Understanding Peer Effects in Educational Decisions: Evidence from Theory and a Field Experiment

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Abstract

While a large literature documents the presence of peer effects in teenage decision-making, researchers know very little about the underlying mechanisms. In this paper, I focus on the decision by high school students to participate in an educational program. I develop a theoretical model based on Brock and Durlauf (2001) with two channels of peer effects: *social learning* (where a peer's decision is informative about the value of a program) and *social utility* (where a peer's participation directly changes the benefits or costs of a program). I conduct a field experiment in three Chicago high schools to disentangle the two channels. In the experiment, I measure students' sign-up rates for a college application assistance program where I randomize (a) whether a student sees a peer's decision, and (b) which type of peer's decision they see. I find large peer effects in the participation decision that are entirely driven by seeing a peer choose not to participate – seeing a peer choose "No" decreases the sign-up rate by 26.9 percentage points. The peer effects are driven by social utility, and seeing a peer choose "No" informs students about the social norms of participation. In this context, smart students' decisions are especially influential. Further, while students want to conform to the social norm, they have very biased beliefs about (they drastically underestimate) their peers' participation. I estimate my model and combine the structural estimates with collected school social network data to run a policy counterfactual. I find that when there are negative peer effects and costly initial adoption, programs targeting smart students may have lower sign-up rates compared to programs targeting highest need students.

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1 Introduction

Teenagers make many educational decisions with lifelong consequences. At the same time, the research shows that they are highly susceptible to peer effects: they make the same choices as their peers do in contexts that range from drug use and crime to academic effort and college choices.[1] Since the influential Coleman Report (1966), researchers have questioned whether peers lead fellow teenagers to an inefficient investment in human capital. The answer to this question has important implications for neighborhood sorting and school choice. While a large literature documents the presence of peer effects in teenage decision-making, researchers know very little about the underlying mechanisms.

I use a field experiment to disentangle two channels of peer effects: social learning and social utility. I do so in the context of high school students' decisions to participate in an educational program. I model the student's participation decision as comprising of a private benefit from attending the program (absent of any social considerations) and a social benefit that depends on her beliefs about her peers' participation. In my model, students have uncertainty about both their private benefit and their peers' participation. Seeing a peer's decision influences a student in two ways: *social learning* occurs if her peer's decision informs the student about her private benefit. In contrast, *social utility* occurs if her peer's decision directly changes the social benefits or costs to the student of attending the program. I further disentangle two subchannels of social utility: she may want to participate together with peers (*consumption externalities*), or she may not want to deviate from what her peers do (*social norms*).

Disentangling social learning and components of social utility is important for policy reasons. While the two channels may seemingly lead to the same peer effect, they lead to different policy implications when maximizing students' participation in a program. If social learning is the dominant peer effect channel, then we would want to subsidize information about the program to students. However, if social utility is the dominant peer effect channel, then we would want to subsidize participation instead.[2] Additionally, there may be heterogeneous effects of social learning and social utility if students learn from or want to participate with specific types of peers.

This paper asks two research questions: (1) Are there peer effects in the decision to participate in educational programs for high school students? And (2) if so, are the peer effects driven by social learning

[1] See, for example: Gaviria and Raphael (2001), Case and Katz (1991), and Argys and Rees (2008), for peer effects in teenagers' alcohol and drug use, criminal behavior, teenage pregnancy, and delinquency. Stinebrickner and Stinebrickner (2006) show peer effects in the hours of study in college, and Goodman et al. (2015) show peer effects in the college choices of siblings.

[2] For example, recent interventions aimed at helping low-income students apply to college have used different dissemination methods. One type targets individual students using mailings to inform students about colleges and the college application process (see, e.g., Hoxby and Turner (2013)). Another type is embodied by the Posse Scholars program, which targets groups of students to apply to college together. Finally, a third type is embodied by the PeerForward program, which helps student role models lead school wide campaigns to increase college applications. The latter two programs have received much funding, including a portion of President Obama's Nobel Peace Prize award money.

or social utility?

To answer these two questions, I conduct a field experiment in three low-income high schools in the Chicago suburbs. The experiment consists of two parts: first, I administer a survey to collect data on the schools' social network. I use the survey to classify students into "smart" students, "popular" students, academically similar students, and friends. Second, I measure student sign-up rates for a college application assistance program, and use a sequential sign-up procedure to exogenously reveal to students their peers' decisions. I conduct sign-up in all classrooms at the same time to shut down communication between students. In each classroom, I randomize at the student level (a) whether a student is revealed one classmate's decision immediately before making her own sign-up decision, and (b) which type of peer's decision she sees. Before and after the sign-up decision, I also collect data on students' prior and posterior values of the program and beliefs about their peers' participation. I use a combination of experimental treatments and data collected on students' beliefs to disentangle the peer effect channels.

I find two main results. First, there are large peer effects in the decision to participate in an educational program. Interestingly, the peer effects are driven entirely by "No" decisions. Compared to a baseline (control group) sign-up rate of 80.7 percent, seeing that a peer chooses "Yes" to sign-up does not change the sign-up rate, but seeing that a peer chooses "No" decreases the sign-up rate by 26.9 percentage points ($p<0.01$).

Second, I find that the dominant peer effect channel is social utility, and not social learning. I start by testing whether students want to participate with their peers (consumption externalities). To do so, I have two treatments that randomize whether students are able to participate in the same program group as the peer whose decision they see. The two treatments vary by only one word and inform students whether they will be participating in the program with students in their current class (in which the sign-up is conducted) or with students in other classes. In the latter case, students can still learn about the value of the program and about social norms from their peer's decision, but cannot experience any consumption externalities from participating with their peer. I do not find strong evidence for consumption externalities — there is no difference in sign-up rates between the two treatments, which suggests that students do not care about participating with any specific peer in the program.

To disentangle social learning and the remaining social utility channel, social norms, I next look at whether seeing a peer's decision changes students' values of the program, or their beliefs about their peers' participation. I find that the peer effect is driven entirely by changing students' beliefs about their peers' participation. Students update their beliefs about peers' participation according to the information they receive. Seeing that a peer chooses "Yes" causes students to think that their classmates are 5.8 percentage points more likely to sign-up for the program ($p<0.05$), and seeing that a peer chooses "No" causes students to think that their classmates are 11.5 percentage points less likely to sign-up ($p<0.01$). In contrast, seeing a peer's decision does not change students' values of the program (measured using willingness to pay, WTP). Because students' beliefs about peers' participation only enter the social benefit terms in my model, and not the private benefit term, this finding suggests that the peer effect operates through informing students about the social norms of participation.

To further understand how social utility affects students' decisions to participate in an educational program, I look at which types of students are influential in the social network. Understanding this heterogeneity in peer effects is important because it sheds light on which types of students to target to maximize participation in a program. I find that smart students' decisions are especially influential. Compared to a baseline (control group) sign-up rate of 80.7 percent, seeing that a smart peer chooses "Yes" to sign-up does not change the sign-up rate, but seeing that a smart peer chooses "No" decreases the sign-up rate by 42.4 percentage points ($p<0.01$). In contrast, popular students' decisions are not influential. This finding suggests that students turn to smart students to learn about the social norms of participation in an academic context. The result is robust to including demographic and friendship controls for both students and different methods to classify smart and popular students.

In addition, I look at whether students have correct beliefs about their peers' participation. Incorrect beliefs about peers' participation in an educational program could lead to a higher or lower equilibrium participation rate than otherwise. I find that while students want to conform to the social norm, they have very biased beliefs about (they drastically underestimate) their peers' participation. This bias is more extreme for students with lower GPAs. I restrict the sample to students in the control group who do not see any peer's decision. While a majority of students in all GPA quartiles sign-up for the college application assistance program in my experiment, only 10.0 percent of the students in the lowest GPA quartile think that a majority of their classmates will sign-up, while 47.5 percent of the students in the highest GPA quartile think that a majority of their classmates will sign-up. This finding combined with the finding that students in lower GPA quartiles have a higher WTP for the program suggests that biased beliefs push students to sign-up at lower rates than they would otherwise.[3] I check the generalizability of this result, and find that students also have biased beliefs about whether their friends plan to go to college.

In the final section of the paper, I estimate my structural model and run a policy counterfactual. Specifically, I interpret my parameter estimates as estimates from a structural decomposition of peer effects into three channels: social learning, consumption externalities, and social norms. I find that the peer effect operates through the social norms channel, supporting my results from the reduced form tests. I also find suggestive evidence that students update their beliefs about their peers' participation most when they see

[3] An explanation for the lower WTP of students with higher GPA could be that students with higher GPA have more available substitutes for the program I offer.

that a smart peer chooses "No." I combine these estimates with the collected school social network data to look at the take-up of targeted educational programs when I vary the type and fraction of students that are targeted as initial adopters of the program. I find that when there are negative peer effects and costly initial adoption, targeting smart students can actually backfire and lead to a lower overall school sign-up rate than targeting non-smart students.

This paper relates to five lines of literature. First, it contributes to a large body of literature on peer effects in education.[4] While researchers acknowledge the need to understand peer effect mechanisms, most papers do not have the data or exogenous variation to identify them. Peer effects have been notoriously difficult to identify due to the three problems of reflection (also known as simultaneity), correlated unobservables, and endogenous peer group membership (Manski, 1993; Moffitt, 2001). I circumvent these problems using three features of my experimental design which allow me to identify peer effect mechanisms: (a) I study a binary decision where students can easily influence the outcome, (b) I observe the school's social network, and (c) I exogenously provide information to students about their peers' decisions. This paper also contributes to the growing literature in the past decade that uses (quasi-)experimental methods to estimate peer effects in education.[5]

Second, a growing empirical literature on social networks seeks to disentangle social learning and social utility as primary motivations in program adoption and so far finds mixed results.[6] This literature builds on a large theoretical literature that studies social learning and social utility separately.[7] I contribute to our understanding of social learning and social utility by developing a model that includes social learning, social utility, and beliefs together. The model gives a comprehensive framework for thinking about how students are influenced by their peers' decisions. In addition, I am the first to disentangle social learning and social utility in an educational context. My finding that students learn from their peers' decisions about social norms, but not about an educational program's value, is consistent with papers finding the presence of social utility effects in U.S. high schools (see the "acting white" literature, e.g., Fryer, 2010, as well as Bursztyn and Jensen, 2015 and Liu et al., 2014).

Third, I contribute to a recent literature on structural behavioral economics (see e.g.: DellaVigna, 2018,

[4] A few good summaries of the literature can be found in Sacerdote (2011, 2014) and Epple and Romano (2011).

[5] See, e.g., Bobonis and Finan (2009), Kremer et al. (2009), Avvisati et al. (2014), Joensen and Nielsen (2015), Bursztyn and Jensen (2015), Goodman et al. (2015).

[6] There are a few papers which find social learning effects but not social utility effects: see Banerjee et al. (2013) on the decision to participate in a microfinance loan program in Indian villages, Kremer and Miguel (2007) on the adoption of deworming pills in Kenya, Dahl et al. (2014) on participation in paid paternity leave in Norway, and Cai et al. (2015) on the adoption of weather insurance in rural China. At the same time, farmers in the latter experiment strongly increased their take-up of weather insurance when peers' decisions were revealed, which suggests that they were influenced by peers' decisions but in general lacked information about them. Furthermore, a few papers find that social utility effects may be important as well: see Maertens (2016) on the adoption of Bt cotton in India, Bursztyn et al. (2014) on the purchase of financial assets in Brazil, and Beaman et al. (2015) on the adoption of "pit planting" technology in Malawi.

[7] For the social learning literature, see, e.g., Banerjee (1992) and Bikhchandani et al. (1992). For the social utility literature, see, e.g., Akerlof and Kranton (2002) and Bernheim (1994).

DellaVigna et al., 2012, and DellaVigna et al., 2017).

Fourth, I contribute to a literature that studies heterogeneity in peer effects. One strand of this literature seeks to identify key players in a social network that are optimally positioned to diffuse information, attitudes, or behaviors.[8] Other recent papers study endogenous social learning where individuals choose who to give information to, and who to receive information from.[9] In an educational context, Patacchini et al. (2017) find that long-lived friends are the most influential for students' long-run educational outcomes. I add a data point that shows that influence is context-specific and that students are influenced most by smart students when making educational decisions.

Fifth, I contribute to a literature that studies whether biased beliefs lead to inefficient human capital investment. Hastings et al. (2016) find that Chilean college students overestimate earnings outcomes for college graduates and thus choose degrees with lower labor market prospects. Similarly, Jensen (2010) finds that eighth-grade boys in the Dominican Republic perceive extremely low returns to secondary school despite high measured returns. So far, the idea that beliefs about *peers' educational decisions* can be biased has not received much attention. A large interdisciplinary body of literature (mostly in sociology and social psychology) has found ample evidence that people can have incorrect beliefs about peers' actions or social norms.[10] If social utility is important in an educational context, then these biased beliefs about peers' human capital investment may need to be corrected for as another source of information frictions.

The rest of the paper proceeds as follows: Section 2 introduces the model and gives intuition for the identification. Section 3 describes the experimental design. Section 4 presents the main results: (a) showing peer effects in the decision to participate in educational programs, and (b) disentangling social learning and social utility. Section 5 presents a deeper look at social utility: (a) identifying which types of students are influential in the social network, and (b) whether students have correct beliefs about their peers' participation. Section 6 describes my structural estimation strategy, presents the results, and runs a counterfactual policy simulation looking at the take-up of targeted educational programs. Section 7 discusses and concludes.

2 Model

In this paper, I disentangle the two peer effect channels of social learning and social utility. Suppose students k and i are making a decision sequentially, with k making his decision before i.

[8] See Zenou (2016) for a summary, as well as Banerjee et al. (2013, 2016), Beaman et al. (2015), and Aral and Walker (2012).

[9] See e.g., Chandrasekhar et al. (2016), Cai and Szeidl (2018), and Banerjee et al. (2018).

[10] A literature on pluralistic ignorance studies when a majority of group members privately reject a social norm, yet incorrectly think that most others accept it (see, e.g., Bursztyn et al., 2017; Bursztyn et al., 2018; Katz and Allport, 1931). An example of pluralistic ignorance often used to explain adolescent behavior is college students' perceptions of their peers' alcohol consumption (Prentice and Miller, 1993). Related to this is the sociological literature on the friendship paradox (Feld, 1991; Jackson, 2017) that posits that people form beliefs about peers' actions based on individuals with more links in a social network. See also Han and Hirshleifer (2015) and Li and Lee (2009).

Social learning occurs in two ways: (1) information transmission, when k's decision influences i's decision by introducing an action to i's choice set, or (2) signaling about value, when k's decision influences i's decision by allowing i to update her beliefs about the value of an action. That is, a student's peer may transmit information to her about a new educational program, or his decision may signal to her the value of the educational program. In this paper, I will focus on the latter by shutting down the information transmission channel.

Social utility occurs when k's action directly influences i's utility from choosing the same action. This can occur if having a peer participate in an educational program changes the costs and benefits to a student from participating in the same program. For example, the students could work on program materials together or carpool, lowering the cost to participating, or derive benefit from attending the program together with friends. Social image concerns may also come into play if students want to participate together with smart or popular classmates. In my model, I will focus on two subchannels of social utility: consumption externalities, where peers' decisions enter a student's utility in a (net) benefit term, and social norms, where peers' decisions enter a student's utility in a term capturing a penalty for deviating from the group average.[11]

The following model formalizes these peer effect channels.

2.1 Preliminaries

There is a finite set $N = \{1, \ldots, n\}$ of students at a high school, with generic indices i and j. Each student decides whether to sign-up for an educational program, and her decision is given by $d_i \in \{-1, 1\}$. The space of all possible students' actions is the n-tuple $\mathbf{d} = (d_1, \ldots, d_n)$, and $\mathbf{d}_{-i}$ denotes $(d_1, \ldots, d_{i-1}, d_{i+1}, \ldots, d_n)$, the choices of all students other than i.

In my experiment, students participate in the college application assistance program with their peers in small groups. Let $\mathbf{d}_{-i,g} = (d_1, \ldots, d_{i-1}, d_{i+1}, \ldots, d_{n_g})$ denote the choices of all students (other than i) who are able to participate in the same group as i.[12]

2.2 Baseline model with rational expectations

First, we look at the baseline model with rational expectations. This model is based on the discrete choice social interactions model in Brock and Durlauf (2001).

Let student i have an intrinsic private benefit of attending the educational program, $\theta_i\left(d_i\right) \sim F\left(\cdot\right)$. I assume that all students have the same constant cost of attending the program, and that $\theta_i(d_i)$ denotes the

[11]These terms correspond to the *local-aggregate* and *local-average* models in the social networks literature, respectively. See, for example, Liu et al. (2014).

[12]In the absence of information about their program group's composition, students will have the same beliefs over $\mathbf{d}_{-i}$ and $\mathbf{d}_{-i,g}$.

student's private net benefit. $F(\cdot)$ is common knowledge to all students, but the realization of $\theta_i(d_i)$ is only seen by student i.

Specifically, let

$$\theta_i(d_i) = u(d_i) + \varepsilon(d_i),$$

where $u(d_i)$ is the deterministic private benefit, and $\varepsilon(d_i)$ is a random utility term that is i.i.d. across students.

Student i's utility, $V(d_i)$, is

$$V(d_i) = \underset{\text{private benefit}}{u(d_i)} + \underbrace{\underset{\text{cons. extern.}}{J_1 d_i E[\mathbf{d}_{-i,g}]} - \underset{\text{social norms}}{\frac{J_2}{2}(d_i - E[\mathbf{d}_{-i}])^2}}_{\text{social benefit}} + \varepsilon(d_i).$$

The addition of the two social benefit terms reflects that students care about their peers' sign-up decisions. Here, $E[\mathbf{d}_{-i,g}]$ and $E[\mathbf{d}_{-i}]$ are student i's beliefs over the vectors of other students' decisions, $\mathbf{d}_{-i,g}$ and $\mathbf{d}_{-i}$ (e.g., the mean sign-up rate of her peers). J_1 and J_2 are parameters which capture the contribution of the consumption externalities and social norms channels to student i's utility.

We can think of the private benefit and social benefit as additively separable by construction – student i's private benefit is the utility that she derives from the program absent of any social considerations. Student i's social benefit is the utility she derives from having other students attend the program, and this includes two terms. The first term, consumption externalities, captures the (net) benefit that a student gets from participating in the program together with peers. For example, there may be spillovers from consumption such that the more her peers participate, the more active and beneficial is the program. The second term, social norms, captures a penalty for deviating from the group average. The farther the student is from the group average participation, the larger is the penalty. For example, the student may fear judgement for making a choice that is different from her peers' choices. The key distinction between the consumption externalities and social norms channels is that students can only derive consumption externalities from peers in their program group who they can participate with.

The equilibrium is characterized by:

1. For all $i \in N$, student i chooses

$$d_i^* = \begin{cases} 1 & V(1) \geq V(-1) \\ -1 & V(1) < V(-1). \end{cases}$$

2. For all $i \in N$, student i has rational expectations over $E[\mathbf{d}_{-i,g}]$ and $E[\mathbf{d}_{-i}]$.

We can think of the following sequence of actions. Each student chooses d_i having perfect information about her private benefit, θ_i (and ε_i), and rational expectations of what the other students will choose, $E\left[\mathbf{d}_{-i,g}\right]$ and $E\left[\mathbf{d}_{-i}\right]$. Brock and Durlauf (2001) show that under rational expectations, there exists at least one self-consistent equilibrium.

I also assume that the errors $\varepsilon(1)$ and $\varepsilon(-1)$ are independent and extreme-value distributed, so that the differences in the errors are logistically distributed,

$$Pr\left\{\varepsilon\left(-1\right)-\varepsilon\left(1\right)\leq x\right\}=\frac{1}{1+\exp\left(-\beta x\right)}.$$

See Appendix C for details on the structural estimation procedure.

