Collective action in networks: Evidence from the Chilean student movement*

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Hundreds of thousands of students skipped school during the 2011 student movement in Chile to protest and reform educational institutions. Using administrative data on millions of students' daily school attendance on protest days, this paper presents robust evidence of school absenteeism following a threshold model of collective behavior. Students skipped school on a protest day only when more than 50% of the members of their networks also skipped school. Importantly, even though I show skipping school imposed significant educational costs on students, I also show it helped to shift votes towards non-traditional opposition parties in the 2012 local elections, candidates who were relatively more aligned with students' demands.

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1 Introduction

Individual participation in collective action has long puzzled social scientists due to the combination of common benefits and private costs. This "collective action problem" has given rise to a theoretical literature emphasizing that the actions of others are crucial in understanding individual participation.[1] Despite its importance for theory, empirical investigations estimating how individuals respond to the participation of others are surprisingly scarce. The reason for the lack of evidence is the enormous data requirements, particularly important when studying protest behavior.

This paper studies the 2011 student movement in Chile, one of the largest mobilizations in the country's history. During days of national protests, hundreds of thousands of high-school students across the country skipped school to protest with the goal of reforming the educational system. After constructing a large, partially overlapping network with billions of links across students, schools, and cities, I provide evidence for the role of networks in protest behavior using administrative data of millions of students' daily school attendance on protest and non-protest days. The main finding is that skipping school on a protest day followed a pattern consistent with Granovetter's (1978) "threshold model of collective behavior." Students were influenced by their networks to skip school on national protest days only when more than 50% of the members in their networks also skipped school. Importantly, even though skipping school imposed significant educational costs on students, it also helped to shift votes towards non-traditional opposition parties in the 2012 local elections, candidates who were relatively more aligned with students' demands.

Two features of Chile allow me to empirically study protest behavior. First, the government assembles an exceptionally rich dataset of daily school attendance. Thus, I can measure protest behavior for more than 500,000 high-school students using school absenteeism on national protest days. Second, students' peer social ties are mainly with classmates (Araos et al., 2014), and information about their *lifetime* history of classmates is available. The latter data allows me to construct a countrywide network with more than 600 billion interactions across students.

The empirical analysis is divided in two parts. The first part focuses on days of national protests to estimate network effects in protest behavior. I use variants of the "partially overlapping networks" approach proposed by Bramoullé et al. (2009) and De Giorgi et al. (2010), in a two-stage non-linear framework, to estimate how school absenteeism in the network affected the individual decision to skip school. Using the non-parametric estimation proposed by Newey et al. (1999), results support Granovetter's (1978) "threshold model of collective behavior." To improve our understanding of the context in which decisions were taking place, the second part presents suggestive

[1] See Olson (1965), Tullock (1971), Granovetter (1978), Tilly (1978), Kuran (1989, 1991), Lohmann (1993), Marwell and Oliver (1993), Chwe (2000), Bueno de Mesquita (2010), Edmond (2013), Little (2016), and Barbera and Jackson (2019) among many others.

evidence of the effect that skipping school on protest days had on students' academic performance and electoral outcomes in the 2012 local elections.

Given that links in the network were not formed at random, I employ school fixed effects and two variants of a "partially overlapping networks" approach. The first strategy focuses on the first *massive* protest of June 16, when school absenteeism in networks varies from zero to one-hundred percent. As plausibly exogenous variation I exploit networks' exposure to the inaugural protest of May 12, organized by college students outside of the high-school network. Exposure is measured as school absenteeism on May 12 among students who (i) belong to the network of networks, and (ii) attend a different school. This strategy is a variant of the partially overlapping networks approach because it uses variation *across* protest days and focuses on students in *different* schools. The second strategy focuses on all days of national protest in May and June, uses fixed effects by student and school-day, and again exploits decisions in the network of networks attending different schools. This strategy is also a variant of the partially overlapping networks approach because it uses student and day fixed effects, and decisions of students in different schools.

Both empirical strategies rely on a strong first-stage and deliver robust findings. Network exposure to the inaugural protest is highly predictive of network absenteeism in June 16, even after controlling for a large set of variables for students, networks, and school fixed effects. Moreover, placebo checks using non-protest days confirm the importance of the inaugural protest. Panel data estimates also deliver similar results and are robust to the inclusion of student and network characteristics interacted with protest day indicators.

The estimated coefficients in the second-stage reveal that a threshold model is a better representation of individual decisions than a linear model. If the share of students in the network that skips school is lower than 50 percent, I observe that the individual decision to skip school is not affected by the network. In contrast, after the 50 percent threshold, individual absenteeism increases rapidly with network absenteeism. This result suggests that a "critical mass" of individuals is needed to facilitate protest behavior.[2] Importantly, results are similar when using different implementations of Newey et al.'s (1999) estimator and are robust to the use of other nonparametric instrumental variables estimators (e.g. Newey and Powell 2003, Rau 2013).

Despite recent evidence showing enhanced coordination in the presence of the internet (Manacorda and Tesei, 2018; Enikolopov et al., 2019), 2G-3G maps in Chile seem to be unrelated to coordination within student networks. However, students in smaller networks do react more to decisions in their networks, result consistent with Olson's (1965) theory of groups. In addition, when augmenting the estimation to allow for differential non-linear effects within networks, the estimates

[2]This tipping behavior is predicted by models of social interactions (e.g. Brock and Durlauf 2001). However, empirical evidence is limited. A notable exception is Card et al. (2008), who use Census tract data to provide evidence of tipping in the context of Schelling's (1971) dynamic model of segregation.

suggest that students are more influenced by others who are similar to them. Taken together, the results suggest a critical mass of others who are similar is needed to foster protest behavior.

The last part of the paper studies the costs of skipping school on protest days and their effect on electoral outcomes. A differences-in-differences analysis among primary and high-school students in the period 2007–2015 reveals that grade repetition increased by 60 percent, from a base of 6 percent, among high-school students in 2011. Skipping school on the June 16 national protest – which led to higher absenteeism in the following months – decreased GPA by 0.1 standard deviations and increased grade repetition by 33 percent. In addition, I provide suggestive evidence that the student movement was able to shift votes towards non-traditional opposition parties, which were relatively more aligned with the movement's demands. A cross-sectional regression using county-level electoral data suggests that a one standard deviation increase in the intensity of the movement in local schools increased vote shares for non-traditional parties by 5 percentage points, crowding-out mostly traditional right-wing candidates.

This paper contributes to the empirical understanding of participation in collective action. Only a few recent papers have studied *protest* behavior, and the role of social effects has been relatively overlooked.[3] Notable exceptions include Cantoni et al. (2019) and Hager et al. (2019), who show that beliefs about others' turnout to a protest affect participation in the context of recent rallies in Hong-Kong and Germany; Enikolopov et al. (2018) who show social image was an important motivation to participate in the 2011-2012 protests in Russia; and Larson et al. (2019) who use Twitter data to show that network position influenced attendance at the 2015 Charlie Hebdo protests in Paris. Recent research has also identified persistence in protest behavior mediated by social interactions (Bursztyn et al., 2019) and has found important interdependencies in other political behaviors (Fujiwara et al., 2016; Coppock and Green, 2016; Perez-Truglia and Cruces, 2017; Hensel et al., 2019). In contrast, my paper focuses on individual-specific networks and uses administrative data to test for threshold models in protest behavior.[4]

An important branch of the previous literature focuses on the role played by information communication technologies (ICT). One part of this research provides estimates of the aggregate contribution of ICT – such as mobile phones and social media – to the formation and spread of protests across cities (Manacorda and Tesei, 2018; Enikolopov et al., 2019). Authors have argued that ICT can help to spread grievances, particularly in times of difficult economic conditions, and enhance the ability of citizens to coordinate for a collective action such as a protest. Another part of this

[3]There are studies of participation in other types of collective action. For example, McAdam (1986) shows that friends' participation in the 1964 Freedom Summer project predicts individual participation, and Yanagizawa-Drott (2014) shows that radios facilitated participation in the Rwandan genocide.

[4]Jackson and Storms (2019) also studies behavior in networks to identify communities using a structural approach. More generally, there is a large literature studying social interactions. See Durlauf and Ioannides (2010); Blume et al. (2010); de Paula (2013, 2017) for important reviews. In relation to this literature, this paper is one of the first to show the existence of a threshold behavior at the individual level in partially overlapping networks.

literature uses disaggregated data to estimate how political participation and information spreads through social networks (e.g. Twitter) depending on the network centrality of individuals (Halberstam and Knight, 2016; Larson et al., 2019). Related research has also estimated the direct impact of media censorship on political engagement (Yang, 2019) and ICT surveillance as a method to prevent the propagation of protests (Qin et al., 2017). In contrast to most research, this paper shows that coordination within student networks is similar in places *without* 2G-3G coverage, perhaps suggesting that ICT has little influence in offline networks with strong ties.

This paper also speaks to a literature estimating the impact of protests.[5] Madestam et al. (2013) uses rainfall shocks as exogenous variation affecting the number of protesters in the Tea Party movement across U.S. counties to show how the movement affected electoral outcomes and policies, while Larreboure and González (2019) uses a similar method to show that the Women's March in the U.S. empowered women and ethnic minorities to run for a seat in Congress. Aidt and Franck (2015) shows that the Swing riots in early 19th century Britain – credible signals of the threat of a revolution – facilitated democratic reforms. Finally, a recent literature also shows that protests can change public support for policies (Enos et al., 2019), racial attitudes (Mazumder, 2019a,b), and social norms such as reporting of sex crimes (Levy and Mattsson, 2019). This paper contributes to this literature by providing novel evidence on the individual costs associated with protest behavior and suggestive evidence on the effect of that protest behavior on electoral outcomes.

2 The Chilean student movement

From the Tunisian demonstrations sparking the Arab Spring to Occupy Wall Street triggering a movement against inequality, 2011 was a year full of protests across the world. The global wave of citizens demanding a "new democracy" also took place in Chile, where high-school and university students revolted to reform the educational system installed by the Pinochet dictatorship, nowadays one of the most expensive and segregated in the world (Hsieh and Urquiola, 2006; OECD, 2013). Organized groups of students triggered one of the largest demonstrations in the country's history, which were recognized worldwide as one of the most important social movements of that year.

The student movement began in May 2011, two months within the academic year, and 14 months after a right-wing government took office democratically for the first time in 50 years.[6] Initial demonstrations were triggered by delays in the assignment of students' scholarships and bus passes. The first student-led national protest took place on May 12 and thousands of high-

[5] There is, of course, a large theoretical literature studying social unrest and political transformation. See, for example, Acemoglu and Robinson (2000) and Passarelli and Tabellini (2017).

[6] Chronicles written by leaders of the student movement include Figueroa (2012), Vallejo (2012), and Jackson (2013). A brief history of the high-school movement can be found in Simonsen (2012).

school and university students participated.[7]

The first protests were organized by the Confederation of Chilean Students, a national student organization, and had the objective of exerting pressure on the annual presidential speech on May 21, in which the government outlines the next year's policies. Students wrote a document proposing policies to decrease segregation in the educational system and increase government spending. After the presidential speech, the Confederation sent a letter to the Ministry of Education expressing their discontent with the announcements (Confech, 2011). Students called for another national protest day in June 1, the last rally before the movement expanded in an unprecedented way.

After the national protest on June 1, and a failure to reach an agreement with the Ministry of Education in meetings held on May 30 and June 8, students intensified their protest activities. The movement was gradually supported by deans, teachers, prominent labor unions, and public figures. Over the weeks that followed, students occupied schools and universities, and protest activities spread across the country. In an attempt to prevent occupations, the Ministry of Education asked students "to stop protesting" and the president stated that "countries do not progress by occupying schools." The government's approval rating was low and continued to plummet after the rise of the movement (Figure A.3). Students called for another national protest day on June 16, at the time the largest mobilization in the country's history. The government responded in June 25 with an offer, which students rejected, calling for yet another national protest day on June 30.

Education was the main topic of conversation during July and August. The leaders of the movement were regularly invited onto television and radio shows, and diverse protest activities filled the country. The president replaced the Ministry of Education on July 18 and the government responded to students' demands with offers on July 5, August 8, and August 17. Students rejected these offers and demonstrations continued after the July winter break, with the largest national protests taking place on August 24 and 25. These two days marked the peak of the student movement, and protest activities declined in the following months. Various reasons explain the decay of the movement, including the beginning of formal negotiations, the focus of media on violent protesters, and students' concerns about grade retention.[8]

After months of protests, what were the consequences? Contemporary surveys show that 80 percent of citizens supported the movement (Adimark, 2011) and that education became a national priority (Figure A.4). Candidates in the 2012 local elections and 2013 Congress and presidential

[7] For additional context, Figure A.1 plots the daily number of protests in Chile in the period 1979-2013, and Figure A.2 plots economic indicators around the beginning of the student movement of 2011.

[8] "The constant emphasis on violence affected the strength of the movement" (Jackson, 2013, p. 22). The government threatened students with being held back, promoting the "Let's save the academic year" plan. In addition, public figures died in an airplane crash in September 2 – shifting public interest away from the movement – the movement's leaders had to face annual elections to renew their leaderships, and summer holidays caused the movement to slow down until the next academic year.

elections were constantly questioned about their ideological positions regarding education. Some of the older leaders of the movement founded political parties and four of them won seats at the congress. There were also changes to laws that regulate state guaranteed loans – used by most students to attend universities and technical schools – including a reduction in the interest rate paid by students, an increase in coverage, and caps to monthly repayments. In addition, the left-wing candidate Michelle Bachelet won the 2013 election with a platform that offered free tertiary education. Although with changes, this policy has been implemented gradually in the last years.

3 Motivating theory

Inspired by Schelling's (1971) tipping model, Granovetter (1978) proposed a theory of individual binary decisions based on thresholds. In particular, he argued that a person's decision can be influenced by the decision of others, but particularly so if there is a "critical mass" making a certain choice. For example, a person might decide to participate in a protest only if more than *x%* of others are also participating, i.e. *x%* represents the threshold. In the original model each person has a different threshold and the distribution of thresholds is exogenous. Importantly, these thresholds can arise from non-linearities in the benefits or the costs derived from the decision. The canonical example is a non-linear decreased in the cost of apprehension when many people participate in a riot. But non-linear benefits are also theoretically possible.

Three aspects of Granovetter's work are important to highlight for this research. First, in his model an individual observes the total number of people making a decision or the share. My empirical application uses shares but it also follows Olson (1965) to provide some evidence on the role of group size.[9] Second, the decision maker might care about the actions of every other person in the population, or she might only care about the decisions of a "reference group." Empirically I will estimate the response of a student to the decisions in her social network, and I flexibly control for decisions at more aggregate levels (e.g. schools and cities). Third, there might be multiple explanations behind the threshold behavior and, although empirically I cannot fully distinguish between these, I will use auxiliary results to discuss which one could be important.

Several mechanisms can explain the existence of a threshold behavior. On the benefits side, students might derive utility from having shared experiences with their networks. Then, when a critical mass of their networks decides to attend a protest, they are pushed to protest as well to share that experience. This could also be the case if conversations in the network are grounded on past experiences and students derive benefits from joining the conversation, as suggested by recent

[9] "In any event, size is one of the determining factors in deciding whether or not it is possible that the voluntary, rational pursuit of individual interest will bring forth group-oriented behavior. Small groups will further their common interests better than large groups." Olson (1965, p. 52).

evidence (Gilchrist and Sands, 2016). Similarly, students might update their information based on the actions of the majority of the network and this might cause a change in behavior. This could be the case if students assign a probability to the protest's success based on how many people in their social networks participate, as in theoretical models emphasizing the importance of group size in intergroup conflict (Blattman and Miguel, 2010). If the majority is protesting, then a student might believe the protest is likely to achieve change. In the case of the Chilean student movement, the success is associated to a higher probability of cheaper tertiary education.

Alternatively, the individual cost of protesting could be a non-linear function of network participants. There are two relevant cases in the context of student protests. First, a punishment from the network for deviating from the social norm. The social norm could be established by the actions of the majority. Examples of punishments are shaming or feelings of guilt (Elster, 1989; Enikolopov et al., 2018). Second, an action from the school such as teachers less likely to teach the syllabus in the absence of many students, or teachers deliberately punishing protesters. In my context a deviation from the social norm is more likely to be relevant because I study a few protest days at the very beginning of the movement. Students presumably perceived the cost of missing a class to be low because it was difficult to anticipate that skipping school in the beginning would lead to significantly more absenteeism in the remaining of the academic year.

