the benchmark IV regression with those weights to obtain . The resulting estimates are then plotted in Figure 2.

[Insert Figure 2 here]

We observe that the IV-estimated convergence coefficient is decreasing in the propensity to become friends between each pair, in contrast to the relative stability of the OLS estimate. It means that among compliers, those who are least likely to comply will experience the greatest convergence due to friendship. We also note that the OLS estimate is indeed larger than the IV estimate in absolute value for pairs with a very high propensity score, which suggests the presence of homophily bias among pairs that are most likely to be friends, i.e. pairs that are most likely subject to the homophily bias.

Overall, convergence takes place a lot more among pairs of students who are the least likely to become friends. It is consistent, for example, with a simple model of belief updating that puts more weight on less correlated signals. The heterogeneous effect that we find thus strengthens the Golub and Jackson's effect. We also find that while, on average, there is little worry about homophily bias in contexts similar to ours, it would raise more concerns among pairs that are more likely to become friends.

VI.B. Convergence among extremists

We further explore the heterogeneity of the convergence coefficient by plotting it against the pair's political opinions. We undertake a similar estimation of that coefficient as a function of the pair's political opinions as follows. For each grid point that corresponds to the two students' political opinions (), we weight the observations by a Gaussian kernel (with bandwidth equal to 2) around the point , so that pairs farther away from receive less weights, and then run the benchmark IV regression with those weights to obtain . The estimates are then plotted on the tri-dimensional Figure 3. For the purpose of exposition, we do not show tri-dimensional confidence bands. Because of the symmetric nature of our regression equation, the graph is symmetric with respect to the main diagonal of all points of political opinion.

[Insert Figure 3 here]

From Figure 3, three stark observations emerge. First, friendship convergence is strongest among the most dissimilar pairs, namely pairs of students with opposite extreme political views before entering Sciences Po. Echoing the previous section, this finding suggests that extremism may be mitigated by exposure and friendship. Second, the coefficient remains negative even among pairs of students with the same moderate pre-Sciences Po views. That is, among similar moderate students, those who do not become friends naturally diverge, but those who end up as friends diverge less, and hold on to each other's opinions more.

Third, and perhaps most striking, pairs of similar extreme leftists diverge in their opinions. The effect is particularly strong and consistent among extreme leftists. Extreme leftists are defined as students with a political opinion from 1 to

3.[11] It means that pairs that become friends tend to separate from each other, probably with one moving closer to the center, more than those who do not.

The divergence effect among extreme leftists can be further tested with different outcome variables, as shown in Table 7. It is strongly significant for political opinion and attitude towards immigration, with very large magnitude (for political opinion, it is 3 times as large in absolute value as the convergence effect of the other pairs). We do not find the similar effect among other types of pairs, as already illustrated in Figure 3.

[Insert Table 7 here]

The divergence effect among extreme leftists is not consistent with standard models of beliefs updating. Instead, a possible explanation is that those students have high needs for self-distinction. It follows that they have become extreme prior to Sciences Po, and when they meet similarly extreme students at Sciences Po, they prefer to differentiate themselves from their friends by adjusting their actions and views away from their friends.

VII. THE ROLE OF THE SOCIAL NETWORK STRUCTURE

We further study how convergence varies by individuals' positions in the social network, notably by the network centrality of each individual. We use two measures: eigenvector centrality and betweenness centrality, as they represent quite different concepts (their correlation in our sample is about 30%).[12] We run

[11] Results remain similar with different threshold of extreme left. There are a lot less extreme rightists, so statistical inference is difficult.

[12] Betweenness centrality of a given agent is equal to the number of shortest paths between all pairs of agents that pass through the given agent. In other words, an agent is central if s/he lies on several shortest paths among other pairs of

statistical tests with pairs of stars and non-stars, by categorizing "star" and "non-star" individuals as those whose centrality are respectively above or below the 90^{th} percentile. The results are reported in Table 8.

The effect is not statistically significant for convergence of political opinion, although we do see that the coefficient of convergence is strongest for the asymmetric pairs of a star and a non-star when using the betweenness centrality (column (6)). In other words, people's beliefs converge towards the beliefs of *stars*, which are the students who have the highest betweenness centrality. Taken together, there seems to be evidence that stars strongly attract non-stars when they become friends.

[Insert Table 8 here]

We have so far considered only the effects of direct links, under the assumption that indirect links do not contribute to the convergence within each group. We now relax this assumption to check if there is evidence of convergence among individuals without immediate links. We address this question by using each pair's same group membership as instrumental variable for their social distance (length of the *shortest path* between them on the network.) Results are reported in Table 9.

To facilitate the comparison, benchmark IV results from Table 4 are shown again in column (1). In column (2), we use same group membership as IV for social distance in the full sample. The estimate is interpretable as the average

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agents. Betweenness centrality thus captures the importance as an intermediary. Eigenvector centrality is a measure of the influence of an agent in a network. It takes all possible paths in a network (not only the shortest ones) and assigns relative scores to all agents in the network based on the concept that connections to high-scoring agents contribute more to the score of the agent in question than equal connections to low-scoring agents. It thus captures indirect reach so that being well-connected to well-connected others makes you more central. For example, Google's PageRank is a variant of the eigenvector centrality measure. See Wasserman and Faust (1994) and Jackson (2008) for precise definitions of all network centrality measures.

causal response, averaged over all pairs that are induced by the IV to move closer in social distance. The magnitude of the effects are a lot smaller than the corresponding benchmark coefficients, suggesting that the effect is not always strong for all values of social distance (convergence is now manifested with a positive coefficient.) We further cut the sample into subsamples to compare uniquely between pairs of consecutive social distances: distance 1 versus 2 in column (3), distance 2 versus 3 in column (4), and distance 3 versus farther distances in column (5). We find a strong concentration of convergence effect when social distance shrinks from 2 to 1 (the pair become direct friends). The magnitude of the convergence effect of this switch is relatively close to the benchmark results: 13% versus 16% for political opinion. Beyond direct friends, there is no significant evidence of convergence of political opinion. Network structure thus does not matter to political opinions convergence beyond direct links.