2.3 Adding imperfect information

Now, I relax the assumption that students have perfect information about their private benefit or other students' decisions. Assume that there is a common benefit from attending the college application assistance program, $v\sim G(\cdot)$. $G(\cdot)$ is common knowledge to all students, but each student only receives a signal $\theta_i\in[v-\delta,v+\delta]$. Thus, students have a prior $E[v|\theta_i]$ over the benefit they will get from attending the program.

In addition, I allow that student expectations about peers' choices depend on the signal θ_i that they received. Thus, students also have priors over other students' decisions, $E\left[\mathbf{d}_{-i,g}|\theta_i\right]$ and $E\left[\mathbf{d}_{-i}|\theta_i\right]$.

Student i's utility function is

$$V\left(d_i,\theta_i\right)=\underbrace{E\left[\nu|\theta_i\right]d_i}_{\text{private benefit}}+\underbrace{\underbrace{J_1 d_i E\left[\mathbf{d}_{-i,g}|\theta_i\right]}_{\text{cons. extern.}}-\underbrace{\frac{J_2}{2}\left(d_i-E\left[\mathbf{d}_{-i}|\theta_i\right]\right)^2}_{\text{social norms}}}_{\text{social benefit}}+\varepsilon\left(d_i\right).$$

In my experiment, I collect data on students' priors over the program benefit and other students' decisions. Because I allow for these priors to be inaccurate, student i's decision does not depend on what other students choose, only on what she *thinks* other students will choose. Thus, all students will choose their best response given their priors $E\left[\nu|\theta_i\right]$, $E\left[\mathbf{d}_{-i,g}|\theta_i\right]$, and $E\left[\mathbf{d}_{-i}|\theta_i\right]$.

2.4 Adding peer effects (seeing a peer's decision)

In my experiment, some students make their sign-up decision after seeing one of their peer's decisions. Seeing their peer's decision causes them to update their beliefs about both the program benefit ν and other students' decisions.

The students in the control group (call this set $K \subset N$) make their decision seeing one signal, θ_i, about ν, $\mathbf{d}_{-i,g}$, and $\mathbf{d}_{-i}$. However, students in set $N \setminus K$ receive an *additional* signal by seeing another student's decision (indexed by k). Thus, student i in $N \setminus K$ sees signals θ_i and $s_{ik} = d_k$, $s_{ik} \in \{-1, 1\}$. Her signals θ_i and s_{ik} inform her about the true values of v, $\mathbf{d}_{-i,g}$, and $\mathbf{d}_{-i}$.

Student i's utility function is

$$V\left(d_i, \theta_i, s_{ik}\right) = \underbrace{E\left[\nu|\theta_i, s_{ik}\right] d_i}_{\text{private benefit}} + \underbrace{\underbrace{J_1 d_i E\left[\mathbf{d}_{-i,g}|\theta_i, s_{ik}\right]}_{\text{cons. extern.}} - \underbrace{\frac{J_2}{2}\left(d_i - E\left[\mathbf{d}_{-i}|\theta_i, s_{ik}\right]\right)^2}_{\text{social norms}}}_{\text{social benefit}} + \varepsilon\left(d_i\right),$$

where the prior beliefs in Section 2.3 are replaced by posterior beliefs. Similar to the case in Section 2.3, all students will choose their best response given their posteriors $E\left[\nu|\theta_i, s_{ik}\right]$, $E\left[\mathbf{d}_{-i,g}|\theta_i, s_{ik}\right]$, and $E\left[\mathbf{d}_{-i}|\theta_i, s_{ik}\right]$.

To test for consumption externalities, I introduce an "other classes" treatment where students see a peer's decision, but are not able to participate with their peer in the same program group. A student in this treatment has the utility function

$$V\left(d_i, \theta_i, s_{ik}\right) = \underbrace{E\left[\nu|\theta_i, s_{ik}\right] d_i}_{\text{private benefit}} + \underbrace{\underbrace{J_1 d_i E\left[\mathbf{d}_{-i,g}|\theta_i\right]}_{\text{cons. extern.}} - \underbrace{\frac{J_2}{2}\left(d_i - E\left[\mathbf{d}_{-i}|\theta_i, s_{ik}\right]\right)^2}_{\text{social norms}}}_{\text{social benefit}} + \varepsilon\left(d_i\right),$$

where I make the assumption that students do not update their beliefs about $\mathbf{d}_{-i,g}$.

2.5 Social learning and social utility in the context of the model

In the context of this model, I revisit the definitions of social learning and social utility. When student i is influenced by student k's decision, social learning is the change to student i's private benefit, and social utility is the change to student i's social benefit.

2.6 Identification

I will briefly summarize the intuition for the identification of this model. I start by testing whether students want to participate together with their peers (consumption externalities). To do so, I have two treatments that randomize whether students are able to participate in the same program group as the peer whose decision they see. In one treatment, their peer's decision informs students about the value of the program and the social norms of participation, but not about peer participation in their program group. In the other treatment, their peer's decision informs students about the value of the program, the social norms of participation, and also about peer participation in their program group. To disentangle the two channels of social learning and social utility, I next look at whether seeing a peer's decision changes students' values of the program, or their beliefs about their peers' participation. Recall that students' beliefs about their peers' participation only enter the social utility term, and not that social learning term.

3 Experimental design

3.1 Participants

My experiment is conducted in the 2017-2018 school year in three high schools in the Chicago suburbs: Hillcrest High School, Thornwood High School, and Proviso West High School. The participants include seniors in Hillcrest High School (in the fall), and juniors in Thornwood High School and Proviso West High School (in the spring).[13] When recruiting schools, I focused on schools that serve primarily low-income students, and have low college enrollment rates. See Appendix A for more details about the recruitment procedure. Table 1 shows summary statistics describing the demographics and performance of the three schools compared to state averages.

3.2 Experimental design

Following the college application cycle, I approached the high schools and offered a free college application assistance program for its students. Only one cohort — seniors or juniors — was able to participate at each school. The college application assistance program consists of a one-time college application information session, as well as ongoing small group mentoring for the students throughout the year. The experiment consists of two main parts: a survey and a program sign-up. See Figure 1 for a depiction of the experiment timeline, and Appendices A and B for all experiment materials.

As a first step, consent letters are sent to all parents/guardians of high school seniors/juniors via robo call and mailing. The default is to participate in the study, and parents are able to opt-out of the study within one week of receiving the consent letter. Parents are only told that their child is participating in a survey study researching ways to motivate high school students to apply to college — nothing about a college application assistance program is mentioned so that parents do not influence their child to participate. Very few students were removed by their parents from the study, suggesting that the remaining students are still representative of their cohort.[14]

Next, a survey is administered to all high school seniors/juniors in their English or History class. The

[13]I also ran a pilot with seniors in Thornwood High School in fall of the 2016-2017 school year.

[14]In Hillcrest High School, out of 291 seniors, 6 were removed from the study. In Thornwood High School, out of 443 juniors, 4 were removed from the study. In Proviso West High School, out of 442 juniors, 3 were removed from the study.

survey contained questions about students' demographics, academics, college and career plans, extracurricular activities, and friendship network.[15] In particular, I ask students to list their top friends in the 12th/11th grade at their school in the following categories: (1) top friends to eat lunch with, (2) top friends to do homework with, and (3) top friends to hang out with after school. I also ask students to name some possible "smart" and "popular" key students,[16] as well as their self-rated popularity and importance of popularity. Students were able to name up to 12 friends each (4 for each question), and up to 4 key students each (1 for each question). Finally, I ask questions to obtain students' prior WTP and beliefs about class participation for a hypothetical college application assistance program.[17] Using the survey, I am able to map out the social network at each school, as well as classify students according to their academic success, work effort, college application plans and progress, perceived importance of popularity, and extracurricular activities. From the high schools, I directly obtain students' GPAs and SAT scores, family income, special education status, and a list of all classes and class periods in which students are enrolled.

A couple of weeks after the survey is administered, I conduct sign-up for the college application assistance program. I shut down information transmission by conducting the sign-up in all senior/junior classrooms in the same class period.[18] I use a sequential sign-up procedure to exogenously reveal to students their peers' decisions. The program sign-up randomizes (a) whether a student sees a peer's decision, and (b) which type of peer's decision they see, and it proceeds in the following way. In each classroom, students are pre-randomized into two groups. I call the students out into the hallway outside of the classroom to make their sign-up decision, one group at a time.

First, I ask the first group of students to come into the hallway to make a one-time decision to sign-up or not sign-up for the program. To do so, I hand each student a clipboard with a stack of decision sheets (one clipboard per student), and ask them to fill out the topmost sheet. Each decision sheet contains a short description of the college application assistance program, and asks students to write their name and circle either "Yes" or "No" as their sign-up decision. After the students are finished making their decisions, I collect the clipboards and ask them to fill out some additional survey questions, before sending them back into the classroom.

[15] The survey questions were influenced by survey questions in the following papers: Levitt et al. (2016), Bursztyn and Jensen (2015), Baerveldt et al. (2004), and Banerjee et al. (2016).

[16] Specifically, I ask the questions: (1) Which 12th/11th grade student do you go to for help with practical problems such as homework or filling out a college application? (2) If we want to spread information to everyone in Hillcrest/Thornwood/Proviso West High School about a college representative visit, to which 12th/11th grade student should we speak? (3) Which 12th/11th grade student do you look up to the most? (4) Which 12th/11th grade student is most popular?

[17] Specifically, I ask them to indicate (in 25% increments) their beliefs for the sign-up rates of the following types of peers at their school: (1) all 12th (11th) grade students, (2) their classmates in their current class, (3) their friends, (4) smart students, and (5) popular students.

[18] Throughout the program sign-up, I am careful to shut down information transmission about the program from teachers and other students. Teachers are instructed not to mention the program to students beforehand, so that students are not influenced by teachers to participate. Students are not told about the program until they come out into the hallway, where research assistants read a short description of the program to students before they fill out their decision sheets. When making their decisions, students are asked to withhold questions, and to refrain from talking to other students.

Next, I ask the second group of students to come into the hallway to make the same decision. To do so, I randomly hand each student a clipboard with a stack of decision sheets (one clipboard per student), *keeping the first student's decision on top of the clipboard*. To some students in the second group, it looks like I carelessly left a sheet of paper on top of the clipboard. However, as a result, these students see one of their peer's decisions immediately before making their own sign-up decision, and are asked to turn to the second page to make their decision. After the students are finished making their decisions, I collect the clipboards and ask them to fill out some additional survey questions, before sending them back into the classroom. The additional survey questions ask about students' posterior WTP for the college application assistance program and obtaining information about peers' decisions, their posterior beliefs about class participation, and also include a manipulation check for the second group of students in the classroom.

In order to have a control group of students who do not see any peer's decision in the second group, 2/5 of the students are randomly assigned to the first group, and 3/5 of the students are randomly assigned to the second group (see Figure 2 for a depiction of the randomization). Thus, students in the second group either see no peer's decision (this is the control group), a "Yes" decision, or a "No" decision immediately before making their own sign-up decision. One additional benefit of using this experimental design is that it allows me to identify heterogeneity in peer effects, as there is natural variation in the characteristics of the students who are paired together. Thus, I can see which types of students (e.g., smart, popular, academically similar, or friends) are most influential in encouraging their peers to sign-up for the college application assistance program. This allows me to look at social learning and social utility from different types of students.

To test whether students want to participate together with their peers (consumption externalities), I randomize whether students are able to participate in the same program group as the peer whose decision they see. This test for consumption externalities is influenced by the one in Bursztyn et al. (2014), and adapted to a school setting. I have two treatments that vary only a couple of words on the students' decision sheets, and the treatments are randomized at the clipboard-level. All students see a short description of the college application assistance program before they are asked whether they would like to sign-up. For the second group of students in the classroom, their description contains either treatment A) "You will be randomly assigned to an information session group with 9 other students from other classes..." or treatment B) "You will be randomly assigned to an information session group with 9 other students from your current class..." Students are told that they will receive mentoring with the same group of students throughout the year. Since students in the second group see one of their peers' decisions before flipping to their own decision sheets, treatments A and B change the expectation that students have for being in the same program group with their paired peer. Thus, compared to the case where students make their sign-up decisions without information about their peers' decisions, seeing their peers' decision + treatment A gives us the effect of social learning and social norms, and seeing their peers' decision + treatment B gives us the effect of social learning, social norms, *and consumption externalities.* That is, if a student sees that her peer has decided to participate in the college application assistance program, but will be put into a different group, her peer's decision causes her to update her beliefs about the program's value and the social norms of participation, but she will not reap any benefits from attending the program with her peer.

To disentangle the two channels of social learning and social utility, I look at whether seeing a peer's decision changes students' WTP for the program, or their beliefs about their peers' participation.

4 Main results

4.1 Summary statistics

Out of the seniors/juniors at Hillcrest High School, Thornwood High School, and Proviso West High School, 42.0% completed the survey administered in English or History class, and 56.5% participated in the sign-up decision. Those who did not participate in either chose to opt-out, were not in class on the survey or sign-up date, or were not able to participate due to teacher/class circumstances. Table 2(a) shows summary statistics of student characteristics obtained from the survey.

From the survey, I obtained the 12th/11th grade social network at the three schools. The average number of friends listed by students was 4.3 out of 12 (counting any of the questions), and I draw a link between two students as long as one of the students named the other as a friend. Conditional on naming any friends, the average number of friends listed by students was 6. The average number of key students listed by students was 1.0 out of 4, and conditional on naming any key students, the average number of key students listed by students was 1.9.[19] Table 2(b) shows summary statistics of the social network obtained from the survey. See Figures 16 to 21 in Appendix D for the school social network graphs.

Finally, I find suggestive evidence that the sign-up decision was consequential to students.[20] Students on average valued the college application assistance program at $90.4.

[19]Recall that students were able to name up to 12 friends and 4 key students; these numbers are not the same as the outdegree as they include repeated names. 71.3% of students filling out the survey named at least one friend, and 49.0% of students filling out the survey named at least one key student.

[20]Unfortunately, due to miscommunications between the schools and students, many students were ex post unable to attend the college application assistance program. However, students believed the program to be valuable at the time of their sign-up decision. The program was modeled after other successful programs. Besides reporting on average a WTP of $90.4, 48% of students named at least one topic they would like me to cover in the information session in a free response question.

4.2 Classifying students

In this paper, I will focus on peer effects from smart students, popular students, and academically similar students. The first step is to classify students by their academic achievement and popularity.

Smart and popular. To split the students into smart students, popular students, and students who are neither popular nor smart, I use the following approach:

- I classify a student as smart if the student had any of the following: (1) the student was nominated by other students to be someone they would go to for homework or college application help, or (2) the student had a GPA or SAT score in the top quartile at their school.[21]

- I classify a student as popular if the student had any of the following: (1) the student was nominated by other students to be "most popular," (2) the student had an out-degree or in-degree in the top quartile at their school,[22] or (3) the student self-rated his or her own popularity to be 5 out of 5.

After splitting up the students, there are 386 smart students, 331 popular students, and 621 students who are neither popular nor smart.[23]

The columns in Table 2 compare student characteristics and social network measures for smart and popular students with the whole sample. Compared to non-smart students, smart students had higher unweighted GPA, higher SAT and PSAT scores, and were more likely to plan to attend college. They also had a higher out-degree and in-degree, but were less likely to rate themselves as popular.[24] Compared to non-popular students, popular students had a higher out-degree and in-degree, and were more likely to rate themselves as popular. Even though they are by construction, these correlations show that students who were classified as smart or popular differed in characteristics from the rest of the student body.

Academically similar. I clasify students as academically similar if they are within 0.5 standard deviations of each other in terms of unweighted GPA.

Key students. Recall that students were also asked to name key students in their 12th/11th grade social network in a few different dimensions on the survey. I identify four categories of key students: (1) students who their peers go to for academic help ("homework help"), (2) students who we should go to to spread academic information to the rest of the student body ("gossip"), (3) students who are most respected

[21] At Hillcrest, this means that they had at least 2.7 unweighted GPA or 990 SAT score. At Thornwood, this means that they had at least 2.8 unweighted GPA or 920 PSAT score. At Proviso West, this means that they had at least 2.7 unweighted GPA.

[22] At Hillcrest, this means that they named at least 6 friends or were named by at least 4 friends. At Thornwood, this means that they named at least 6 friends or were named by at least 3 friends. At Proviso West, this means that they named at least 6 friends or were named by at least 2 friends.

[23] There are 162 students who are classified as both popular and smart (r=0.21).

[24] The finding that smart students had a higher out-degree and in-degree than the rest of the students could be due to the fact that smart students were both more likely to complete the survey, and more likely to exert more effort on it (name more friends). This contributes to some of the positive correlation between whether a students is classified as smart and whether a student is classified as popular.

by their peers ("respect"), and (4) students who are most popular ("most popular"). I classify a student as a key student in one category if they received at least one nomination in that category. See Figures 22 to 25 in Appendix D for graphs showing the distribution of key student nominations.

Table 3 compares student characteristics and social network measures for key students who were nominated by their fellow students with the whole sample. Compared to non-key students, key students in the academic categories (homework help and respect) had higher unweighted GPA, higher SAT and PSAT scores, and were more likely to plan to attend college. They also had a higher out-degree and in-degree, but were less likely to rate themselves as popular. Compared to non-key students, key students in the social categories (gossip and most popular) had a higher out-degree and in-degree, and were more likely to rate themselves as popular.

Since the key student classifications are based on student nominations, these correlations are not by construction. The fact that the key students differed in characteristics from the rest of the student body suggests that students took the survey seriously. Similarly, the students receiving the most nominations at each school in the key student categories truly were unique – the student receiving the most nominations for the gossip category tended to be the 12th/11th grade class president, the student receiving the most nominations for the respect category tended to be the 12th/11th grade class valedictorian, and the student receiving the most nominations for the most popular category tended to be the high school football or basketball team captain.

4.3 Are there peer effects in the sign-up decision?

First, Figure 3 and Table 4 show large peer effects in the decision to participate in a college application assistance program. Interestingly, the peer effects are driven entirely by "No" decisions. Compared to a baseline (control group) sign-up rate of 80.7 percent, seeing that a peer chooses "Yes" to sign-up does not change the sign-up rate, but seeing that a peer chooses "No" decreases the sign-up rate by 26.9 percentage points ($p<0.01$).

Table 4 shows linear probability model regressions where the dependent variable is the student's sign-up decision. Column (1) shows the effect of being in the second group of students on the sign-up rate. I compare students in the first group to students in the second group (control group only), and find that there is no statistically significant difference. Hence in the rest of the paper, I pool together students in the first group with control students in the second group to form a pooled control group. Column (2) shows, conditional on being in the second group of students, the effect of seeing a "No" or "Yes" decision (compared to control) on the sign-up rate. I use the specification,

$$Signup_{is} = \beta_1 SawNo_{is} + \beta_2 SawYes_{is} + X'_{is}\gamma + \alpha_s + \varepsilon_{is},$$

where X_{is} includes student i's GPA, race (black), and gender, and α_s are school fixed effects.

Since I find large peer effects in the participation decision, I use a combination of experimental treatments and data collected on students' beliefs to disentangle the underlying peer effect channels.

4.4 Are consumption externalities important?

First, I test whether students want to participate with their peers (consumption externalities). Figure 4 shows the sign-up rates under treatments A and B. Under treatment A, students are told that they will participate in the college application assistance program with nine other students from other classes. In this treatment, there are no consumption externalities, as students can learn from seeing their peer's decision (either about the program's value or about the social norms of participation) but will not be able to participate together with their paired peer. Under treatment B, students are told that they will participate in the program with nine other students from their current class. In this treatment, there are consumption externalities, as students will be able to participate together with their paired peer. In Figure 4, there is no statistically significant difference between the sign-up rates under treatments A and B, suggesting that students do not care about participating with any specific peer in the program.

Figures 5 and 6 break down Figure 4 based on whether the decision-making student saw a "Yes" decision or a "No" decision. Note that students in the control group were also randomized into treatments A and B. In all cases, I find no difference in sign-up rates between the two treatments.