All in all, Granovetter's and Olson's framework delivers three predictions I can test empirically. First, a non-linear increase (decrease) in the benefits (costs) of skipping school on a protest day – both coming from the actions of the network – means that the individual probability of skipping school should be a non-linear function of absenteeism in students' networks. Second, if smaller groups of students can coordinate more easily, as suggested by Olson (1965), then the previous threshold behavior should be easier to observe in smaller groups. Third, if the internet improves coordination then the threshold behavior should also be easier to observe in student networks more connected to the internet, as recent evidence suggests (Manacorda and Tesei, 2018).

Some final remarks are necessary to understand coordination in student networks. In nonlinear models of social interactions there is always the possibility of multiple equilibria, and this can create challenges for (but does not prevent) estimation (Jovanovic, 1989; de Paula, 2013). However, in the case of the Chilean students one equilibrium is more likely to be played than others. As emphasized by Mailath (1998), an equilibrium is likely to be chosen by agents who are culturally or geographically close. In this case students in a network are culturally similar, live in the same neighborhoods, and are likely to have played similar games in the past, particularly in Chile where protests of different sizes occur every year. In this sense, the setting mimics a dynamic game in which people communicate before choosing their actions and as such coordination in student networks is likely to occur in equilibrium. A second aspect of the context that helps to coordinate students' actions is the existence of institutions calling for the national protests I study, i.e. the

Chilean Confederation of Students and the Coordinating Assembly of Secondary Students.

4 Data

4.1 Daily school absenteeism and student networks

The analysis uses four administrative datasets. The first measures *daily* school attendance in 2011. The academic year in Chile starts in March and ends in November, with a winter break in July. The second reveals students' enrollment information (school, grade, and classroom) for 2011 and previous years. There were approximately 975,000 high school students enrolled in 2,700 high-schools in 2011. However, after restricting attention to students with all covariates this number decreases to 760,000. Moreover, when I focus on schools with daily attendance available for the June 16 protest there are 500,000 students in 1,700 high-schools. The third measures students' annual academic performance, i.e. GPA. The last dataset describes schools. In the final data approximately 20 percent of students were enrolled in public schools and 80 percent in private schools. School addresses are also available and I use these to construct geographic clusters that I refer to as "cities." There are 226 cities in the final data, with 7 high schools and 2,160 high-school students in the average city.[10] Table 1 presents descriptive statistics for the sample of students in high-schools opened in June 16 (column 1) and for all students for comparison (column 3).

Student networks. Because students mainly interact with other students in their classrooms, I define student i's network $j(i)$ as her lifetime history of classmates, including the current ones. As shown in Figure A.6, past classmates in $j(i)$ live in i's neighborhood, hence their interactions are likely to remain. As of 2011, each high-school student had a unique set of past classmates that I identify from enrollment information in previous years. This definition gives rise to a large network of students linked within *and* across classrooms, schools, and cities. Links across schools originate in the predetermined switching of students across schools before 2011. Overall, this network contains more than 600 billion potential interactions among students across the entire country, and more than 60 million existing links. The average student has 80 other students in her network, 60 percent attending the same school and 40 percent attending a different school in 2011.[11] Importantly, 88% of private schools in 2011 had students who attended a public schools in previous years and hence public and private schools are highly connected in this network.

[10]In practice, cities are isolated components in the spatial network of schools, where two schools are linked if these are closer than 5 kilometers from each other. These can also be thought as clusters of counties that approximate conurbations. Figure A.5 presents a map of cities.

[11]For computational reasons I only consider classmates in years 2007-2011. The calculation of student-specific network variables takes substantially more computational time when including more years. In addition, the network is unfortunately too large to calculate network statistics and solutions to this problem rely on approximations that are currently being evaluated (e.g. Brandes and Pich 2007 and Alghamdi et al. 2017).

Protest days. To measure protest behavior related to student strikes I use school absenteeism among high-school students on national protests days. The government collects daily school attendance to track performance and allocate public programs. Several patterns in the data suggest school absenteeism is a useful way to measure protest behavior. First, there are significant spikes in school absenteeism on protest days. The upper panel in Figure 1 plots absenteeism throughout the 2011 school year. The first two national protest days (May 12 and June 1) are easy to observe. The sharp increase in school absenteeism between June 1 and June 16 corresponds to the real-time escalation of protest activities. Second, some schools were temporarily taken over by students, and these closures are observed in the data with the same dates reported in local newspapers. As examples, the lower panels in Figure 1 present daily absenteeism in 2011 for three schools.

4.2 High-school absenteeism and rally attendance

How does high-school absenteeism in a protest day relates to protest participation? By far the most common definition of protest participation is rally attendance (Fisher et al., 2019), and the usual location for this rally is a city's main square. In the case of Chilean protests, however, this definition is incomplete as there were also protest activities different from the rally taken place inside and around schools. It is important to keep in mind these other activities when interpreting the following calculations that relate high-school absenteeism and rally attendance.

To estimate how many high-school students were at a rally I proceed in three steps. First, using data for the June 16 rally – the main protest day to be studied in the following sections – and comparing this day to a "business-as-usual" (non-protest) day, I can tell that there were approximately 100,000 additional high-school students skipping school in Santiago. Second, I gathered the reported number of people attending the June 16 rally in Santiago from different sources, including police reports and data collected by organizers, and use the average of estimates as the best guess for rally size: 87,500 people.[12] Third, I use a sample of 24 images taken from a 13-minute video of the June 16 rally, together with a crowd counting method, to calculate the percentage of high-school students in the rally. Those in charge of identifying high-school students in the "crowd" were fifth and sixth year university students in 2019 – i.e. high-school students at the time of these protests – who performed the image analysis task a total of 520 times. High schoolers are identifiable because most of them wore school uniforms during the protest. This crowd-counting method delivers that 25% of people at the rally were high-school students.[13]

[12]The four estimates I was able to collect are: two of 100,000 people, one of 80,000, and one of 70,000. Similar methods to calculate the size of rallies can be found in Acemoglu et al. (2018) and Enikolopov et al. (2019).

[13]The link to the video is here. Six of the 24 images were selected at random, six were selected form the longest shot to maximize crowd flow, six from the two largest shots, and six were taken at random from the set of large shots. The 25% number may seem low but recall that many protesters were university students, workers from labor unions, and other citizens. In addition, this is likely to be a lower bound as some students might not have been wearing

The previous calculations imply that 22% of students who skipped school attended the rally in Santiago's main square ($[0.25 \times 87,500]/100,000 = 0.22$). The remaining high-school students either protested in a different way or stayed at home. In what follows I use these numbers to provide some intuition for the relationship between network absenteeism and protest behavior.

5 Econometric strategies

5.1 Exposure to the first protest

Consider the following regression relating a student's decision to skip school on a protest day as a function of school absenteeism in her network:

$$A_{isc} \quad = \quad f(A_{j(i)}) + g_1(x_i) + g_2(x_{j(i)}) + \zeta_s + \epsilon_{isc} \tag{1}$$

where $A_{isc} \in \{0, 1\}$ takes the value of one if student i in school s, located in city c, decides to skip school on June 16. In addition, $f(A_{j(i)})$ is a function of a vector of absenteeism decisions in i's network $j(i)$, and $g_1(x_i)$ and $g_2(x_{j(i)})$ are flexible functions of observables that account for benefits and costs that may affect a student's decision. Finally, ζ_s is a full set of school fixed effects, and ϵ_{isc} is an error term clustered by city.

The vector x_i includes average school attendance in 2010, GPA in 2010, an indicator for grade retention in 2010, an indicator for gender, an indicator for students who switched school in 2010, and age. Averages of the same variables are included in $x_{j(i)}$, although results are robust to the use of more flexible functions such as fully saturated bins for all controls. In addition, student controls also include school absenteeism on previous (and smaller) protest days, i.e. May 12 and June 1.

The first part of the analysis uses a linear-in-means function f, i.e. the average absenteeism in networks $f(A_{j(i)}) = \frac{\sum_{k\in j(i)} A_k}{N_{j(i)}} \equiv \overline{A}_{j(i)}$. Then, I allow network absenteeism to flexibly influence individual decisions by using the following functional form for network decisions:

$$f(A_{j(i)}) = \beta_1 \cdot 1\left[\overline{A}_{j(i)} \in [0.1, 0.2)\right] + \cdots + \beta_9 \cdot 1\left[\overline{A}_{j(i)} \in [0.9, 1)\right] + \beta_{10} \cdot 1\left[\overline{A}_{j(i)} = 1\right] \tag{2}$$

where $\beta_1, \ldots, \beta_{10}$ are the parameters of interest and $1[\cdot]$ is an indicator function that takes the value of one when the statement in square brackets is true. I use eleven indicators, although results are robust to using more; the first takes the value of one if absenteeism in networks is between 0 and 10 percent, the second takes the value of one for 10-20 percent absenteeism in networks, and so on progressively until I reach 100 percent absenteeism in networks. The omitted category is network

uniforms during the rally. Figure A.8 provides more details about the implementation of this method.

school absenteeism lower than 10 percent.

There are three concerns with an estimation of equation (1) using OLS. First is the classical reflection problem emphasized by Manski (1993): students affect their networks and networks affect students. Second, given the absence of random allocation of students across classrooms, there may be unobservable variables causing students and their networks to make similar decisions. Both concerns imply that an OLS estimation will overestimate the effect of networks. A third problem is known as "exclusion bias" and causes OLS estimates to be biased *downwards* (Guryan et al., 2009; Angrist, 2014; Stevenson, 2015; Caeyers and Fafchamps, 2016). To solve the former two issues, I use three sources of variation in an instrumental variables approach that exploits partially overlapping networks. To solve the third issue, I follow Caeyers and Fafchamps (2016) and include the student's value of the instrument as an additional control.

The first source of identifying variation is the exposure of networks $j(i)$ to protests in their networks, i.e. the "excluded network," which directly addresses the reflection problem. The second source is a restriction to the set of students in the "excluded network"; I focus only on those attending a *different* school than i in 2011, approximately 2,000 students. This restriction addresses concerns regarding unobservable variables and shocks affecting students in the same school. The third source of variation corresponds to school absenteeism on the first national protest day, May 12, organized outside of the network of high-school students (see Section 2). This final source of variation can be thought of as similar to the "partial population approach" in Dahl et al. (2014) in which a subset of the population is exogenously exposed to participation in a program (a protest in this case). All in all, this strategy is a variant of the "partially overlapping networks" approach proposed by Bramoullé et al. (2009) and De Giorgi et al. (2010).

To gain intuition about the strategy, recall student i's network is $j(i)$. The exposure of students in $j(i)$ is measured by how much *their* networks $j(j(i))$ skipped school on May 12, with $i \notin j(j(i))$. Students in the set $j(j(i))$ may however still have unobservables similar to those of i. To deal with this concern, I restrict attention to a subset of students. Given the predetermined switching across schools, many students in $j(j(i))$ are attending a different school than i in 2011. Let $s(i)$ denote the set of students attending the same school than i in 2011 and let A/B denote agents in A who are not in B. Then, the identification assumption is that school absenteeism on May 12 among students in the set $j(j(i))/s(i)$ only affects student i's absenteeism on June 16 through the absenteeism of $j(i)$.

5.2 *Partially overlapping networks in panel data*

The second strategy exploits the multiple protest days observed in the data. I focus on all national protest days before the winter break of July. This decision is motivated by a potential change in the structure of networks after the break, but given the large number of observations it does not affect the statistical power of the analysis. In particular, I estimate versions of the following equation:

$$A_{isct} \quad = \quad f(A_{j(i)t}) + \sum_t \left(\delta_{1t}x_i + \delta_{2t}x_{j(i)}\right) + \xi_i + \zeta_{st} + \epsilon_{isct} \tag{3}$$

where A_{isct} is an indicator that takes the value of one if student i, in school s, located in city c, skipped school on day t, a day of national protest. In addition, $f(A_{j(i)t})$ is a function of a vector of absenteeism decisions in i's network $j(i)$ in day t, and x_i and $x_{j(i)}$ are control variables by students and networks. The baseline specification includes student's past GPA and the average GPA in social networks, although results are robust to include more variables. Finally, ξ_i is a student fixed effect, ζ_{st} is a school by day fixed effect, and ϵ_{isct} is an error term clustered by city. As in equation (1), I employ the functional form in equation (2) to test for non-linear network effects.

Note that, when using an OLS approach, the assumption for a consistent estimation of the parameters $\beta_1, \ldots, \beta_{10}$ is different than in the previous strategy. Indeed, because I am now using *within student* variation in absenteeism decisions, the main threat is the reflection problem and unobservable variables that vary over time. To deal with the reflection problem I again use the partially overlapping networks approach, restricting attention to students in *other* schools. In addition, to control for potential unobservable variables I interact protest day indicators with (1) student and network characteristics, and (2) include protest day by school fixed effects.

5.3 Identification and first-stage

A final remark regarding the identification of $f(\cdot)$ in equations (1) and (3) is necessary. As emphasized by Newey and Powell (2003), when the endogenous variable and the instrument are continuous the conditions for identification exist, but these are stronger than in linear models. Specification decisions are particularly important. The relative flexibility of bins in equation (2) and the use of Newey and Powell's (2003) series approximations help in this regard. However, the use of bins could also be problematic because it entails some discretization of the endogenous variable. Fortunately, as emphasized by Horowitz (2011) the continuous nature of the instrument helps to identify the parameters. Intuitively, it is crucial that the variation in the instrument shifts the endogenous variable from one bin to the other across the entire distribution.

The lower panel in Table 2 shows that the first stage is strong, with coefficients having the expected positive sign – higher exposure to initial protests fosters future absenteeism – and corresponding F-stats that are always far from a weak instrument problem (Stock and Yogo, 2005). Reassuringly, the value of the instrument *before* the first protest (May 12) does not predict networks' absenteeism on June 16, suggesting that unobservables that affect absenteeism in non-protest days are unlikely to affect results. The first-stage is strong under both econometric strategies and, similarly, absenteeism in social networks also varies significantly for different values of the instrument in the two cases (see Figure A.7 for details).

6 Main results

I begin by briefly describing linear estimates of equation (1), but their panel counterparts are similar. Table 2-A presents OLS estimates, panel B 2SLS estimates, and panel D the reduced forms.[14] Column 1 uses school fixed effects, and columns 2-4 progressively include controls for student and network characteristics. Column 4 is my preferred specification. Coefficients estimated using 2SLS are positive and smaller than their OLS counterparts. In terms of magnitude, column 4 suggests that a one standard deviation in network absenteeism is associated to an increase of 2 p.p. in individual school absenteeism (0.20×0.09), a 10% increase over the mean. Put differently, when all members of a student's network skip school, then the student's probability of also skipping increases by 20 p.p. Hence, these linear estimates suggest that protest decisions are strategic complements within student networks.

6.1 Non-linear estimates

Let me now discuss estimates of equation (1), now using the functional form in equation (2) and the approach proposed by Newey et al. (1999). This estimation corresponds to a control function, and the coefficients of interest are associated with indicators for different values of absenteeism in the network. Importantly, in the following regressions the coefficient associated with the control function parameter is always statistically different from zero, as expected given the difference between 2SLS and OLS estimates. Panel A in Figure 2 presents OLS estimates of $\left(\widehat{\beta}_1, \ldots, \widehat{\beta}_{10}\right)$ and panel B presents 2SLS estimates. The exact specification corresponds to that in Table 2 column 4. As before, 2SLS estimates are lower than their OLS counterparts.

The 2SLS estimates are consistent with Granovetter's (1978) threshold model of collective behavior in the following sense. The school absenteeism decision of a student seems to not be affected by low values of school absenteeism in her networks. In contrast, large values of network absenteeism do seem to have strong effects on her decision to skip school. To more clearly show the marginal contribution of additional absenteeism in networks, Figure 2-C plots the sequential difference between estimated coefficients, i.e. $\widehat{\beta}_k - \widehat{\beta}_{k-1}$ with $k = 1, \ldots, 10$, where $\beta_0 = 0$, and $\widehat{\beta}_1, \ldots, \widehat{\beta}_{10}$ correspond to the estimated coefficients in equation (2). This figure suggests that the

[14] The number of observations is presented at the bottom of Table 2. Differences in observations are due to missing values, which are more common for small schools located in rural areas. Table 2 also shows that standard errors are virtually unchanged when using the 53 provinces as clusters instead of the 240 cities.

influence of networks on individual decisions is positive only after absenteeism reaches 50 percent of a network, and reaches a maximum around the 60-70 percent mark.[15]

Figure 3 confirms previous results using 2SLS panel data estimates of equation (3), the functional form in equation (2), and Newey et al.'s (1999) estimation. These regressions employ more than five million observations, coming from more than 700 thousand students during eight protest days. The estimates in Figure 3-B reveal the same non-linear network patterns from the previous section: networks begin to influence individual decisions after 50 percent absenteeism and the marginal contribution of additional absenteeism is again maximized at 60 percent.

