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Education Transmission and Network Formation

Vincent Boucher
Carlo L. Del Bello
Fabrizio Panebianco
Thierry Verdier
Yves Zenou

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ABSTRACT

We propose a model of intergenerational transmission of education wherein children belong to either high-educated or low-educated families. Children choose the intensity of their social activities, while parents decide how much educational effort to exert. We characterize the equilibrium and show the conditions under which cultural substitution or complementarity emerges. Using data on adolescents in the United States, we structurally estimate our model and find that, on average, children's homophily acts as a complement to the educational effort of high-educated parents but as a substitute for the educational effort of low-educated parents. We also perform some policy simulations. We find that policies that subsidize social interactions can backfire for low-educated students because they tend to increase their interactions with other low-educated students, which reduce the education effort of their parents and, thus, their chance of becoming educated.

JEL Classification: D85, I21, Z13.

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Vincent Boucher : Department of Economics, Université Laval. CRREP. CREATE.
Carlo L. Del Bello : Italian Tax Agency, Italy.
Fabrizio Panebianco : Catholic University of Milan, Italy.
Thierry Verdier : Paris School of Economics, Ecole des Ponts ParisTech, PUC-Rio, and CEPR
Yves Zenou : Department of Economics, Monash University, CEPR, and IZA

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Replication codes are available here: https://github.com/vincentboucherecn/CulturalTransmission

1 Introduction

Education is a crucial aspect of the implementation of any policy in any country. However, it remains unclear which specific policy or set of policies should be implemented to improve education in the population. In this paper, we investigate the intergenerational transmission of education by studying how parental educational effort (vertical transmission) as well as children's social networks (horizontal transmission) have an impact on educational outcomes. Intergenerational transmission of education is indeed important for studying social mobility and the persistence of economic inequalities. What is less clear in the literature is why parental education should be important for children's education, other than an obvious wealth/income channel. Black and Devereux (2011) propose two channels: time allocation and higher productivity in child-enhancing activities. In this paper, we explicitly model not only parental effort in education but also the friendship formation of children and how both affect education outcomes.

We propose a model with two types of parents, high-educated (type H) and low-educated (type L), and examine a cultural transmission mechanism wherein children belonging to each group choose a certain level of socialization effort that determines the probability of forming links with other students and their degree of *homophily* with respect to their own type.[1] In particular, the way two children of different types form friendship links depends on their pairwise characteristics and their degree of socialization. The latter, in turn, depends not only on its respective characteristics but also on the complementarity in socialization efforts between different individuals.

Parents determine their education effort by trading off the cost of such an effort against the benefit of having an educated child. What is key and new in this transmission process is that parents determine their level of effort by looking at the (expected) degree of homophily of their children (i.e., the degree to which they form friendship links with children of their own types). We fully characterize the equilibrium of this model and determine under which conditions cultural complementarity and cultural substitution exist. Cultural substitution is present if parents decrease their education effort when their child socializes more with other children of the same type as their parents, whereas cultural complementarity occurs if parents increase their education effort under these same circumstances.

We then structurally estimate our model using the AddHealth data, which provide informa-

[1] Homophily is the tendency of agents to associate with other agents who have similar characteristics. It refers to a fairly pervasive observation in social networks. Having similar characteristics (age, race, religion, profession, education, etc.) is often a strong and significant predictor of two individuals being connected (McPherson et al., 2011).

tion on the impact of the social environment (i.e., friends, family, neighborhood, and school) on adolescents' outcomes in the United States. First, we find that there is complementarity in students' socialization efforts and that both types of parents prefer their children to interact with those of high-educated parents. We also find that on average, high-educated parents exhibit cultural complementarity (i.e., the more their children are homophilous, the more educational effort the parents exert), whereas low-educated parents exhibit cultural substitutability (i.e., the more heterophilous their children are, the more educational effort they exert).

We then look at two different policy experiments. In the first one, we subsidize the private returns of socialization for all children. We show that the implementation of such a policy reduces the probability of becoming educated for children from low-educated families, while it increases the probability of becoming educated for children from high-educated families. This is because the policy increases socialization efforts and homophily for both types of children. This leads educated parents to increase their effort (cultural complementarity) but uneducated parents to decrease their effort (cultural substitutability). Thus, for children with low-educated parents, there are two negative effects at play: a decrease in parental effort and a decrease in the average friend's "quality" due to more homophily. For children from high-educated families, the effects are exactly the opposite: their parents increase their effort and, because of their increased homophily, the average "quality" of their friends increases. As a result, their probability of becoming educated increases, while that of their low-educated counterparts decreases.

We then consider a targeted policy that consists in subsidizing the private returns of socialization for low-educated children only. We show that this policy yields even worse education outcomes for children from low-educated families. They socialize even more with other low-educated kids and, therefore, their parents reduce their education effort.

In summary, school-based policies that favor socialization can backfire for low-educated students because they favor homophily and reduce the education effort of their parents even if parents of both types value high-education over low-education for their offspring.

1.1 Related literature

There is a significant body of theoretical and empirical literature on cultural transmission, initiated by the seminal papers of Bisin and Verdier (2000, 2001). In this research stream, cultural transmission is conceptualized as the result of interactions between purposeful socialization decisions inside the family (*direct vertical socialization*) and other socialization processes, including social imitation and learning, which govern identity formation (*oblique and horizontal socialization-*

tion). These two types of socialization are cultural substitutes or complements if the level of parents' incentive to socialize their children depends on how widely dominant their values are in the population. Allowing for interesting socio-economic effects interacting with the socialization choices of parents, the basic cultural transmission model of Bisin and Verdier has been extended in different directions and been tested from different perspectives.[2]

In contributing to this literature, we endogenize the social network, which is formed by socialization efforts from children.[3] In other words, we consider a model in which children play an active role in the socialization process by choosing their socializing activities but the exact identity of a child's friends is not an object of choice.[4] In this respect, we provide one of the very few models that endogenizes oblique socialization using an explicit network-formation framework. We also establish a setting in which children are first and temporarily socialized in accordance with the parental trait (early socialization); then, children choose socialization effort, and, at last, parents exert an educational effort that takes into account their offspring's choice. This allows us to have the parental socialization effort depend on the homophily choices of their children, which is crucial for understanding our policy experiments.

There is also a recent body of literature, surveyed by Doepke et al. (2019) and Doepke and Zilibotti (2019), that also models the interplay between parents' education effort and children's choices. This literature has focused on the various parenting styles and estimated different models of children's accumulation of cognitive and noncognitive skills in response to parental inputs. For example, Doepke and Zilibotti (2017) develop a model that allows for both altruism (parents care about their children's utility) and paternalism (parents care about their children's actions in ways that potentially conflict with the children's own preferences) and study the parent–child interactions by allowing for children taking actions on their own. This research has also modeled the parents' choice in terms of neighborhood, which influences with which their children interact.

Our approach is different but complementary. We only have one parenting style (paternalism) and focus on the friendship (network) formation of children and how it influences the choice of education effort of their parents. We are aware that parents can partially anticipate children's choices by choosing the neighborhood where their children live or their school. While this is,

[2]For an overview, see Bisin and Verdier (2011).

[3]For overviews on the social network literature, see Jackson (2008), Ioannides (2012), Bramoullé et al. (2016), Topa and Zenou (2015) and Jackson et al. (2017).

[4]This approach, initiated by Cabrales et al. (2011), provides a simple way of solving the multiple equilibria issue that plagues network-formation models. See also Albornoz-Crespo et al. (2019) and Canen et al. (2020), who use a similar approach.

of course, of extreme importance, in this paper, we take as given the neighborhood structure and school choice and analyze how parents react to children's choices in terms of friendship formation.

2 The Model

Consider a cultural transmission model with a *two-cultural-trait population* of individuals. We build on the model of cultural transmission of Bisin and Verdier (2001), in which vertical socialization inside the family interacts with horizontal socialization outside the family. However, contrary to Bisin and Verdier (2001), we assume that children are active in the socialization process. Specifically, we assume that children choose how much social interactions they have with other children. Together with their preference biases toward other children, this socialization endogenously determines the role of horizontal socialization on cultural transmission.