[Insert Table 9 here]

VIII. CONCLUDING REMARKS

In this paper, we have studied how a public policy (random allocation of students to tutorials) shapes convergence of political beliefs through newly-formed social networks. We find that students' political opinions converge particularly strongly between friends and the magnitude of the convergence is quite substantial: around 0.16 points over a scale from 1 to 10 in political opinions, which accounts for 11% of the standard deviation. We also show that convergence in political opinion happens only among friends, while the effect would be insignificant if we were focusing on pairs of non-friends belonging to the same group. Moreover, friends not only converge in political beliefs, but also in behaviors: pairs of friends significantly converge in their associative lives and among those who do enroll in a political party; a pair of friends becomes more likely to enroll in the same political party.

We next analyze potential heterogeneous effects to analyze the mechanisms and channels behind this convergence process. A first important finding is that convergence is higher among students with more initial differences in political attitudes. We also find that convergence works partly thanks to common friends: convergence is higher when more common friends hold opinion in between. Strikingly, people's beliefs converge towards the beliefs of *stars*, which are the students who have the highest network centrality (especially in terms of betweenness centrality). The last main heterogeneous effect is related to *extremists:* while there is a stronger convergence in beliefs among friends with opposite political priors, in contrast there is a divergence among friends who initially share extreme left priors.

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Tables and Figures

Table 1 - Panel A: "OR" Network statistics

Mean of degree per individual	8.8625
Variance of degree per individual	18.4842
Median of degree per individual	10
Maximum of degree per individual	21
Minimum of degree per individual	0
Diameter of the network	9
Average path length	3.7008
Overall clustering coefficient	0.241
Average clustering coefficient	0.271

Notes: Summary statistics are computed on the full sample.

Table 1 - Panel B: Centrality Measures

Variable	Mean	Standard Deviation
Betweenness	2,606	(1,744)
Eigenvector	0.0361	(0.0200)
Degree	10.91	(2.941)

Notes: Summary statistics are computed on the reduced sample used for estimation.

Table 1 - Panel C: Political opinions (individual variables)

	(1)		(2)	
Variable	Mean	Standard deviation	Mean	Standard deviation
Political opinion (March 2014) (1-10)	5.044	(1.755)	5.060	(1.709)
Pre-Sciences Po political opinion (August 2013) (1-10)	5.108	(1.957)	5.116	(1.936)
Enrolled in a political party (March 2014) (yes / no)	0.103	(0.251)	0.118	(0.322)
Enrolled in a political party (August 2013) (yes / no)	0.067	(0.305)	0.0775	(0.267)
Should firms hire national first? (1-10)	3.835	(2.615)	3.784	(2.596)

Notes: Summary statistics (1) refer to the full sample. Summary statistics (2) refer to the reduced sample used in estimation.

Table 1 - Panel D: Political opinions (dyadic variables)

	(1)		(2)	
Variable	Mean	Standard deviation	Mean	Standard deviation
Difference in political opinion (March 2014)	1.931	(1.467)	1.924	(1.467)
Initial difference in political opinion (August 2013)	2.211	(1.631)	2.205	(1.629)
c.Enrolled in a political party (March 2014)	(0.815)	(0.388)	(0.790)	(0.407)
c.Enrolled in a political party (August 2013)	0.874	(0.332)	0.855	(0.352)
c.Enrolled in the same political party (March 2014)	0.868	(0.339)	0.862	(0.345)

Notes: Summary statistics (1) refer to the full sample. Summary statistics (2) refer to the reduced sample used in estimation. The prefix ”c.” in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair.

Table 2: Balance Test

	(1)	(2)	(3)	(4)
Dependent Variable:		Common Group		
c. Gender	0.000595	0.000597	0.000589	0.000591
	(0.00120)	(0.00120)	(0.00120)	(0.00120)
c. Nationality	0.00222	0.00224	0.00199	0.00201
	(0.00338)	(0.00341)	(0.00334)	(0.00337)
c. Admission	0.00311**	0.00311**	0.00280*	0.00280*
	(0.00150)	(0.00150)	(0.00148)	(0.00148)
c. Program	0.0210***	-	0.0213***	-
	(0.00109)		(0.00125)	
c. Honors Graduation (High School)	0.00108	0.00108	0.00113	0.00113
	(0.00148)	(0.00149)	(0.00147)	(0.00148)
c. Dpartment of High School	0.000328	0.000329	8.12e-05	7.99e-05
	(0.00283)	(0.00283)	(0.00288)	(0.00288)
Diff. in Tuition Fees	-1.16e-07	-1.17e-07	-1.34e-07	-1.35e-07
	(2.28e-07)	(2.28e-07)	(2.33e-07)	(2.34e-07)
c. Parents Profession	0.00128	0.00128	0.00130	0.00130
	(0.00114)	(0.00115)	(0.00115)	(0.00115)
Initial Diff. in Political Opinion (August 2013)	-0.000148	-0.000148	-0.000571	-0.000572
	(0.000349)	(0.000350)	(0.000472)	(0.000473)
c. ZIP code	0.00287	0.00288	0.00226	0.00227
	(0.00422)	(0.00423)	(0.00412)	(0.00414)
c. Priority Admission	-	-	0.00233	0.00233
			(0.00484)	(0.00484)
c. Left -Left	-	-	-0.00152	-0.00152
			(0.00157)	(0.00157)
c. Left - Right	-	-	0.00113	0.00114
			(0.00189)	(0.00190)
c. Living in Paris	-	-	0.00119	0.00119
			(0.00156)	(0.00157)
Observations	60,726	60,516	60,726	60,516
Sample:	Benchmark Plus Different Programs	Benchmark	Benchmark Plus Different Programs	Benchmark
Individual Clustering	Yes	Yes	Yes	Yes
R-squared	0.000	0.000	0.000	0.000
F-stat	245.4	1.106	118.8	1.018

Notes: The benchmark sample includes those couple that are in the upper triangular part of the adjacency matrix, whose individuals both answered to the question on their friendship network and for which we have values for the controls and for the variable "Difference in Political Opinion (March 2014). The prefix "c." in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. F-stats are for the joint significance of the variables included in the model. Standard errors are clustered at the individual 1 and individual 2 level.