The difference between OLS and estimates 2SLS could be explained by the characteristics of the compliers, but also by other factors such as the reflection problem or some omitted variable. Regardless, a characterization of the compliers is always helpful. Using Abadie et al.'s (2002) method I calculate that the compliers are more likely to attend private schools but have similar levels of school absenteeism in their networks. Table A.1 presents the full characterization of compliers. If students in private schools are less likely to respond to social effects than students in public schools, then the characteristics of the compliers contribute to 2SLS estimates being smaller than OLS estimates. In addition, the difference between OLS and 2SLS estimates in the linear and non-linear models can be explained by linear estimates placing relative more weight on observations in the median of the distribution (Yitzhaki, 1996).

How was *network* absenteeism related to the number of protesters in main square? On one side, section 4.2 showed that one of every four students who skipped school on June 16 was in Santiago's main square. On the other side, this section showed that when network absenteeism was close to 100% the individual probability of skipping school increased by 20 p.p. By combining both sets of numbers we conclude that 20 networks with full absenteeism created one additional protester in main square (i.e. $20 \times 0.20 = 4$). If we recall that the average network was composed by 80 students – and assume non-overlapping networks as a bound – then 1,600 students skipping school induced one additional student to attend the rally due to the network effects documented (i.e. $20 \times 80 = 1,600$). Considering that only 25% of students skipping school in the network attended the rally, we could also say that 400 high-school students in the rally induced one additional student to attend ($0.25 \times 1,600 = 400$). However, this number is likely to be a lower bound of social effects because (i) those in one network are likely appear in other networks (Jackson, 2019), and (ii) the estimate for the percentage of high-school students in the rally (25%) is presumably a lower bound.

[15] Additional coefficients might be of interest for the reader. School absenteeism in previous (smaller) protest days (May 12 and June 1) are highly predictive of school absenteeism on June 16 (coef. 0.09 and 0.12, p-values <0.01) and students of high-academic achievement are less likely to protest. In addition, students linked to students of high-academic achievement and low historical absenteeism are more likely to skip school on June 16.

6.2 *Robustness of non-linear estimates*

The non-linear reaction of students to decisions in their networks are robust to a variety of specification checks and estimation methods. Let me begin by documenting the robustness to three specification exercises. First, non-linear estimates are similar when using different combinations of controls, including a set chosen using Belloni et al.'s (2013) LASSO procedure (see Table A.2). Second, results are similar when focusing on the sub-samples of students in 1st, 2nd, 3rd, and 4th grade of high-school (see Figure A.9). This is an important check because the composition of middle and high-school classmates in the networks of students in different grades is different. And third, Figure A.10 shows that 2SLS estimates using panel data are also robust to the inclusion of one, two, or three lags of individual and network absenteeism. This last check is particularly important in the presence of habit formation in absenteeism decisions.

Previous results are also robust to the use of alternative implementations of the Newey et al.'s (1999) estimator and alternative nonparametric instrumental variables methods. First I checked for the robustness of results to the use of different functions of network absenteeism $f(A_{j(i)})$, i.e. third and fourth degree polynomials. Point estimates are presented in Table A.3 and graphically in panels B and C of Figure A.11. To facilitate the comparison with previous estimates I show the predicted values of individual absenteeism for different values of network absenteeism. As can be seen from the figure, the threshold behavior is still clearly visible. Second, panel D in the same figure shows that estimates are also robust to controlling for flexible functions of the error term from the first-stage. This panel presents 2SLS estimates using saturated bins but results are similar to other functional forms such as third-degree polynomials.

In terms of alternative nonparametric instrumental variables methods, results are robust to the use of Newey and Powell's (2003) and Rau's (2013) estimators. Operationally the former methodology uses basis functions for the first-stage and polynomials of the instrument, while the latter uses saturated interaction terms between the error term from the first-stage and control variables and fixed effects from the second-stage. Panels E and F in Figure A.11 presents results again using predicted values of student absenteeism to facilitate comparison with previous estimates.

6.3 *The internet, group size, and homophilic influence*

This section explores the heterogeneity of previous 2SLS non-linear results in three dimensions. The first is related to existing research arguing that the internet might increase coordination between individuals and their networks (e.g. Enikolopov et al. 2019; Manacorda and Tesei 2018). Second, it explores if the threshold behavior is easier to observe in small groups of students, as suggested by Olson's (1965) classic work. Third, it provides an exploration of homophilic influence, i.e. a test for enhanced coordination within networks that are more similar in terms of observables.

To test for enhanced coordination in student networks arising from the internet, I gathered administrative data from the Subsecretary of Telecommunications measuring the number of antennas operating in April of 2011 with their corresponding geographic location. These antennas emit radio electric signals that make connection to the internet possible using mobile phones. In practice, I constructed the number of antennas per 1,000 students in a $1km \times 1km$ gridded dataset spanning the entire country. Then I estimated the baseline specification in two sub-samples, (i) students located in cells without antennas (N =131,691) and, (ii) students located in cells with antennas (N =364,584). Results are presented in Figure 3-D and Figure 4-A. Overall, these estimates reveal that, if anything, students in places without antennas are *more* likely to be influenced by their networks. Although suggestive, this result points towards social influence being more important in the absence of information-communication technologies, perhaps due to a substitution between online and offline network interactions.

As argued in section 3, the maximum influence of networks around 50-60% should be interpreted as the average threshold in Granovetter's model. Consistent with Olson's (1965) theory, panel B in Figure 4 shows that students in smaller networks are more likely to respond to the network's decisions. In contrast, school or city size have smaller impacts on student networks (panels C and D), and students in private and public schools react similarly (panel E).

Potential heterogeneous results by baseline absenteeism are also particularly important. If students with historically low school attendance are reacting more to social effects, then skipping school as a reaction to network absenteeism is more likely to be a pretext to simply skip school instead of a behavior related to the protests. The data, however, suggest this is unlikely to be the case. I estimated the baseline 2SLS specification in two groups: (i) students above the median of school attendance in 2010 (above 94% of attendance), and (ii) students below the median. If anything, estimates in panel F of Figure 4 suggest that students who historically skipped school *less* often ("High" school attendance) are the ones reacting more to social effects.

Does the strength of influence in student networks follows homophily patterns? Figure 5 presents results. Panels A and B test for gender homophily patterns of influence by estimating equation (1), restricting attention to males or females, and splitting the network into males and females. Under the null hypothesis of equal influence we should observe similar coefficients for the male and the female networks. Results, however, indicate strong homophily patterns: same gender influence is more than ten times stronger than cross gender influence. Panels C and D use the same estimation strategy but restrict attention to students with and without internet access, again splitting the network into two: students with and without internet access. The influence of students with internet access on other students with access is almost three times larger. The influence of students without internet access on students also without access is two times larger.[16] Similar patterns of

[16]This is a partial test for the hypothesis of stronger coordination with internet access because students may also

influence arise when restricting attention to the position of students' parents in the income distribution. Panels E and F show that students from low-income households are more influenced by students also from low-income households, and students from high-income households are more influenced by students also from high-income households.[17]

6.4 Discussion of mechanisms

The estimates presented so far constitute, to the best of my knowledge, one of the first empirical evidence supporting critical mass models of collective action in protest behavior. In this sense, my results are important because they suggest that this class of models seems more appropriate than other models as a foundation to understand individual decisions to protest.

What is the mechanism behind the threshold behavior? Although the data prevents me from providing one explanation, the collection of evidence suggests that social effects are likely to be important for at least four reasons. First, the threshold behavior appears in early protests, when the educational cost of skipping school was low, both in terms of absenteeism itself and the likelihood of getting punished by teachers. Early protests were also unlikely to have changed the probability of achieving the desired policy change, i.e. cheaper tertiary education. Second, the similarity of results in places with differential access to the internet suggests *offline* connections were more important than *online* connections. Social effects such as reputation, retaliation, conformity, and reciprocity are arguably more salient in offline relationships. Additionally, the similarity of results across low-income (public) and high-income (private) schools also suggests social effects are likely to be more important than information about the social dimension of the protests. Third, the use of within school variation makes information unlikely to be the explanation since students in the same school are presumably equally informed. And fourth, the threshold behavior is more clearly visible in small networks where social effects are probably stronger.

To improve our understanding of previous estimates, the following section studies the consequences of protests. The motivation is to gain insights about the context in which decisions were taking place during the entire duration of the student movement. Skipping classes without real costs for students nor political consequences would imply that school absenteeism decisions are of minor importance. The next section shows, however, that this protest behavior had educational costs for students, and helped to shift voting patterns in subsequent elections. In this sense, results suggest that these decisions were taking place in a high-stakes environment.

have internet access at school. Manacorda and Tesei (2018) and Enikolopov et al. (2019) provide city-level evidence of stronger network coordination with increased access to cell phones and social media.

[17] High-income households are defined as those with reported annual income higher than US$16,000, low-income households with reported annual income lower than US$5,000, and the remainder is defined as the middle class.

7 Consequences of protests

This section estimates the cost of skipping school in the second half of the 2011 academic year (June through November) and its effects on electoral outcomes.

7.1 The cost of skipping school

An analysis of administrative data for the period 2007–2015 shows that skipping school led to increased grade retention, an outcome causally associated with dropout, lower educational attainment, and more criminal activities (Manacorda, 2012; Díaz et al., 2017). To estimate the change in grade retention among high-school students in 2011, I estimate the following regression:

$$y_{hst} = \beta_t \times (G_{hs} \times T_t) + \zeta_{hs} + \lambda_t + \varepsilon_{hst} \tag{4}$$

where y_{hst} is retention of students in grade h of school s in year t, with h representing either students in 1st-4th grade (non-protesters) or students in 9-12th grade (high-school, i.e. protesters). The indicator G_{hs} is equal to one for grades 9-12th and zero otherwise, T_t is a vector of indicator variables for years $t = 2007, \ldots, 2015$ (with 2010 as the omitted category), ζ_{hs} and λ_t are school-grade and year fixed effects, and ε_{hst} is an error term correlated within schools. An increase in grade retention among high-school students in 2011 translates into $\beta_{2011} > \beta_t$, with $t \neq 2011$.

Figures 6-A and 6-B present coefficients $\widehat{\beta_t}$. Figure 6-A uses absenteeism as dependent variable and Figure 6-B uses grade retention. High-school absenteeism increased by 4.5 percentage points in annual official statistics, a 60 percent increase from a base of 8 percent absenteeism in 2010.[18] Retention among high-school students increased by 3.5 percentage points in 2011, a 60 percent increase from a base of 6 percent in 2010.

Let me now estimate student-level costs using equation (1) and academic performance at the end of the 2011 academic year (December) as dependent variable. The coefficients of interest are again flexible estimates of network absenteeism on June 16. This is a reduced form relationship but network absenteeism on June 16 is highly predictive of the percentage of days of school a student missed in 2011 (slope 0.41, p-value<0.01). Figures 6-C and 6-D present estimates using grade point average (standardized GPA) and an indicator for grade retention as dependent variables. A 100 percent absenteeism in networks on June 16 is associated with (i) a decrease of 0.16 standard deviations in academic performance, and (ii) a 38 percent increase in grade retention (from a base retention of 6 percent in 2010).

[18]This increase in absenteeism needs to be interpreted with caution as both the denominator and the numerator are changing. The central government decreased the total number of official days of school in 2011 (i.e. the denominator).

Finally, consider the same regression but using student-level absenteeism on June 16 as the main independent variable. Students who skipped school that day missed 24 percentage points more days of school in 2011 (p-value<0.01). The estimate suggest that absenteeism in June 16 leads to (i) a decrease of 0.10 standard deviations in GPA (coefficient of -0.07, p-value<0.01), and (ii) a 33 percent increase in grade retention (coefficient of 0.02, p-value<0.01). Results using *annual* school absenteeism as independent variable imply that a one standard deviation increase in absenteeism decreases GPA by 0.15 standard deviations and increases grade retention by 31 percent. Overall, estimates suggest sizable costs of skipping school on protest days.

7.2 The political effects of the student movement

The first election after the rise of the student movement was held on October 2012.[19] In these elections citizens elected mayors in all 345 counties in Chile. Traditional parties, organized into left and right wing coalitions, competed against each other and against candidates from "non-traditional" parties. Although with new leaders and lower participation rates, the student movement was still active and many anticipated it would have an effect on electoral outcomes. The movement showed its discontent with traditional politics and publicly supported non-traditional parties.[20]

Despite its contemporary relevance, there is no research on the impact of the student movement on these elections. To estimate the effect of the student movement in the 2012 local elections, I estimate versions of the following regression equation:

$$V_{c,2012} = \alpha + \beta \cdot \text{Student Movement}_{c,2011} + \gamma V_{c,2008} + \delta X_{c,2009} + \varepsilon_c \tag{5}$$

where $V_{c,2012}$ and $V_{c,2008}$ are electoral outcomes in the 2012 and 2008 local elections in county c and $X_{c,2009}$ is a vector of controls available for 324 counties, i.e. population, average household income, and average years of education. Student Movement$_{c,2011}$ is the county-level average *increase* in high-school absenteeism after the beginning of strikes, calculated as high-school absenteeism between May and November minus high-school absenteeism in March and April. By measuring absenteeism all days after May, I am able to capture absenteeism in schools that were temporarily closed by students. Finally, ε_c is a robust error term. The dependent variables are the vote shares for non-traditional candidates, left and right-wing candidates, the percentage of voters in the county population, number of non-traditional candidates competing, and total number of candidates.[21]

[19] There was an informal plebiscite previously organized by citizens, in October 2011. Figure A.4 shows that participation was higher and people agreed more with students' demands in counties with higher school absenteeism.

[20] One popular election involved the non-traditional (independent) candidate Josefa Errázuriz – explicitly supported by the student movement – competing against the traditional (right-wing) candidate Cristián Labbé, mayor of *Providencia* county between 1996 and 2012. Errázuriz won that election.

[21] Electoral outcomes are administrative data reported by the Electoral Service of Chile. Population data come from censuses. Figure A.12 plots the student movement variable for all counties.

The main concern with an OLS estimation of β is the potential existence of omitted variables correlated with the student movement and electoral outcomes. Three exercises suggest this is unlikely to be a threat. First are regressions controlling for electoral outcomes in previous elections, which captures cross-sectional variation in political preferences. Second are placebo checks using school absenteeism and elections in previous years. Third, I use the method proposed by Altonji et al. (2005) to construct bounds for estimates and conclusions remain.

Table 3 presents estimates. Column 1 indicates that a one standard deviation increase in the intensity of the student movement is associated with a 5 p.p. increase in the vote share for non-traditional candidates, an increase of 15 percent (base of 34 percent in 2008). Columns 2 and 3 show that this increase in vote shares is mostly explained by a decrease in vote shares for right-wing candidates, the coalition of the incumbent president. Column 4 suggests that the same increase in the movement intensity is associated with a decrease of 0.6 percentage points in votes. Column 5 and 6 suggest there were little changes in the number of competitors at these elections.

As placebo checks, I create fake local movements using the increase in county-level school absenteeism between 2008 and 2007, i.e. before the student movement, and examine their impact in the 2008 local elections. I also re-estimate equation (5) using 2008 vote shares as dependent variable and 2004 vote shares as controls. Reassuringly, the "fake movements" do not have an effect on electoral outcomes and the 2011 student movement does not predict 2008 electoral outcomes.

Local elections are a natural setting to use the Altonji et al. (2005) method to study a potential bias due to unobservable variables because past electoral outcomes are powerful predictors of outcomes at the county level. Oster (2019) emphasizes that changes in the r-squared from an uncontrolled to a controlled regression can be used to obtain an adjusted coefficient that accounts for unobservables. This "coefficient stability approach" confirms previous results and suggests the effect of the movement on votes for non-traditional candidates is in the range $[0.050, 0.086]$.[22]

8 Conclusion

Studying the Chilean student movement of 2011, this paper showed that students were influenced by their networks to skip school on a protest day only when a "critical mass" of 50 percent of their networks also skipped school. These results support the popular idea of a tipping point in behavior (Gladwell, 2000) and the importance of strong ties to promote political activism (McAdam, 1986).