To be more specific, define T as the set of possible types of traits in the population. Assume $T = \{H, L\}$, where H refers to *high educated* (e.g., college degree) and L to *low educated* (e.g., less than a college degree). In our model (also in the data), children are still at school and have, therefore, not yet been educated. As a result, when we say that "a child has trait $t \in T$," it means that this child has a parent who is of type t. Families are composed of one parent and one child; hence, reproduction is asexual.

Socialization operates in two stages. First, children are temporarily socialized to the trait of their parent (*early socialization*) in the sense that they are exposed to the education level of their parents without acquiring their education level. Second, children choose their social interactions with other children of different types. Interaction choices are strategic and are a function of children's preference biases (e.g., homophily) and their socialization preferences (e.g., some children may like to interact more with other children, all else being equal).

Before the network is realized, parents anticipate their child's choices and choose the level of education effort to exert. Parents have explicit preferences regarding their child's friends. For example, parents may have lower (or higher) costs of exerting educational effort if their child make socialization choices that are in line with their type (i.e., homophily). In the end, the probability of a child becoming educated depends on the parent's education effort and the average type of the youngster's friends if the parent fails to transmit his or her trait.[5]

[5] We assume that children are not farsighted. Indeed, children make socialization choices that have an impact on the probability of having some type of friends, but do not anticipate the impact on their parents' educational choices.

2.1 Children's choices and network formation

We, first, describe the network-formation process, taking the children's socialization choices as given. Let $\mathbf{s} = (s_1, ..., s_n)$ be a profile of children's socialization efforts, where $s_i \geq 0$ for each child $i = 1, , ..., n$. The probability p_{ij} that a child i creates a link with a child $j \neq i$ is given by

$$p_{ij} = \frac{1}{c} d_{ij}(t_i, t_j) s_i s_j. \tag{1}$$

In (1), $d_{ij}(t_i, t_j) \in [0, 1]$ represents the preference bias between i and j, that is, how much i of type t_i likes or dislikes interacting with j of type t_j (Currarini et al., 2009). In our empirical application, we allow $d_{ij}(t_i, t_j)$ to depend on the observable characteristics of i and j, such as their age, gender, race, and geographical proximity. It is natural to assume that $d_{ij}(L, L) = d_{ij}(H, H) > d_{ij}(H, L), d_{ij}(L, H)$ so that the model features *homophily* with respect to the children's types.

From (1), we can see that the greater both socialization efforts s_i and s_j are, the more likely a link will be formed. Note that the $c > 0$ is a normalization scalar that ensures that p_{ij} is always between 0 and 1.[6]

As in Cabrales et al. (2011), in (1), the exact identity of a child's friends is not an object of choice. Rather, each child i chooses an aggregate level of socialization effort s_i. This total effort is then distributed across each and every possible bilateral interaction, in proportion to the partner's socialization effort and the preference biases $d_{ij}(t_i, t_j)$. This interaction pattern arises naturally when meetings result from casual encounters rather than from an earmarked socialization process. In our context, children may participate in after-school activities (such as dance, music, honors club, foreign language clubs, etc.), and s_i may reflect the number of activities and how often they engage in these activities. Two children who spend a lot of time engaging in these after-school activities are then more likely to be friends than those who do not.

We consider the following linear quadratic specification of the expected utility of child i choosing socialization effort s_i. It is given by

$$\mathbb{E}_i[u_i] = b_i s_i + \phi \sum_{j \neq i} \mathbb{E}_i^{p_{ij}} [g_{ij} | s_i, s_j] - \frac{1}{2} s_i^2, \tag{2}$$

[6] We show in Appendix A that it is sufficient to impose that $c \geq \left(\bar{b} + \sqrt{\bar{b}^2 + 4\phi(n-1)}\right)^2 / 4$, where $\bar{b} = \max_i b_i$ and b_i are defined in (2) below.

where the expectation is computed using distribution (1) and where $g_{ij} = 1$ denotes a link between i and j. Note that $g_{ij} = 1$ is the realization of the link ij, while p_{ij} is the probability of forming the link ij.

In (2), the (expected) utility of individual i who exerts a socialization effort s_i is the sum of a private component ($b_i s_i - \frac{1}{2}s_i^2$) and a social component ($\sum_{j\neq i} \mathbb{E}_i^{p_{ij}}[g_{ij}|s_i, s_j]$). The private benefit b_i of socialization may be a function of the ex ante heterogeneity of child i (e.g., represented by the child's gender, race, etc.). The benefit of socialization (given $\phi \geq 0$) is due to child i's expected number of friends $\sum_{j\neq i} \mathbb{E}_i^{p_{ij}}[g_{ij}|s_i, s_j]$, which is a function not only of the child's own socialization effort but also of other children's socialization efforts.

Using (1), we can rewrite (2) as:

$$\mathbb{E}_i[u_i] = b_i s_i + \frac{1}{c}\phi \sum_{j\neq i} d_{ij}(t_i, t_j) s_i s_j - \frac{1}{2}s_i^2. \tag{3}$$

Importantly, and as discussed above, observe that each child i's socialization effort choice s_i is independent of the education effort of the parent. This assumption is made both for simplicity and credibility reasons. Note, however, that the parent's type *does* affect the child's payoff and, therefore, his or her choice, through its effect on b_i and $d_{ij}(t_i, t_j)$. By maximizing expected utility (3) with respect to s_i, for each child i, we obtain[7]

$$s_i^* = \max\{b_i + \frac{1}{c}\phi \sum_{j\neq i} d_{ij}(t_i, t_j) s_j^*, 0\}. \tag{4}$$

If the solution is interior for all children, we can then write (4) in matrix form as follows:

$$\mathbf{s}^* = \mathbf{b} + \frac{\phi}{c}\mathbf{D}\,\mathbf{s}^*, \tag{5}$$

where $\mathbf{D}$ has zeros on the diagonal and $d_{ij}(t_i, t_j)$ off diagonal. By letting $\|\cdot\|$ be any sub-multiplicative matrix norm,[8] we obtain the following result:

Proposition 1. *If $|\phi| < c/\|\mathbf{D}\|$, then there exists a unique equilibrium of the children's socialization choices. If the equilibrium is interior, it is given by*

$$\mathbf{s}^* = \left(\mathbf{I} - \frac{\phi}{c}\mathbf{D}\right)^{-1} \mathbf{b}. \tag{6}$$

[7]The solution may not be interior because b_i, which, in the data, captures the observable characteristics of individual i, may take negative values.

[8]i.e., $\|\mathbf{AB}\| \leq \|\mathbf{A}\| \cdot \|\mathbf{B}\|$ for any two matrices $\mathbf{A}$ and $\mathbf{B}$.

The proof relies on a standard contraction mapping argument and is therefore omitted (see, for example, Hsieh et al. (2020), for a proof). A sufficient condition for interiority is $\phi \geq 0$ and $b_i \geq 0$ for all i. If the solution is interior, we can write the expected network structure in closed form as follows:

$$\mathbf{P}^* = \frac{1}{c}\mathbf{D} \circ \left[(\mathbf{I} - \frac{\phi}{c}\mathbf{D})^{-1}\mathbf{b}\mathbf{b}^T(\mathbf{I} - \frac{\phi}{c}\mathbf{D}^T)^{-1} \right], \tag{7}$$

where $\circ$ is the (Hadamard) element-wise product. If the solution is not interior, it can easily be computed iteratively by virtue of the contraction mapping theorem. We now turn to the parents' decision.