Table 3: First Stage

	(1)	(2)	(3)
Dependent Variable:		Undirected Friendship	
c. Group	0.352***	0.351***	0.351***
	(0.0201)	(0.0201)	(0.0201)
Initial Diff. in Political Opinion (August 2013)	-	-0.000962***	-0.000679
		(0.000351)	(0.000498)
c. Gender	-	0.00583***	0.00583***
		(0.000923)	(0.000920)
c. Nationality	-	0.000725	-0.000277
		(0.00425)	(0.00413)
c. Admission	-	0.00495***	0.00415***
		(0.00124)	(0.00129)
c. Honours Graduation (High School)	-	0.00278*	0.00290*
		(0.00152)	(0.00152)
c. District of High School	-	0.0159***	0.0158***
		(0.00354)	(0.00349)
Diff. in Tuition Fees	-	-5.94e-07***	-6.36e-07***
		(2.01e-07)	(2.10e-07)
c. Parents Profession	-	0.00130	0.00125
		(0.00100)	(0.00104)
c. ZIP code	-	0.00987**	0.0100**
		(0.00451)	(0.00455)
c. Priority Admission	-	-	0.00715
			(0.00555)
c. Left - Left	-	-	-0.00621***
			(0.00218)
c. Left - Right	-	-	-0.00494***
			(0.00162)
c. Living in Paris	-	-	-0.000539
			(0.00104)
Observations	60,516	60,516	60,516
R-squared	0.167	0.170	0.170
Group Clustering	Yes	Yes	Yes
F-stat	298.9	68.75	39.81

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. The prefix "c." in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. F-stats are for the joint significance of the variables included in the model. The sample used is the benchmark sample described in the footnote to the Table 1. Left is defined as having an initial political position of 5 or less (possible answers goes from 1 to 10). Right is defined as having an initial political position of 6 or more.

Table 4: Friendship Convergence of Political Opinion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:				Difference in Political Opinion			
	OLS	OLS	OLS	IV	IV	IV	Reduced Form
Undirected Friendship	-0.223***	-0.133***	-0.129***	-0.188*	-0.160***	-0.155***	-
	(0.0579)	(0.0398)	(0.0409)	(0.108)	(0.0419)	(0.0431)	
Initial Diff. in Political Opinion (August 2013)	-	0.527***	0.528***	-	0.527***	0.528***	0.528
		(0.0244)	(0.0243)		(0.0244)	(0.0243)	(0.0243)
c. Group	-	-	-	-	-	-	-0.0546***
							(0.0145)
Controls	-	-	Yes	-	-	Yes	Yes
Observations	60,516	60,516	60,516	60,516	60,516	60,516	60,516
IV	No	No	No	Same Group	Same Group	Same Group	Same Group
Group Clustering	Yes	Yes	Yes	No	Yes	Yes	Yes
Weak IV test stat.	-	-	-	749.4	298.8	299.2	-

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. When the number of cluster is to small to compute clustered standard errors we report robust standard errors. The prefix "c." in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. The sample used is the benchmark sample described in the footnote to the Table 1. Controls included the following variables: c. Gender, c. Nationality, c. Admission, c. Honour Graduation (High School), c. District of High School, Diff. in Tuition Fees, c. Parents Profession, c. ZIP Code. Weak IV stat reports the Kleibergen-Paap cluster-robust statistic, distributed as a Chi-squared under the null hypothesis of weak identification.

Table 5 - Panel A: Convergence of Political and Associative Activities

	(1)	(2)	(3)	(4)
Dependent Variables:	c. Enrolment in Student Associations	c. Enrolment in Same Association	c. Enrolment in a Political Party	c. Enrolment in the Same Political Party
Undirected Friendship	-0.108**	-0.0565***	-0.0187	-0.1403
	(0.0481)	(0.0216)	(0.0314)	(0.1065)
Observations	55,409	27,145	61,564	820
Controls	Yes	Yes	Yes	Yes
Group Clustering	Yes	No	No	Yes
Weak IV test stat.	254.4	344.5	753.1	8.529

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. When the number of cluster is to small to compute clustered standard errors we report robust standard errors. The prefix "c." in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. The sample used is the benchmark sample described in the footnote to the Table 1. Controls included the following variables: c. Gender, c. Nationality, c. Admission, c. Honour Graduation (High School), c. District of High School, Diff. in Tuition Fees, c. Parents Profession, c. ZIP Code. Weak IV stat reports the Kleibergen-Paap cluster-robust statistic, distributed as a Chi-squared under the null hypothesis of weak identification.

Table 5 - Panel B: Convergence of Opinions on Determinants of Success

	(1)	(2)	(3)	(4)	(5)
Dependent Variables:			c. Importance of		
	Sc Po Degree	Individual Network	Individual Effort	Sc Po Network	Family Network
Undirected Friendship	-0.0619	-0.0161	0.0285	0.00957	-0.0892***
	(0.0526)	(0.0342)	(0.0201)	(0.0176)	(0.0328)
Observations	62,267	62,267	62,267	62,267	62,267
Controls	Yes	Yes	Yes	Yes	Yes
Group Clustering	Yes	Yes	Yes	Yes	Yes
Weak IV test stat.	297	297	297	297	297

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. The prefix "c." in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. The sample used is the benchmark sample described in the footnote to the Table 1, removing those observation where the "Difference in Trust" is missing. Controls included the following variables: c. Gender, c. Nationality, c. Admission, c. Honour Graduation (High School), c. District of High School, Diff. in Tuition Fees, c. Parents Profession, c. ZIP Code. Weak IV stat reports the Kleibergen-Paap cluster-robust statistic, distributed as a Chi-squared under the null hypothesis of weak identification.