The findings in this paper have at least two implications. First, results are relevant for the modeling of collective action in networks. Theoretical work has emphasized that protest partici-

[22]Bounds use $\widehat{\beta} = \beta_c - (\beta_{nc} - \beta_c)\frac{R_{max}-R_c}{R_c-R_{nc}}$, where β_c and β_{nc} are coefficients from a regression with and without controls with corresponding R-squared of R_c and R_{nc}, and R_{max} is an unknown parameter in the interval $[R_c, 1]$. I use the conservative assumption of $R_{max} = 1$. See Oster (2019) for details.

pation may be modeled as a game of strategic complements or strategic substitutes. The "critical mass" type of influence found in this paper suggests that complementarities are relevant for at least some participation levels. Second, complementarities in protest behavior imply that individuals with larger networks are more influential. This corollary is important for both the organization of a social movement and its disruption. For example, imagine a group of individuals organizing a social movement to bring down a dictatorship, as the Otpor! movement in Serbia in the 1990s. My findings suggest that the marginal return of enrolling one additional citizen in the movement is higher for individuals with larger networks. In addition, an organization may exploit the "critical mass" patterns by exerting effort to go beyond the threshold. In the same way, a state could decrease participation in a social movement by preventing central individuals from participating or by exerting effort to avoid reaching a "critical mass."

Two additional remarks are necessary to interpret results more broadly. Firstly, students may be subject to more or less influence from their networks than the non-student population. This is more than a passing concern – after all many important movements have been started by students – the setting may restrict the external validity of results to interpret social movements originating in non-student populations. In the second place, the lack of a precise identification of the mechanisms behind the results may also hinder their external validity. The lack of emphasis on beliefs about the actions of others and the missing dynamics in network structure also prevent us from a full understanding of the decision to participate in a social movement.

Finally, my findings suggest that social dimensions in protest behavior are important, and open new and interesting questions to explore. For example, future empirical studies of social movements may explore how protests create network links among participants and the consequences, how police violence in protests disrupt (or foster) participation, and how habit formation contributes to the escalation of a mobilization.

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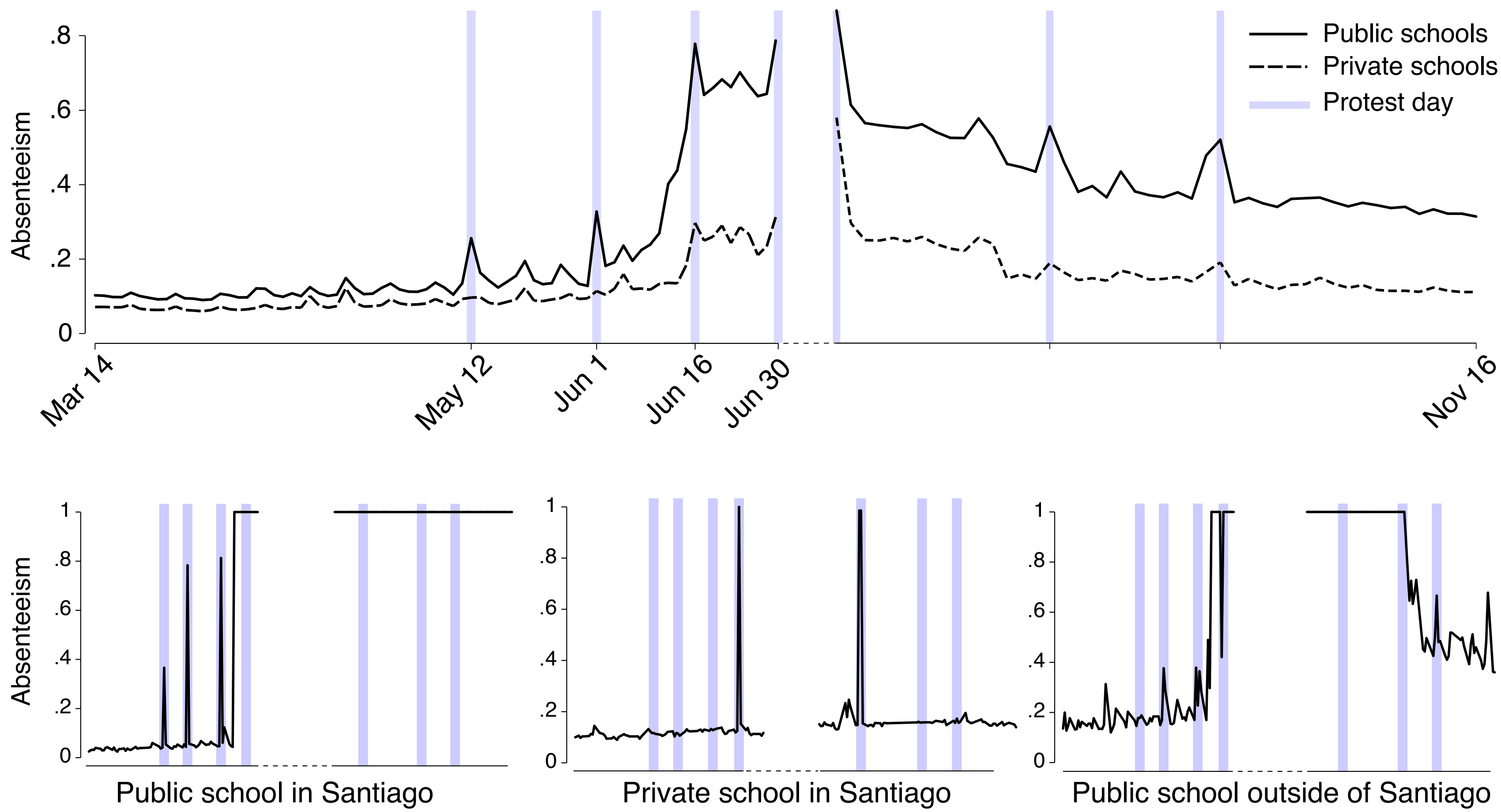
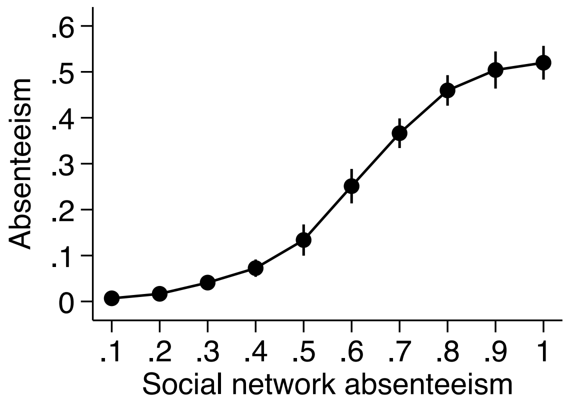
Figure 1: Absenteeism of high-school students in 2011

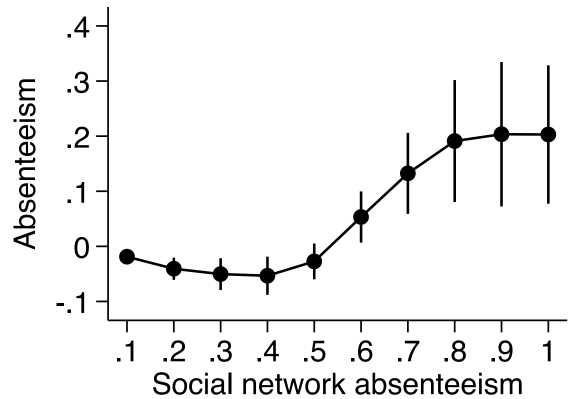


Notes: Own construction using administrative data for all students with school absenteeism data. The *y*-axis is the average school absenteeism among high-school students (in percentages) and the *x*-axis represents days in 2011. Vertical lines denote the most important national protest days during week days (as measured by number of protesters in newspapers). The gap in the center of the figures corresponds to the winter break. More details in section 4.1.

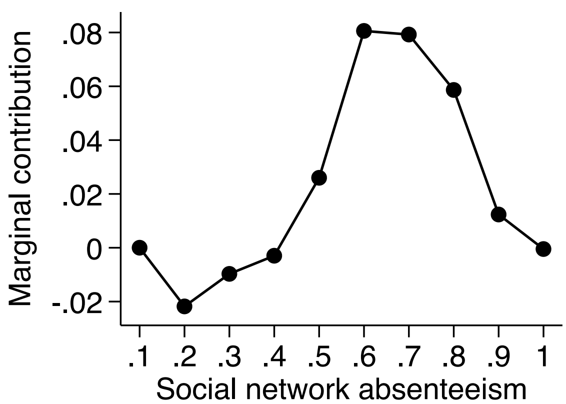
Figure 2: Results for the June 16 massive protest



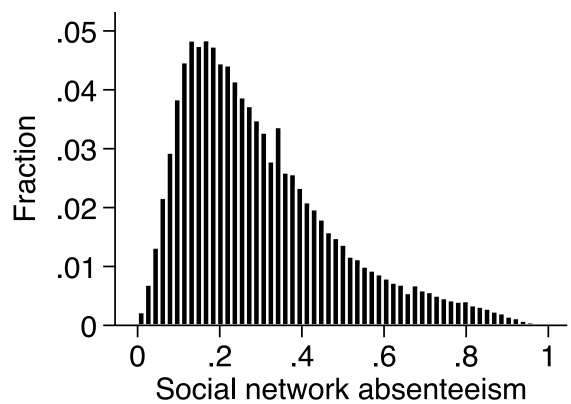
(a) OLS estimates



(b) 2SLS estimates



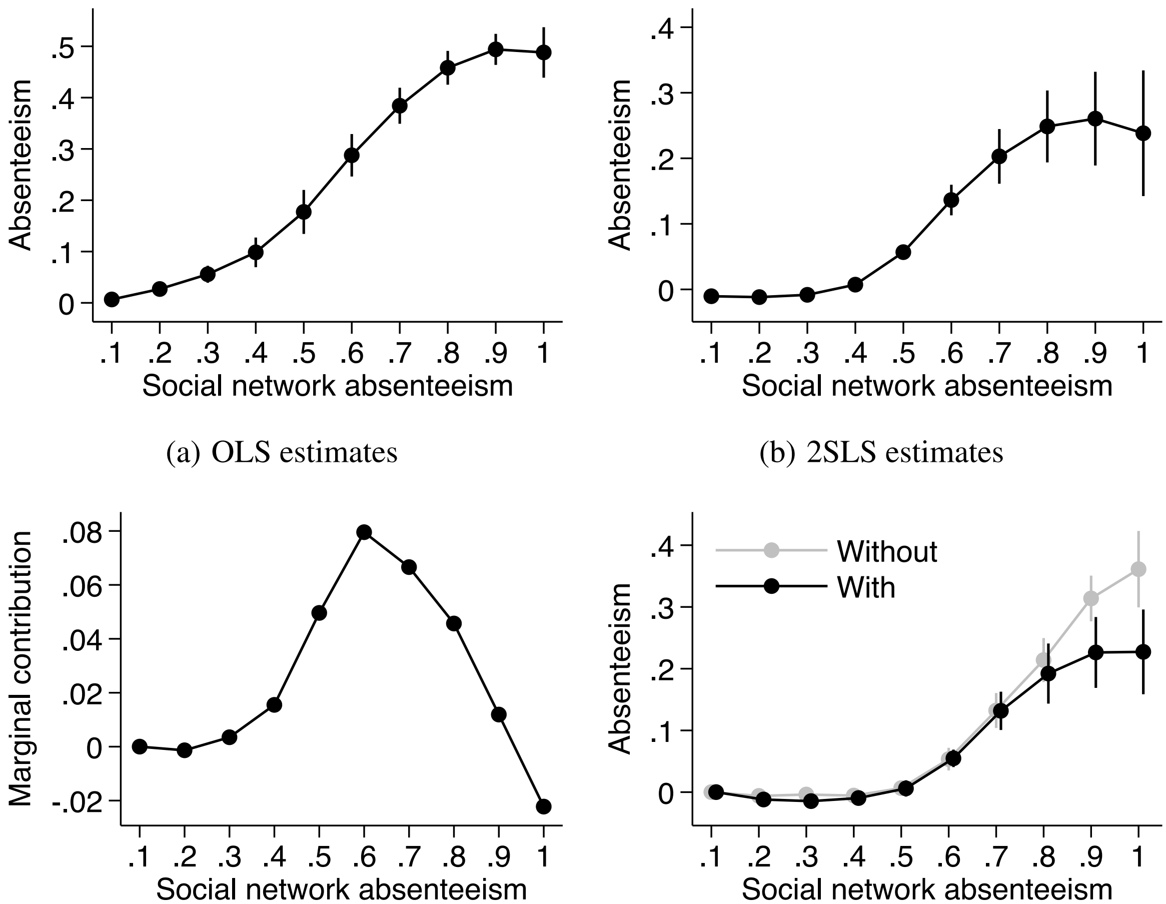
(c) Marginal contribution



(d) Distribution of network absenteeism

Notes: Panels (a) and (b) plot OLS and 2SLS estimates from a regression of individual school absenteeism on 10 indicators of network absenteeism on June 16, controlling for network characteristics and school fixed effects (see equations 1 and 2). Vertical lines denote 95 percent confidence intervals (s.e. clustered at the city level). Panel (c) plots the difference in the estimated 2SLS coefficients in Panel (b). Panel (d) plots the empirical distribution of network absenteeism in June 16. More details in section 6.1.

Figure 3: Panel data estimates using multiple protest days



(a) OLS estimates

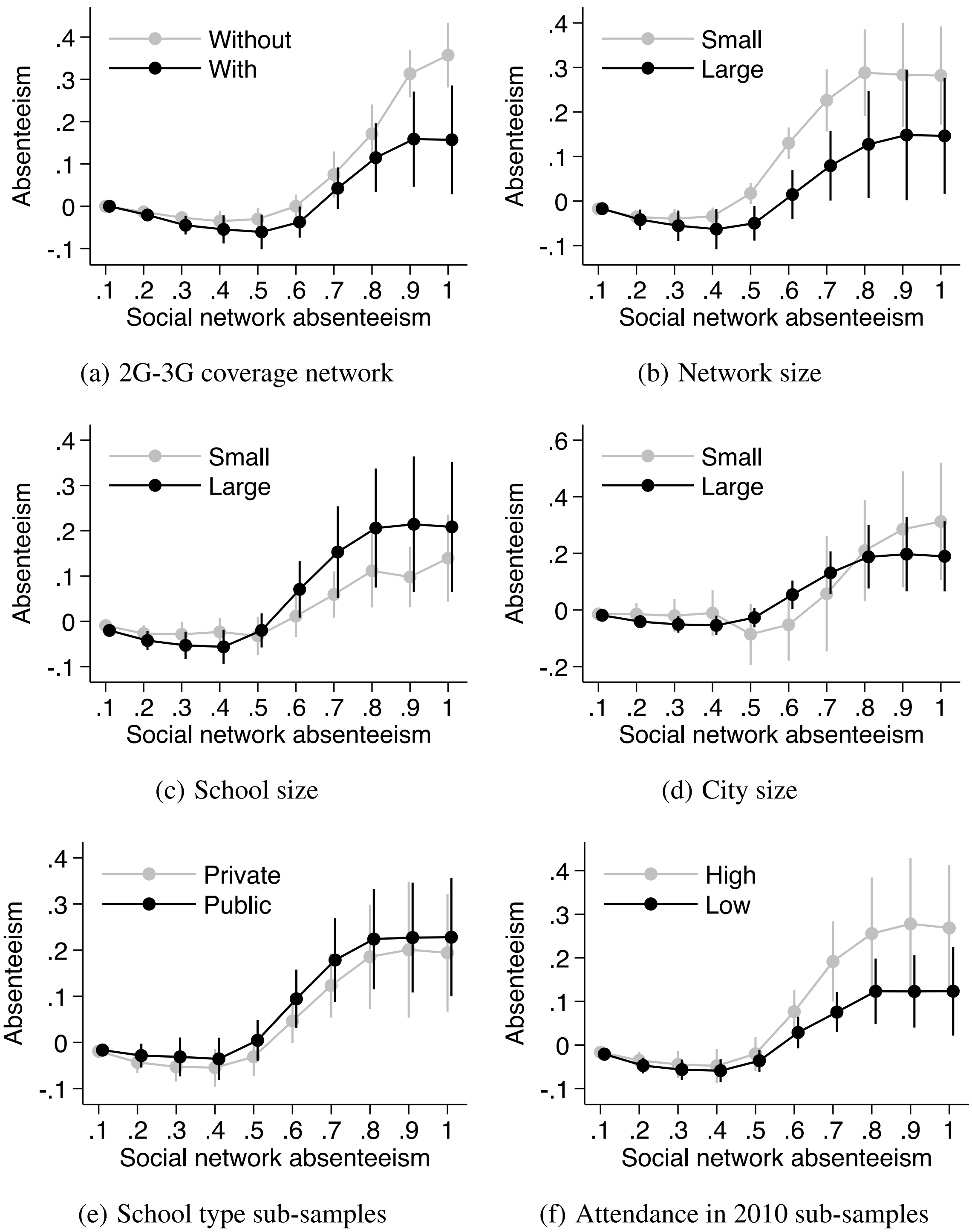
(b) 2SLS estimates

(c) Marginal contribution

(d) 2G-3G coverage network

Notes: These estimates correspond to two-stage control function estimates of network effects in school absenteeism on protest days. The estimating sample includes a panel of students observed daily during protest days in schools that were opened that day (excludes school closures). The total number of observations is 5,140,042. All regressions include student and school-by-day fixed effects. For reference, the analogue linear estimate is 0.10 (s.e. 0.01). Vertical lines denote 95 percent confidence intervals (s.e. clustered at the city level). More details in Section 6.1.