2.2 Parents' education effort

We assume that parents' incentives are partly driven by the expected education level of their child. Here, the effective education level of a child depends not only on the parents' education level and effort (vertical socialization) but also on the education level of the parents of their child's friends (horizontal socialization). For each child i of type t, let

$$h_i^t = \frac{\sum_j g_{ij} \mathbb{1}\{t_j = t\}}{\sum_j g_{ij}} \tag{8}$$

denote the fraction of i's friends who are of type $t = H, L$, where $g_{ij} = 1$ if i is friends with j, and $g_{ij} = 0$ otherwise. h_i^t captures i's *homophily* since it measures the fraction of same-type friends of individual i of type t. Denote by $\pi_i^{tt'}$ the probability that a child from a parent of type t becomes of type t' when adult. The education mechanism is characterized by the following transition probabilities:

$$\pi_i^{HH} = \tau_i^H + (1 - \tau_i^H)h_i^H, \tag{9}$$

$$\pi_i^{HL} = (1 - \tau_i^H)(1 - h_i^H), \tag{10}$$

$$\pi_i^{LH} = \tau_i^L + (1 - \tau_i^L)(1 - h_i^L), \tag{11}$$

$$\pi_i^{LL} = (1 - \tau_i^L)h_i^L, \tag{12}$$

where $0 \leq \tau_i^t \leq 1$ is the socialization effort of a type$-t$ parent who has a child i; τ_i^t is also the probability that *direct vertical socialization* to the parent's trait (t) will occur.

As an illustration, consider equation (9). Child i, whose parent is high-educated (type H), will be socialized to trait H if either the direct socialization from the child's parent H

succeeds (which occurs with a probability of τ_i^H) or, if it does not succeed (which occurs with a probability of $1-\tau_i^H$), the child i is subject to *horizontal socialization* captured by h_i^H, the fraction of the child's friends who are of type H. Here, the horizontal socialization is endogenous and determined by the network of social interactions described in the previous section. The probability that the horizontal socialization is successful is given by h_i^H, the fraction of friends of child i who have educated parents, and is defined by (8). The interpretation of (10) is similar.

Regarding the interpretation of equations (11) and (12), one needs to be careful because low-educated parents also want their children to be educated. Thus, τ_i^L, the low-educated parental effort, is the probability that a child from a low-educated family will become high educated. Take, for example, π_i^{LL}. In this case, for a child from a low-educated family to stay low educated, both the vertical (parents) and horizontal (friends) socializations must fail, which is given by (12).

For children of educated parents, this means that *homophily* increases the probability that child i will become educated. The opposite is true for children of uneducated parents: homophily decreases the probability that their child will become educated. We will show that this fundamental difference has important consequences for the optimal choice of education effort for both types of parents.

Finally, instead of considering the average population with trait t as in Bisin and Verdier (2001), we look at the average among each child's friends. This has the striking implication of preventing us from formulating a unique equation that represents the entire set of agents of any given type. Accordingly, the transition probabilities are indexed by i since they depend on the social behavior of child i and not on the average population with trait t. In this respect, Bisin and Verdier (2001) can be seen as a *mean-field approximation* of this process, with the additional simplification of network exogeneity.

Observing that $h_i^H = 1 - h_i^L$, we can now define the expected utility of a parent of a child i of type $t = H, L$ as follows:

$$\mathbb{E}_i[U_i^t] = \mathbb{E}_i^h \left\{ \underbrace{\left(\pi_i^{tH} V_i^{tH} + \pi_i^{tL} V_i^{tL}\right) - \frac{1}{2}\left(\tau_i^t\right)^2}_{\text{Bisin-Verdier}} + \underbrace{\alpha^t \tau_i^t h_i^H}_{\text{Reciprocate Homophily}} \right\}, \tag{13}$$

where the expectation is taken with respect to the probabilities in (1) at equilibrium (see Proposition 1). The payoffs $V_i^{tH} > 0$ and $V_i^{tL} > 0$ denote the utility that a type$-t$ parent derives from having a child of type H and L, respectively, and $\frac{1}{2}\left(\tau_i^t\right)^2$ is a quadratic parental socialization cost function. For $t = H, L$, let us have the following notation: $\Delta V_i^t \equiv V_i^{tH} - V_i^{tL}$. Quite naturally, we assume that, for both $t = H$ and $t = L$, $V_i^{tH} > V_i^{tL}$, so that $\Delta V_i^t > 0$, i.e., there is a positive utility associated with having a high educated child for *both* types of parents.

The (expected) utility (13) is composed of two parts: (i) the standard utility function used in Bisin and Verdier (2001), which depends on the benefits and costs of socialization, and (ii) a new part, which we refer to as *reciprocate homophily*. This is the utility that the parent derives from his or her child interacting with children of highly educated parents. If parents are homophilous, i.e., each type of parent wants their children to interact with those of the same type as their parents, we expect $\alpha^L < 0$ and $\alpha^H > 0$. However, it might also be possible, for example, that low-educated parents prefer their child to interact with children of high-educated parents, independently of the impact on the transition probability. This would imply that $\alpha^L > 0$. We do not make any assumption of the sign of α^H and α^L; these parameters will be estimated structurally.

Below, we show that the sign and magnitude of α^t have important consequences for the optimal choice of education effort each parent exerts. In particular, our utility function is more flexible than that of Bisin and Verdier (2001), in which high importance of the peer group (reciprocate homophily) necessarily translates into low effort by the parent. In our framework, when α^t is positive and large enough, there can be *cultural complementarity* between parental effort and the expected homophily of the child's friendship network. The next proposition formally derives this idea.

Proposition 2. *Given the equilibrium distribution of the network-formation process (see Proposition 1), denote by $\bar{h}_i^t$ the expected value of h_i^t. Thus, we have the following:*

(i) *The optimal education effort of each type of parent is given by:*

$$\tau_i^{L*} = \Delta V_i^L \bar{h}_i^L + \alpha^L (1 - \bar{h}_i^L), \qquad \tau_i^{H*} = \Delta V_i^H (1 - \bar{h}_i^H) + \alpha^H \bar{h}_i^H. \tag{14}$$

(ii) *The behavior of type$-L$ parents exhibits cultural substitution (cultural complementarity) if and only if $\alpha^L > \Delta V_i^L$ ($\alpha^L < \Delta V_i^L$) since $\frac{\partial \tau_i^{L*}}{\partial h_i^L} = \Delta V_i^L - \alpha^L$.*

(iii) *The behavior of type$-H$ parents exhibits cultural substitution (cultural complementarity) if and only if $\alpha^H < \Delta V_i^H$ ($\alpha^H > \Delta V_i^H$) since $\frac{\partial \tau_i^{H*}}{\partial h_i^H} = \alpha^H - \Delta V_i^H$.*

Proposition 2 follows from simple optimization of the parents' utility function and a simple comparative statics analysis. First, as shown in (14), parents of each type $t = H, L$ exert socialization effort differently, which depends on their own α^t, i.e., the extent to which they value the homophily or heterophily of their children's friendship network, the specific (expected) network their children belong to, and, thus, the homophily behavior of their children. Second, the parents' effort may exhibit either cultural complementarity (i.e., they exert *more* effort the more homophilous their children are) or substitutability (i.e., they exert *less* effort, the more homophilous their children are) depending on $\Delta V_i^t > 0$ (the benefits of having an educated child) and α^t (their preference regarding the fraction of high-type friends of their children).

Regarding low-educated parents, cultural substitution or complementarity depends on whether or not there is reciprocated homophily, i.e., whether α^L is positive or negative. If $\alpha^L < 0$, which means that parents value homophily in their children's network (i.e., their children have a high fraction of low-educated friends), then there will always be cultural complementarity. If $\alpha^L > 0$, then, there will be a trade-off between the value of α^L and ΔV_i^L. The empirical estimation of our model will tell us the sign of α^L.

For high-educated parents, to exhibit cultural complementarity (substitutability), α^H must be large (small) enough and higher (lower) than ΔV_i^H. Indeed, if parents are very (not very) homophilous and/or the benefits of having an educated child is quite small (large), then they exert more (less) effort when their children increase h_i^H, their (expected) homophily network.

3 Structural estimation

Let us now structurally estimate our model.