Table 6: Heterogeneity of Convergence

	(1)	(2)	(3)	(4)
Dependent Variable:	Difference in Political Opinion			
Undirected Friendship	0.0549	-0.318***	-0.348	-0.380***
	(0.112)	(0.114)	(0.226)	(0.119)
Friendship*Initial Pol. Opinion	-0.101**	-	-	-
	(0.0417)			
Initial Diff. in Political Opinion (August 2013)	0.530***	-	-	
	(0.0240)			
Friendship*Gender	-	0.273	-	
		(0.178)		
c. Gender	-	-0.0268	-	
		(0.0194)		
Friendship*Admission	-	-	0.247	
			(0.222)	
c. Admission	-	-	-0.0112	
			(0.0423)	
Friendship*Propensity Score	-	-	-	21.85*
				(11.30)
Observations	60,516	60,516	60,516	60,516
IV	Same Group and Interactions			
Controls	Yes	Yes	Yes	Yes
Group Clustering	Yes	Yes	Yes	Yes
WeakIV test stat.	55.48	99.33	24.04	89.78

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. The prefix "c." in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. The sample used is the benchmark sample described in the footnote to the Table 1. Controls included the following variables: c. Gender, c. Nationality, c. Admission, c. Honour Graduation (High School), c. District of High School, Diff. in Tuition Fees, c. Parents Profession, c. ZIP Code. Weak IV stat reports the Kleibergen-Paap cluster-robust statistic, distributed as a Chi-squared under the null hypothesis of weak identification.

Table 7: Political Extremism and Divergence in Opinion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:		Difference in Political Opinion				Attitude Towards Immigrants		
Sub-samples:	Two Extreme Leftists	No Leftists	Two Extreme Rightists	Two Rightists	Two Extreme Leftists	No Leftists	Two Extreme Rightists	Two Rightists
Undirected Friendship	0.477*	-0.154**	0.0185	0.0339	0.344***	0.109	-1.475	-0.0875
	(0.285)	(0.0705)	(0.244)	(0.142)	(0.0736)	(0.129)	(0.897)	(0.236)
Initial Diff. in Political Opinion	0.257**	0.472***	0.274	0.379***	-0.269***	0.184***	0.376**	0.454***
	(0.104)	(0.0290)	(0.209)	(0.0672)	(0.0870)	(0.0436)	(0.162)	(0.113)
Observations	2,977	50,219	990	11,286	2,825	49,995	990	11,026
IV	Same Group	Same Group	Same Group	Same Group	Same Group	Same Group	Same Group	Same Group
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weak IV test stat.	51.62	283.3	27.04	105.4	-	269.3	26.49	112.3

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. The prefix ”c.” in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. The sample used is the benchmark sample described in the footnote to the Table 1. Controls included the following variables: c. Gender, c. Nationality, c. Admission, c. Honour Graduation (High School), c. District of High School, Diff. in Tuition Fees, c. Parents Profession, c. ZIP Code. Weak IV stat reports the Kleibergen-Paap cluster-robust statistic, distributed as a Chi-squared under the null hypothesis of weak identification.

Table 8: Convergence of Political Opinion and Centrality

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			Diff. in Political Opinion (March 2014)			
Centrality measure:		Eigenvector centrality			Betweenness centrality	
Sub-samples:	Two 90th Stars	One 90th Star	No 90th Star	Two 90th Stars	One 90th Star	No 90th Star
Undirected Friendship	0.0571	-0.323	-0.155	-0.299	-0.359	-0.115***
	(0.249)	(0.276)	(0.122)	(0.867)	(0.220)	(0.0444)
Observations	666	11,508	48,342	555	10,605	49,356
IV	Same Group	Same Group	Same Group	Same Group	Same Group	Same Group
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Group Clustering	Yes	Yes	Yes	Yes	Yes	Yes
WeakIV test stat.	49.59	50.03	244.0	25.33	91.42	254.7

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. The prefix ”c.” in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. The sample used is the benchmark sample described in the footnote to the Table 1. Controls included the following variables: c. Gender, c. Nationality, c. Admission, c. Honour Graduation (High School), c. District of High School, Diff. in Tuition Fees, c. Parents Profession, c. ZIP Code. Weak IV stat reports the Kleibergen-Paap cluster-robust statistic, distributed as a Chi-squared under the null hypothesis of weak identification.

Table 9: Convergence by Shortest Path

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Diff. in Political Opinion (March 2014)				
Undirected Friendship	-0.155***	-	-	-	-
	(0.0431)				
Shortest Path	-	0.0394***	-	-	-
		(0.00989)			
1st vs 2nd order only	-	-	0.134**	-	-
			(0.0559)		
2nd vs 3rd order only	-	-	-	-0.0206	-
				(0.0934)	
3rd vs more order only	-	-	-	-	-0.160
					(0.328)
Observations	60,516	60,516	6,921	29,958	53,595
IV	Same Group and Interactions				
Controls	Yes	Yes	Yes	Yes	Yes
Group Clustering	Yes	Yes	Yes	Yes	Yes
Weak IV test stat.	299.2	282.1	503.7	229.7	12.99

Notes: Standard errors are clustered at the group of individual 1 and at the group of individual 2 level. The prefix "c." in front of certain variables signifies a dummy variable that is equal to 1 iff the corresponding variable is the same for both students in the pair. The sample used is the benchmark sample described in the footnote to the Table 1. Controls included the following variables: c. Gender, c. Nationality, c. Admission, c. Honour Graduation (High School), c. District of High School, Diff. in Tuition Fees, c. Parents Profession, c. ZIP Code. Weak IV stat reports the Kleibergen-Paap cluster-robust statistic, distributed as a Chi-squared under the null hypothesis of weak identification.