One caveat to the consumption externalities test is that students in treatment A ("other classes") may have updated their beliefs about their program group composition when seeing their peer's decision, even if their peer was not in their program group. Alternatively, students could have expected to talk to peers in other program groups about what they learned, after attending the college application assistance program. In these cases, the consumption externalities test would not shut down the consumption externalities channel completely. However, the fact that I find no difference between treatments suggests that at least consumption externalities are not a first-order concern in this setting.

4.5 Are the peer effects driven by social learning or social norms?

While I do not find strong evidence for consumption externalities, students may still be influenced by their peer's decision because their peer's decision informs them about the value of the program (social learning), or the social norms of participation. Next, I look at whether seeing a peer's decision changes students' values of the program, or their beliefs about their peers' participation.

Social learning. First, I look at whether seeing a peer's decision changes students' values of the program. This is measured by a hypothetical question asking for their WTP for the program. Table 5 shows OLS regressions where the dependent variable is the student's WTP. Columns (1) and (2) use the student's posterior WTP, and columns (3) and (4) use a normalized measure which is the student's posterior WTP divided by their reported weekly money earned (from their allowance or a job). Columns (2) and (4) control for the student's prior WTP for the program (collected from the survey). Because this restricts the sample to students who participated in both the survey and the program sign-up, it drops a large number of observations. Columns (1) and (3) control for the student's weekly money earned instead. In all cases, I winsorize the prior WTP, posterior WTP, and weekly money earned variables at the 1st and 99th percentiles to account for outliers. Figure 36 in Appendix D shows the effect of seeing a "No" or "Yes" decision (compared to control) on the distribution of students' WTP, and Figure 37 in Appendix D shows the effect of seeing a "No" or "Yes" decision on the distribution of students' change in WTP (from prior to posterior). I do not find any evidence that seeing a peer's decision (either "No" or "Yes") changes students' values of the program, and thus do not find any evidence for social learning from peers' decisions.

Social norms. Next, I look at whether seeing a peer's decision changes students' beliefs about their peers' participation in the program. The beliefs variable comes from a question I ask in the survey immediately following students' sign-up decisions – I ask students to estimate the percentage of their classmates they think will participate in 25% increments (taking values 0%, 25%, 50%, 75%, and 100%). Figure 7 shows that compared to the control group, seeing a peer choose "Yes" shifts the distribution of students' beliefs about class participation to the right, and seeing a peer choose "No" shifts the distribution to the left. I also ask the same beliefs question to students about different types of peers – all 12th/11th grade students, friends, smart students, and popular students. Figures 26 to 35 in Appendix D show that in all cases but one, students update their beliefs about peers' participation according to the information they receive.[25] Table 12 (column (2)) of Appendix D shows the OLS regression of student's beliefs about class participation on their information seen. Compared to the control group, I find that seeing a peer choose "Yes" causes students to think that their classmates are 5.8 percentage points more likely to sign-up for the program ($p<0.05$), and seeing a peer choose "No" causes students to think that their classmates are 11.5 percentage points less likely to sign-up ($p<0.01$).

When students see one of their peers' decisions, they learn about (update their beliefs about) their peers'

[25]The only exception is for all 12th/11th grade students. It could be that it is too much for students to extrapolate from seeing one peer's decision to learn about the entire 12th/11th grade.

participation, but do not learn about the value of the program. Taken together, these results suggest that the peer effect is operating through social utility instead of social learning. In particular, these results suggest that the peer effect operates through informing students about the social norms of participation.

Another way of viewing the experiment is that I am manipulating student beliefs about their peers' decisions instead of peers' decisions directly. Table 12 in Appendix D shows 2SLS regressions where I use revealed peers' decisions as an instrumental variable for students' beliefs about their classmates' decisions. Column (4) shows the OLS regression of whether the student signed-up on their beliefs about class participation. Column (2) shows the first stage regression of the student's beliefs about class participation on whether they saw no information, a "No" decision, or a "Yes" decision. Column (3) shows the second stage regression, suggesting that seeing a peer's decision influences students' sign-up decisions because it changes their beliefs about class participation.

5 A deeper look at social utility

Because I find that the peer effects are driven by social utility, I perform two additional analyses to understand how social utility affects students' decisions to participate in an educational program.

5.1 Which types of students are influential in the social network?

First, I look at which types of students are influential in the social network. I use the survey and administrative data from schools to classify students into smart students, popular students, academically similar students, and friends. I also identify key students in the four categories of homework help, gossip, respect, and most popular. My experimental design allows me to test which of these types of students are influential in the social network. For example, to see if smart students are influential, I use the specification,

$$\begin{aligned} Signup_{ijs} = {} & \beta_1 SawYes_{ijs} + \beta_2 PairedSmart_{ijs} + \beta_3 SawYes_{ijs} \times PairedSmart_{ijs} \\ & + \beta_4 PairedFriend_{ijs} + X_{is}'\gamma_1 + X_{js}'\gamma_2 + \alpha_s + \varepsilon_{ijs}, \end{aligned}$$

where student i sees student j's decision before making her own decision. The variables $PairedSmart_{ijs}$ and $PairedFriend_{ijs}$ are indicator variables for whether j is classified as smart and i and j are classified as friends, respectively. Also, X_{is} includes student i's GPA, race (black), and gender, X_{js} includes student j's race (black) and gender, and α_s are school fixed effects. The coefficient of interest is the one associated with the interaction term, β_3. Because I control for both students' demographics, the sample is restricted to only students who saw a peer's decision (and thus the baseline in the regressions is seeing a "No" decision instead of control).

Table 6 shows linear probability model regressions where the dependent variable is the student's sign-up decision. Column (1) shows the effect of seeing a smart student choose "Yes" on the sign-up rate, column (2) shows the effect of seeing a popular student choose "Yes" on the sign-up rate, and column (3) shows the effect of seeing a key student choose "Yes" on the sign-up rate. Because there were a low number of key students identified, I pooled all types of key students together. Even so, unfortunately I do not have the variation needed to identify whether key students are influential.[26] I find that smart students' decisions are influential to their peers, but that popular students' decisions are not.

Table 7 shows similar regressions using alternative classifications of smart and popular students. Column (1) shows the effect of seeing an academically similar student choose "Yes" on the sign-up rate, column (2) shows the effect of seeing a (locally) smart student choose "Yes" on the sign-up rate, and column (3) shows the effect of seeing a (locally) popular student choose "Yes" on the sign-up rate. Since who is smart and popular might differ to different students in a school (e.g., in honors vs. non-honors classes), I classify "locally smart" students as those students who are "smart" for students with similar GPA, and "locally popular" students as those students who are "popular" for students with similar GPA. I find that similar to smart students' decisions, academically similar students' decisions are influential to their peers. Locally smart students are marginally influential ($p<0.1$). Overall I find that the local measures of smart and popular are noisier than the global measures, with little gain. I still find no evidence that popular students' decisions are influential to their peers in this context.

I examine the effect of smart students' decisions in more detail, and find that once again the peer effects are driven entirely by "No" decisions. See Figure 8 and Table 8: compared to a baseline (control group) sign-up rate of 80.7 percent, seeing that a smart peer chooses "Yes" to sign-up does not change the sign-up rate, but seeing that a smart peer chooses "No" decreases the sign-up rate by 42.4 percentage points ($p<0.01$).

5.2 Do students have correct beliefs about their peers' decisions?

If social utility is important in an educational context, then beliefs about peers' decisions are an important component of the model. This is especially the case when students are making decisions without seeing what their peers do. Incorrect beliefs about peers' participation in an educational program could lead to a higher or lower equilibrium participation rate than otherwise. Even once students are shown information about their peers' participation, their prior beliefs may influence the direction and magnitude of the peer effect.

In this section, I look at whether students have correct beliefs about their peers' decisions. I find that while students want to conform to the social norm, they have very biased beliefs about (they drastically

[26] Only three of the identified key students chose "No."

underestimate) their peers' participation. This bias is more extreme for students with lower GPAs. Figures 9 and 10 show that, while a majority of students in all GPA quartiles sign-up for the college application assistance program in my experiment, only 10.0 percent of the students in the lowest GPA quartile think that a majority of their classmates will sign-up, while 47.5 percent of the students in the highest GPA quartile think that a majority of their classmates will sign-up. These graphs restrict the sample to students in the control group who do not see any peer's decision.

To address the concern that the peer effects may not be strong (students in the lowest GPA quartile believed their peers were not signing-up, and yet a majority of them still signed-up), I look at students' WTP for the program by GPA quartile. Figure 38 of Appendix D shows that students in lower GPA quartiles had *higher* WTP for the program than students in higher GPA quartiles. An explanation for this could be that students with higher GPA have more available substitutes for the program I offer. Recall that in my model, a student's decision to sign-up depends on both her private benefit and her social benefit. This shows that, if anything, students in lower GPA quartiles should have been *more* likely to sign-up for the program, and yet their biased beliefs push them to sign-up at lower rates than they would otherwise.

Finally, I check the external validity of this result. One could argue that the student's decision to sign-up for an (experimental) educational program is an unfamiliar one, and thus students don't have information about their peers' decisions in this situation. I use two questions in the survey that ask students (1) if they plan to go to college, and (2) if they expect their friends to plan to go to college. Figures 11 and 12 show that, while a majority of students in all GPA quartiles plan to go to college, students in lower GPA quartiles are less likely to think that a majority of their friends are planning to go to college. In this case, students' beliefs about their peers' college plans – while still biased – are closer to the actual plans, which may reflect that students learn more about their peers' decisions as they communicate with each other.

6 Structural estimation and counterfactuals

Sections 4 and 5 presented reduced form tests to disentangle social learning and social utility. In this section, I use the data I collected from the field experiment to estimate the structural model in Section 2. Specifically, I interpret my model as a structural decomposition of peer effects into three channels: social learning, consumption externalities, and social norms. I find that the peer effect operates through the social norms channel, supporting my results from the reduced form tests.

I combine the structural estimates with the collected school social network data to run a policy counterfactual. I look at the take-up of targeted educational programs when I vary the type and fraction of students that are targeted as initial adopters of the program. My results show that when there are negative peer effects and costly initial adoption, targeting smart students can actually backfire and lead to a lower overall school sign-up rate than targeting non-smart students.

6.1 Set-up

I estimate the model of Section 2, and impose several assumptions. For details about the estimation procedure, refer to Appendix C.

Private benefit. First, I parameterize the private benefit as a linear function of students' WTP and student-specific covariates,

$$E[\nu\left(1\right)|X_{is}] = X_{is}'\beta_1$$
$$E\left[\nu(-1)|X_{is}\right] = X_{is}'\beta_2,$$

where X_{is} includes student i's posterior WTP, GPA, gender, race (black), family education, log weekly money earned, and school fixed effects.

Social benefit. I parameterize the social benefit as the following. For students in the pooled control group (first and second group) who do not see a peer's decision, we have

$$s\left(1|PriorBeliefs_i\right) = J_1 PriorBeliefs_i - \frac{J_2}{2}\left(1 - PriorBeliefs_i\right)^2$$
$$s\left(-1|PriorBeliefs_i\right) = -J_1 PriorBeliefs_i - \frac{J_2}{2}\left(-1 - PriorBeliefs_i\right)^2.$$

For students in the second group who saw a peer's decision ("other classes" treatment), we have

$$s\left(1|PriorBeliefs_i, PosteriorBeliefs_i\right) = J_1 PriorBeliefs_i - \frac{J_2}{2}\left(1 - PosteriorBeliefs\right)^2$$
$$s\left(-1|PriorBeliefs_i, PosteriorBeliefs_i\right) = -J_1 PriorBeliefs_i - \frac{J_2}{2}\left(-1 - PosteriorBeliefs_i\right)^2.$$

For students in the second group who saw a peer's decision ("current class" treatment), we have

$$s\left(1|PosteriorBeliefs\right) = J_1 PosteriorBeliefs - \frac{J_2}{2}\left(1 - PosteriorBeliefs\right)^2$$
$$s\left(-1|PosteriorBeliefs_i\right) = -J_1 PosteriorBeliefs_i - \frac{J_2}{2}\left(-1 - PosteriorBeliefs_i\right)^2.$$

Here, $PriorBeliefs_i$ is the student's prior beliefs about her classmates' participation, and $PosteriorBeliefs_i$ is the student's posterior beliefs about her classmates' participation. I assume that in the "other classes" treatment, when seeing a peer's decision, students update their beliefs about the social norms of participation but not their consumption externalities. Thus, the parameters J_1 and J_2 are identified using only students in the "other classes" treatment.

I assume the errors $\varepsilon(1)$ and $\varepsilon(-1)$ are independent and extreme-value distributed, so that the differences in the errors are logistically distributed. Thus, for students in the pooled control group, we have

$$Pr\left(d_i = 1 | X_{is}, PriorBeliefs_i\right) = \frac{1}{1+\exp\left(-2X_{is}'\beta - 2\left(J_1+J_2\right)PriorBeliefs_i\right)}$$
$$Pr\left(d_i = -1 | X_{is}, PriorBeliefs_i\right) = \frac{1}{1+\exp\left(2X_{is}'\beta + 2\left(J_1+J_2\right)PriorBeliefs_i\right)}.$$

For students in the second group who saw a peer's decision ("other classes" treatment), we have

$$\begin{aligned}
&Pr\left(d_i = 1 | X_{is}, PriorBeliefs_i, PosteriorBeliefs_i\right)\\
&= \frac{1}{1+\exp\left(-2X_{is}'\beta - 2J_1 PriorBeliefs_i - 2J_2 PosteriorBeliefs_i\right)}\\
&Pr\left(d_i = -1 | X_{is}, PriorBeliefs_i, PosteriorBeliefs_i\right)\\
&= \frac{1}{1+\exp\left(2X_{is}'\beta + 2J_1 PriorBeliefs_i + 2J_2 PosteriorBeliefs_i\right)}.
\end{aligned}$$

For students in the second group who saw a peer's decision ("current class" treatment), we have

$$Pr\left(d_i = 1 | X_{is}, PosteriorBeliefs_i\right) = \frac{1}{1+\exp\left(-2X_{is}'\beta - 2\left(J_1+J_2\right)PosteriorBeliefs_i\right)}$$
$$Pr\left(d_i = -1 | X_{is}, PosteriorBeliefs_i\right) = \frac{1}{1+\exp\left(2X_{is}'\beta + 2\left(J_1+J_2\right)PosteriorBeliefs_i\right)}.$$

Here, $\beta = \frac{1}{2}\left(\beta_1 - \beta_2\right)$.

Belief updating. I consider a simple model of student i's belief updating. After seeing s_{ik}, student i updates her expectations of v, $\mathbf{d}_{-i,g}$, and $\mathbf{d}_{-i}$, taking a weighted average of her prior and the signal.[27] Thus,

$$E\left[v|\theta_i, s_{ik}\right] \equiv \left(1-\gamma\right)E\left[v|\theta_i\right] + \gamma\hat{v}$$
$$E\left[\mathbf{d}_{-i,g}|\theta_i, s_{ik}\right] \equiv \left(1-\eta\right)E\left[\mathbf{d}_{-i,g}|\theta_i\right] + \eta s_{ik}$$
$$E\left[\mathbf{d}_{-i}|\theta_i, s_{ik}\right] \equiv \left(1-\eta\right)E\left[\mathbf{d}_{-i}|\theta_i\right] + \eta s_{ik}.$$

Here, $\hat{v}$ is the inferred v that student i gets from seeing student k's decision.[28] Also, γ and η are the

[27] Recall that ν is the program's value, $\mathbf{d}_{-i,g}$ is the vector of other student's choices who are able to participate in the same group as i, and $\mathbf{d}_{-i}$ is the vector of all other student's choices. $E[\nu|\theta_i]$, $E[\mathbf{d}_{-i,g}|\theta_i]$, and $E[\mathbf{d}_{-i}|\theta_i]$ are the student's prior beliefs over ν, $\mathbf{d}_{-i,g}$, and $\mathbf{d}_{-i}$, and $E[\nu|\theta_i, s_{ik}]$, $E[\mathbf{d}_{-i,g}|\theta_i, s_{ik}]$, and $E[\mathbf{d}_{-i}|\theta_i, s_{ik}]$ are the student's posterior beliefs.

[28] For example, student k does not see any other student's decision, so he chooses d_k^* to maximize

$$V\left(d_k, \theta_k\right) = E\left[\nu|\theta_k\right]d_k + J_1 d_k E\left[\mathbf{d}_{-k,g}|\theta_k\right] - \frac{J_2}{2}\left(d_k - E\left[\mathbf{d}_{-k}|\theta_k\right]\right) + \varepsilon\left(d_k\right).$$

belief updating weights that student i places on her signal relative to her prior.

I estimate the updating term η using

$$\hat{\eta} = \frac{1}{n}\sum_{i=1}^{n}\frac{PosteriorBeliefs_i - PriorBeliefs_i}{SignalBeliefs_{ik} - PriorBeliefs_i},$$

where $SignalBeliefs_{ik}$ is the peer's decision that student i sees, $SignalBeliefs_{ik} \in \{-1, 1\}$.[29]

6.2 Structural estimation results

Table 9 shows maximum likelihood estimates of the structural parameters β, J_1, and J_2. Column (1) estimates the model with only one channel of peer effects, social norms. Column (2) estimates the model with two channels of peer effects, consumption externalities and social norms. Column (3) estimates the model with two channels of peer effects, social learning and social norms. Column (4) estimates the model with all three channels of peer effects. Because columns (2) and (4) use both students' prior and posterior beliefs about peers' participation, this restricts the sample to students who participated in both the survey and the program sign-up, and drops a large number of observations. In all regressions, I find the strongest evidence for the social norms channel (J_2), which supports my results from the reduced form tests.

Table 10 shows estimates of the belief updating parameter η, and Table 11 shows the underlying changes in beliefs. In this paper's model, η is the weight that students place on their signal relative to their prior. A higher η indicates that students update their beliefs about their peers' participation more when they see a peer's decision. I calculate $\hat{\eta}$ separately for students who see that a smart peer chooses "No", students who see that a smart peer chooses "Yes", students who see that a non-smart peer chooses "No", and students who see that a non-smart peer chooses "Yes". I find that students update their beliefs about their peers' participation more when they see that a smart peer chooses "No" than when they see that a smart peer chooses "Yes". When students see that a smart peer chooses "No", they place about equal weight on their prior and their signal ($\hat{\eta} = 0.528$). In contrast, when students see that a smart peer chooses "Yes", they place all of the weight on their prior ($\hat{\eta} = -0.025$). I find that students update their beliefs about their peers'

Under certain assumptions – for example, assuming that all students have the same social benefit term – there should be a cutoff v_c such that student k chooses $d_k^* = 1$ iff $E[v|\theta_k] \geq v_c$. So if student i sees that student k chose to sign-up for the educational program, then she infers that student k's expected benefit is *at least* v_c (let $\hat{v} = v_c$). On the other hand, if student i sees that student k chose not to sign-up for the educational program, then she infers that student k's expected benefit is less than v_c (let $\hat{v}$ equal the lower bound of $G(\cdot)$).

[29]Similarly, one could estimate the updating term γ using

$$\hat{\gamma} = \frac{1}{n}\sum_{i=1}^{n}\frac{PosteriorWTP_i - PriorWTP_i}{SignalWTP_{ik} - PriorWTP_i},$$

where $SignalWTP_{ik}$ is the $\hat{\nu}$ from the model in Section 2. However, this estimate is very sensitive to the choice of $SignalWTP_{ik}$, and so it requires strong assumptions. I do not estimate γ in this paper for this reason, and also because I do not find strong evidence that students update their beliefs about the value of the program in my reduced form tests.

participation slightly more when they see that a non-smart peer chooses "Yes" than when they see that a non-smart peer chooses "No" ($\hat{\eta} = 0.248$ vs. $\hat{\eta} = 0.104$).

One possible explanation for these results could be that students on average thought that a majority of smart students would choose to sign-up for the college application assistance program (see Figures 32 and 33 in Appendix D). Thus, seeing that a smart peer chooses "No" could be a stronger signal – students revise their expectations more when they think that even a smart peer will not sign-up. However, the estimates of η should be interpreted with caution due to the small sample size used in the calculation.