3.1 Data

We use a (relatively) well-known database on friendship networks from the National Longitudinal Survey of Adolescent Health (AddHealth). The AddHealth survey has been designed to study the impact of the social environment (i.e., friends, family, neighborhood and school) on adolescents' behavior in the United States by collecting data on students in grades 7–12 from a nationally representative sample of roughly 130 private and public schools in years 1994–95. A subset of these adolescents, about 20,000 individuals, are also asked to complete a longer questionnaire containing sensitive individual and household information, which includes the (normalized) geographical coordinates of their residential address.

From a network perspective, the most interesting aspect of the AddHealth data is the friendship information, which is based upon actual friends' nominations. For a subset of 16 schools,[9] all of the pupils were asked to identify their best friends from a school roster (up to five males and five females).[10] From the data, one can reconstruct the entire friendship network. We follow Lee et al. (2014) and Miyauchi (2016) and restrict our analysis to friendship relations with students of the same school and the same grade level. We will refer to a student's school-grade level as their *group*. We retain groups of at least 10 students. The final sample comprises 3,471 students, in 57 groups, in 14 schools.

In the context of these data, we say that a child is of type H if either parent (father or mother) is a college graduate. Otherwise, the child is of type L. We also use a series of students' individual characteristics, such as age, gender, racial group, as well as the (normalized) geographical location of their house. The students' level of socialization (s_i for a student i in our model) is constructed from: (i) the number of extracurricular activities in which the child participates, (ii) the child's self-reported level of daily interactions with friends, and (iii) the child's self-reported level of interaction in their neighborhood. We then construct a composite index variable for each student i, which is equal to the sum of these three after-school activities of student i, and then we normalize this index s_i to between 0 and 1.[11]

The parental education effort level τ_i is constructed from three types of questions: (i) parental control over the children's decisions, (ii) children's assessment of how much their parents care about them, and (iii) parents' involvement in the school-related activities of their child.[12] We take the average of the answers to these three questions and obtain a value of τ_i, which is between 0 and 1.

Summary statistics are presented in Table 1 for students from low-educated families, and Table 2 for students from high-educated families for all our *individual* variables. Table 3 presents the summary statistics for our *pairwise* variables.

First, we see that the percentage of Whites is higher among low-educated families than the high-educated ones, while it is the opposite for the Black population. Hispanics are much more likely to belong to low-educated than high-educated families (26.7% versus 6.3%). This is not surprising as the surveyed schools are spread around the United States, and many areas include

[9] These 16 schools are those from the saturated sample of Wave I, i.e., the schools for which we have the whole network and each student in this sample completed both the in-school and in-home questionnaires. See, also Mele (2020), who uses the same sample.

[10] The limit on the total number of friends' nominations is not binding. Previous studies have shown that missing links are likely to have small impacts on the estimated coefficients. See, for example, Lewbel et al. (2019) or Boucher and Houndetoungan (2020).

[11] See Appendix B.1 for additional details.

[12] See Appendix B.1 for additional details.

Table 1: Summary statistics, individual variables – Low-educated students

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
White	0.616	0.486	0	0	1	1
Black	0.135	0.342	0	0	0	1
Hisp.	0.267	0.443	0	0	1	1
Asian	0.112	0.315	0	0	0	1
Mother works	0.684	0.465	0	0	1	1
Female	0.494	0.500	0	0	1	1
Age	16.201	1.420	12	15.3	17.3	18
s_i	0.597	0.180	0.055	0.477	0.720	1.000
τ_i^t	0.449	0.176	0.000	0.325	0.587	0.952

Notes: Total number of low-educated students: 2,360 (out of 3,471). Only groups of size 10 or more have been kept. We also removed two small schools with only one grade level. Pctl(25) and Pctl(75) mean the 25th and 75th percentiles, respectively.

Table 2: Summary statistics, individual variables – High-educated students

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
White	0.500	0.500	0	0	1	1
Black	0.216	0.412	0	0	0	1
Hisp.	0.063	0.243	0	0	0	1
Asian	0.273	0.446	0	0	1	1
Mother works	0.823	0.382	0	1	1	1
Female	0.483	0.500	0	0	1	1
Age	15.938	1.599	12	15.1	17.2	18
s_i	0.621	0.184	0.055	0.497	0.754	1.000
τ_i^t	0.509	0.157	0.133	0.389	0.611	0.952

Notes: Total number of high–educated students: 1,111 (out of 3,471). Only groups of size 10 or more have been kept. We also removed two small schools with only one grade level. Pctl(25) and Pctl(75) mean the 25th and 75th percentiles, respectively.

poor white families. Even though there are (small) differences in the racial group compositions of low-educated and high-educated students, none of these differences are statistically significant. We observe that among the high-educated families, the mother is more likely to work.

Second, the average socialization effort s_i is 0.597 for low-educated students and 0.621 high-educated students. This indicates that on average, students from high-educated families socialize more than those from low-educated families, although there is substantial variation within types.

Finally, the average value of τ^t is 0.449 for low-educated parents (type L) and 0.509 for high-educated parents (type H). This indicates that on average, high-educated parents put more effort into education-related activities than do low-educated parents, although, here also, there is substantial variation within types.

Table 3: Summary statistics, pairwise variables

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
g_{ij}	0.006	0.076	0	0	0	1
Both White	0.203	0.402	0	0	0	1
Both Black	0.053	0.223	0	0	0	1
Both Hisp.	0.127	0.333	0	0	0	1
Both Asian	0.093	0.291	0	0	0	1
Both mothers work	0.511	0.500	0	0	1	1
Same gender	0.500	0.500	0	0	1	1
Age difference	0.550	0.468	0.000	0.167	0.750	3.583
Geographical distance	0.031	0.046	0.000	0.012	0.034	1.000
$t = L$ with $t = H$	0.212	0.409	0	0	0	1
$t = H$ with $t = L$	0.212	0.409	0	0	0	1
$s_i s_j$	0.348	0.152	0.003	0.236	0.445	1.000

Notes: Total number of individuals: 3,471; total number of pairs: 1,085,606. Only groups of size 10 or more have been kept. We also removed two small schools with only one grade level. Pctl(25) and Pctl(75) mean the 25th and 75th percentiles, respectively.

For the *pairwise* variables (Table 3), we observe some homophily in terms of race, gender, age, and geographical distance, even though the network is quite sparse.

3.2 Empirical strategy: Children's decisions

Recall that the (conditional) network-formation process (1) is given by[13]

$$p_{ij,r} = d_{ij,r} s_{i,r} s_{j,r}, \tag{15}$$

[13]To facilitate the notations, we use: $d_{ij} := d_{ij}(t_i, t_j)$.

where we normalize $c = 1$ and add the subscript r to denote the group $r = 1, ..., \bar{r}$.[14] We use the following parametrization: $d_{ij,r} = \Phi(\mathbf{z}_{ij,r}\boldsymbol{\gamma})$, where Φ is the standardized normal cumulative distribution, $\mathbf{z}_{ij}$ is a vector of pairwise characteristics of the directed pair ij in group r, and $\boldsymbol{\gamma}$ is a vector of parameters to estimate. Notably, $\mathbf{z}_{ij}$ includes t_i and t_j, but also other characteristics of i and j, such as their gender, age, geographical distance, or racial group, as well as a school fixed effect. Precise definitions for constructed variables are presented in Appendix B.1, and summary statistics are presented in Table 3.