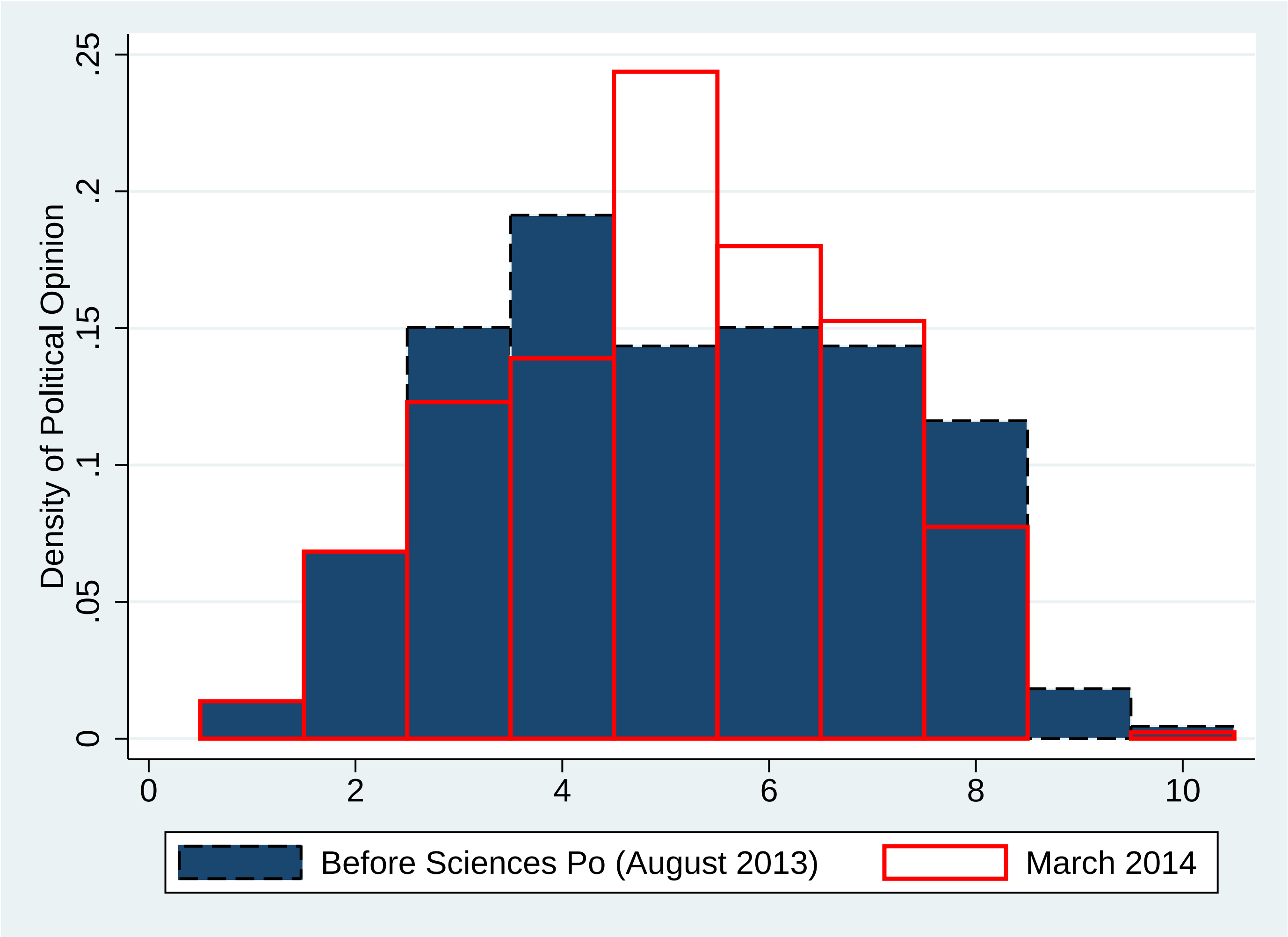


Figure 1: Distributions of Political Opinions Before and After First Year.