6.3 Policy counterfactual: Targeted educational programs

I combine the structural estimates of β, J_1, J_2, and η with the collected school adjacency matrices to run a policy counterfactual. Specifically, I look at the take-up of targeted educational programs when I vary the type and fraction of students that are targeted as initial adopters of the program. When resources are scarce, educational programs commonly target certain types of students to adopt the program, such as the highest-achieving students or the highest-need students at a school. Even if there is no explicit targeting, programs that allow students to select in to participation will see the highest-achieving students ("smart" students in this paper) as early adopters. If there are peer effects to participation, the overall school sign-up rate for a program depends on which type of student is targeted.

In my counterfactual, I vary: (1) whether smart or non-smart students are targeted as initial adopters of a program, and (2) whether a random 1%, 5%, or 10% of students are targeted. I focus on the case where it is costly for targeted students to take-up the program, and so I add an initial cost shock (to their WTP) for the targeted students that makes it prohibitively costly for them to sign-up for the program. I run these simulations for each of Hillcrest High School, Thornwood High School, and Proviso West High School separately, and look at the resulting school sign-up rates for the program.

Because this paper only looks at peer effects from seeing a peer's decision (shutting down the information transmission channel), I have to make some assumptions about the information transmission process along the school social networks. I take the collected school adjacency matrices as given. In my simulations, I use an information transmission process similar to the one in Banerjee et al. (2013), and also take from the paper an exogenous probability of information transmission, $p = 0.35$. I simulate the process for $T = 4$ time periods of information transmission, and run $S = 100$ simulations for each school.

The simulations take the following steps. For each school:

1. First, I choose the targeted students who are informed about the program: either a random 1%, 5%, or 10% of the smart or the non-smart students at each school

2. The targeted students choose to sign-up if $V(1) > V(-1)$, given their own characteristics and prior beliefs about peers' participation. Here, due to the initial cost shock, all of the targeted students choose not to sign-up

3. In each subsequent period, $t = 1, \ldots, T$, students who are informed spread information about the program and their decision to each of their friends (in the adjacency matrix), independently, with probability $p = 0.35$

4. The newly informed students update their prior beliefs about their peers' participation given the signal they receive (their friend's decision, and whether their friend is smart or non-smart)

5. The newly informed students choose to sign-up if $V(1) > V(-1)$, given their own characteristics and posterior beliefs about peers' participation

6. The process ends after $T = 4$ periods of information transmission

Figures 13 to 15 show the distributions of counterfactual school sign-up rates varying the type and fraction of students that are targeted, over 100 simulations. The results follow the same pattern at each school. My results show that when there are negative peer effects and costly initial adoption, targeting smart students can actually backfire and lead to a lower overall school sign-up rate than targeting non-smart students. When a small fraction of students are targeted (1% of smart or non-smart students), the sign-up rates are similar when targeting smart or non-smart students. As the fraction of students that are targeted grows, the sign-up rate when smart students are targeted decreases relative to the sign-up rate when non-smart students are targeted. The intuition behind this result is that students update their beliefs about their peers' participation negatively when they see that a peer chooses "No", and this is especially the case when they see that a smart peer chooses "No." In contrast, as non-smart students' decisions are less influential to their peers, a low initial adoption by non-smart students does not decrease the school sign-up rate as much.

7 Discussion and conclusion

In this paper, I find large negative peer effects in the decision to participate in an educational program for high school students. I develop a theoretical model with two channels of peer effects, social learning and social utility (further splitting social utility into the consumption externalities and social norms subchannels), and conduct a field experiment in three Chicago high schools to disentangle the peer effect channels.

First, I perform some reduced form tests to disentangle the peer effect channels. I find that the peer effect operates through informing students about the social norms of participation, as seeing a peer's decision causes students to update their beliefs about their peers' participation. In contrast, I do not find strong evidence for the social learning or consumption externalities channels. Since the peer effects are driven by social utility, I do two additional analyses to understand how social utility affects students' decisions to participate in an educational program. I find that smart students' decisions are especially influential to their peers. Further, while students want to conform to the social norm, they have very biased beliefs about (they drastically underestimate) their peers' participation.

Next, I estimate my model, and interpret my model as a structural decomposition of peer effects into three channels: social learning, consumption externalities, and social norms. I find that the peer effect operates through the social norms channel, supporting my results from the reduced form tests. I also find suggestive evidence that students update their beliefs about their peers' participation most when they see that a smart student chooses "No." I combine the structural estimates with the collected school social network data to look at the take-up of targeted educational programs when I vary the type and fraction of students that are targeted as initial adopters of the program. I find that when there are negative peer effects and costly initial adoption, targeting smart students can actually backfire and lead to a lower overall school sign-up rate than targeting non-smart students.

I will conclude the paper with a comment, some policy implications, and some avenues for future research. First, I want to address the asymmetric result in this paper. I find large peer effects in the participation decision that are entirely driven by seeing that a peer chooses not to participate. In contrast, seeing that a peer chooses to participate does not affect the sign-up rate. There are three possible reasons for the asymmetric result that I am unable to disentangle in the paper. First, because I have a very high overall school sign-up rate, there could be ceiling effects. Second, because the sign-up decision was binding only in the negative direction, seeing that a peer chooses "No" could be a stronger signal for students than seeing that a peer chooses "Yes." Third, seeing that a peer chooses "No" could be more salient to students.

My paper has a few policy implications. The finding that social utility is the dominant peer effect channel, instead of social learning, implies that group-based educational programs will have higher participation rates than individual-based educational programs. In particular, students care about the social norms of participation. Many existing educational programs target individual students – for example, some recent interventions aimed at helping low-income students apply to college use mailings to inform students about colleges and the college application process (see, e.g., Hoxby and Turner (2013)). In cases where there is a prevailing social norm not to make human capital investments, the overall participation rate could be lower than intended, as students may be reluctant to take advantage of a program if their peers do not do so. Moreover, I find that students underestimate their peers' human capital investments. My findings suggest that the overall take-up rate for an educational program depends on the complex relationship between many factors, including heterogeneity in peer effects, students' prior beliefs, which students are targeted by an educational program, and what fraction of students are targeted.

Finally, this paper suggests two potential avenues of future research. First, the fact that students have biased beliefs about their peers' participation in an educational program begs the question, *How do students form beliefs about their peers' educational decisions?* Second, while I don't find strong evidence for social learning in this paper, it would be interesting to see in which contexts social learning is important. In this paper, I look at peer effects from seeing a peer's decision, shutting down the information transmission channel. I find that students do not learn from observing their peers' decisions about the value of a program. It could be the case that social learning requires students to communicate with each other, instead of observing each other's decisions.

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	Hillcrest	Thornwood	Proviso West	State
N(Students)	1,110	1,796	1,850	-
N(Seniors/Juniors)	291	443	442	-
% Female	53	49	48	-
% African-American	89	83.4	47.1	17
% Hispanic	4.8	11.5	44.3	25.7
% White	0.8	2.7	2.6	48.5
% Low-Income	56.1	91.5	24.6	50
% Graduation Rate	77	81	81	87
% Ready for College	15	15	14	51
% College Enrollment	54	55	57	70

Table 1: Summary statistics of demographics and performance of Hillcrest High School, Thornwood High School, and Proviso West High School, compared to state averages. "Low-Income" refers to students who are eligible to receive free or reduced-price lunches, live in substitute care, or whose families receive public aid. "Graduation Rate" refers to 4-year high school graduation rate. "Ready for College" shows the percentage of students who achieved a combined score of at least 21 on the ACT (classified as being Ready for College Coursework). "College Enrollment" refers to the percentage of graduating students who are enrolled in a two-year or four-year college in the U.S. within 12 months. Source: Illinois Report Card 2016-2017, Illinois State Board of Education; "% Female" from U.S. News & World Report; "% African-American," "% Hispanic," "% White," and "% Low-Income" are state K-12 averages from the Illinois State Board of Education; N(Seniors/Juniors) obtained directly from the high schools.

	All students		"Popular" students	"Smart" students
	Mean	SD	Mean	Mean
Panel A: Student characteristics				
Female* (%)	52.3		55.9	65.8***
White* (%)	1.0		0.3	0.8
Black* (%)	72.4		70.1	70.2
Hispanic* (%)	24.0		26.9	25.7
Low-income* (%)	40.3		46.2***	43.0
Special education status* (%)	12.7		3.0***	7.8***
Any family members attended college (%)	83.3		84.9	81.7
Unweighted GPA*	2.11	0.83	2.34***	2.93***
SAT score/PSAT score*	889/833	139/116	919***/852**	1002***/933***
Number of Honors classes enrolled*				
Plan to attend college (%)	86.8		91.3***	92.7***
Number of extracurricular activities				
Panel B: Social network measures				
Out-degree (number of friends listed)	3.1	2.8	5.0***	3.7***
In-degree (number of students who listed student as friend)	1.3	1.5	2.9***	1.8***
[Centrality measures]				
Self-rated popularity (1 = not popular, 5 = very popular)	3.0	1.2	3.5***	2.8***
Importance of popularity (1 = not important, 5 = very important)	1.7	1.1	1.7	1.4***
Number of students completing survey	494		221	205
Number of students	1,176		331	386

Table 2: Summary statistics obtained from student survey, comparing students classified as "popular" and "smart" to all students. *Gender, race, low-income, special education status, GPA, standardized test scores, and student classes are directly obtained from high schools. This table also reports results from t-tests or chi-squared tests comparing characteristics of popular and smart students to non-popular and non-smart students, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	All Mean	Homework Help Mean	Gossip Mean	Respect Mean	Most Popular Mean
Panel A: Student characteristics					
Female* (%)	52.3	72.2***	72.6***	72.2***	61.8
White* (%)	1.0	0.8	0.0	0.0	0.0
Black* (%)	72.4	69.9	69.9	64.8	67.7
Hispanic* (%)	24.0	27.1	24.7	31.5	23.5
Low-income* (%)	40.3	45.1	49.3	42.6	32.4
Special education status* (%)	12.7	2.3***	5.5*	3.7**	5.9
Any family members attended college (%)	83.3	87.3	81.5	83.3	87.5
Unweighted GPA*	2.11	2.84***	2.69***	2.94***	2.45**
SAT score/	889	988***	931	1016***	924
PSAT score*	833	918***	882**	931***	860
Number of Honors classes*					
Plan to attend college (%)	86.8	93.8**	90.7	94.4	100.0**
No. of extracurricular activities					
Panel B: Social network measures					
Out-degree (number of friends listed)	3.1	4.4***	4.5***	4.8***	4.3**
In-degree (number of students who listed student as friend)	1.3	2.9***	3.2***	3.2***	3.4***
[Centrality measures]					
Self-rated popularity (5 = very popular)	3.0	2.8**	3.2	2.7*	3.2
Importance of popularity (5 = very important)	1.7	1.4**	1.7	1.5	2.1
No. of students completing survey	494	79	53	35	24
Number of students	1,176	133	73	54	34

Table 3: Summary statistics obtained from student survey, comparing students nominated as "key students" to all students. *Gender, race, low-income, special education status, GPA, standardized test scores, and student classes are directly obtained from high schools. This table also reports results from t-tests or chi-squared tests comparing characteristics of key students to non-key students. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) All students	(2) Group 2 students
In group 2	0.068	
(control only)	(0.042)	
Saw "No" decision		-0.269***
		(0.065)
Saw "Yes" decision		-0.008
		(0.046)
Constant	0.648***	0.658***
	(0.088)	(0.095)
Demographics	Yes	Yes
School FE	Yes	Yes
Obs.	427	372
R^2	0.070	0.101

Table 4: Linear probability model regressions of student's sign-up decision on information received. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) Group 2 students	(2) Group 2 students	(3) Group 2 students	(4) Group 2 students
Saw "No" decision	22.07	-4.31	0.701	0.162
	(50.00)	(30.21)	(0.826)	(0.819)
Saw "Yes" decision	28.47	22.67	0.985	0.946
	(37.5)	(25.67)	(0.648)	(0.782)
Constant	111.88	80.21*	4.167***	0.959
	(86.39)	(42.01)	(1.492)	(1.208)
DV	WTP	WTP	Norm. WTP	Norm. WTP
Demographics	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Weekly allowance	Yes	No	Yes	No
Prior WTP	No	Yes	No	Yes
Obs.	284	95	236	71
R^2	0.03	0.54	0.07	0.35

Table 5: OLS regressions of student's posterior WTP for program on information received. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) Group 2 students	(2) Group 2 students	(3) Group 2 students
Saw "Yes"	0.173**	0.230***	0.274***
	(0.082)	(0.078)	(0.069)
Saw "Yes" of smart student	0.280**		
	(0.138)		
Saw "Yes" of popular student		0.154	
		(0.151)	
Saw "Yes" of key student			-0.106
			(0.256)
Constant	0.364**	0.312**	0.293**
	(0.149)	(0.148)	(0.146)
Demographics	Yes	Yes	Yes
Paired student's demographics	Yes	Yes	Yes
School FE	Yes	Yes	Yes
Obs.	228	228	228
R^2	0.209	0.198	0.197

Table 6: Linear probability model regressions of student's sign-up decision on information received. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) Group 2 students	(2) Group 2 students	(3) Group 2 students
Saw “Yes”	0.186**	0.177**	0.252***
	(0.080)	(0.082)	(0.078)
Saw “Yes” of academically similar student	0.269**		
	(0.136)		
Saw “Yes” of (locally) smart student		0.271*	
		(0.138)	
Saw “Yes” of (locally) popular student			0.062
			(0.145)
Constant	0.373**	0.358**	0.292*
	(0.150)	(0.148)	(0.150)
Demographics	Yes	Yes	Yes
Paired student’s demographics	Yes	Yes	Yes
School FE	Yes	Yes	Yes
Obs.	228	228	228
R^2	0.209	0.208	0.196

Table 7: Linear probability model regressions of student’s sign-up decision on information received. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) Group 2 students	(2) Group 2 students
Saw “No” decision	-0.269***	
	(0.065)	
Saw “Yes” decision	-0.008	
	(0.046)	
Saw “No” of smart student		-0.424***
		(0.104)
Saw “Yes” of smart student		0.014
		(0.062)
Constant	0.658***	0.680***
	(0.095)	(0.116)
Demographics	Yes	Yes
School FE	Yes	Yes
Obs.	372	231
R^2	0.101	0.088

Table 8: Linear probability model regressions of student's sign-up decision on information received (seeing smart students' decisions only). Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) MLE	(2) MLE	(3) MLE	(4) MLE
Log WTP			0.027*	0.040
			(0.015)	(0.029)
Consumption externalities (J_1)		0.157		0.100
		(0.312)		(0.305)
Social norms (J_2)	0.863***	0.486	0.843***	0.545*
	(0.149)	(0.320)	(0.150)	(0.316)
GPA	0.019	0.058	0.012	0.043
	(0.064)	(0.098)	(0.064)	(0.099)
Female	0.583***	0.312	0.565***	0.305
	(0.128)	(0.197)	(0.129)	(0.201)
Black	0.181	0.219	0.171	0.183
	(0.121)	(0.210)	(0.122)	(0.214)
Any family members attended college		-0.224		-0.226
		(0.251)		(0.259)
Log weekly allowance	0.020*	0.019	0.015	0.008
	(0.011)	(0.017)	(0.011)	(0.019)
School = Proviso West	0.351**	0.597**	0.306*	0.567**
	(0.175)	(0.244)	(0.178)	(0.251)
School = Thornwood	0.141	0.410	0.121	0.388
	(0.161)	(0.253)	(0.165)	(0.265)
Obs.	477	203	471	201

Table 9: Maximum likelihood estimates. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Belief updating for peers' decisions (η)	
Saw "No" (all)	0.328
Saw "Yes" (all)	0.155
Saw Smart "No"	0.528
Saw Smart "Yes"	-0.025
Saw Non-smart "No"	0.104
Saw Non-smart "Yes"	0.248

Table 10: Estimates of belief updating parameters

Change in beliefs about class participation (posterior - prior)	Control (%)	Saw “No” (%)	Saw “Yes” (%)	Saw Smart “No” (%)	Saw Smart “Yes” (%)
< 0	28.9	52.4	18.5	80.0	26.1
0	35.3	23.8	38.5	10.0	34.8
> 0	35.9	23.8	43.1	10.0	39.1
Obs.	156	21	65	10	23

Table 11: Change in beliefs (posterior - prior), conditional on information received