Figure 4: Additional results for the June 16 massive protest



(a) 2G-3G coverage network

(b) Network size

(c) School size

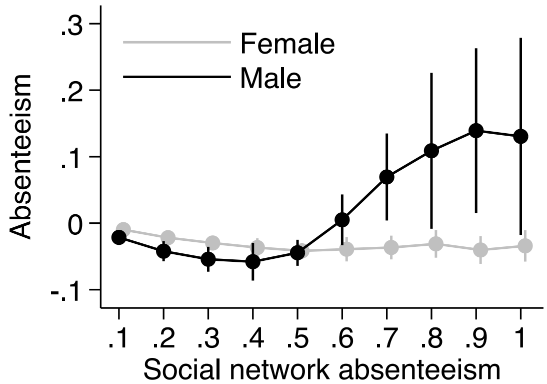
(d) City size

(e) School type sub-samples

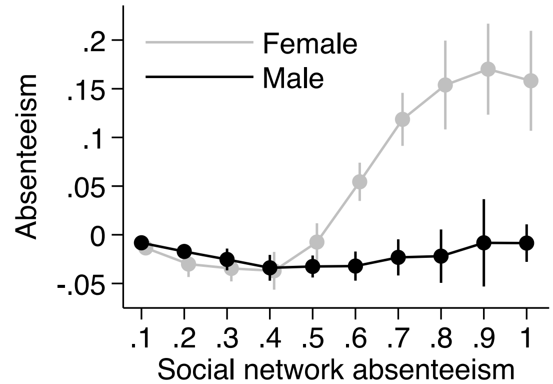
(f) Attendance in 2010 sub-samples

Notes: Panels (a) and (b) plot 2SLS estimates from a regression of individual school absenteeism on 10 indicators of network absenteeism, controlling for student and network characteristics, and school fixed effects (see equations 1 and 2). Panels (c)-(f) present 2SLS estimates in sub-samples. More details in section 6.3.

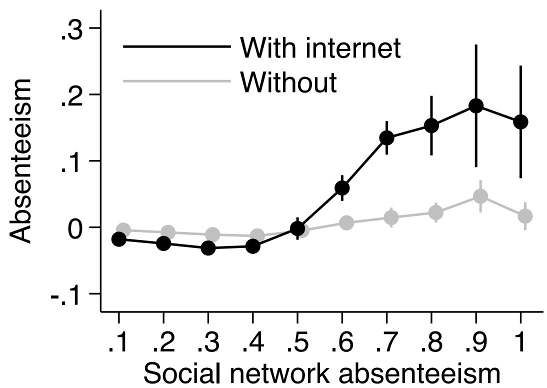
Figure 5: Differential influence within networks



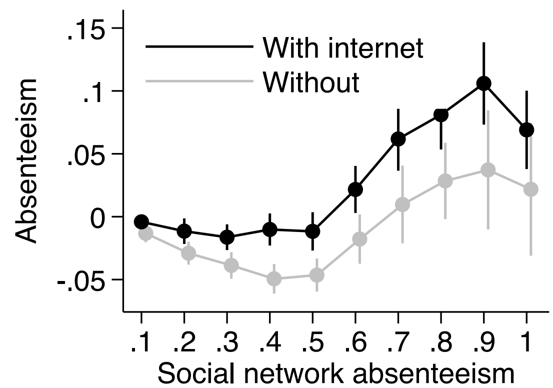
(a) Subsample of males



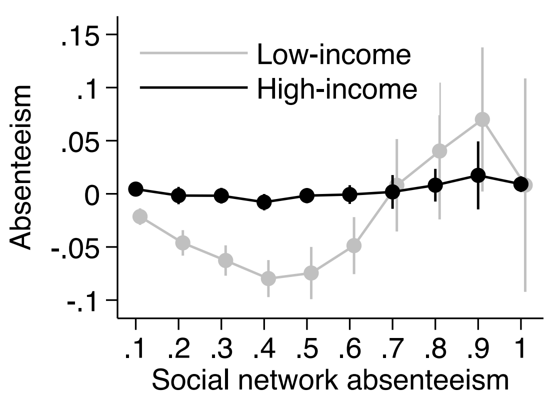
(b) Subsample of females



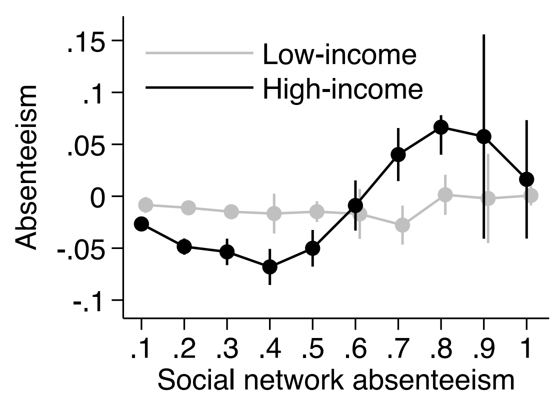
(c) Subsample with internet



(d) Subsample without internet



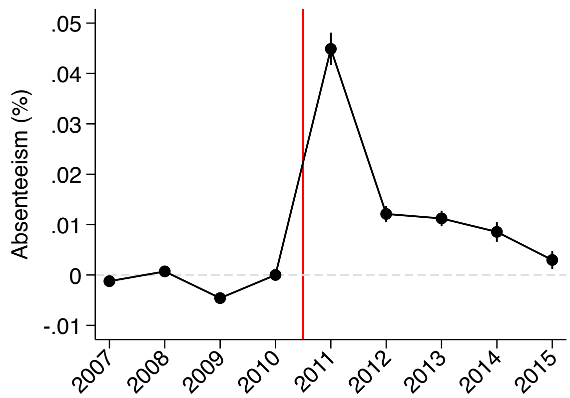
(e) Low-income households



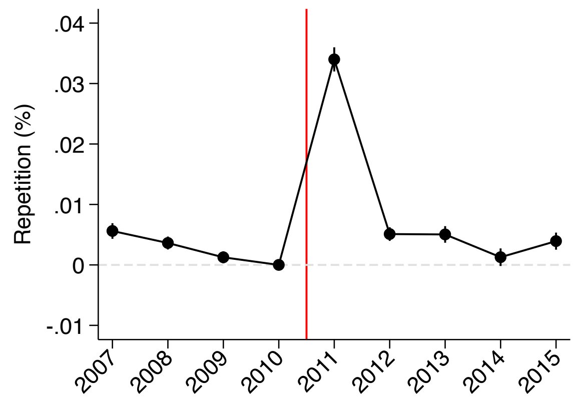
(f) High-income households

Notes: All panels plot 2SLS estimates from a regression of individual school absenteeism on 10 indicators of network absenteeism, controlling for student and network characteristics, and school fixed effects. Regressions are in sub-samples and split the network in groups. More details in Section 6.3.

Figure 6: The cost of skipping school

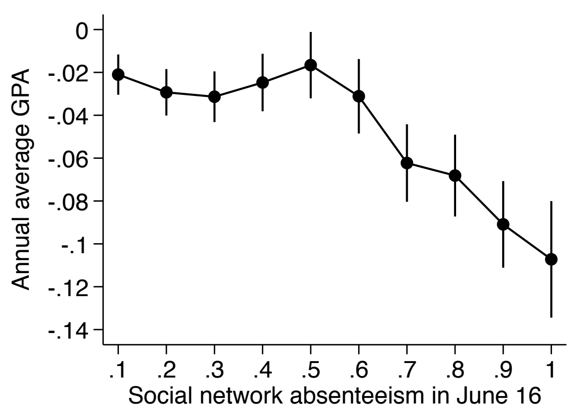


(a) Absenteeism 2002–2015

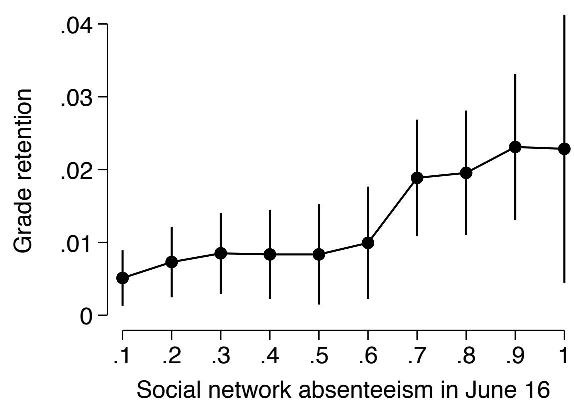


(b) Grade retention 2002–2015

Notes: Panels (a) and (b) plot differences-in-differences estimates of absenteeism/retention rates between high-school students (protesters) and primary students (non-protesters) in the period 2007-2015. Vertical lines denote 95 percent confidence intervals and standard errors are clustered at the school level. The omitted category is 2010. In both figures the *y*-axis is measured in percentage points. More details in section 7.1.



(c) GPA (N =755,874)



(d) Retention ($N = 780,306$)

Notes: Panels (c) and (d) plot OLS estimates from a regression of academic performance on network absenteeism in June 16, controlling for student controls, network controls, and school fixed effects. Vertical lines denote 95 percent confidence intervals and standard errors are clustered at the school level. The *y*-axis in Panel (c) is GPA. The standard deviation of GPA is 0.67. The *y*-axis in Panel (d) is in percentages. More details in section 7.1.

Table 1: Descriptive statistics

Students	Students in high-schools opened in June 16 (1)	Observations (2)	All high-schools (3)	Observations (4)
Absenteeism in May 12, 2011	0.10	500,935	0.15	760,801
	(0.30)		(0.36)	
Absenteeism in June 1, 2011	0.12		0.19	
	(0.32)		(0.39)	
Absenteeism in June 16, 2011	0.21		0.49	
	(0.40)		(0.50)	
Average absenteeism in 2010	0.07		0.07	
	(0.07)		(0.07)	
Schools				
Indicator for public	0.16	1,719	0.30	2,224
	(0.37)		(0.46)	
Number of high-school students	289		342	
	(283)		(345)	
Cities				
High-schools in the city	7.2	240	7.7	290
	(36.9)		(44.3)	
High-school students in the city	2,067		2,623	
	(11,958)		(16,134)	

Notes: Own construction based on administrative data provided by the Ministry of Education. Descriptive statistics for the sample of high-school students enrolled in schools opened in June 16 in column 1, and for all high-schools in column 3. All variables are measured in 2011 unless otherwise stated. More details in section 4.1.

Table 2: Linear estimates

Dependent variable is absenteeism on June 16, first massive protest

	(1)	(2)	(3)	(4)
Panel A – OLS estimates				
Network absenteeism on June 16	0.48***	0.46***	0.44***	0.49***
	(0.06)	(0.06)	(0.06)	(0.06)
	[0.07]	[0.06]	[0.06]	[0.07]
Panel B – 2SLS estimates				
Network absenteeism on June 16	0.26***	0.20***	0.05**	0.09**
	(0.04)	(0.04)	(0.03)	(0.04)
	[0.04]	[0.04]	[0.04]	[0.04]
Panel C – First-stage				
Instrument	0.69***	0.68***	0.68***	0.53***
	(0.05)	(0.05)	(0.05)	(0.04)
	[0.05]	[0.05]	[0.05]	[0.04]
Panel D – Reduced form				
Instrument	0.17***	0.14***	0.04*	0.05**
	(0.03)	(0.03)	(0.02)	(0.02)
	[0.03]	[0.03]	[0.02]	[0.02]
School fixed effects	X	X	X	X
Daily absenteeism before June 16		X	X	X
Student controls			X	X
Network controls				X
Kleibergen-Paap F-statistic	226.6	225.9	211.0	192.0
Mean of dependent variable	0.21	0.21	0.20	0.20
R-squared (Panel A)	0.30	0.33	0.34	0.34
Students	501,139	500,935	500,904	496,275

Notes: "Daily absenteeism before June 16" includes student-level indicators for school absenteeism in May 12 and June 1. "Student controls" include academic performance and average school attendance in previous years and predetermined socioeconomic characteristics. "Network controls" include average student controls at the network level. The instrument is past classmates of 2011 classmates. Standard errors clustered at the city level in parentheses and at the province level in square brackets (240 and 53 clusters respectively). Significance level: *** $p < 0.01$.

Table 3: The political effects of the student movement

Dependent variables are electoral outcomes

	Vote shares					
	Non traditional parties	Left wing	Right wing	Voters in population	Non traditional candidates	Total number of candidates
2012 local elections	(1)	(2)	(3)	(4)	(5)	(6)
Student movement	0.050**	-0.000	-0.044***	-0.006	0.10	0.09
	(0.025)	(0.018)	(0.013)	(0.004)	(0.12)	(0.10)
2008 local elections (placebo I)						
Δ school absenteeism 2008-2007	0.024	-0.028	0.003	0.002	0.39	0.22
	(0.020)	(0.017)	(0.010)	(0.001)	(0.37)	(0.41)
2008 local elections (placebo II)						
Student movement	-0.020	0.001	0.017	-0.002	0.09	-0.15
	(0.021)	(0.016)	(0.017)	(0.002)	(0.48)	(0.55)
Socio-economic controls	X	X	X	X	X	X
Dep. variable in previous election	X	X	X	X	X	X
Mean dep. variable (upper panel)	0.347	0.375	0.278	0.492	1.55	3.36
R-squared	0.23	0.13	0.49	0.88	0.12	0.18
Counties	324	324	324	324	324	324

Notes: Regressions are weighted by the total number of voters in 2008 (upper panel) and 2004 (lower panels). "Student movement" and "Δ school absenteeism 2008-2007" have been standardized to facilitate the interpretation of coefficients. Non-traditional parties correspond to parties that are different from the left-wing and right-wing coalitions. The coefficients for "placebos I and II" come from separate regressions. Robust standard errors are reported in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$.

ONLINE APPENDIX

Collective Action in Networks: Evidence from the Chilean Student Movement

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Table A.1: Additional summary statistics and characteristics of compliers

	Treated compliers	Untreated compliers	Full sample
	(1)	(2)	(3)
Student enrolled in public school in 2011	0.12	0.08	0.21
			(0.41)
Student absenteeism May 12, 2011	0.10	0.06	0.10
			(0.30)
Student absenteeism June 1, 2011	0.12	0.09	0.12
			(0.33)
Student GPA in 2010	5.53	5.44	5.42
			(0.59)
Student retention in 2010	0.05	0.03	0.05
			(0.22)
Student attendance in 2010	92.3	93.8	93.1
			(6.72)
Student gender (female)	0.51	0.51	0.51
			(0.50)
Student age	15.4	15.4	15.7
			(1.27)
Student switched in 2010	0.32	0.18	0.23
			(0.42)
Network GPA in 2010	5.40	5.47	5.40
			(0.25)
Network retention in 2010	0.06	0.06	0.06
			(0.54)
Network attendance in 2010	91.7	93.6	92.9
			(2.26)
Network female in 2010	0.51	0.51	0.51
			(0.18)
Network age in 2010	15.8	14.9	15.7
			(1.1)
Network switcher in 2010	0.79	0.66	0.77
			(0.23)
Students			496,275

Notes: Columns 1 and 2 present the characteristics of compliers using the Abadie et al.'s (2002) method. Column 3 presents summary statistics (mean and standard deviation) for the full sample of students used in the analysis.