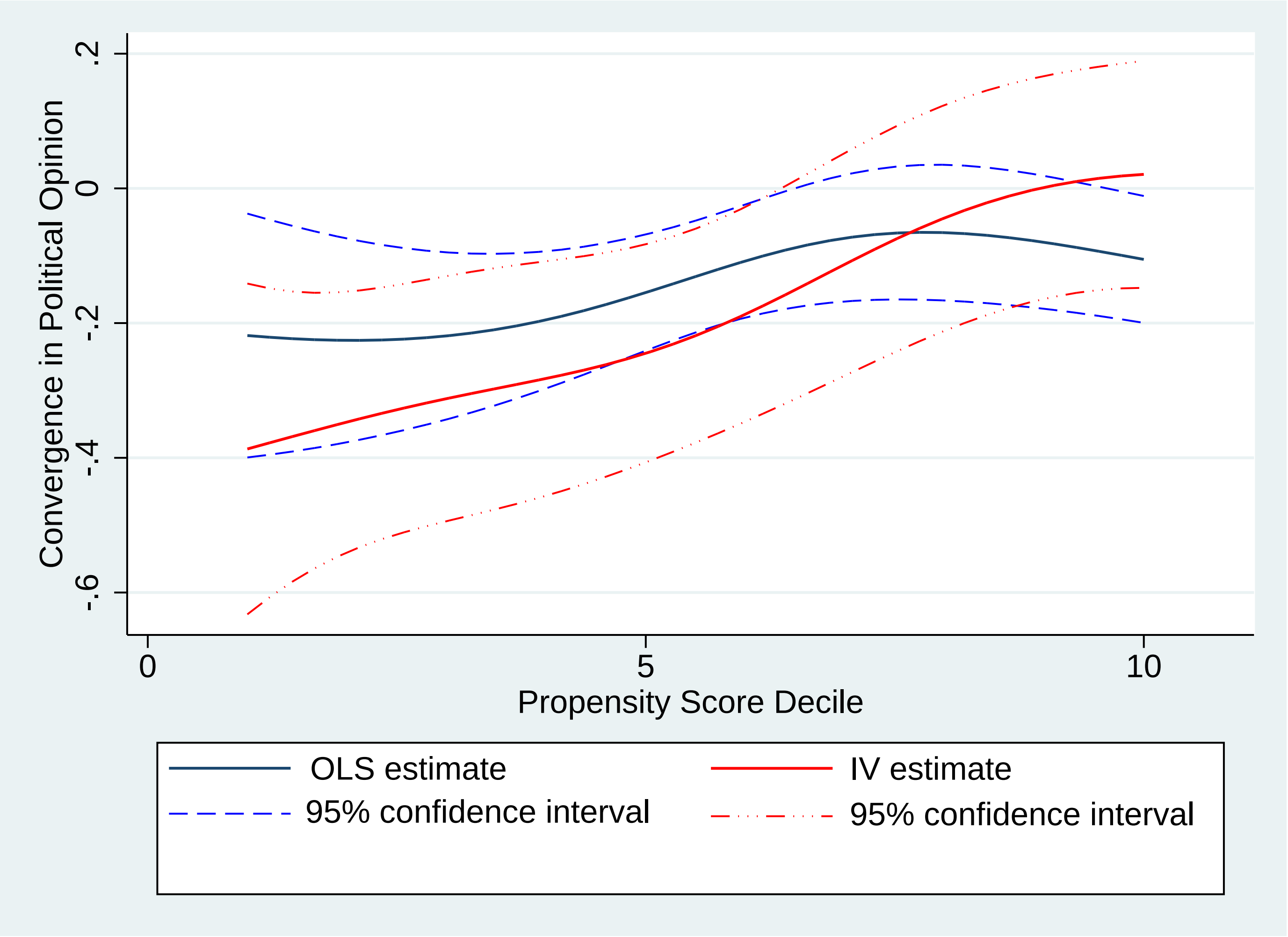


Figure 2: Convergence Coefficient in Political Opinion by Deciles of the Propensity Score of Friendship.

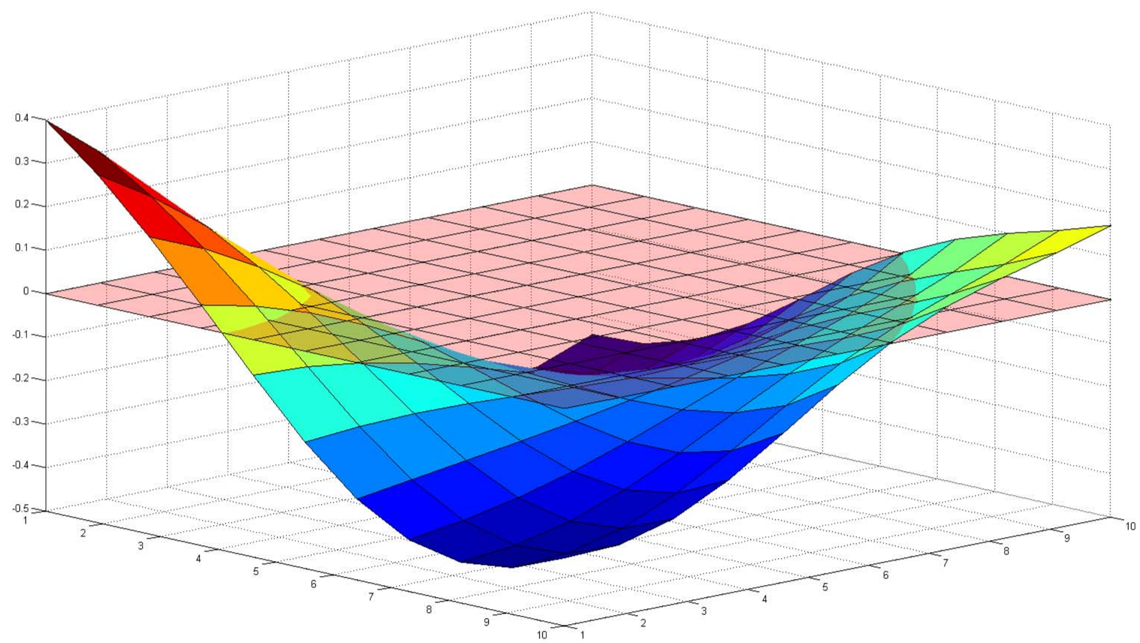


Figure 3: Convergence Coefficient in Political Opinion by the Pair's Original Political Opinion.