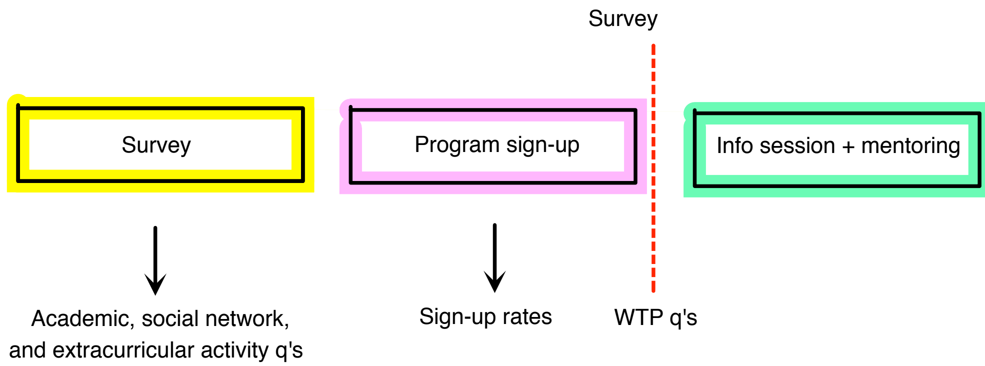

Figure 1: Experiment timeline

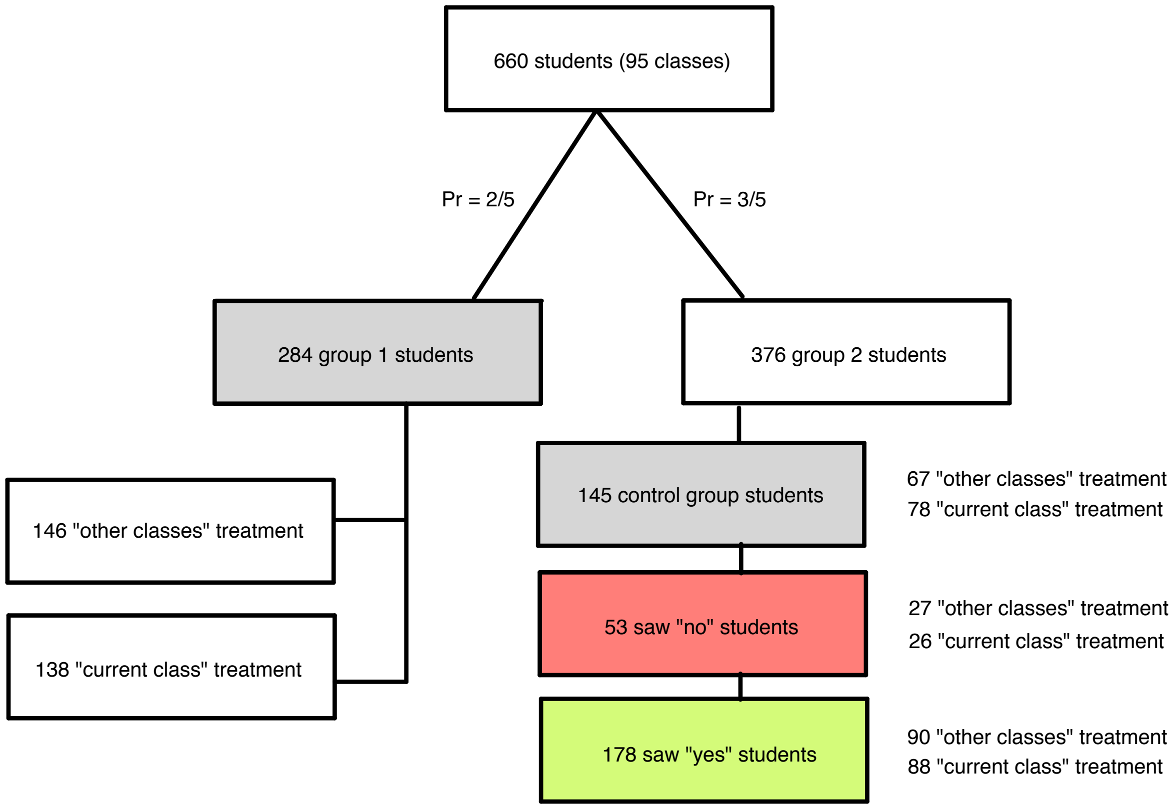

Figure 2: Randomization

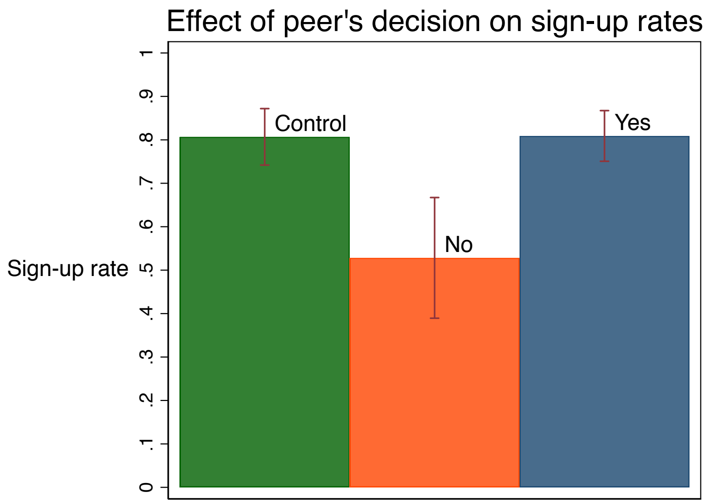

Figure 3: Effect of seeing peer's decision on sign-up rate

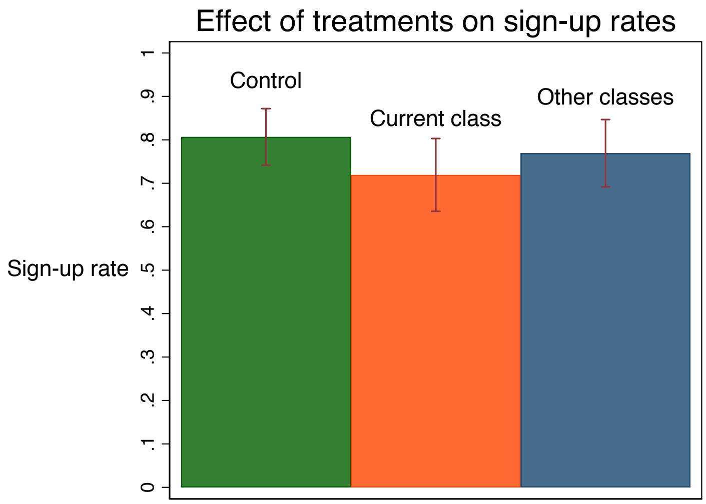

Figure 4: Treatments testing for consumption externalities

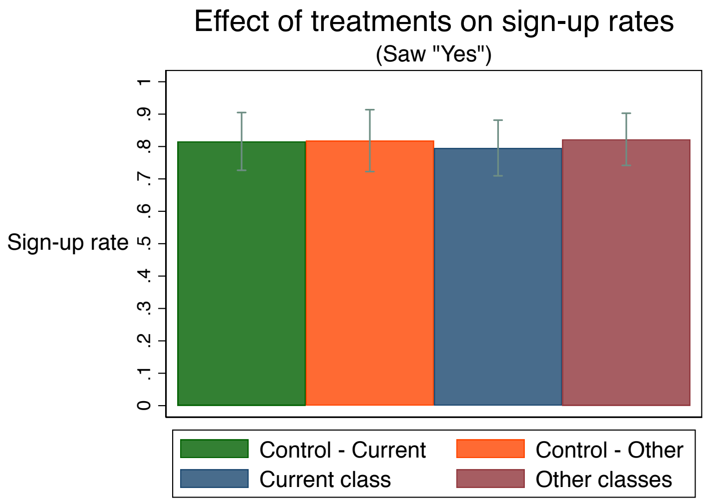

Figure 5: Treatments testing for consumption externalities – Group 2 students who saw “Yes” decision

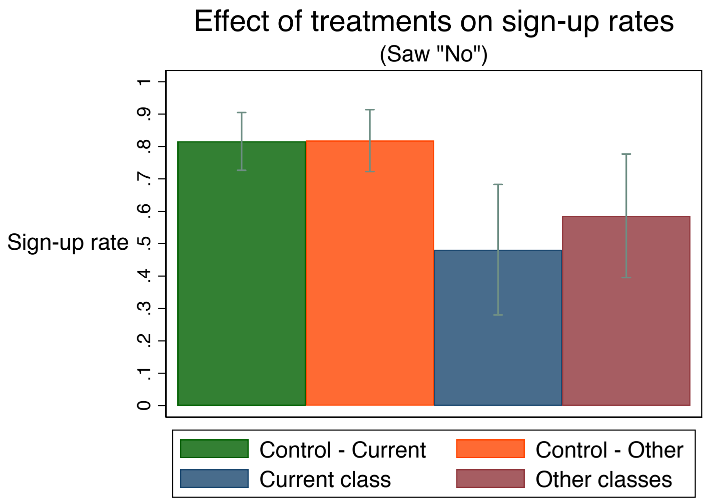

Figure 6: Treatments testing for consumption externalities – Group 2 students who saw “No” decision

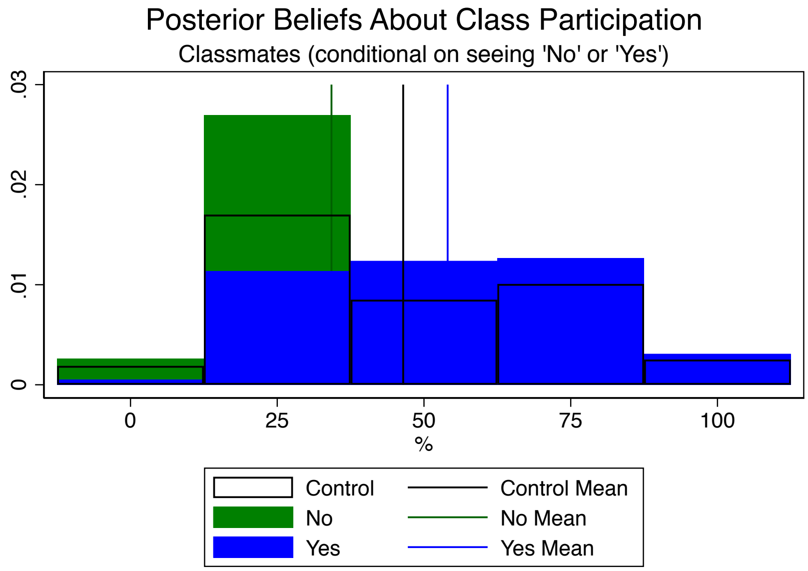

Figure 7: Effect of information seen on beliefs about class participation

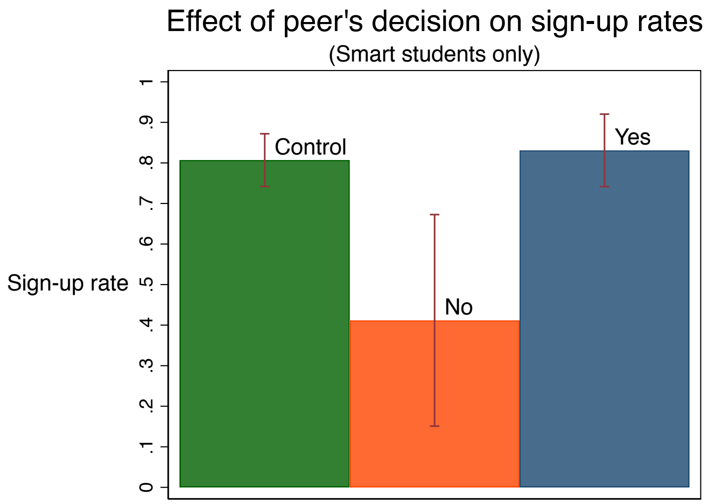

Figure 8: Effect of seeing peer's decision on sign-up rate (seeing smart students' decisions only)

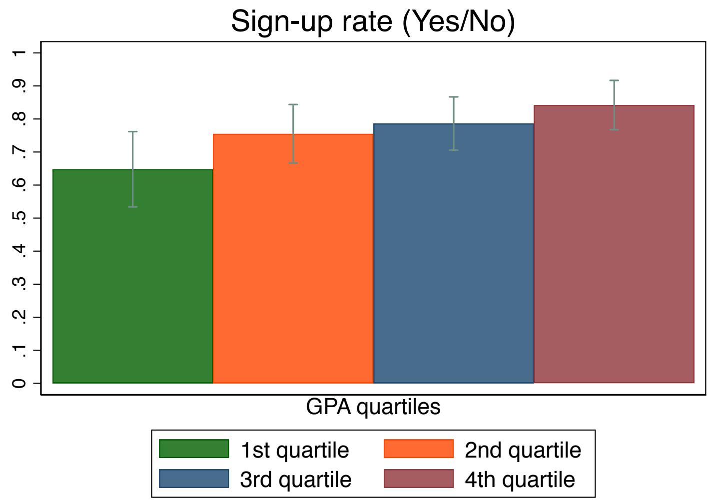

Figure 9: Sign-up rates by GPA quartile

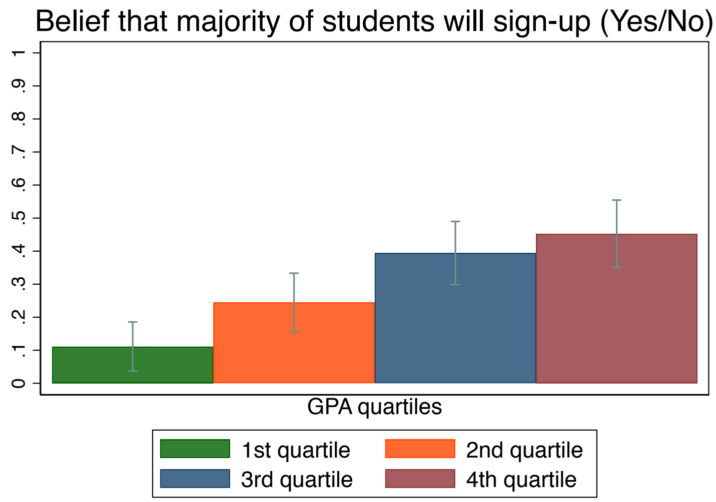

Figure 10: Beliefs about class participation by GPA quartile

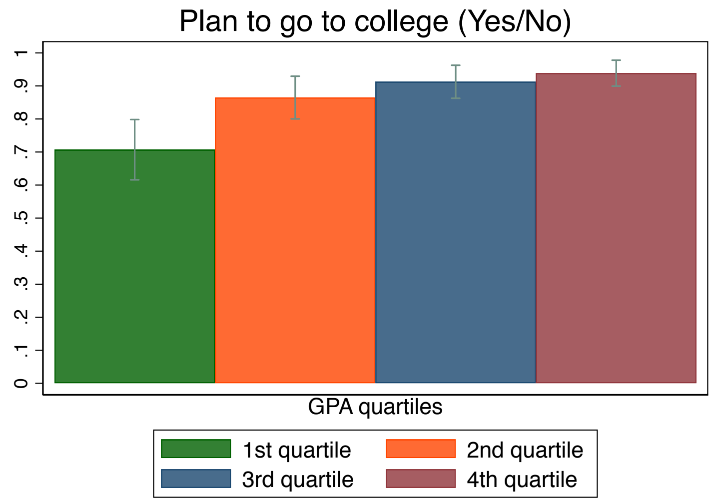

Figure 11: College plans by GPA quartile

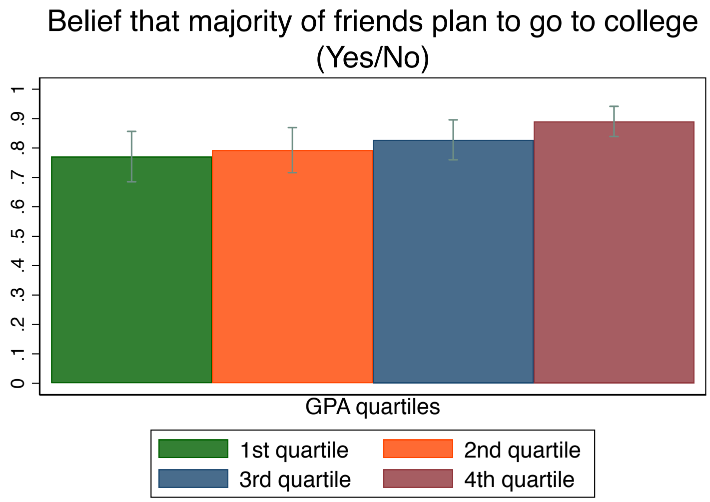

Figure 12: Beliefs about friends' college plans by GPA quartile

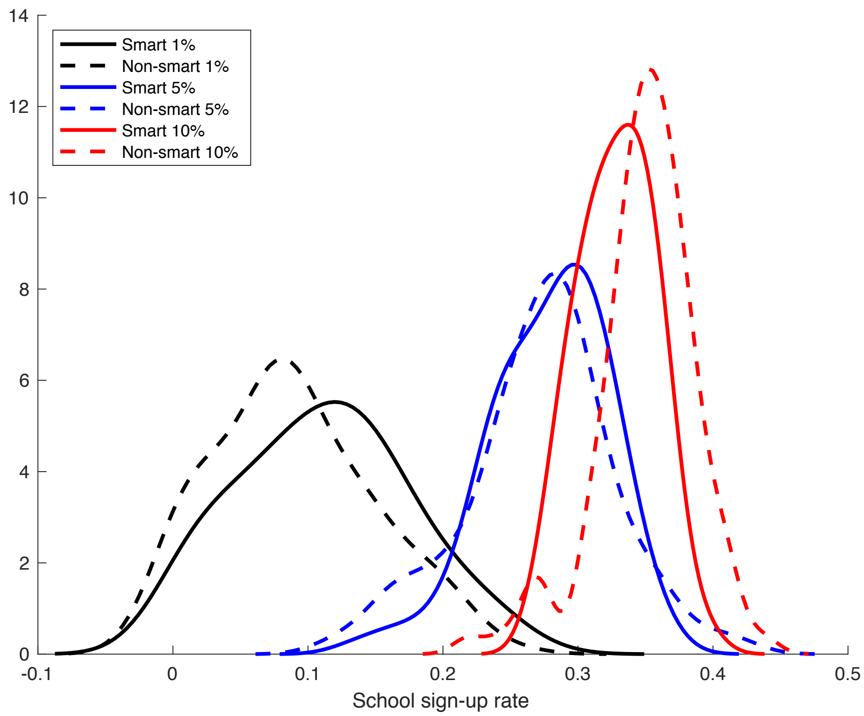

Figure 13: Distributions of counterfactual school sign-up rates varying the type and fraction of students that are targeted (Hillcrest). This figure plots kernel density estimates of the sign-up rate over 100 simulations.

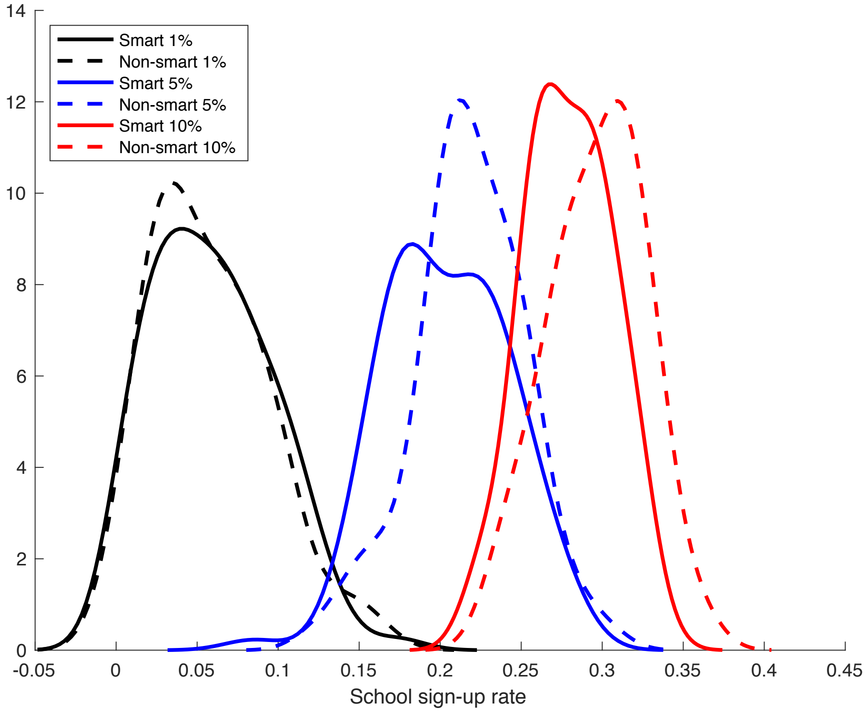

Figure 14: Distributions of counterfactual school sign-up rates varying the type and fraction of students that are targeted (Thornwood). This figure plots kernel density estimates of the sign-up rate over 100 simulations.

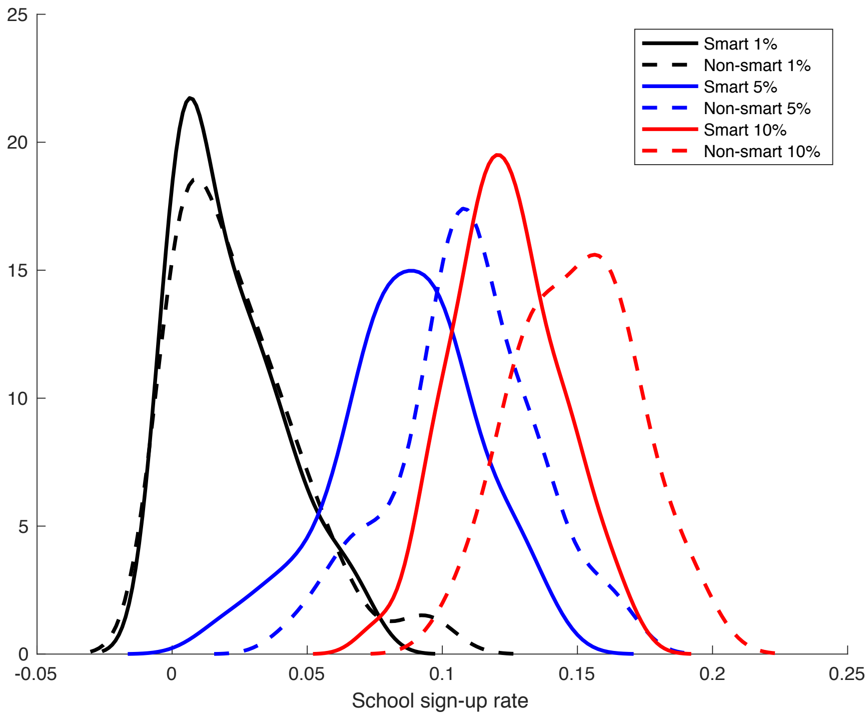

Figure 15: Distributions of counterfactual school sign-up rates varying the type and fraction of students that are targeted (Proviso West). This figure plots kernel density estimates of the sign-up rate over 100 simulations.

A Experiment procedure

A.1 Recruitment procedure

Schools considered for the study had the following criteria: (1) within 1 hour driving distance from the University of Chicago, (2) greater than 750 enrolled students,[30] (3) over 50% low-income students, and (4) had a college enrollment rate below the Illinois state average (68% at the time of recruitment). I sent recruitment emails to all of the principals and college counselors (if identified) at the schools on this list, and included in the study any school that was willing to participate. Participating schools had two options: due to the timing of the college application cycle, they could either (1) participate with their senior class in early fall (before November), or (2) participate with their junior class in the spring.