Table A.2: Robustness of 2SLS non-linear estimates (I)

Dependent variable is absenteeism on June 16 (columns 1-6) or several protest days (column 7)

	Empirical strategy:						
	Exposure to first protest						Panel data
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social network absenteeism							
$\in [0.10, 0.20)$	-0.00	-0.01***	-0.02***	-0.02***	-0.02***	-0.02***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
$\in [0.20, 0.30)$	-0.01*	-0.02***	-0.04***	-0.04***	-0.04***	-0.04***	-0.01***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
$\in [0.30, 0.40)$	0.00	-0.02**	-0.05***	-0.05***	-0.05***	-0.06***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\in [0.40, 0.50)$	0.02***	-0.01	-0.06***	-0.05***	-0.05***	-0.06***	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
$\in [0.50, 0.60)$	0.07***	0.04***	-0.03***	-0.03*	-0.03*	-0.04**	0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.00)
$\in [0.60, 0.70)$	0.18***	0.13***	0.05***	0.05**	0.05**	0.04*	0.14***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
$\in [0.70, 0.80)$	0.28***	0.23***	0.13***	0.13***	0.13***	0.12***	0.20***
	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.02)
$\in [0.80, 0.90)$	0.35***	0.30***	0.18***	0.19***	0.19***	0.18***	0.25***
	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.03)
$\in [0.90, 1)$	0.39***	0.32***	0.19***	0.20***	0.20***	0.19***	0.26***
	(0.04)	(0.04)	(0.05)	(0.07)	(0.07)	(0.07)	(0.04)
= 100%	0.41***	0.33***	0.19***	0.20***	0.20***	0.18***	0.24***
	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)
School fixed effects	X	X	X	X	X	X	X
Daily absenteeism before June 16		X	X	X	X		
Student controls			X	X	X		X
Network controls				X	X		X
LASSO-chosen controls						X	
Observations	496,275	496,275	496,275	496,275	496,275	496,275	5,133,035

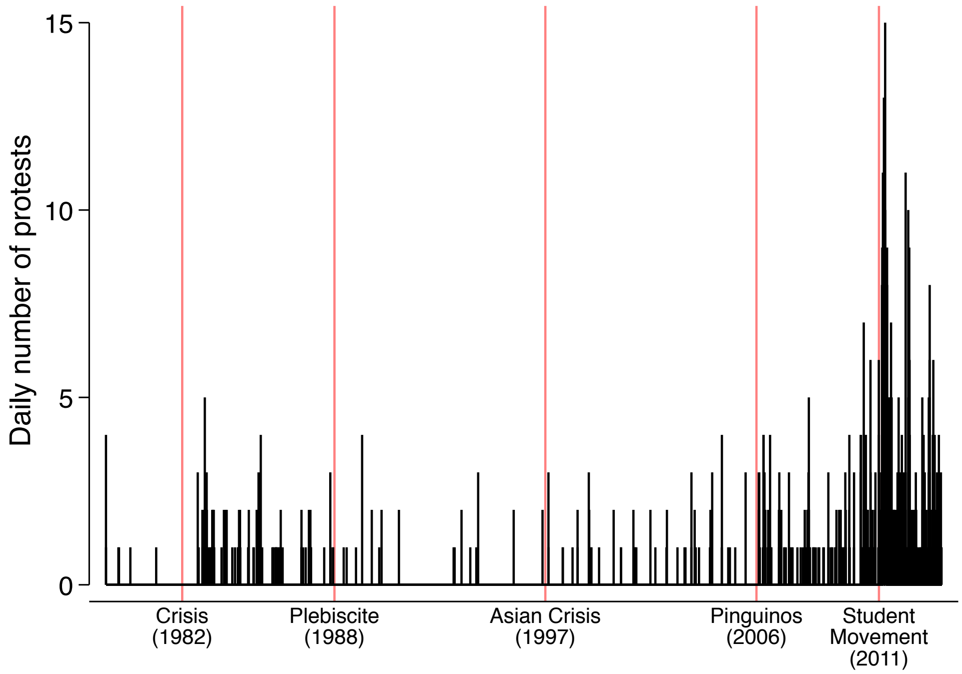
Notes: Each observation corresponds to a student (columns 1-6) or a student-day (column 7). These estimates correspond to two-stage control function estimates of network effects in school absenteeism on June 16, day of the first massive protest, or a protest day (column 7). School, student, and network controls are interacted with protest day fixed effects in column 7. Standard errors clustered by city are reported in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$.

Table A.3: Robustness of 2SLS non-linear estimates (II)

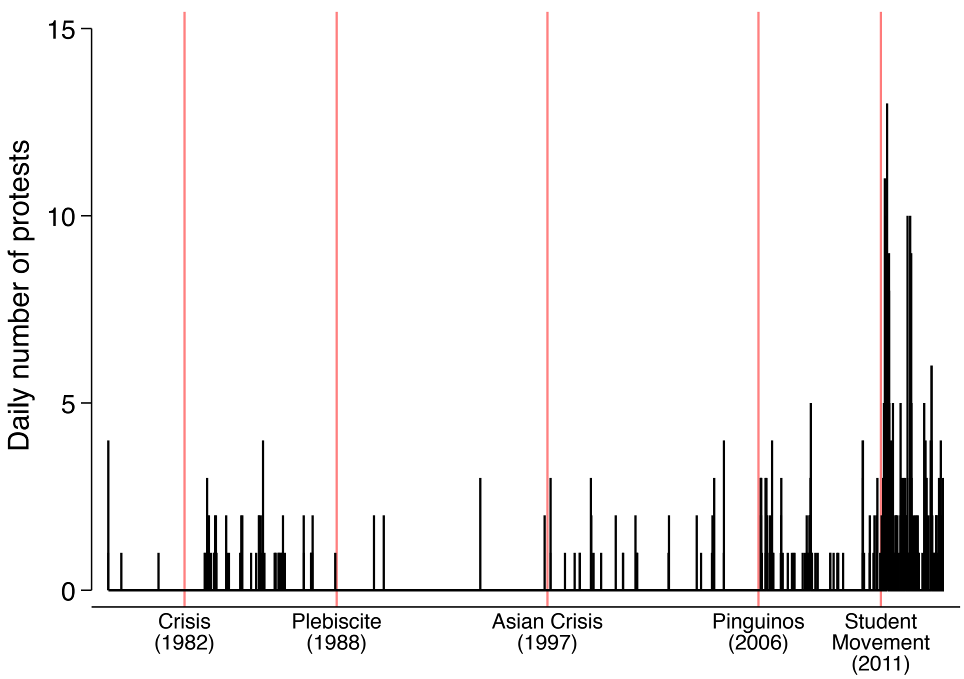
	Splines	
	(1)	(2)
Social network absenteeism	-0.58***	-0.29***
	(0.19)	(0.11)
Social network absenteeism^2	0.99**	-3.06***
	(0.41)	(0.40)
Social network absenteeism^3	-0.08	6.75***
	(0.31)	(0.78)
Social network absenteeism^4		-3.71***
		(0.49)
School fixed effects	X	X
Daily absenteeism before June 16	X	X
Student controls	X	X
Network controls	X	X
Observations	496,275	496,275

Notes: Each observation corresponds to a student. These estimates correspond to two-stage control function estimates of network effects in school absenteeism on June 16, day of the first massive protest. Standard errors clustered by city are reported in parentheses. Significance level: *** $p < 0.01$, ** $p < 0.05$.

Figure A.1: Protests in Chile 1979–2013



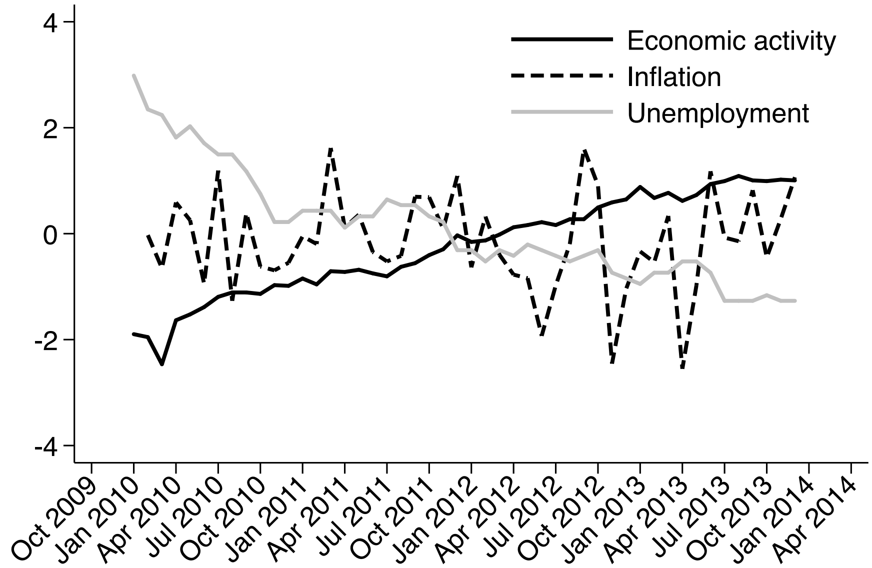
(a) Any type of protest event



(b) Protest events related to education

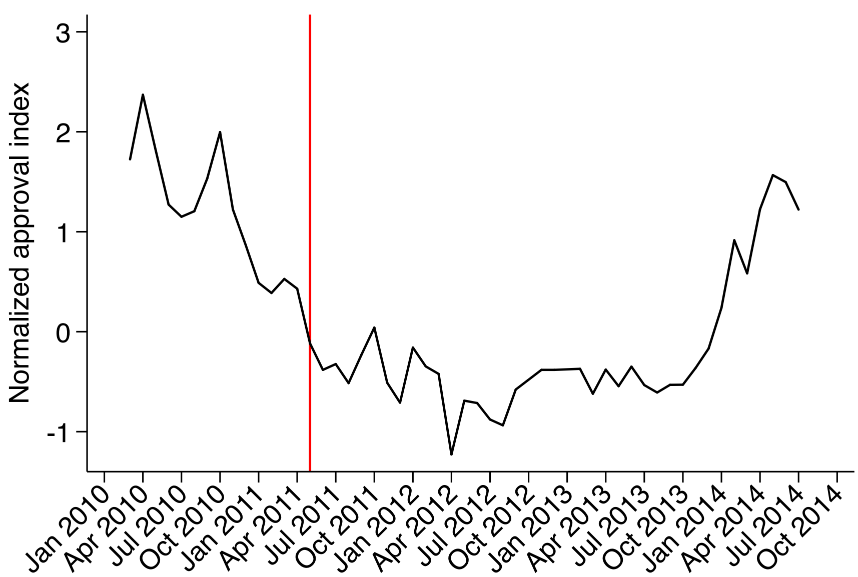
Notes: Data from the Global Dataset of Events, Language, and Tone.

Figure A.2: Economic indicators



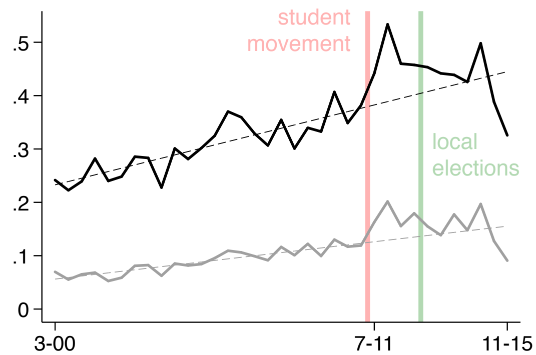
Notes: Data from the Central Bank of Chile. All variables have been normalized by subtracting their average and dividing by their standard deviation in the time series. The vertical red line denotes the beginning of the student movement.

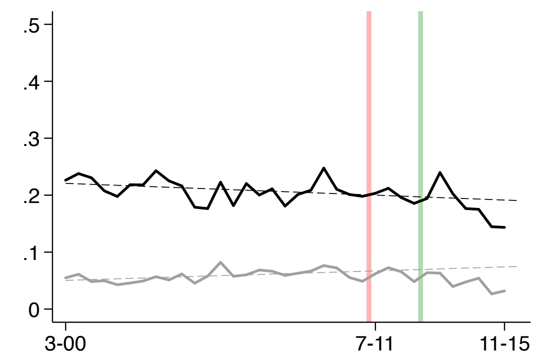
Figure A.3: Citizens' evaluation of incumbent politicians



Notes: Normalized index (minus average and divide by standard deviation) for the approval of incumbent politicians. Data from the Centro de Estudios Públicos and Adimark.

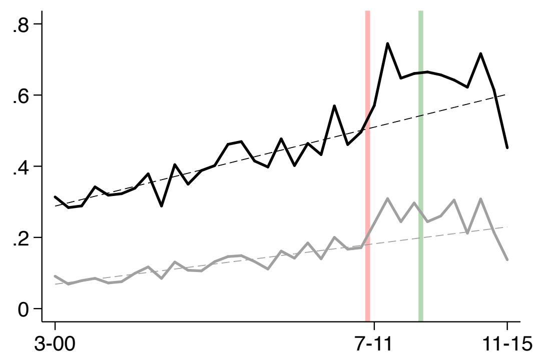
Figure A.4: Survey evidence for the impact of the student movement

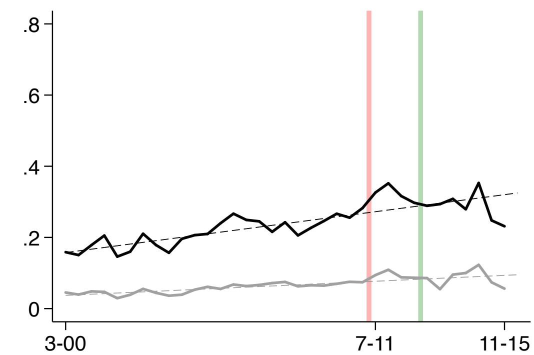




(a) Education should be priority

(b) Placebo

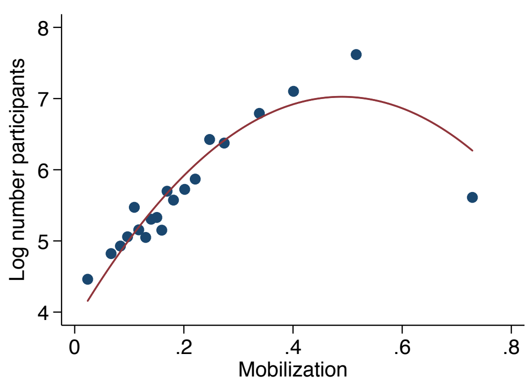


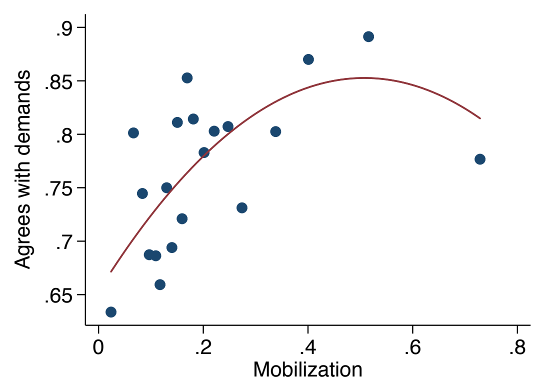


(c) Individuals 18–44 years old

(d) Older than 44 years old

Notes: Panels (a)-(d) plot the percentage of people that answer the question "What should be the government's priority?" with "Education" ("Drugs" in Panel B). The gray line denotes the top 1 priority and the black line the top 3 priority.