If the socialization efforts $\mathbf{s}$ were exogenous, and since we observe the network structure $\mathbf{G}$, the parameters $\boldsymbol{\gamma}$ could simply be recovered using a simple maximum likelihood estimator (MLE) given by

$$\ln P(\mathbf{G}_r|\mathbf{s}_r, \mathbf{Z}_r; \boldsymbol{\gamma}) = \sum_{i \neq j} g_{ij,r} \ln[\Phi(\mathbf{z}_{ij,r}\boldsymbol{\gamma})s_{i,r}s_{j,r}] + (1 - g_{ij,r}) \ln[1 - \Phi(\mathbf{z}_{ij,r}\boldsymbol{\gamma})s_{i,r}s_{j,r}] \tag{16}$$

for any school r, which is a simple variation on a probit model. However, here, $s_{i,r}$ and $s_{j,r}$ are choice variables for any ordered pair (i, j). In particular, students choose their socialization efforts anticipating the network-formation process (15). As such, the equilibrium value of $\mathbf{s}_r$ is a function of $\boldsymbol{\gamma}$. Therefore, we need to estimate the network-formation model jointly with the model reflecting the optimal choice of $\mathbf{s}_r$.

In this section, we assume that the equilibrium socialization effort is interior. This is coherent with the data since all values of s_i are strictly above 0.[15] As such, the equilibrium socialization efforts are given by:

$$s_{i,r} = b_{i,r} + \phi \sum_j d_{ij,r}s_{j,r}, \tag{17}$$

for all i and r. We assume that $b_{i,r} = \mathbf{x}_{i,r}\boldsymbol{\beta} + \varepsilon_{i,r}$, where $\mathbf{x}_{i,r}$ is a vector of the characteristics of student i in group r (e.g., age, gender, racial group; see Table 1 and Table 2),[16] and where $\varepsilon_{ij} \sim N(0, \sigma^2)$. Then, following Lee et al. (2010), the likelihood of the students' socialization efforts, for any school r, is given by[17]

$$\begin{aligned} \ln P(\mathbf{s}_r|\mathbf{Z}_r, \mathbf{X}_r; \boldsymbol{\theta}) \quad = \quad & \frac{n_r}{2} \ln(\sigma^2) - \ln |\mathbf{M}_r(\boldsymbol{\theta})| - n_r \ln[\pi] \\ & - \frac{1}{2\sigma^2} \left[\mathbf{s}_r^T \mathbf{M}_r^T(\boldsymbol{\theta})\mathbf{M}_r(\boldsymbol{\theta})\mathbf{s}_r - 2\mathbf{s}_r^T \mathbf{M}_r^T(\boldsymbol{\theta})\mathbf{X}_r\boldsymbol{\beta} + \boldsymbol{\beta}^T \mathbf{X}_r^T \mathbf{X}_r \boldsymbol{\beta} \right], \end{aligned} \tag{18}$$

[14] The normalization of c follows from defining s_i as an index in $[0, 1]$.
[15] The distribution of s is fairly continuous; there is no obvious mass point.
[16] We also include a school fixed effect.
[17] Remember from the model that $\mathbf{D}$ has zeros on the diagonal and $d_{ij,r}$ off diagonal.

Table 4: Estimation results: Joint likelihood of the network and the socialization efforts

Network formation			**Socialization effort**		
Variable	Estimate	S.E.	Variable	Estimate	S.E.
Both White	0.205***	(0.026)	White	0.005	(0.011)
Both Black	0.731***	(0.026)	Black	0.019	(0.015)
Both Hisp.	0.703***	(0.021)	Hisp.	0.000	(0.014)
Both Asian	0.921***	(0.021)	Asian	-0.007	(0.018)
Both Mother Work	0.089***	(0.012)	Mother works	0.005	(0.007)
Same Gender	0.280***	(0.012)	Female	-0.058***	(0.006)
Age Difference	-0.257***	(0.014)	Age	-0.023***	(0.003)
Geographical distance	-1.126***	(0.143)	Type H	0.02***	(0.007)
$d_{ij}(H,L)$	-0.066***	(0.015)	ϕ	0.011***	(0.005)
$d_{ij}(L,H)$	-0.058***	(0.015)	σ^2	0.029***	(0.001)

Notes: Estimation of (19). Both the network-formation specification (16) and the socialization effort specification (18) control for school fixed effects. Geographical distance is normalized (in the original data) between 0 and 1 for anonymity reasons. The point estimate for the effect of Hisp. on s_i is equal to -0.0002256738, but rounded to 0.000 in the table. Standard errors are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

where $\mathbf{M}_r(\boldsymbol{\theta}) = \mathbf{I}_r - \phi\mathbf{D}_r(\boldsymbol{\gamma})$, and $\boldsymbol{\theta} = [\boldsymbol{\beta}, \boldsymbol{\gamma}, \phi, \sigma]$. The likelihood (18) is similar to the one in Lee et al. (2010), with the notable difference that the interaction matrices (here $\mathbf{D}_r$, $r = 1, ..., \bar{r}$) are not row-normalized. While (18) can still be concentrated around ϕ, which facilitates the numerical optimization, we cannot adapt the within-group transformation used in Lee et al. (2010).[18]

Here, if $\mathbf{D}_r(\boldsymbol{\gamma})$ was known, then $\boldsymbol{\beta}$ and ϕ could be estimated by maximizing (18) under similar identification conditions as in Lee et al. (2010) or Bramoullé et al. (2009). However, since $\boldsymbol{\gamma}$, and therefore $\mathbf{D}_r(\boldsymbol{\gamma})$, are not known, the entire vector of unknown parameters $\boldsymbol{\theta} = [\boldsymbol{\beta}, \boldsymbol{\gamma}, \phi, \sigma]$ is likely *not* point identified using (18) alone.

Therefore, we propose to estimate $\boldsymbol{\theta}$ using the joint likelihood of the network and of the equilibrium socialization efforts, that is

$$\ln P(\mathbf{G}_r, \mathbf{s}_r | \mathbf{Z}_r, \mathbf{X}_r; \boldsymbol{\theta}) = \ln P(\mathbf{G}_r | \mathbf{s}_r, \mathbf{Z}_r; \boldsymbol{\gamma}) + \ln P(\mathbf{s}_r | \mathbf{Z}_r, \mathbf{X}_r; \boldsymbol{\theta}), \tag{19}$$

for $r = 1, ..., \bar{r}$. Estimated coefficients are presented in Table 4. We present a discussion of the results in Section 3.4.

[18]Unfortunately, group sizes are too small to allow for a consistent estimation of group-level dummies. We therefore rely on school-level dummies.

3.3 Empirical strategy: Parents' decisions

Recall that, from Proposition 2, we have, for each parent i of type t and group r

$$\tau^t_{i,r} = \Delta V^t_{i,r}(1 - \bar{h}^H_{i,r}) + \alpha^t \bar{h}^H_{i,r}. \tag{20}$$

Here, we assume a simple linear specification for $\Delta V^t_{i,r} = \mathbf{w}_{i,r}\boldsymbol{\delta}_t + \eta^t_{i,r}$, where $\mathbf{w}_{i,r}$ is a vector of observable characteristics for parent i, $\boldsymbol{\delta}_t$ is a type-dependent vector of parameters to be estimated, and $\eta^t_{i,r}$ is unobserved error.

If $\bar{h}^H_{i,r}$, the expected fraction of friends of type-H, was observed, the model would be easily estimated by OLS. However, here $\bar{h}^H_{i,r}$ has to be constructed using the estimated parameters from $P(\mathbf{G}_r, \mathbf{s}_r|\mathbf{Z}_r, \mathbf{X}_r; \boldsymbol{\theta})$. Indeed, using the maximum likelihood estimator $\hat{\boldsymbol{\gamma}}$, we compute the predicted probabilities

$$\hat{p}_{ij,r} = \Phi(\mathbf{z}_{ij,r}\hat{\boldsymbol{\gamma}})s_{i,r}s_{j,r}, \tag{21}$$

which is a consistent estimate of the true probability $p_{ij,r}$.

Using these predicted probabilities, we can therefore simulate $\bar{h}^H_{i,r}$. Since the simulated value for $\bar{h}^H_{i,r}$ is consistent as the number of simulations gets large, we simply replace $\bar{h}^H_{i,r}$ by its simulated value in (20). This can, in fact, be viewed as a two-step estimator, with the addition of a simulation step. As such, we compute the standard errors using a bootstrap procedure described in Appendix B.2. The results are presented in Table 5. We discuss these results in the next section.