A.2 Detailed timeline at a school

When a school responded to my recruitment email, I arranged a series of meetings with the school. The first meeting introduced the project to the school, including data and logistics requirements. The second meeting planned the project logistics and clarified expectations from all parties.

The following is an example timeline of events at a school:

- Introductory meeting
- Logistics meeting
- I send consent letters to parents of all 12th/11th grade students via robo call, email, and mailing
- I collect opt-out consents
- I present research project to teachers at faculty meeting
- School administers survey to all 12th/11th grade students in English/History class[31]
- I bring research assistants with me to conduct sign-up in one class period, or two adjacent class periods
- School notifies students about their assigned program date, time, and location
- I hold one-time college application information session, and set up small group mentoring on Facebook

[30] Because most Chicago Public School system schools are very small, this restricted the sample of schools to larger schools in the Chicago suburbs.

[31] The schools and I chose to administer the survey in English and History classes, as all students take English and History classes with their grade.

A.3 Program sign-up: randomization procedure

In each classroom, students were pre-randomized into two groups. The randomization was implemented using the following procedure. For each classroom, I generated a random sequence of 1's and 2's (depending on the number of students in the class). These were printed on the top right corner of students' consent forms such that each consent form had either a "1" or "2" printed. In order to have a control group of students who do not see any peer's decision in the second group, 1's were generated with probability 2/5, and 2's were generated with probability 3/5.

In each classroom, we handed out the consent forms to students in order. Students with a "1" on their consent form were called out of the classroom as the first group of students, and students with a "2" on their consent form were called out of the classroom as the second group of students.

A.4 Program sign-up: experimenter script

Arriving at the classroom:

Hi! I am from the University of Chicago, and I am conducting a research study with [seniors/juniors] at [Hillcrest/Thornwood/Proviso West] High School. I am going to pass out a form for each of you. Please read the form carefully and sign your name. [Pass out assent/consent forms and pens] Next, I will ask the [seniors/juniors] to come out into the hallway in two groups (1/2 of the [seniors/juniors] at a time). Can the students with a "1" on the top right corner of their form follow me? I will be back in 5 minutes for the other [seniors/juniors]. When you come out into the hallway, bring your signed form so that you can give it to me.

In the hallway, first group:

In this research study, I will ask you to make one decision, and then answer some questions about your decision. We are holding a free college application assistance program at [Hillcrest/Thornwood/Proviso West] High School. The program consists of an information session next week after school, as well as small group mentoring from now until the end of the year. The program will provide strategies for applying to college. Please take a moment to decide whether you would like to sign-up for the program. Please do this quietly since we are in the hallway. [Wait 1 minute, then collect the clipboards.]

OK, I just have one last survey for you. You will have 2 minutes to complete this survey. When your 2 minutes are up, I will let you know. Please complete the survey quietly since we are in the hallway. [Time 2 minutes.]

OK, your 2 minutes are up! Thanks for participating in our research study! If you chose to sign-up for the college application assistance program, you will receive further details in a school announcement.

In the hallway, second group:

In this research study, I will ask you to make one decision, and then answer some questions about your decision. We are holding a free college application assistance program at [Hillcrest/Thornwood/Proviso West] High School. The program consists of an information session next week after school, as well as small group mentoring from now until the end of the year. The program will provide strategies for applying to college. Please take a moment to decide whether you would like to sign-up for the program, and ***turn to the second page to make your decision****. Please do this quietly since we are in the hallway. [Wait 1 minute, then collect the clipboards.]*

OK, I just have one last survey for you. You will have 2 minutes to complete this survey. When your 2 minutes are up, I will let you know. Please complete the survey quietly since we are in the hallway. [Time 2 minutes.]

OK, your 2 minutes are up! Thanks for participating in our research study! If you chose to sign-up for the college application assistance program, you will receive further details in a school announcement.

A.5 Program sign-up: decision sheet text

Treatment A ("other classes")

Researchers will be holding a free **college application assistance program** at [Hillcrest/Thornwood/Proviso West] High School.

The program will proceed as follows:

- First, we will randomly assign you to a mentoring group. The group will contain 9 other students **who are not in your current class**. You will participate in group activities together in the program.
- Your group will meet at an **information session next week after school**, which will provide strategies for applying to college, information about colleges, as well as advice about financial aid and FAFSA.
- Your group will meet at **small group mentoring from now until the end of the year**.

First name: ____________________

Last name: ____________________

Would you like to sign-up for the college application assistance program (please circle "Yes" or "No")?

Yes No

This is your only chance to sign-up before the information session next week, and you must sign-up in order to participate. If you choose "Yes," you will receive a school pass with your assigned information session date & time.

Treatment B ("current class")

Researchers will be holding a free **college application assistance program** at [Hillcrest/Thornwood/Proviso West] High School.

The program will proceed as follows:

- First, we will randomly assign you to a mentoring group. The group will contain 9 other students **who are in your current class**. You will participate in group activities together in the program.
- Your group will meet at an **information session next week after school**, which will provide strategies for applying to college, information about colleges, as well as advice about financial aid and FAFSA.
- Your group will meet at **small group mentoring from now until the end of the year**.

First name: ____________________

Last name: ____________________

Would you like to sign-up for the college application assistance program (please circle "Yes" or "No")?

Yes No

This is your only chance to sign-up before the information session next week, and you must sign-up in order to participate. If you choose "Yes," you will receive a school pass with your assigned information session date & time.

B Description of data

B.1 Administrative data

I received the following student-level administrative data from schools (H = Hillcrest, T = Thornwood, PW = Proviso West):[32][33]

Variable	School
School ID	H, T, PW
State ID	H, T
First and last name	H, T, PW
Gender	H, T, PW
Race	H, T, PW
Age (DOB)	PW
Special education status	H, T, PW
Low-income/free lunch status	H, T, PW
Homeless status	PW
Migrant status	PW
English language learner status	PW
Unweighted GPA	H, T, PW
SAT total score	H
SAT reading score	H
SAT math score	H
PSAT total score	T
List of all student's classes and teachers, including whether they are regular, honors, AP, or IB classes	H, T

[32] Proviso West has a big non-native English speaker student population, so "English language learner status" was a relevant variable for the school. Hillcrest and Thornwood did not have big non-native English speaker student populations.

[33] Proviso West gave me only a partial list of student's classes (two class periods).

B.2 Pre-survey questions

The following questions were asked to students on the pre-survey. Students completed the survey in English/History class. They were given 45 minutes to complete the survey, and were not compensated for their participation. The survey contained questions about students' demographics, academic effort, college and career plans and progress, social network, prior WTP and beliefs about peers' participation, and extracurricular activities.

Category	A: *Demographics*	School
A.1.1-5	Have any of your family members ever attended a 4-year college or university? (circle "Yes," "No," or "Not Applicable")	H, T, PW
A.1.1	Mom	
A.1.2	Dad	
A.1.3	Other Guardian	
A.1.4	Older Sibling	
A.1.5	Other Family Member	
Category	B: *Academic effort*	
B.1.1-5	This year, have you done any of the following? (circle "Yes" or "No")	H
B.1.1	Turned in missing homework assignments	
B.1.2	Turned in extra credit work	
B.1.3	Gone to school tutoring (before or after school)	
B.1.4	Gone to tutoring outside of school (e.g., Sylvan)	
B.1.5	Skipped/ditched school with your friends	
Category	C: *College and career plans and progress*	
C.1	Do you plan to attend college after high school? (circle "Yes, four-year college," "Yes, two-year college/community college," "No," or "Don't know")	H, T, PW
C.2	If you plan to attend college after high school, which college(s) are you considering? (List names of colleges; if you don't know, you can write "I don't know yet")	H, T, PW
C.3	Are you considering joining the military? (circle "Yes" or "No")	H, T, PW
C.4	What career(s) do you want to pursue after high school or college? (please list)	H, T, PW

Category C: *College and career plans and progress (cont.)*		School
C.5.1-6	Before today, have you done any of the following? (circle "Yes" or "No")	
C.5.1	Visited [college counselor] at the College & Career Center	H, T, PW
C.5.2	Attended a college representative visit	H, T, PW
C.5.3	Worked on a college application essay	H, T, PW
C.5.4	Decided on a final list of colleges to apply to	H, T, PW
C.5.5	Talked to your parent/guardian about the FAFSA	H, T, PW
C.5.6	Submitted a college application	H
C.6.1-3	How much money do you think you can earn in a year once you start working if you: (write $ amount)	H, T, PW
6.1	Drop out of High School	
6.2	Graduate from High School	
6.3	Graduate from College	
C.7	Do most of your closest friends plan to graduate and go to a good college? (circle "Yes," "No," or "Don't Know")	H, T, PW
C.8	Do your parents/guardian(s) expect you to graduate and go to a good college? (circle "Yes," "No," or "Don't Know")	H, T, PW
Category D: *Social network*		
D.1.1-D.7	In the following questions, we will ask you to list the names of ***other [12th/11th] grade students attending [Hillcrest/Thornwood/Proviso West] High School.*** They do not need to be in your [English/History] class. If you can't think of anyone for the question, you can leave the question blank and move on to the next question.	
D.1.1-4	Which [12th/11th] grade students do you eat lunch with at school? (list up to 4 names, both first name and last name)	H, T, PW
D.2.1-4	Which [12th/11th] grade students do you do homework with? (list up to 4 names, both first name and last name)	H, T, PW
D.3.1-4	Which [12th/11th] grade students do you like to hang out with after school? (list up to 4 names, both first name and last name)	H, T, PW
D.4	Which [12th/11th] grade student do you go to for help with practical problems such as homework or filling out a college application? (list up to 1 name, both first name and last name)	H, T, PW

Category D: *Social network (cont.)*		School
D.5	If we want to spread information to everyone in [Hillcrest/Thornwood/Proviso West] High School about a college representative visit, to which [12th/11th] grade student should we speak? (list up to 1 name, both first name and last name)	H, T, PW
D.6	Which [12th/11th] grade student do you look up to the most? (list up to 1 name, both first name and last name)	H, T, PW
D.7	Which [12th/11th] grade student is most popular? (list up to 1 name, both first name and last name)	H, T, PW
D.8	On a scale of 1-5, how popular would you say you are in your school? (1 = not popular, 5 = very popular)	H, T, PW
D.9	On a scale of 1-5, how important is it to be popular? (1 = not important, 5 = very important)	H, T, PW
Category E: *Prior WTP and beliefs about peers' participation*		
E.1.1-E.2	Suppose researchers were to offer a free program at [Hillcrest/Thornwood/Proviso West] High School to give advice to students about applying to college. To the best of your knowledge, tell us: (circle "0%," "25%," "50%," "75%," or "100%")	
E.1.1	What percentage of the [12th/11th] grade students at [Hillcrest/Thornwood/Proviso West] High School would attend?	H, T, PW
E.1.2	What percentage of your classmates in [English/History] class would attend?	H, T, PW
E.1.3	What percentage of your friends at [Hillcrest/Thornwood/Proviso West] High School would attend?	H, T, PW
E.1.4	What percentage of the smart students at [Hillcrest/Thornwood/Proviso West] High School would attend?	H, T, PW
E.1.5	What percentage of the popular students at [Hillcrest/Thornwood/Proviso West] High School would attend?	H, T, PW
E.2	Now suppose that the program was not free. How much would you be willing to pay to participate in the program? (write $ amount)	T, PW
Category F: *Extracurricular activities*		
F.1	Which sports, clubs, or other school activities do you participate in? (list all)	H, T, PW
F.2.1	Do you have a leadership role in any sports, clubs, or other school activities? (circle "Yes" or "No")	H, T, PW
F.2.2	If "Yes," which ones? (list all)	H, T, PW

B.3 Post-survey questions

The following questions were asked to students on the post-survey, immediately following their sign-up decision. Students were given 2 minutes to complete the survey, and were not compensated for their participation. The survey included a manipulation check (checking whether students looked at the first student's decision) for students in the second group, and contained questions about students' posterior WTP and beliefs about peers' participation.

Category A: *Manipulation check*		School
A.1	Did the student who signed up before you choose to sign up for the college application assistance program? (circle "Yes," "No," or "Don't Know")	H, T, PW
Category B: *Posterior beliefs about peers' participation*		
B.1.1-B.1.5	To the best of your knowledge, tell us: (circle "0%," "25%," "50%," "75%," or "100%")	
B.1.1	What percentage of the [12th/11th] grade students at [Hillcrest/Thornwood/ Proviso West] High School do you think will sign up?	H, T, PW
B.1.2	What percentage of your classmates in your current class do you think will sign up?	H, T, PW
B.1.3	What percentage of your friends at [Hillcrest/Thornwood/Proviso West] High School do you think will sign up?	H, T, PW
B.1.4	What percentage of the smart students at [Hillcrest/Thornwood/Proviso West] High School do you think will sign up?	H, T, PW
B.1.5	What percentage of the popular students at [Hillcrest/Thornwood/Proviso West] do you think will sign up?	H, T, PW
B.2.1-B.2.4	To the best of your knowledge, tell us: (circle "0," "1," "2," "3," "4," "5," "6," "7," "8," "9")	
B.2.1	Out of the 9 other students in your information session group, how many will be students with *similar grades* as you?	H
B.2.2	Out of the 9 other students in your information session group, how many will be your friends?	H
B.2.3	Out of the 9 other students in your information session group, how many will be smart students?	H
B.2.4	Out of the 9 other students in your information session group, how many will be popular students?	H

Category C: *Posterior WTP*		School
C.1	Suppose the college application assistance program were not free. How much would you be willing to pay to participate in the program? (write $ amount)	H, T, PW
C.2	How much would you be willing to pay to find out if your classmates were participating in the program? (write $ amount)	H, T, PW
C.3	How much money do you make in a week (either from your allowance or a job)? (write $ amount)	H, T, PW
Category D: *Other*		
D.1	If you chose "Yes": What information would be most useful for you (e.g., information about choosing colleges, information about financial aid, college essay-writing tips)? (free response)	H
D.2	If you chose "Yes": Please circle which days of the week you are free after school (that is, you don't have an extracurricular activity, job, or appointment). (circle "Mon," "Tues," "Wed," "Thurs," or "Fri")	T
D.3	If you chose "Yes": Would you prefer to attend the English information session or the Spanish information session? (circle "English" or "Spanish")	PW
D.4	If you chose "No": Why did you choose not to sign up? (free response)	H, T, PW
D.5	Do you already participate in a similar college application assistance program? (circle "Yes" or "No")	T, PW

C Estimation details

Let N_{ctrl}, N_{oc}, and N_{cc} denote the sets of students in the pooled control group, "other classes" treatment, and "current class" treatment, respectively.

For students in the pooled control group (first and second group), $i \in N_{ctrl}$, payoffs take the form

$$\begin{aligned} V_i^*(1) &= X_{is}'\beta_1 + J_1 PriorBeliefs_i - \frac{J_2}{2}\left(1 - PriorBeliefs_i\right)^2 + \varepsilon_i(1) \\ V_i^*(-1) &= X_{is}'\beta_2 - J_1 PriorBeliefs_i - \frac{J_2}{2}\left(-1 - PriorBeliefs_i\right)^2 + \varepsilon_i(-1). \end{aligned}$$

For students in the second group who saw a peer's decision ("other classes" treatment), $i \in N_{oc}$, payoffs take the form

$$\begin{aligned} V_i^*(1) &= X_{is}'\beta_1 + J_1 PriorBeliefs_i - \frac{J_2}{2}\left(1 - PosteriorBeliefs_i\right)^2 + \varepsilon_i(1) \\ V_i^*(-1) &= X_{is}'\beta_2 - J_1 PriorBeliefs_i - \frac{J_2}{2}\left(-1 - PosteriorBeliefs_i\right)^2 + \varepsilon_i(-1). \end{aligned}$$

For students in the second group who saw a peer's decision ("current class" treatment), $i \in N_{cc}$, payoffs take the form

$$\begin{aligned} V_i^*(1) &= X_{is}'\beta_1 + J_1 PosteriorBeliefs_i - \frac{J_2}{2}\left(1 - PosteriorBeliefs_i\right)^2 + \varepsilon_i(1) \\ V_i^*(-1) &= X_{is}'\beta_2 - J_1 PosteriorBeliefs_i - \frac{J_2}{2}\left(-1 - PosteriorBeliefs_i\right)^2 + \varepsilon_i(-1). \end{aligned}$$

I assume $\varepsilon_i(1) - \varepsilon_i(-1)$ is i.i.d. logistic-distributed as follows:

$$Pr\left(\varepsilon_i(-1) - \varepsilon_i(1) < c\right) = \frac{1}{1 + \exp(-c)},$$

and thus, for students in the pooled control group, we have

$$\begin{aligned} Pr\left(d_i = 1 | X_{is}, PriorBeliefs_i\right) &= \frac{1}{1 + \exp\left(-2X_{is}'\beta - 2\left(J_1 + J_2\right) PriorBeliefs_i\right)} \\ Pr\left(d_i = -1 | X_{is}, PriorBeliefs_i\right) &= \frac{1}{1 + \exp\left(2X_{is}'\beta + 2\left(J_1 + J_2\right) PriorBeliefs_i\right)}. \end{aligned}$$

For students in the second group who saw a peer's decision ("other classes" treatment), we have

$$\begin{aligned}
&Pr\left(d_i = 1 | X_{is}, PriorBeliefs_i, PosteriorBeliefs_i\right) \\
&= \frac{1}{1+\exp\left(-2X_{is}'\beta - 2J_1 PriorBeliefs_i - 2J_2 PosteriorBeliefs_i\right)} \\
&Pr\left(d_i = -1 | X_{is}, PriorBeliefs_i, PosteriorBeliefs_i\right) \\
&= \frac{1}{1+\exp\left(2X_{is}'\beta + 2J_1 PriorBeliefs_i + 2J_2 PosteriorBeliefs_i\right)}.
\end{aligned}$$

For students in the second group who saw a peer's decision ("current class" treatment), we have

$$\begin{aligned}
Pr\left(d_i = 1 | X_{is}, PosteriorBeliefs_i\right) &= \frac{1}{1+\exp\left(-2X_{is}'\beta - 2\left(J_1 + J_2\right) PosteriorBeliefs_i\right)} \\
Pr\left(d_i = -1 | X_{is}, PosteriorBeliefs_i\right) &= \frac{1}{1+\exp\left(2X_{is}'\beta + 2\left(J_1 + J_2\right) PosteriorBeliefs_i\right)}.
\end{aligned}$$

Here, $\beta = \frac{1}{2}\left(\beta_1 - \beta_2\right)$.