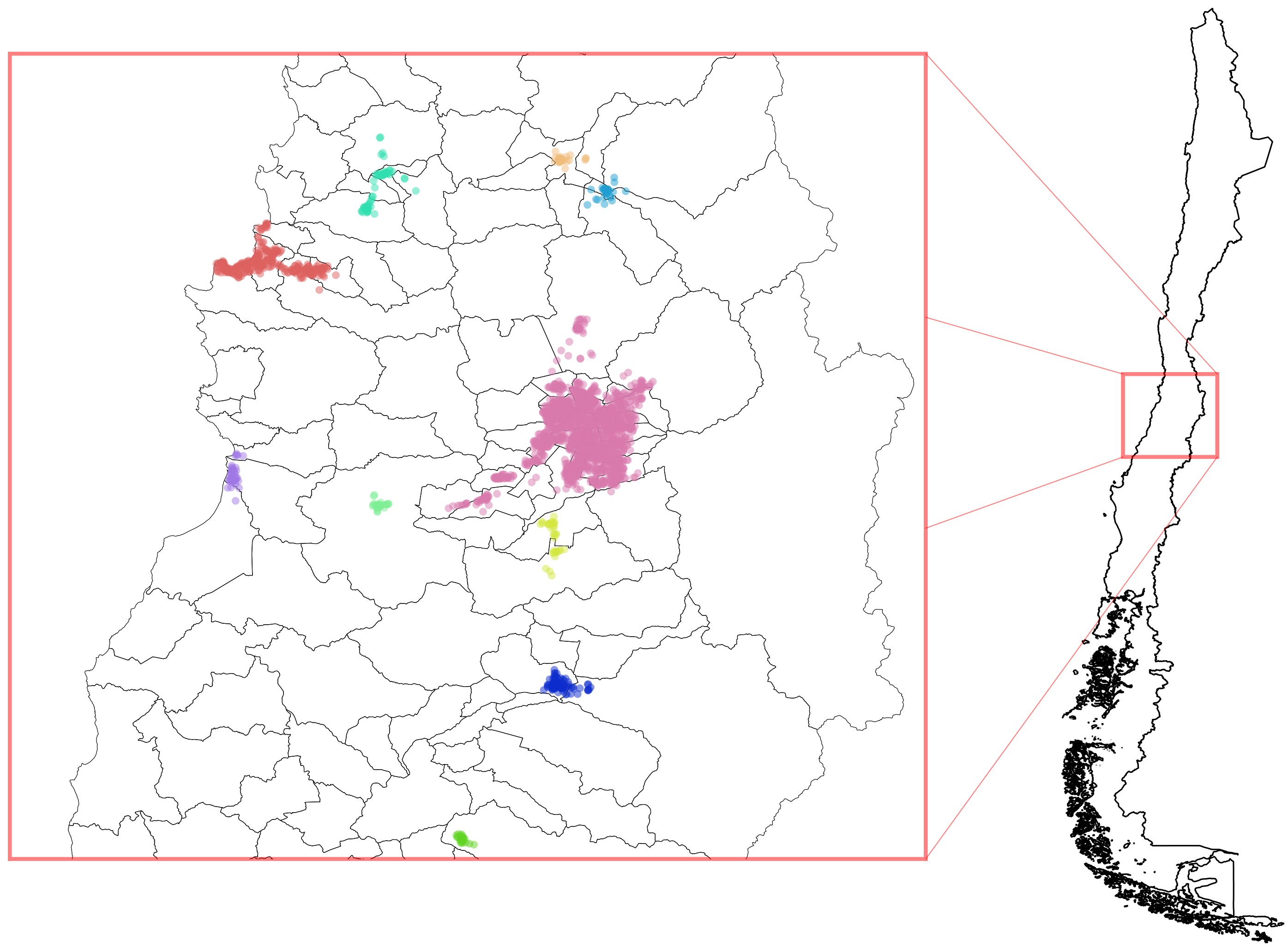


(e) Participation in plebiscite

(f) Agrees with demands

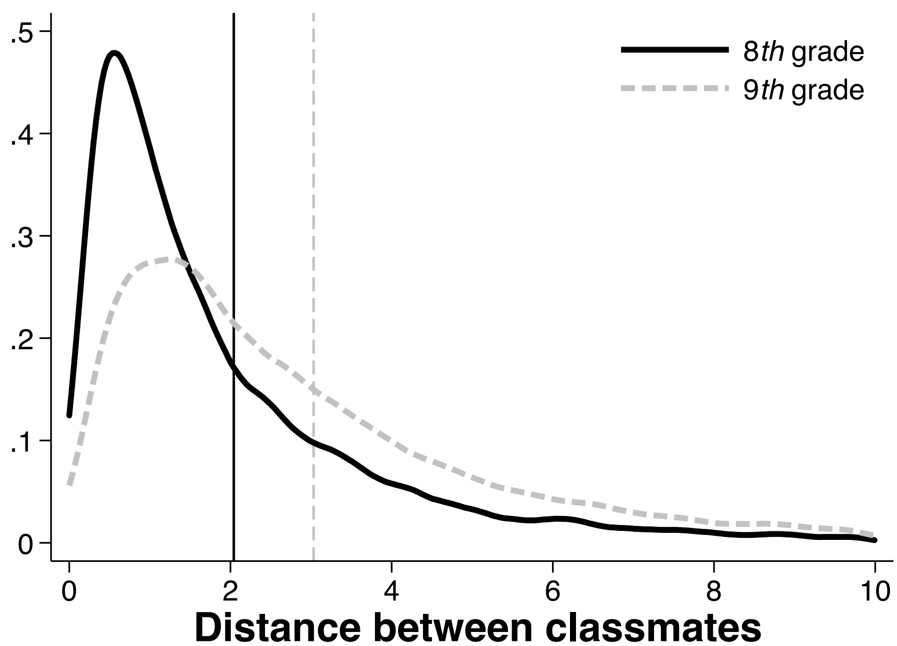
Notes: Panels (e) and (f) plot citizens' participation in the "National plebiscite for education" in October of 2011 at the county level and the percentage of people that agrees with the students' demands among those who participated.

Figure A.5: Cities



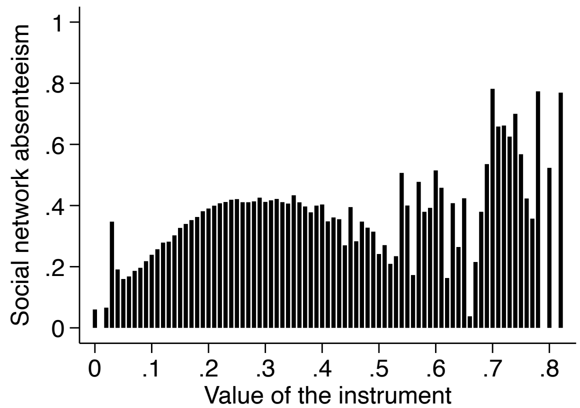
Notes: This map plots the ten largest cities in the most populated area of the country. Cities are defined as closed geographic polygons with schools closer than 5 kilometers.

Figure A.6: Social interactions with past classmates

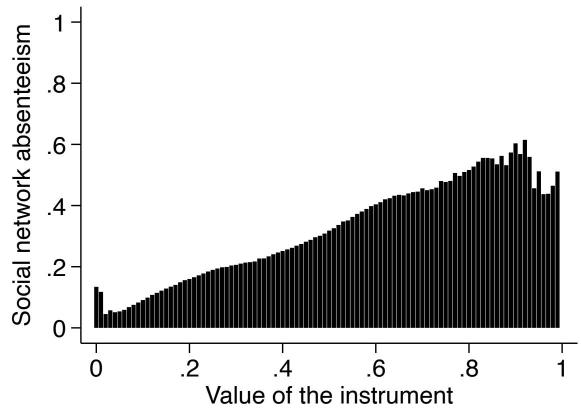


Notes: Distribution of Euclidean distances between the homes of contemporaneous classmates in 8th grade and 9th grade. The *y*-axis measures the density of the distribution and the *x*-axis the distance in kilometers. Each observation corresponds to the average distance between student *i*'s home and the homes of her current classmates. Students' home addresses is administrative data collected by the Ministry of Education. Most students live closer than 1 kilometer from their classmates in 8th grade, implying that they live mostly in the same neighborhood. The average distance between classmates increases by almost 50% from 8th to 9th grade.

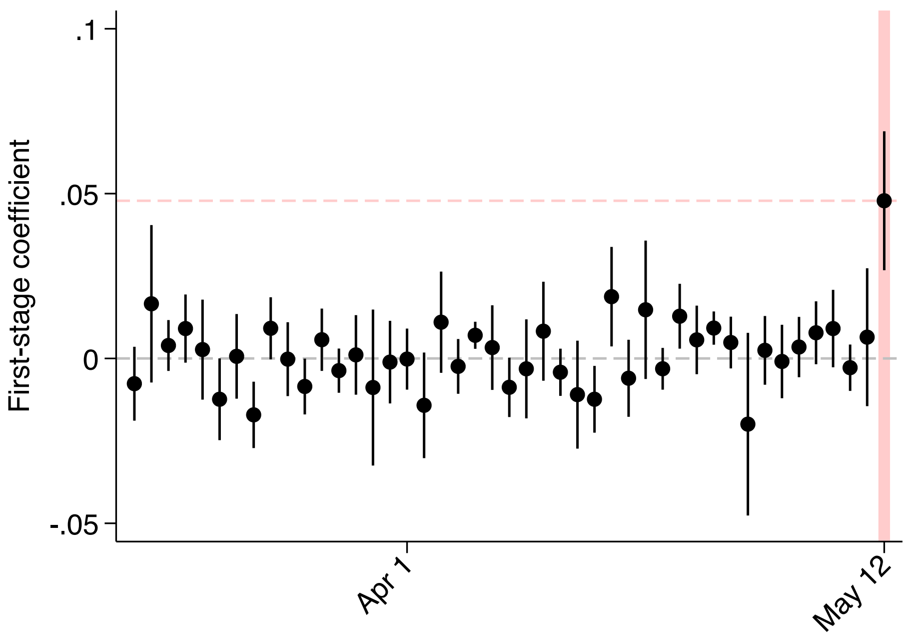
Figure A.7: First-stage



(a) June 16 protest



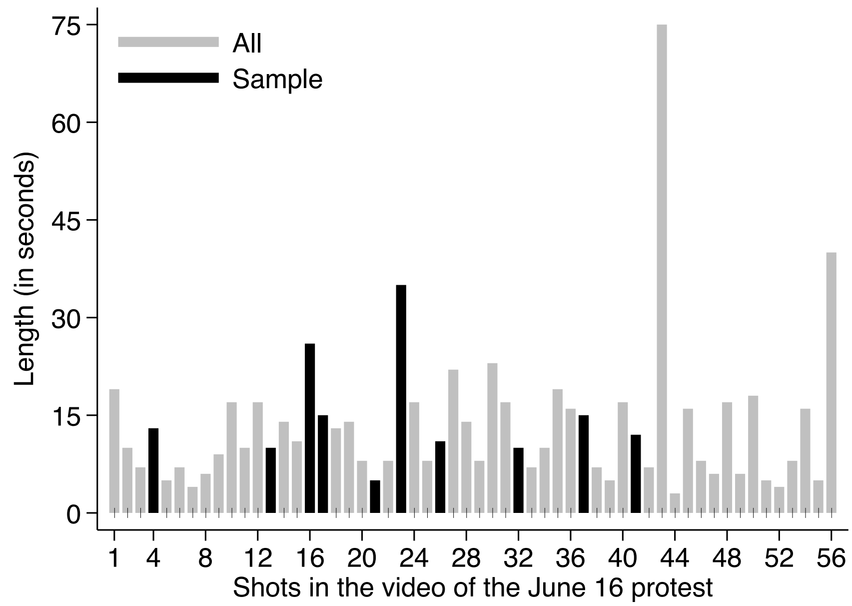
(b) Panel data



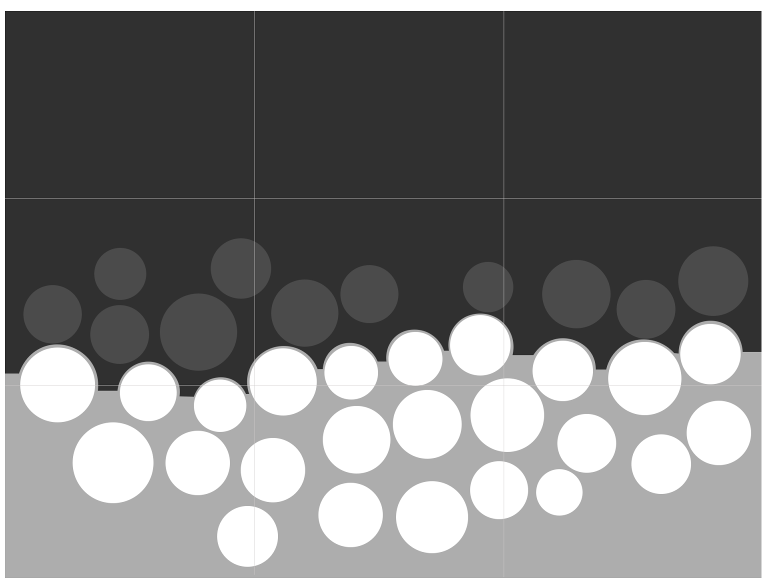
(c) Placebos

Notes: Panels (a) and (b) plot the average social network absenteeism for different values of the instrument in both econometric strategies. Panel (c) plots OLS estimates from a single cross-sectional regression. The dependent variable is June 16 school absenteeism in students' social networks. The figure presents standardized coefficients for absenteeism in May 12 among out-of-school students in the "excluded network." Regression includes student absenteeism in May 12 and June 1, student controls, network controls, school controls, and city fixed effects. Vertical lines denote 95 percent confidence intervals with standard errors clustered at the city level. The coefficient highlighted in red (May 12) corresponds to the first-stage. All other coefficients are placebos for the first-stage. As expected, only 5 percent of coefficients are different from zero before May 12.

Figure A.8: Crowd counting high-school students in the June 16 protest



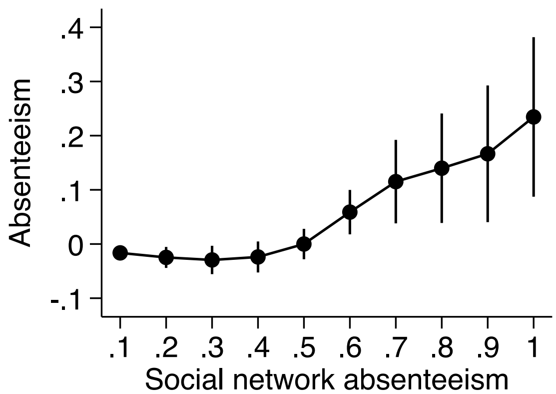
(a) Images in video of the protest



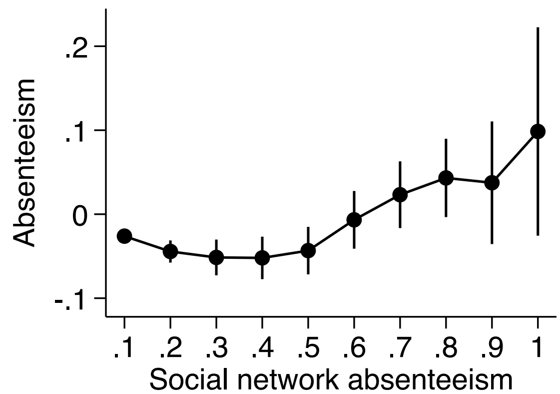
(b) Protocol for crowd-counting

Notes: Panel (a) presents a graphical description of the video of the June 16 rally. The video is composed by 56 shots (*x*-axis) of varying length (*y*-axis, from less than 5 to 75 seconds). Black bars represent the location of the images we use as a sample. Panel (b) shows the sketch of an image, where a crowd is identifiable in the front, and a non-identifiable crowd is located in the back. We asked 100 university students to count the number of high-school students in the front of the image using an economic incentive to do it right. High-schoolers were counted in a total of 520 images.