3.4 Empirical results

We first discuss the children's decisions and outcomes. The results for the estimation of (19) are displayed in Table 4.

For the network-formation process (left panel of Table 4), the results show significant homophily behaviors for all observable characteristics. Ethnic bias appears to be more important for Asians, followed by Blacks and Hispanics. The labor market status of the mother appears to be of comparatively small importance; this is also true for the impact of the education level of the parents, *conditional* on the contribution of the other characteristics. We also see that there is strong homophily in terms of age, gender, and geographical location. In particular, we show that students living closer are more likely to form links. Other studies have also shown that social interactions decline with the geographic distance between locations (Kim et al., 2017;

Table 5: Estimation results: Parents' education effort

Low-educated parents			**High-educated parents**		
Variable	Estimate	S.E.	Variable	Estimate	S.E.
White	-0.044*	(0.025)	White	-0.031	(0.041)
Black	-0.096***	(0.034)	Black	-0.081*	(0.044)
Hisp.	0.065***	(0.028)	Hisp.	0.037	(0.044)
Asian	-0.013	(0.036)	Asian	0.044	(0.045)
Mother Works	0.095***	(0.016)	Mother Works	0.034	(0.023)
Female	-0.020	(0.014)	Female	-0.008	(0.016)
Age	-0.061***	(0.006)	Age	-0.043***	(0.007)
α^L	0.455***	(0.009)	α^H	0.521***	(0.014)
$P(\partial\hat{\tau}_i^L/\partial h_i^L \geq 0)$		0.452	$P(\partial\hat{\tau}_i^H/\partial h_i^H \geq 0)$		0.626

Note: Estimation of (20). Both specifications control for school fixed effects. The last row in the table shows the fraction of parents of each type for which education effort exhibits cultural complementarity. Standard errors are reported in parentheses and are bootstrapped using the procedure described in Appendix B.2. ***p<0.01, **p<0.05, *p<0.1.

Bailey et al., 2020).

Finally, students from different types of parents are less likely to form links. However, homophily with respect to the type of parents (high-educated versus low-educated) does not appear to be heterogeneous, i.e., $d_{ij}(L, H)$ and $d_{ij}(H, L)$ are not statistically different.

If we now consider the right panel of Table 4, we see that the socialization effort is higher for Blacks than for any other ethnic groups (even if it is not significant), something that has been documented before (List et al., 2019). Girls, older students, and low-educated students exert less socialization effort. We also find that there is complementarity in socialization efforts since $\hat{\phi} > 0$ and is highly significant. Further, we check whether $|\phi| < c/\|\mathbf{D}\|$, the equilibrium uniqueness condition in Proposition 1, is satisfied here. It is indeed satisfied since, with $c = 1$, the predicted upper-bound based on the spectral norm of $\mathbf{D}$ is $\phi \leq 0.123$ and therefore relatively large compared to the estimated value of $\hat{\phi} = 0.011$. This means that preference biases (leading to $\mathbf{D}$) could, in principle, sustain much higher levels of complementarity between socialization efforts.

We now discuss the parents' decisions and outcomes. Results for the estimation of (20) are displayed in Table 5. Low-educated parents (left panel) of White or Black students, as well as those of older students are less likely to exert education effort, while those of Hispanic students are more likely to exert education effort. High-educated parents (right panel) of Black or older students are also less likely to exert education effort, while those of Asian students are more likely to exert education effort (even if it is not significant).

Interestingly, we find that high-educated parents have *homophilous* preferences (i.e., $\alpha^H > 0$), while low-educated parents have *heterophilous* preferences (i.e., $\alpha^L > 0$). This means that even after controlling for the effects of their child's friends on their probability to become educated, both types of parents would prefer their child to spend time with children of high-educated parents (see (13)).

Using the estimated coefficients from (20), we are now able to compute the predicted cultural substitutability or complementarity for both types of parents (see Proposition 2, parts (*ii*) and (*iii*)), that is,

$$\frac{\hat{\tau}_{i,r}^{L}}{\partial \bar{h}_{i,r}^{L}} = \mathbf{w}_{i,r}\hat{\boldsymbol{\delta}}^{L} - \hat{\alpha}^{L},$$

and

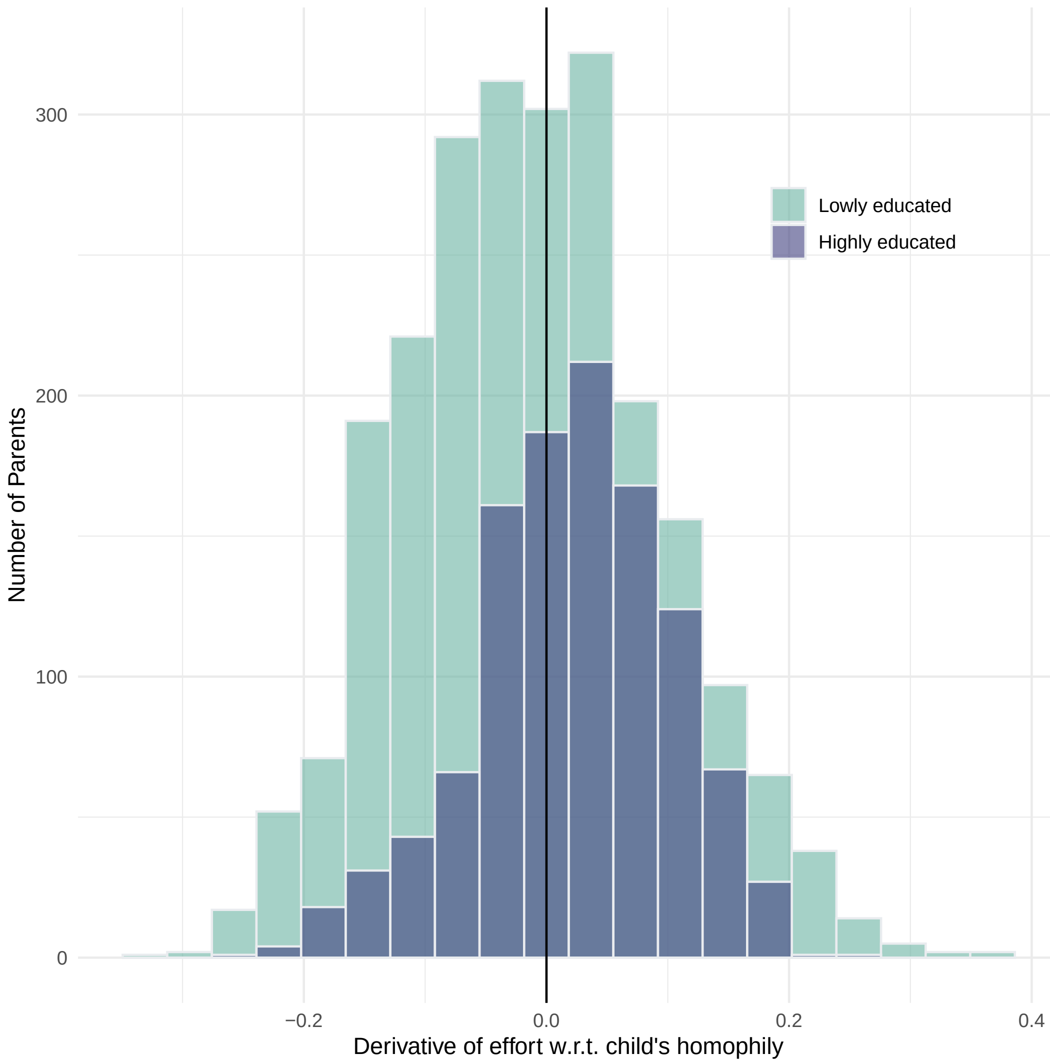
$$\frac{\hat{\tau}_{i,r}^{H}}{\partial \bar{h}_{i,r}^{H}} = \hat{\alpha}^{H} - \mathbf{w}_{i,r}\hat{\boldsymbol{\delta}}^{H}.$$

The results are displayed in the last row of Table 5 and Figure 1. On average, the socialization effort of high-educated parents is more than 15% more likely to exhibit cultural complementarity than that of low-educated parents. In particular, the fraction of high-educated parents for which there is cultural complementarity is greater than 62.6%, while, for low-educated parents, this figure is 45.2%, which means that they are more likely to exhibit cultural substitutability (last row of Table 5). This implies that for both types of parents, the more their children interact with youngsters from high-educated families, the more likely they are to exert greater educational effort. This result is also confirmed by Figure 1, where the values to the left of the 0–axis exhibit cultural substitutability, while those to the right of the 0–axis exhibit cultural complementarity. There is, however, substantial heterogeneity.