The maximum likelihood estimation is based on the log-likelihood function,

$$\begin{aligned}
&\ln L\left(\beta, J_1, J_2; \{d_i\}_{i=1,\ldots,n} \,|\, \{X_{is}\}_{i=1,\ldots,n}\right) \\
&= \sum_{i\in N_{ctrl}} \left\{\frac{1+d_i}{2}\ln\left(Pr\left(d_i = 1|X_{is}, PriorBeliefs_i\right)\right) + \frac{1-d_i}{2}\ln\left(Pr\left(d_i = -1|X_{is}, PriorBeliefs_i\right)\right)\right\} \\
&\quad + \sum_{i\in N_{oc}} \left\{\frac{1+d_i}{2}\ln\left(Pr\left(d_i = 1|X_{is}, PriorBeliefs_i, PosteriorBeliefs_i\right)\right)\right. \\
&\qquad\qquad \left. + \frac{1-d_i}{2}\ln\left(Pr\left(d_i = -1|X_{is}, PriorBeliefs_i, PosteriorBeliefs_i\right)\right)\right\} \\
&\quad + \sum_{i\in N_{cc}} \left\{\frac{1+d_i}{2}\ln\left(Pr\left(d_i = 1|X_{is}, PosteriorBeliefs_i\right)\right) + \frac{1-d_i}{2}\ln\left(Pr\left(d_i = -1|X_{is}, PosteriorBeliefs_i\right)\right)\right\}.
\end{aligned}$$

D Additional tables and figures

D.1 School network graphs

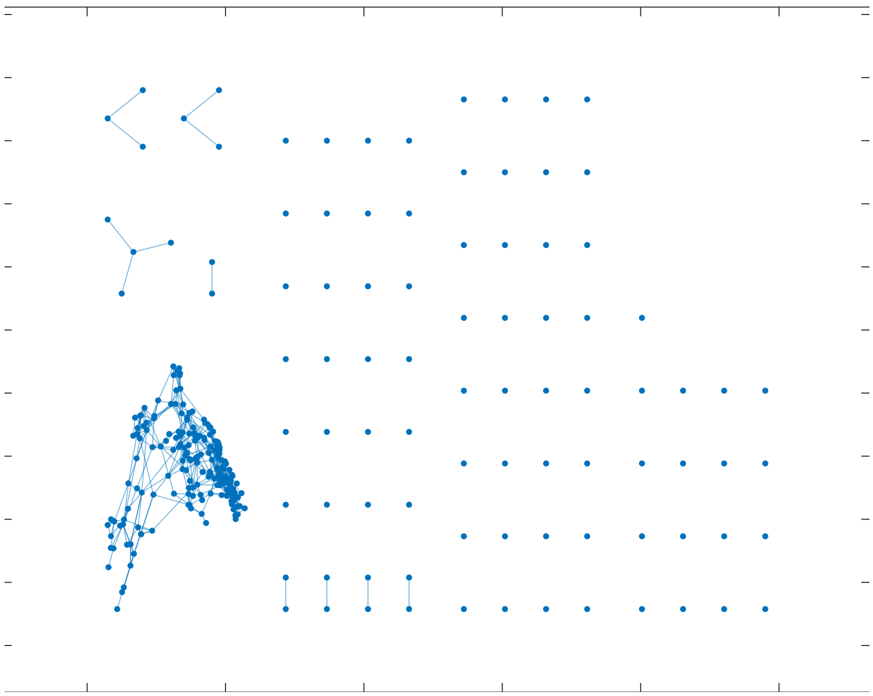

Figure 16: Hillcrest 12th grade network graph

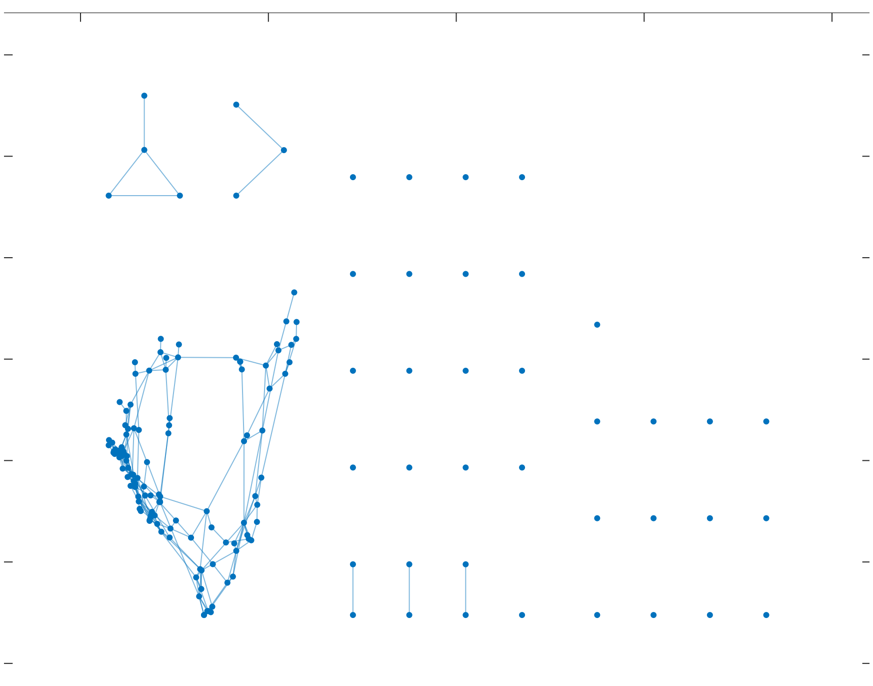

Figure 17: Hillcrest 12th grade network graph (non-missing survey)

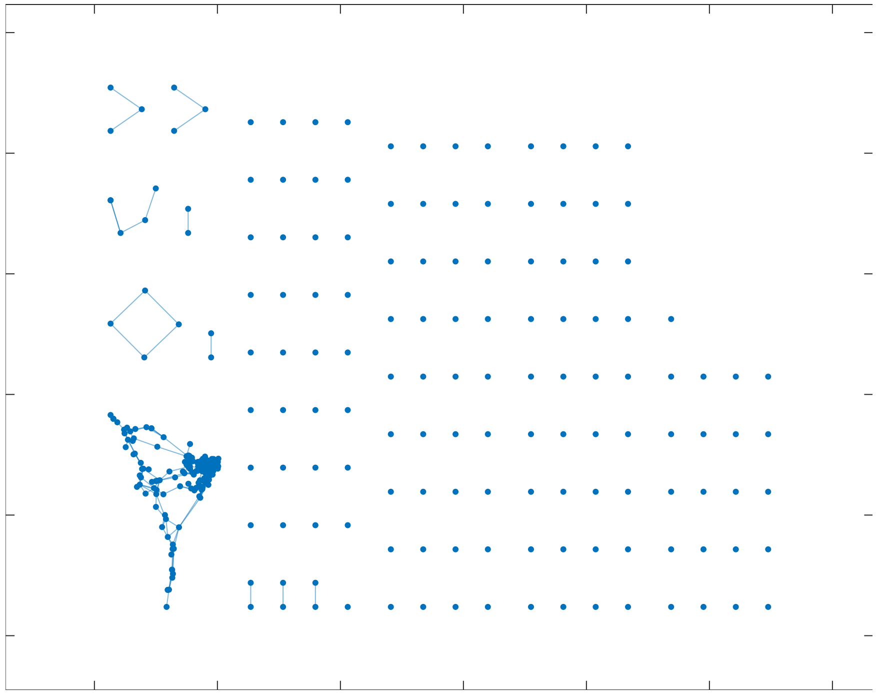

Figure 18: Thornwood 11th grade network graph

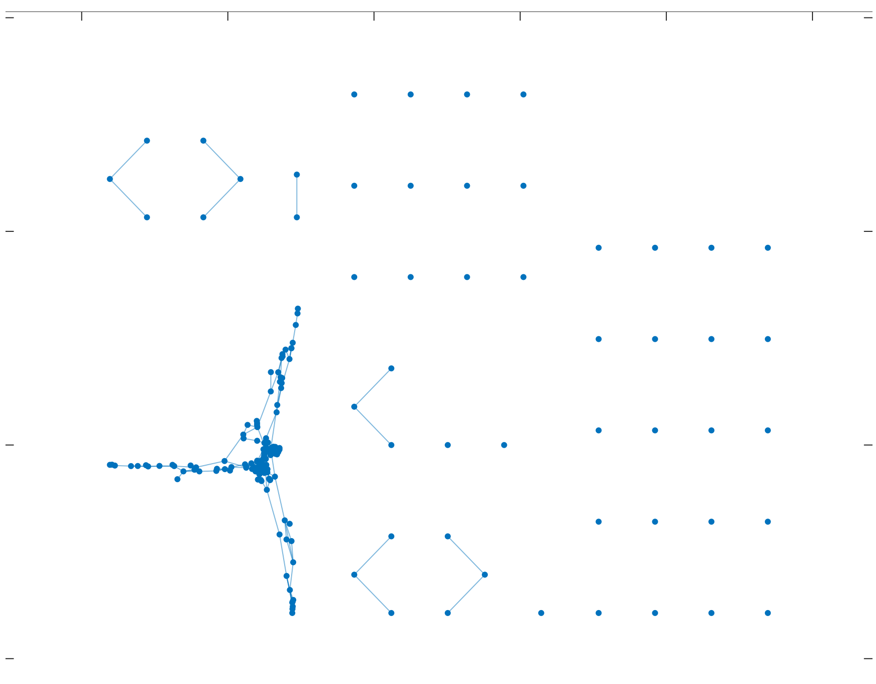

Figure 19: Thornwood 11th grade network graph (non-missing survey)

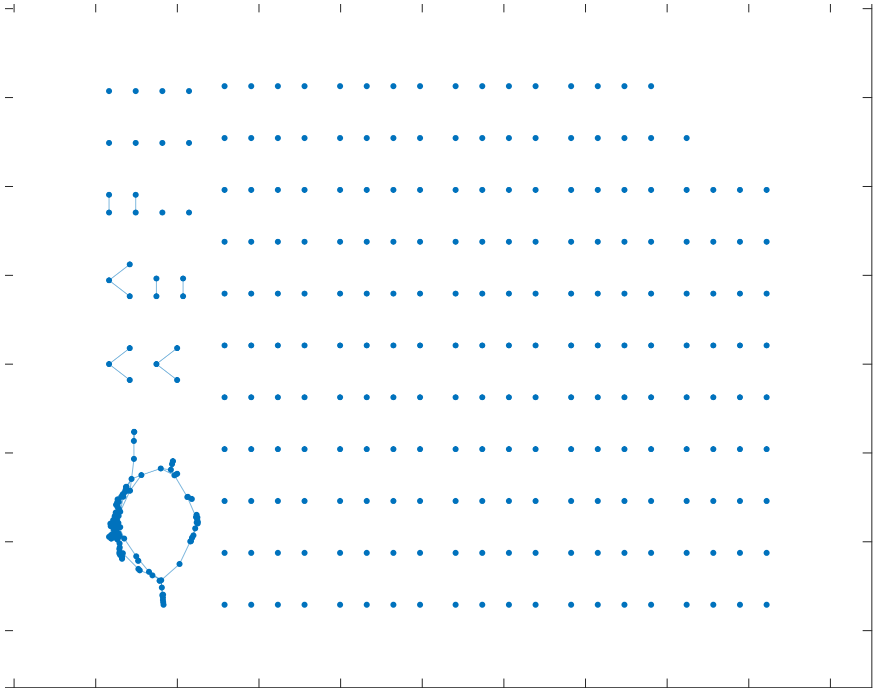

Figure 20: Proviso West 11th grade network graph

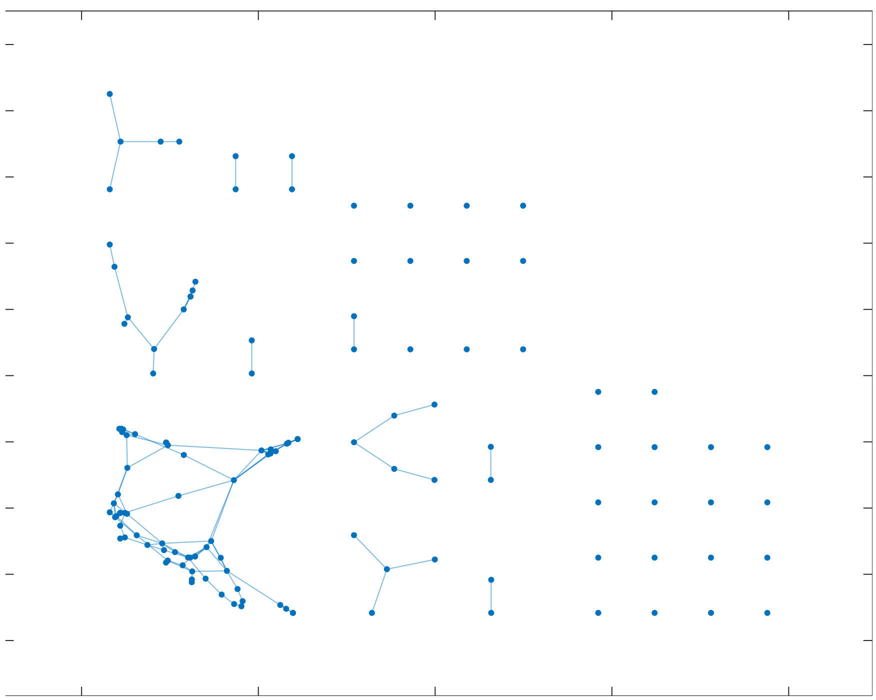

Figure 21: Proviso West 11th grade network graph (non-missing survey)

D.2 Histograms of key student nominations

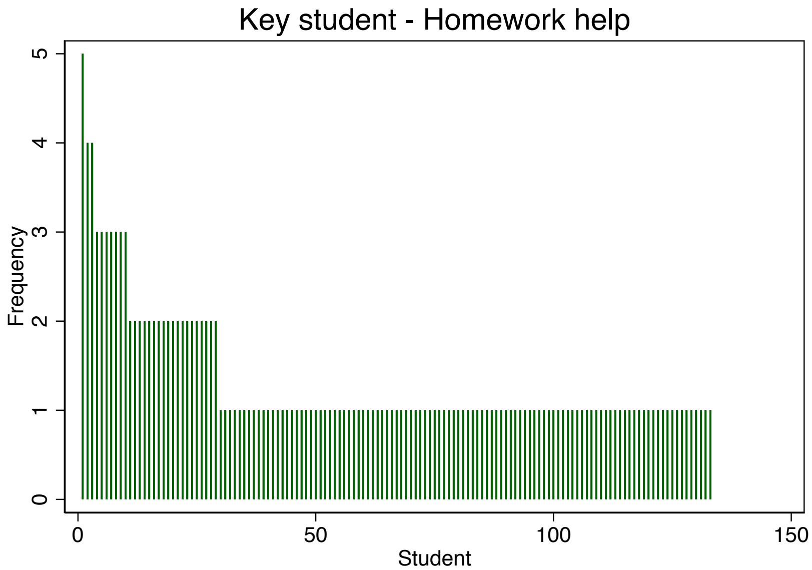

Figure 22: Frequency of key student (homework help) nominations by student

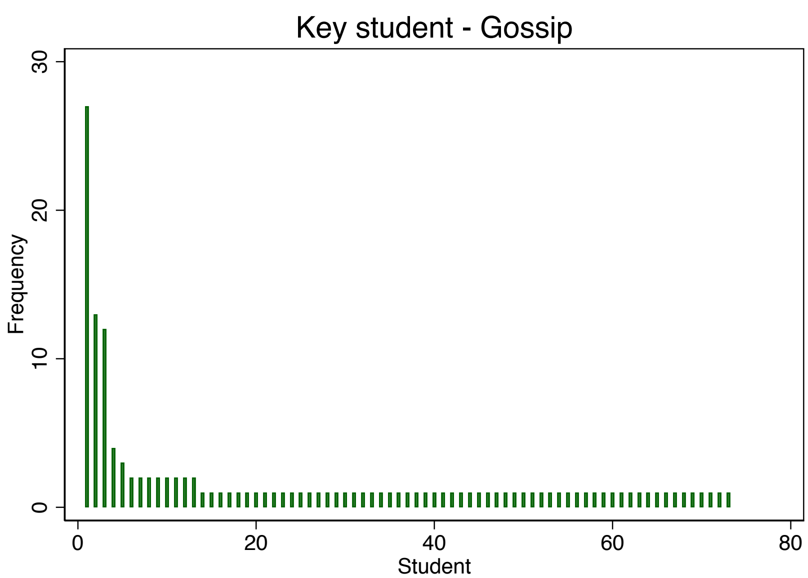

Figure 23: Frequency of key student (gossip) nominations by student

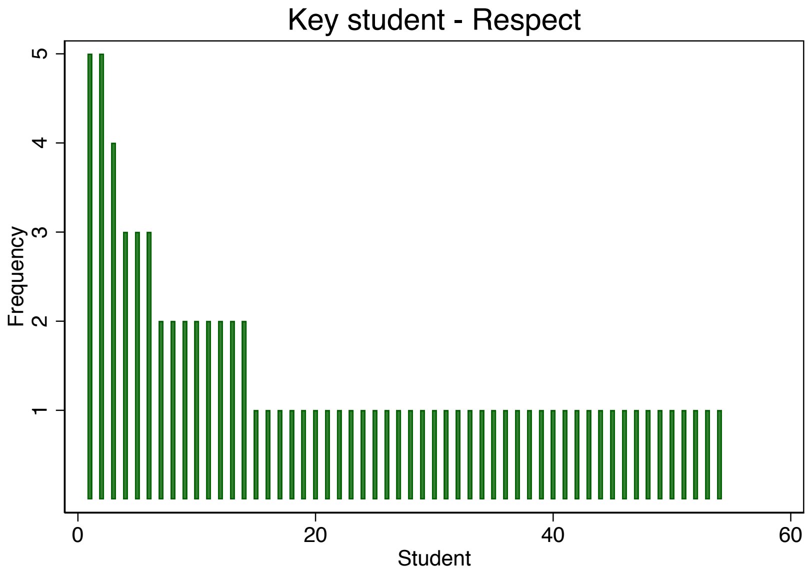

Figure 24: Frequency of key student (respect) nominations by student

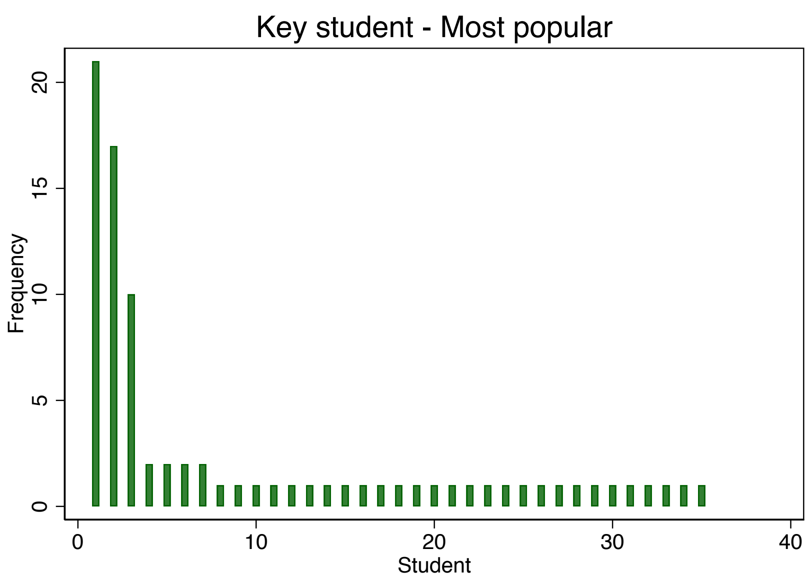

Figure 25: Frequency of key student (most popular) nominations by student

D.3 Histograms of prior and posterior beliefs

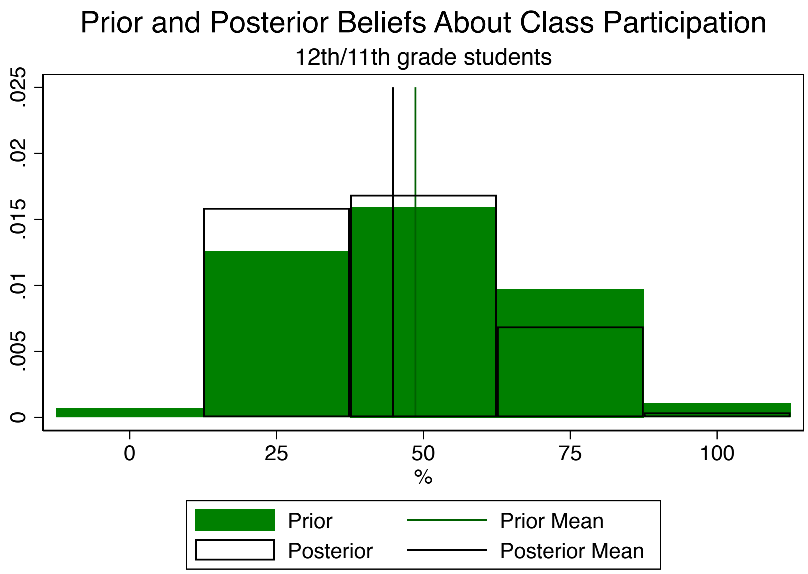

Figure 26: Distributions of prior and posterior beliefs about class participation (all 12th/11th grade students)