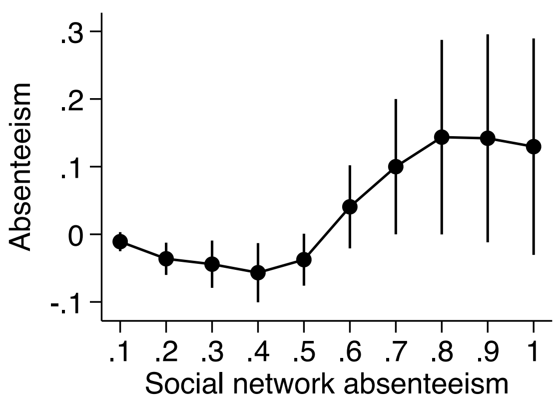
Figure A.9: Threshold model in sub-samples



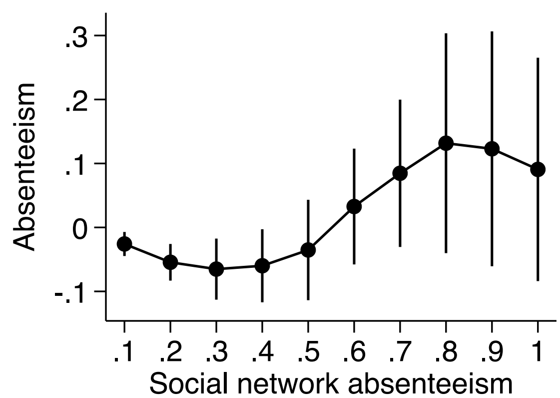
(a) Students in 1st year of high-school



(b) Students in 2nd year of high-school



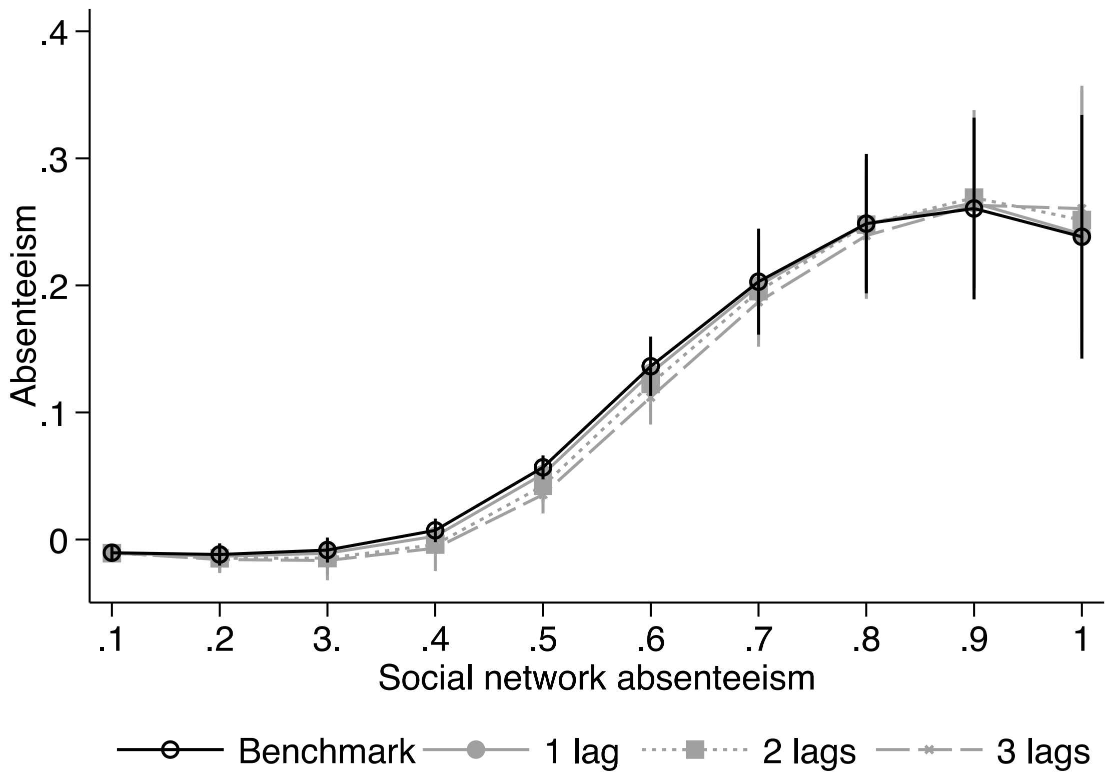
(c) Students in 3rd year of high-school



(d) Students in 4th year of high-school

Notes: All panels plot 2SLS estimates from a regression of individual school absenteeism on 10 indicators of network absenteeism, controlling for student and network characteristics, and school fixed effects in sub-samples.

Figure A.10: Panel data specification with lags



Notes: This figure presents β estimates of the following 4 specifications:

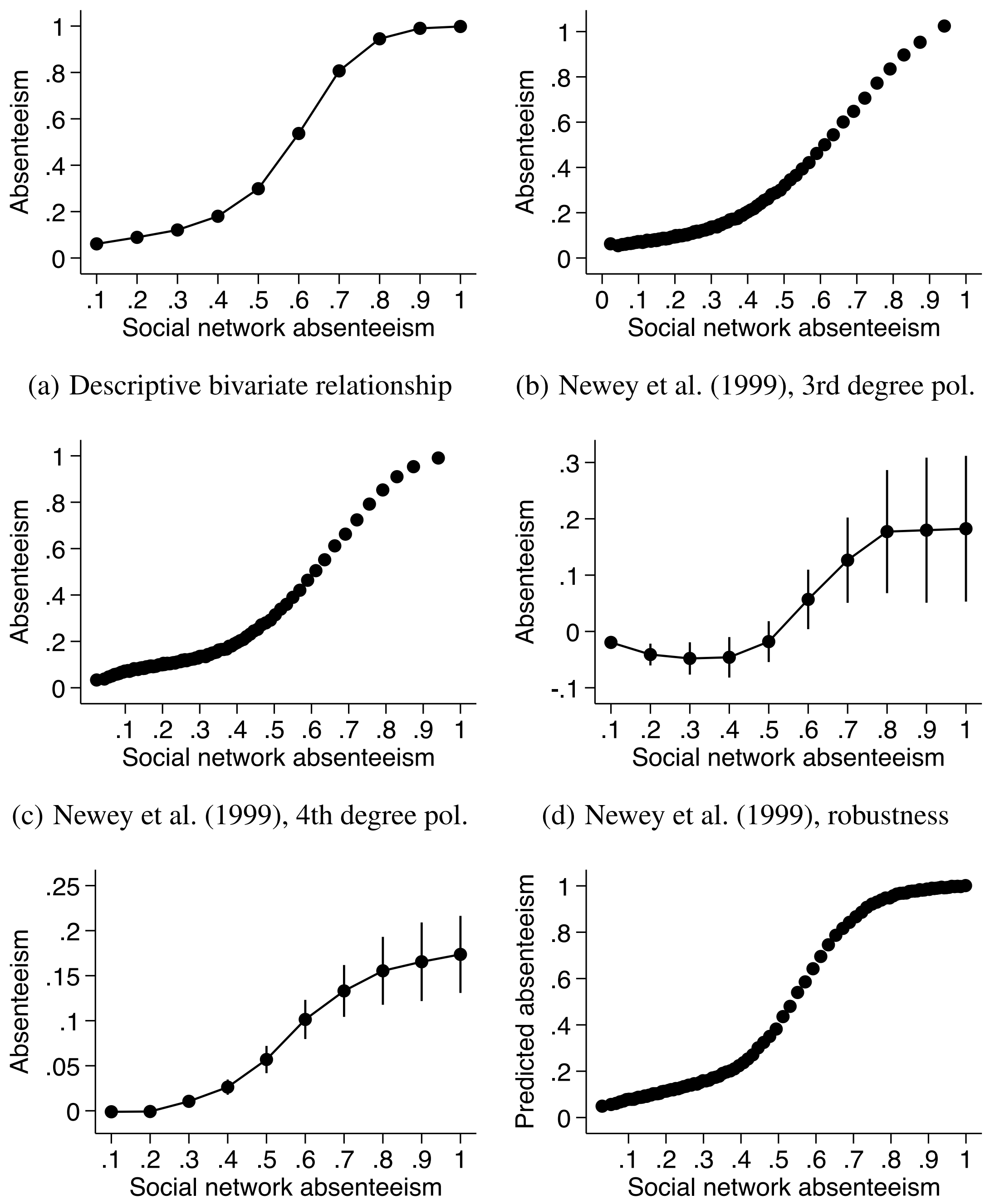
$$
\begin{aligned}
A_{isct} &= f(A_{j(i)t}) + \xi_i + \zeta_{ct} + \epsilon_{isct} \\
A_{isct} &= f(A_{j(i)t}) + A_{isc,t-1} + A_{j(i),t-1} + \xi_i + \zeta_{ct} + \epsilon_{isct} \\
A_{isct} &= f(A_{j(i)t}) + A_{isc,t-1} + A_{isc,t-2} + A_{j(i),t-1} + A_{j(i),t-2} + \xi_i + \zeta_{ct} + \epsilon_{isct} \\
A_{isct} &= f(A_{j(i)t}) + A_{isc,t-1} + A_{isc,t-2} + A_{isc,t-3} + A_{j(i),t-1} + A_{j(i),t-2} + A_{j(i),t-3} + \xi_i + \zeta_{ct} + \epsilon_{isct}
\end{aligned}
$$

where A_{isct} is an indicator that takes the value of one if student i, who attends school s, located in city c, is absent from school in day t. Similarly $A_{j(i),t} \in [0, 1]$ is the percentage of students in i's social network who are absent from school in day t. Finally, the β estimates come from the following parameterization of $f(\cdot)$:

$$
f(A_{j(i)}) = \beta_1 \cdot 1\left[\overline{A}_{j(i)} \in [0.1, 0.2)\right] + \cdots + \beta_9 \cdot 1\left[\overline{A}_{j(i)} \in [0.9, 1)\right] + \beta_{10} \cdot 1\left[\overline{A}_{j(i)} = 1\right]
$$

where $1[\cdot]$ is an indicator function that takes the value of one when the statement within square brackets is true.

Figure A.11: Robustness of results to estimation method



(a) Descriptive bivariate relationship

(b) Newey et al. (1999), 3rd degree pol.

(c) Newey et al. (1999), 4th degree pol.

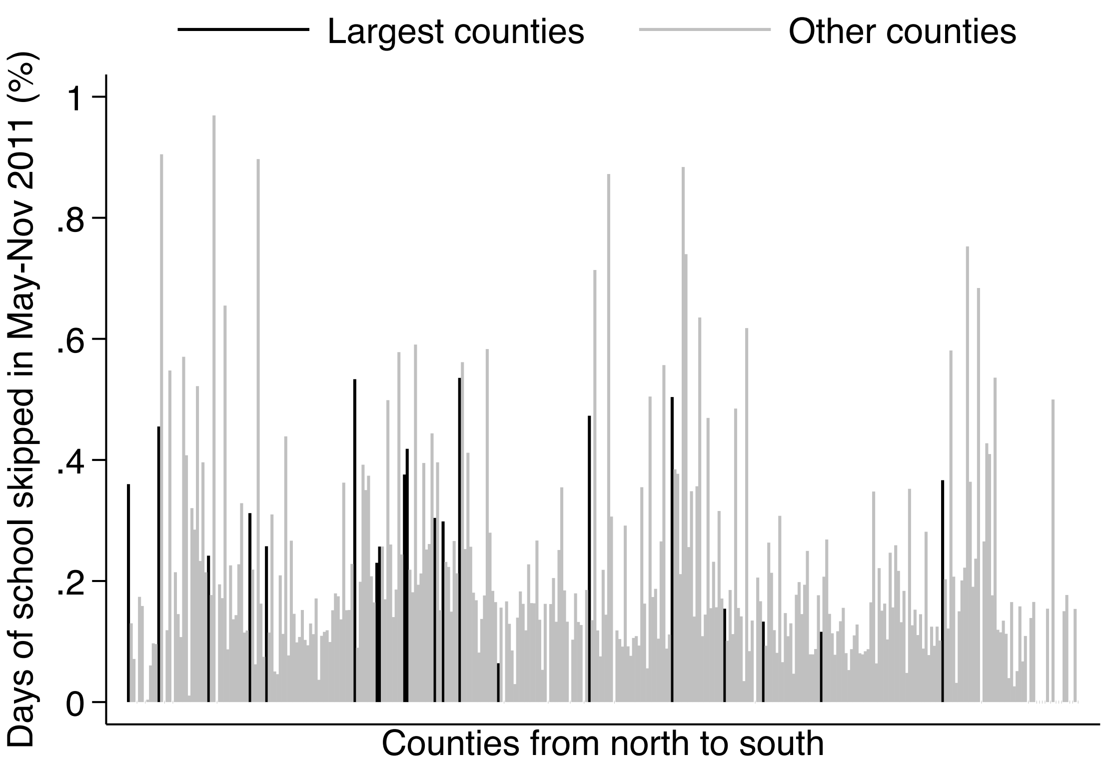
(d) Newey et al. (1999), robustness

(e) Rau (2013)

(f) Newey and Powell (2003)

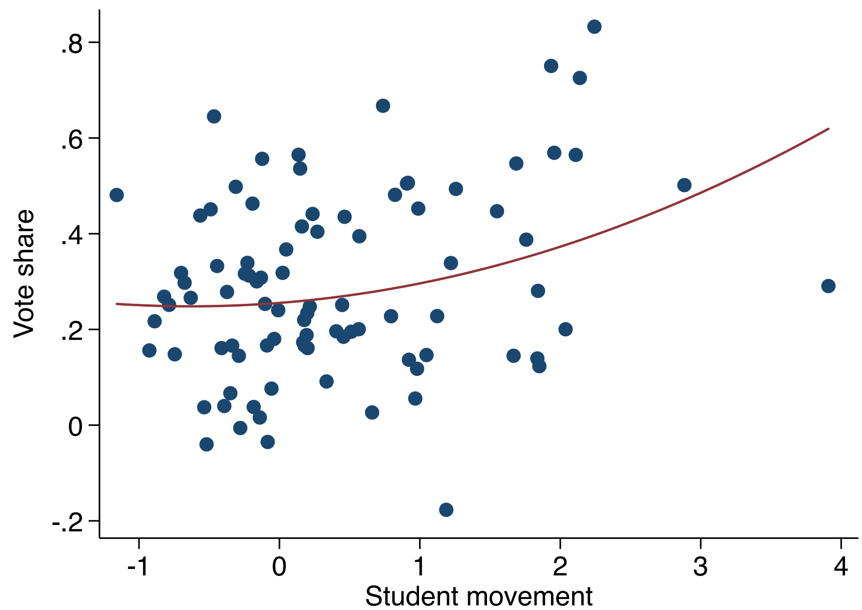
Notes: Each panel presents estimation results from an alternative nonparametric instrumental variables estimation. The exception is panel (a) in which the descriptive bivariate relationship between individual absenteeism and social network absenteeism is plotted. Panels (b), (c), and (f) present predicted values of individual absenteeism, and panels (d) and (e) present regression coefficients associated to indicators of social network absenteeism. More details in section 6.2.

Figure A.12: The intensity of the student movement by county

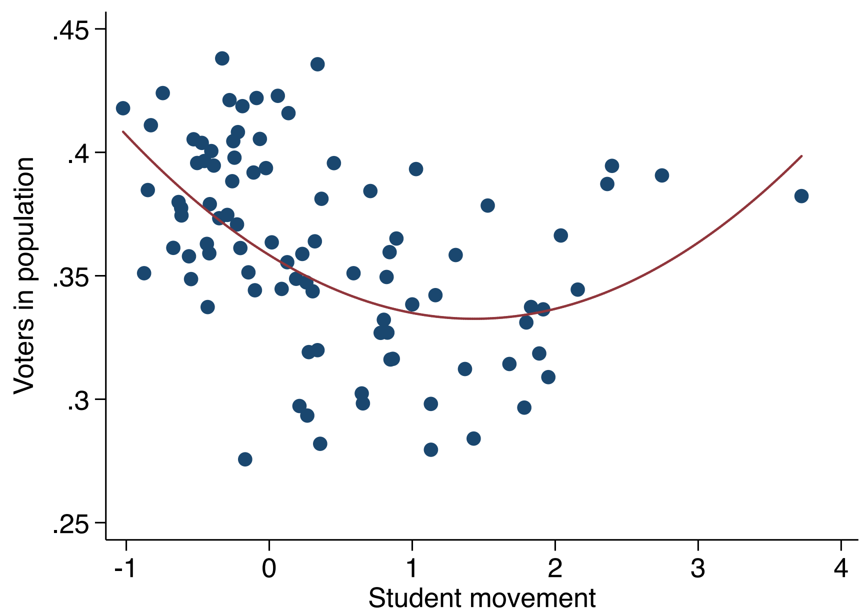


Notes: Own construction based on administrative data. Counties are ordered from north to south in the *x*-axis. The *y*-axis is defined as the percentage of additional days that high-school students skipped school between May and November 2011. There are 324 (out of 346) counties with non-zero intensity. "Large counties" are defined as counties with more than 10,000 students.

Figure A.13: The student movement and the 2012 local elections



(a) Vote share for non-traditional candidates



(b) Voters in population

Notes: This figure presents binned scatter plots and the quadratic fit of electoral outcomes in the 2012 elections (*y*-axis) on the intensity of the student movement in 2011 (*x*-axis, standardized). There are 345 counties in the country.