4 Policy experiments

Next, we study the impact of some policy interventions on the main outcomes of the model. In Figure 2, we plot the simulated distribution of the main outcome variables before the implementation of any policy. In panel (a), we see that the students from high-educated families are more likely to exert greater effort than those from low-educated families. In Tables 1 and 2, we saw that this was true, on average, in the data, while, in Table 4, this was also true, on average, in the simulations. Here, we plot the whole (simulated) distribution. In panel (b), we perform the same exercise for homophily. We see that low-educated students are more homophilous

Figure 1: Cultural substitution and cultural complementarity



Note: Histogram for $\partial\hat{\tau}_i^t/\partial h_i^t$, for $t = L, H$. Parents to the left (right) of the 0.0−vertical line are predicted to exhibit cultural substitution (complementarity).

(i.e., have more same-type friends) than high-educated students. This is because among the low-educated children, there are many more Hispanics (26.7% versus 6.3%; see Tables 1 and 2), and they tend to form links with each other (Table 4). Among the high-educated children, there are more Asians (27.3% versus 11.2%; see Tables 1 and 2), who also tend to form links with each other (Table 4), but the difference is less important. Panel (c) confirms what we knew: high-educated parents are more likely to exert education effort than are low-educated parents even if there is some variation. Finally, in panel (d), we provide the (simulated) probability distribution of becoming educated. Even though children from high-educated parents are more likely to be educated, there is a wide dispersion.

Given these distributions, let us, now, implement two policies. A natural policy to increase education would be to promote social interactions between students. For example, the government could subsidize the cost of extracurricular activities, such as sports' teams, chess clubs, etc. School administrators and teachers could also promote students' interactions by facilitating project-based learning or other approaches favoring teamwork.

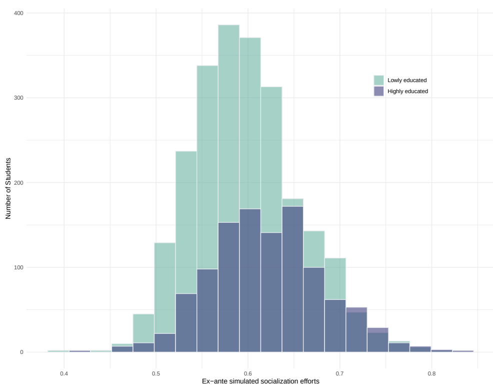
To study the impact of such policies, we exogenously increase b_i in our model, that is, the students' private benefit of socialization effort. We consider two policies, one uniform and one targeted. In each of these policies, we increase b_i by the fraction of the standard deviation of s_i in the data, from 0 (no intervention) to 1 standard deviation. This means that in the absence of network effects, $\phi = 0$, the maximal policy would increase socialization effort by one standard deviation.

4.1 Increasing social interactions for all students

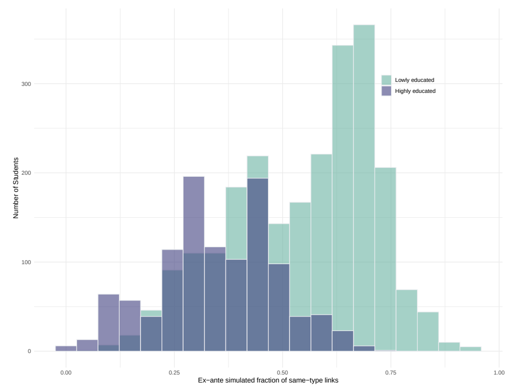
The first policy consists in increasing b_i by the same amount for *all* students (uniform policy). The results of this *uniform* policy are presented in Figure 3.

As expected, in panel (a), we see that s_i, the socialization effort of each student i, increases for both low- and high-educated families. The overall effect is slightly magnified by the effect of the complementarity of investments (i.e., positive ϕ), with a multiplier of roughly 1.05. This increase in socialization effort translates into an increase in the fraction of same-type links and, therefore, more homophily (panel (b)). Indeed, an increase of b_i from 0 (no intervention) to 1 of the fraction of the standard deviation of s_i, increases (the median of) the fraction of same-type friends from 58% to 71% for low-educated students and from 34% to 41% for high-educated students. In panel (c), we see that this increase in the expected fraction of same-type links barely affects the education effort of the parents. Finally, in panel (d), we study the impact of

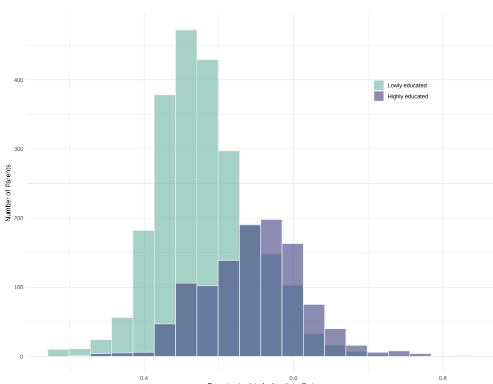
Figure 2: Ex ante simulated distribution for the main outcomes



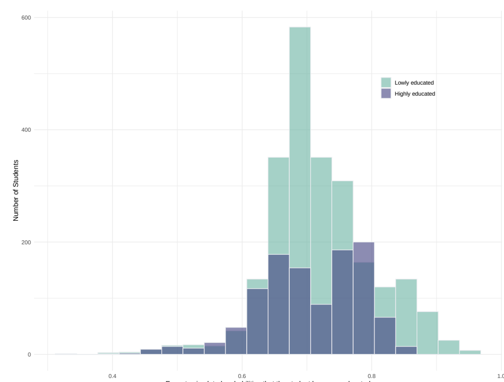
(a) Socialization effort (s_i)



(b) Fraction of same-type friends (h_i^t)



(c) Education effort (τ_i^t)



(d) Proba. of becoming educated (π_i^{tH})

Notes: Simulated values for the main outcomes of the model before the policy is introduced.

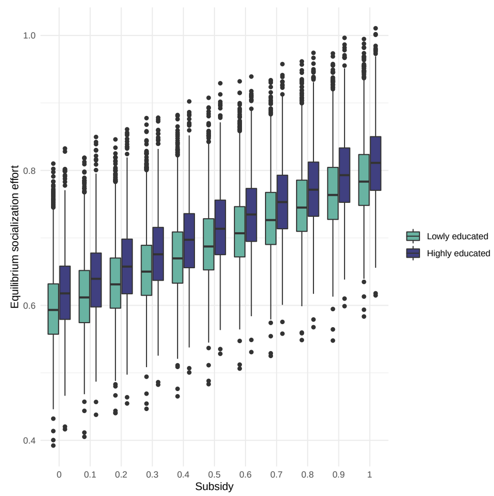
this policy on the (expected) probability for a child i of type t of becoming educated (π_i^{tH}). We see that this policy *reduces* the probability of becoming educated for children from low-educated families (from 71% to 66%), while it *increases* the probability of becoming educated for children from high-educated families (from 71% to 73%). This is because the policy increases socialization efforts and homophily for both types of children. Thus, for children from low-educated parents, there is a decrease in the average friend's "quality" because of more homophily. This leads to a decrease in the (expected) probability of becoming educated. For children from high-educated families, the effects are exactly the opposite: because of their increased homophily, the average "quality" of their friends increases. As a result, their probability of becoming educated increases.