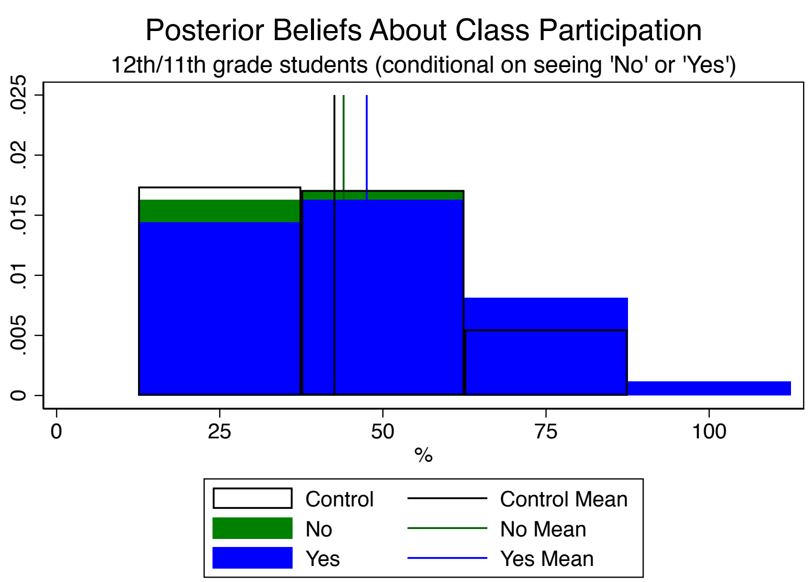

Figure 27: Distributions of posterior beliefs about class participation (all 12th/11th grade students), conditional on information received

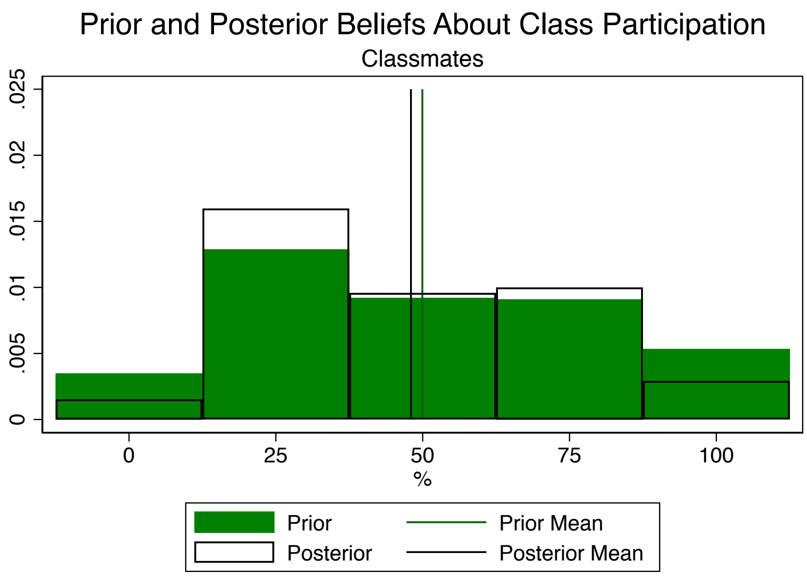

Figure 28: Distributions of prior and posterior beliefs about class participation (classmates)

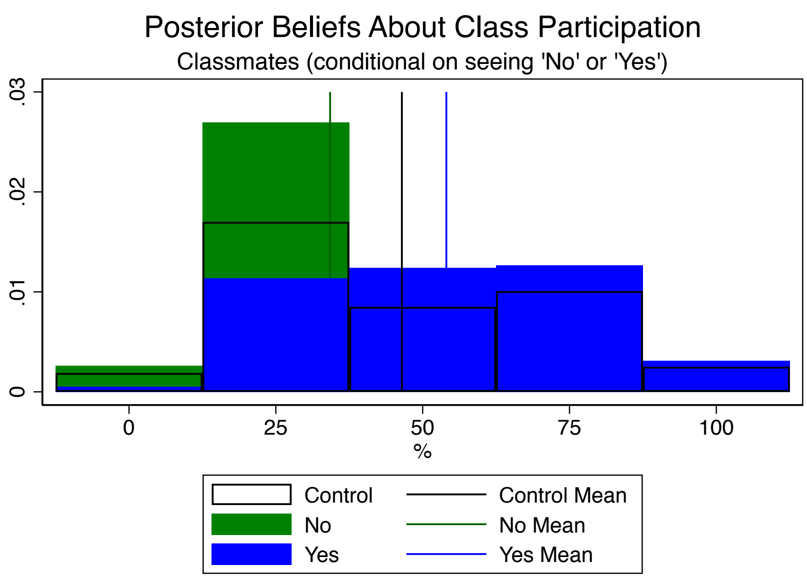

Figure 29: Distributions of posterior beliefs about class participation (classmates), conditional on information received

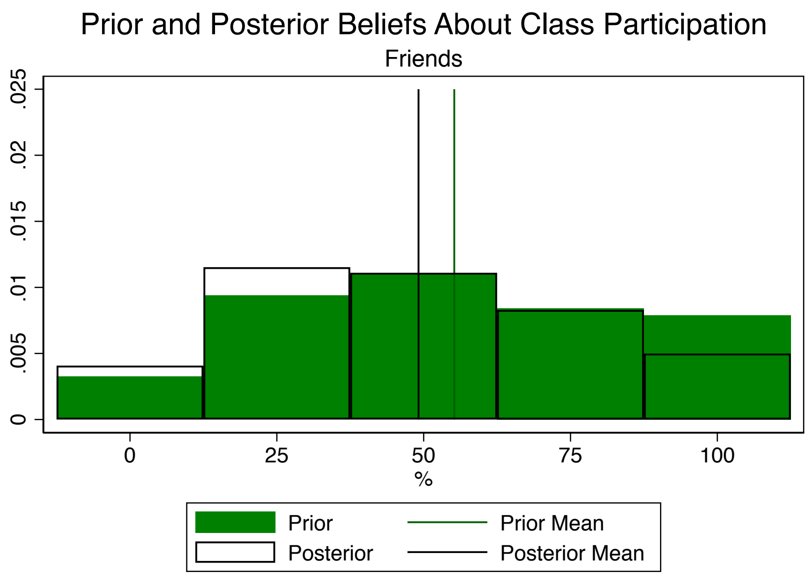

Figure 30: Distributions of prior and posterior beliefs about class participation (friends)

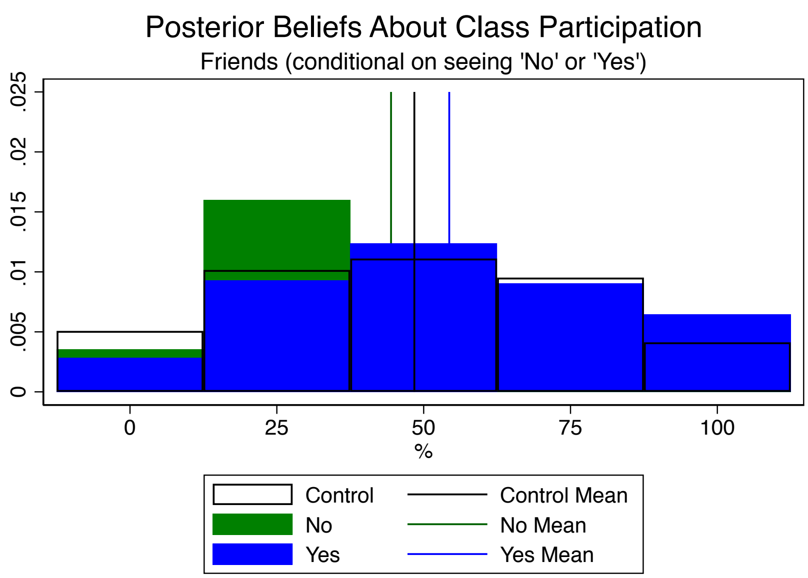

Figure 31: Distributions of posterior beliefs about class participation (friends), conditional on information received

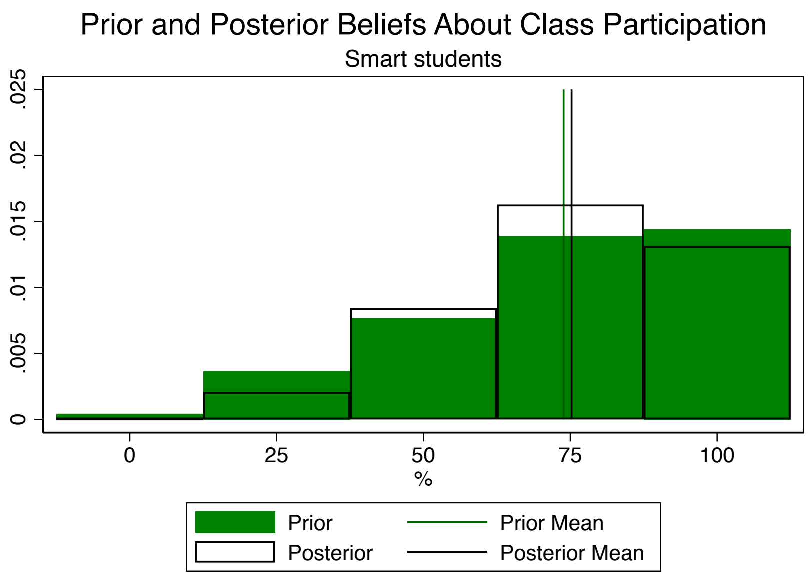

Figure 32: Distributions of prior and posterior beliefs about class participation (smart students)

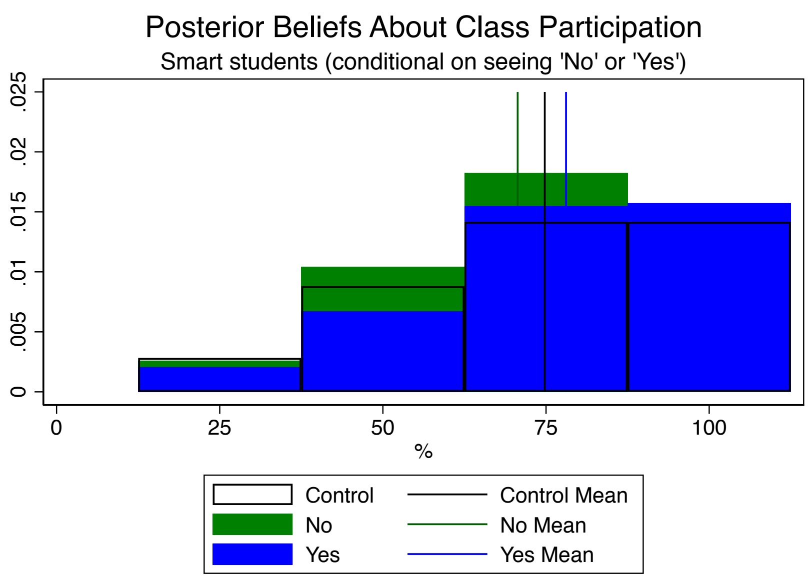

Figure 33: Distributions of posterior beliefs about class participation (smart students), conditional on information received

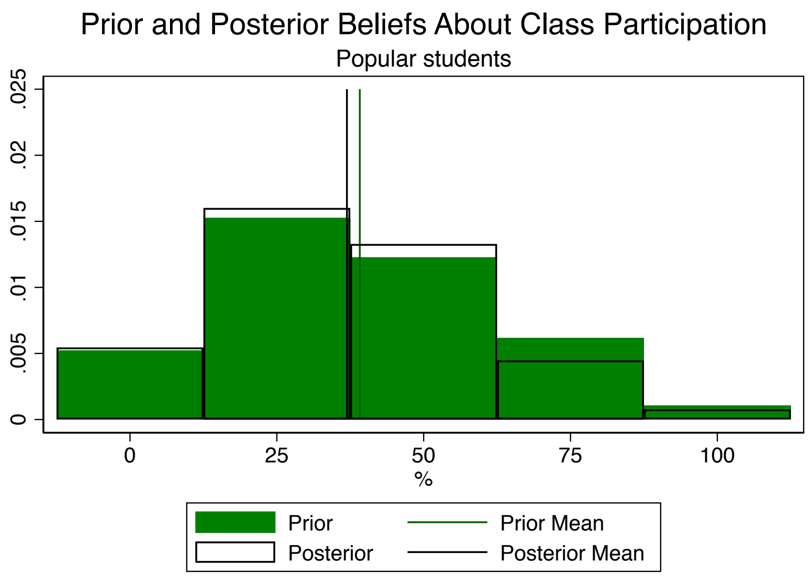

Figure 34: Distributions of prior and posterior beliefs about class participation (popular students)

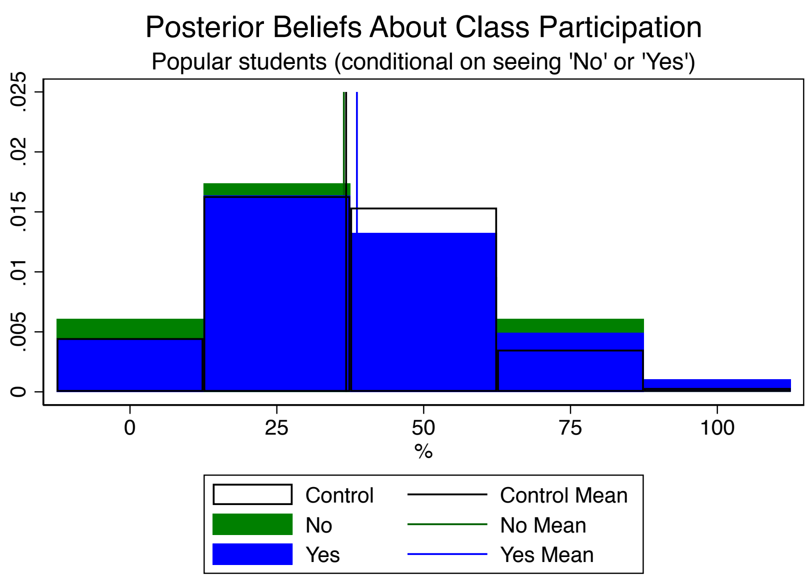

Figure 35: Distributions of posterior beliefs about class participation (popular students), conditional on information received

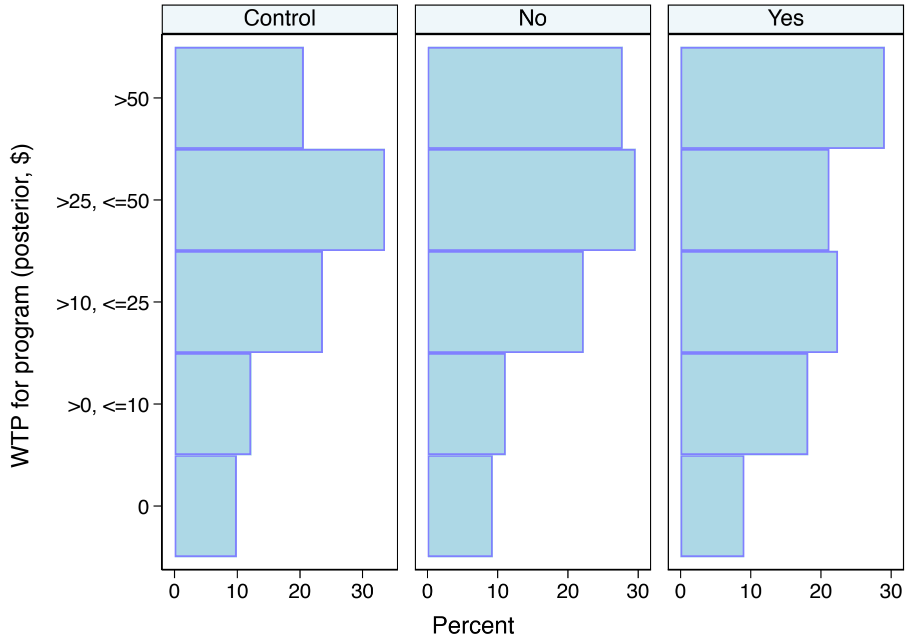

Figure 36: Effect of information seen on WTP for program

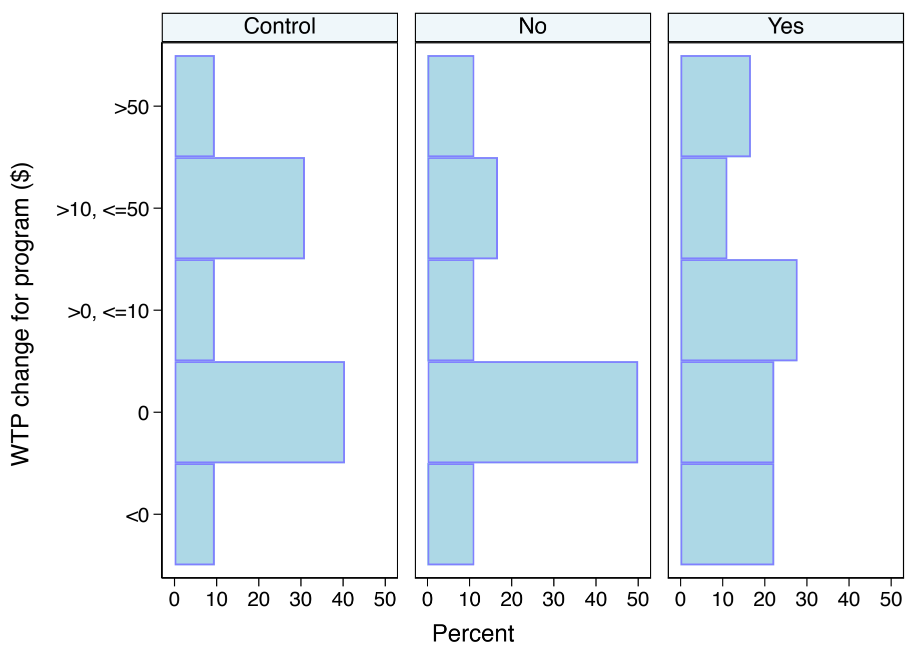

Figure 37: Effect of information seen on WTP change for program

D.4 2SLS results

Variables	Reduced form DV = sign-up	First stage DV = beliefs	Second stage DV = sign-up	OLS DV = sign-up
Saw "No"	-0.200***	-13.52***		
	(0.066)	(3.827)		
Beliefs			0.015***	0.005***
			(0.005)	(0.001)
Constant	0.531***	45.73***	-0.146	0.285***
	(0.105)	(6.109)	(0.265)	(0.109)
Demog. & School FE	Y	Y	Y	Y
Obs.	327	327	327	327
R^2	0.097	0.170		0.146
Cragg-Donald Wald F-statistic			12.473	
Anderson underidentification test p-value			0.0005	
Sargan-Hansen test			Exactly identified	

Table 12: 2SLS regressions of student's sign-up decision on beliefs about class participation, using revealed peers' decisions as an instrumental variable for beliefs about class participation. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.5 WTP by GPA quartile

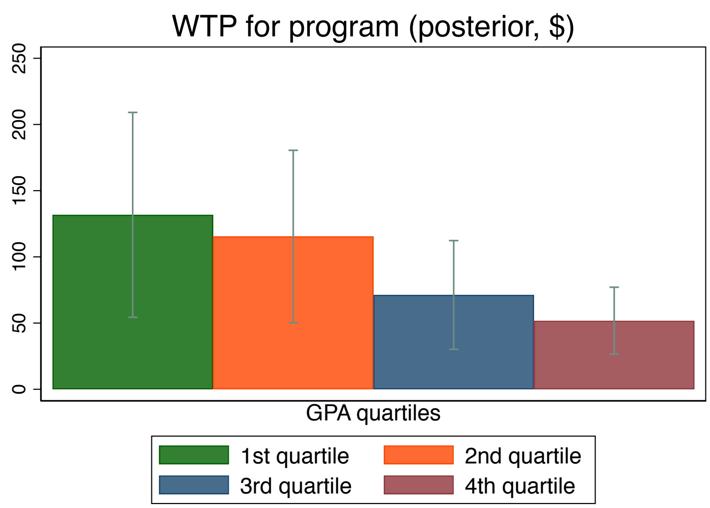

Figure 38: WTP for program by GPA quartile