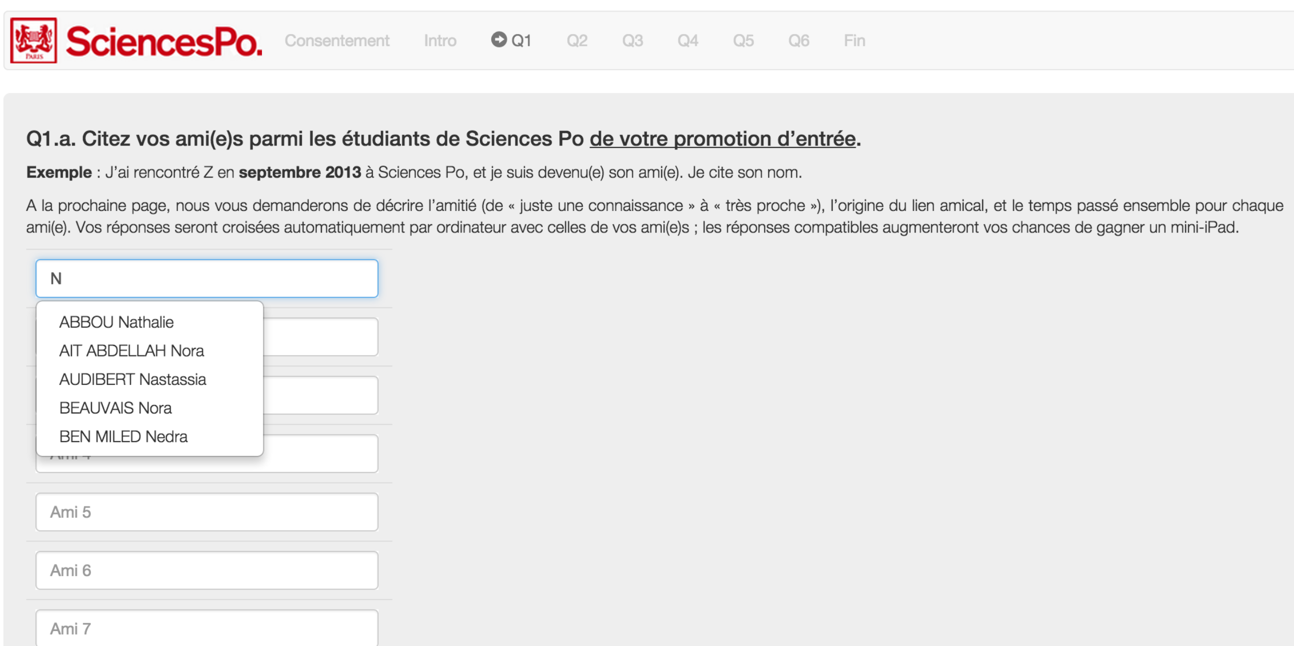
Appendix Tables

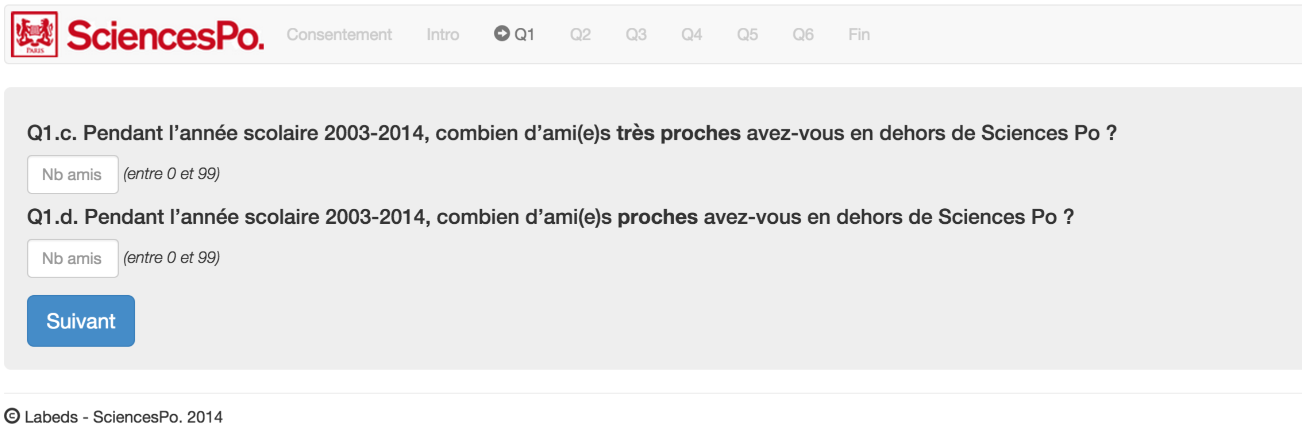
Table A1 - Individual Characteristics

Variable	Mean	Standard Deviation
Very high social status	0.670	(0.471)
High social status	0.124	(0.330)
Average social status	0.0817	(0.274)
Low social status	0.0879	(0.283)
Social status unknown	0.0138	(0.117)
Median annual income	85336	-
Gender	0.592	(0.492)
Highest honor at high school exam	0.754	(0.431)
Foreigner	0.0704	(0.256)
Dual nationalities	0.133	(0.340)
Affirmative action recipient	0.198	(0.399)
Dual major in math	0.0477	(0.213)
Dual major in humanities	0.144	(0.352)
Dual major in sciences	0.0465	(0.211)
Dual major in African studies	0.0666	(0.249)

Notes: Summary statistics are computed on the full sample.

Survey instructions

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Q4
Q5
Q6
Fin
Q1.c. Pendant l'année scolaire 2003-2014, combien d'ami(e)s **très proches** avez-vous en dehors de Sciences Po ?
Nb amis
(entre 0 et 99)
Q1.d. Pendant l'année scolaire 2003-2014, combien d'ami(e)s **proches** avez-vous en dehors de Sciences Po ?
Nb amis
(entre 0 et 99)
Suivant
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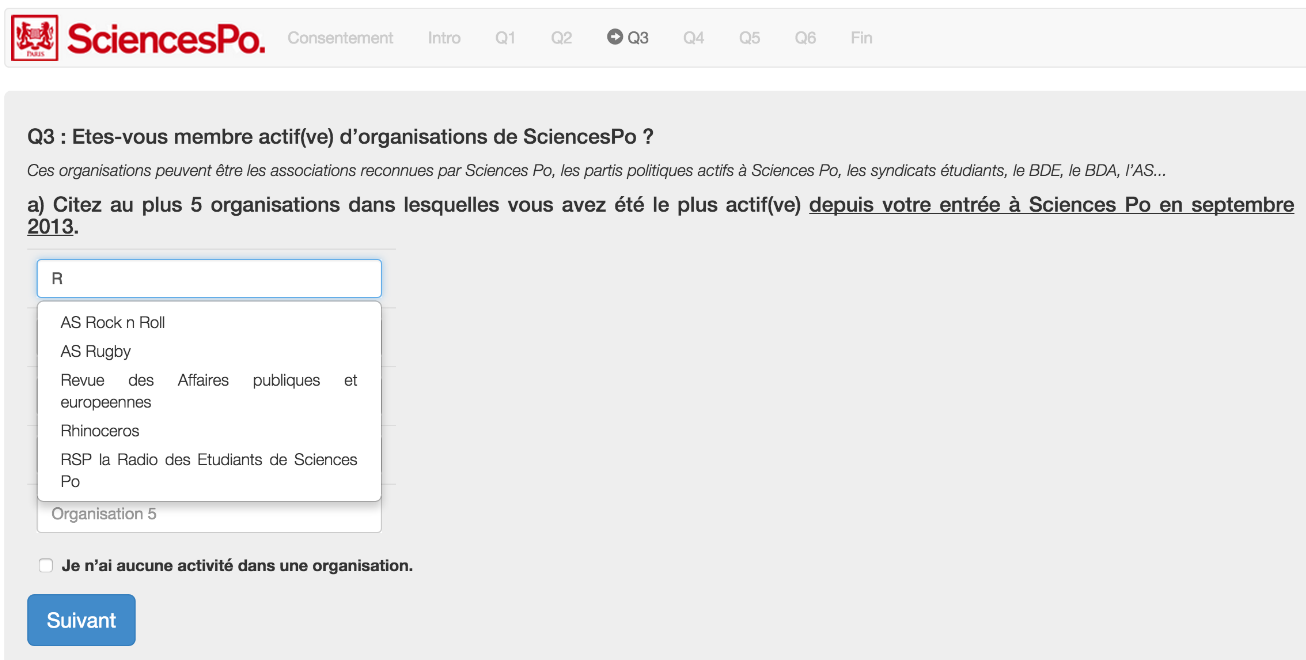
SciencesPo.
Consentement
Intro
Q1
Q2
Q3
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Q5
Q6
Fin
Q3 : Etes-vous membre actif(ve) d'organisations de SciencesPo ?
Ces organisations peuvent être les associations reconnues par Sciences Po, les partis politiques actifs à Sciences Po, les syndicats étudiants, le BDE, le BDA, l'AS...
a) Citez au plus 5 organisations dans lesquelles vous avez été le plus actif(ve) depuis votre entrée à Sciences Po en septembre 2013.
R
AS Rock n Roll
AS Rugby
Revue des Affaires publiques et europeennes
Rhinoceros
RSP la Radio des Etudiants de Sciences Po
Organisation 5
Je n'ai aucune activité dans une organisation.
Suivant

SciencesPo. Consentement Intro Q1 Q2 Q3 Q4 Q5 Q6 Fin

Q4.a : Aujourd'hui, comment vous situez-vous en terme d'opinion politique
sur une échelle de 1 à 10 où 1 correspond à l'extrême gauche, 5-6, au centre gauche / centre droit, et 10 l'extrême droite ?

○ 1	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7	○ 8	○ 9	○ 10	○ je ne sais pas / je préfère ne pas répondre

Q4.b : En juillet 2012, comment vous situiez-vous en terme d'opinion politique
sur une échelle de 1 à 10 où 1 correspond à l'extrême gauche, 5-6, au centre gauche / centre droit, et 10 l'extrême droite ?

○ 1	○ 2	○ 3	○ 4	○ 5	○ 6	○ 7	○ 8	○ 9	○ 10	○ je ne sais pas / je préfère ne pas répondre

Suivant

SciencesPo. Consentement Intro Q1 Q2 Q3 Q4 Q5 Q6 Fin

Q5.a Avez-vous été membre d'un parti politique dans le passé ?

○ Oui ○ Non ○ Je ne souhaite pas répondre

Lesquels :

Parti 1 : nom du parti politique — Période d'adhésion : période d'adhésion

Parti 2 : nom du parti politique — Période d'adhésion : période d'adhésion

Q5.b Etes-vous membre aujourd'hui d'un parti politique ?

○ Oui ○ Non ○ Je ne souhaite pas répondre

Lequel :

Parti : nom du parti politique — Depuis quelle date ? date d'adhésion

Suivant

SciencesPo. Consentement Intro Q1 Q2 Q3 Q4 Q5 Q6 Fin

Q6.a1 D'une manière générale, diriez-vous que l'on peut faire confiance à la plupart des gens ou que l'on n'est jamais assez prudent quand on a affaire aux autres ?

Q6.a2 D'une manière générale, sur cette échelle de 1 à 10, diriez-vous que la plupart des gens cherchent à profiter de vous quand ils le peuvent ou qu'ils font leur possible pour se conduire correctement ? (1 si tout le monde cherche toujours à profiter de vous, et 10 si tout le monde se conduit toujours correctement. Les notes intermédiaires vous serviront à nuancer votre jugement.)

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 ○ je préfère ne pas répondre

Q6.b1 Nous allons maintenant parler des gens qui viennent de pays moins développés pour travailler ici. Qu'est-ce que le gouvernement devrait faire selon vous ?

- Laissez venir toute personne qui le désire
- Laissez venir les gens tant qu'il y a du travail disponible
- Mettre des limites strictes au nombre d'étrangers pouvant venir ici
- Interdire aux gens des autres pays de venir ici
- Je ne sais pas

… 10, êtes vous d'accord ou pas d'accord avec l'affirmation suivante : Quand … ucher en priorité des Français? (1 si vous n'êtes pas du tout d'accord, 10 si … vous serviront à nuancer votre jugement.)

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 ○ je préfère ne pas répondre

Q6.c. Pensez-vous que les facteurs suivants auront de l'influence sur votre succès professionnel dans le futur :

Votre diplôme	Essentiel / Beaucoup / Peu / Pas du tout
Les connaissances et compétences acquises au cours de vos études	
Vos efforts personnels	
Votre réseau formé à Sciences Po	
Votre réseau familial	

Q6.e : Quelle est votre préférence pour l'organisation des enseignements autour des triplettes en 1A (en comparaison avec l'organisation sans triplette comme dans les campus de provinces) ? (10 étant la préférence la plus forte pour les triplettes, et 1 étant la préférence la plus faible)

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10

Q6.f Quels en sont les avantages ?

- ☐ Faciliter l'intégration à Sciences Po
- ☐ Se faire des ami(e)s plus facilement
- ☐ Se faire des ami(e)s plus divers
- ☐ Permettre le travail en commun
- ☐ Améliorer la qualité du travail en commun
- ☐ Autre : Précisez