4.2 Increasing social interactions for students from low-educated families

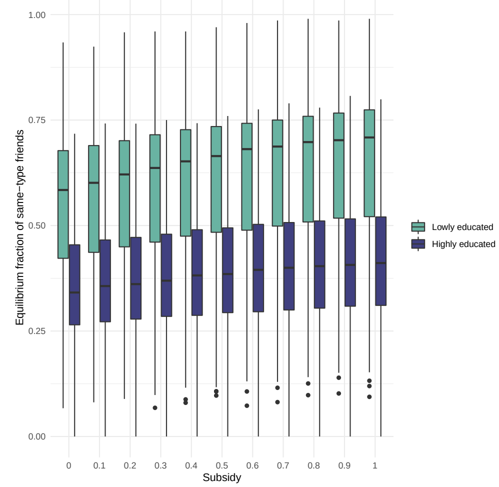
Next, we consider a second policy that consists in subsidizing only children from low-educated families. The results of this *targeted* policy are presented in Figure 4.

In panel (a), we see that the effect on socialization effort s_i is very significant for low-educated children. While their socialization effort is lower than that of high-educated children when there is no policy, under the targeted policy, they strongly increase their (median level of) effort from 0.59 to 0.78, while high-educated kids stay around 0.62. This leads to a big increase in homophily for low-educated kids and a slight decrease for high-educated kids (panel (b)). For low-educated students, homophily strongly increases because all low-educated students increase their socialization effort much more than do high-educated students and, thus, are more likely to form friendship links with other low-educated students (see (1) or (15)). Here again, parents barely change their education effort (panel (c)). As a result, the (expected) probability of becoming educated for low-educated kids (π_i^{LH}) decreases from 71% to 65% because of the increased homophily (panel (d)). For high-educated children, this policy has a small negative effect on π_i^{HH} (from 70% to 69%), which is due to the slight decrease in homophily levels. As a result, subsidizing social interactions of children from low-educated families backfires because it decreases rather than increases their probability of becoming educated. This is because such a policy increases homophily among low-educated students, which means that they interact more with students of the same type. The small change in the parents' education effort does not compensate for the change in homophily. Thus, increasing socialization reduces their chances of becoming educated.

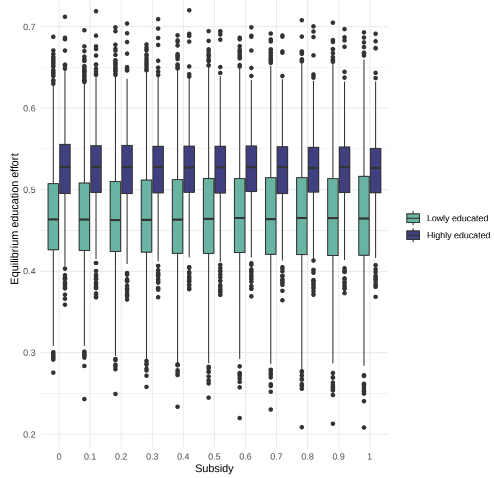
Figure 3: Increasing social interactions of all students



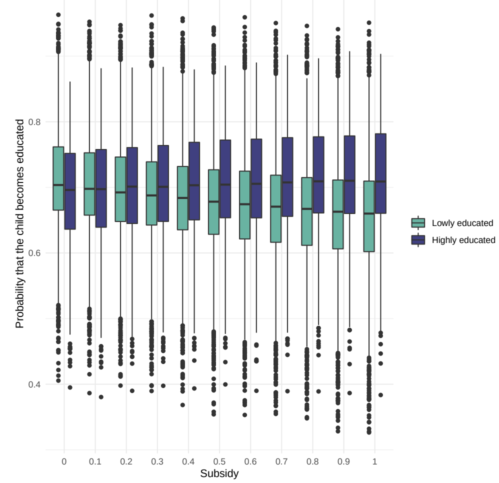
(a) Socialization effort (s_i)



(b) Fraction of same-type friends (h_i^t)



(c) Education effort (τ_i^t)



(d) Probability that the child becomes educated (π_i^{tH})

Notes: Counterfactual policy simulations for the main outcomes of the model. The policy corresponds to a uniform shift in b_i for all i: $b_i \rightarrow b_i + policy$, where *policy* ranges from zero to one standard deviation of s_i in the data ($\sqrt{Var(s_i)}$) by increments of $0.1\sqrt{Var(s_i)}$. Box plots show the 25th, 50th, and 75th percentiles.

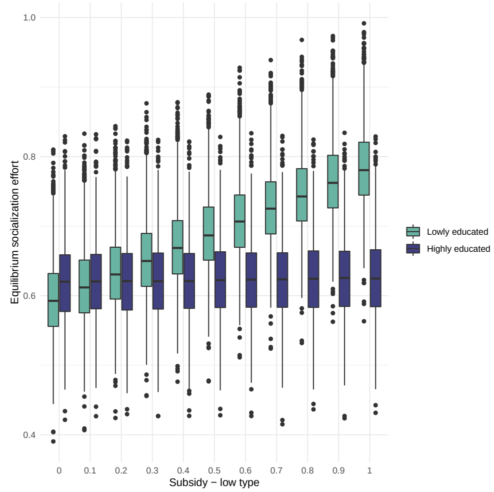
In summary, subsidizing social interactions (by targeting certain types of students or not) is detrimental to the possibility of education for children coming from low-educated families. This is because these children tend to react to this policy by increasing their social interactions mostly with children of the same type, which, in turn, causes their parents to reduce their education effort. Both effects have a negative impact on the probability of becoming educated because of negative vertical transmission (parents) and negative horizontal transmission (peer effects). Moreover, even in cases where the parents increase their education effort in response to their child's network, our simulations indicate that the magnitude of the parents' response is not enough to compensate for the child's network choices.

5 Concluding remarks

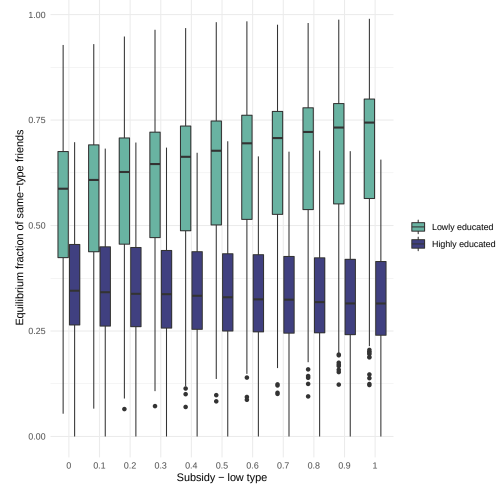
In this paper, we develop a model of intergenerational transmission of preference for high education, in the presence of an endogenously determined social context. In particular, we study the formation of a network of students as an equilibrium outcome of socializing activities between students. Parents observe the (expected) homophily of their children (i.e., the share of own-type friends) and decide accordingly how much educational effort to exert. We structurally estimated all parameters of the model using adolescent friendship networks in the United States. We find that, on average, children's homophily acts as a complement to the educational effort of high-educated parents but as a substitute for the educational effort of low-educated parents.

With the goal of increasing the probability of becoming educated for all students, we use the estimated parameters to run some policy experiments. We find that increasing socialization among students (such as *school-based policies*) has a negative effect on the educational outcomes of low-educated students, while not necessarily improving those of high-educated students. This is due to the fact that by subsidizing socialization, low-educated students become more "social" and, because of complementarity in socialization efforts, tend to interact more with other students of the same type. This is also true for high-educated students when subsidies are not targeted. However, the key difference is that, there is *cultural complementarity* for high-educated parents, which means that more homophily from their children leads to greater parental education effort, while there is *cultural substitutability* for low-educated parents, which implies that more homophily from their children leads to a reduction in the education effort of these parents.

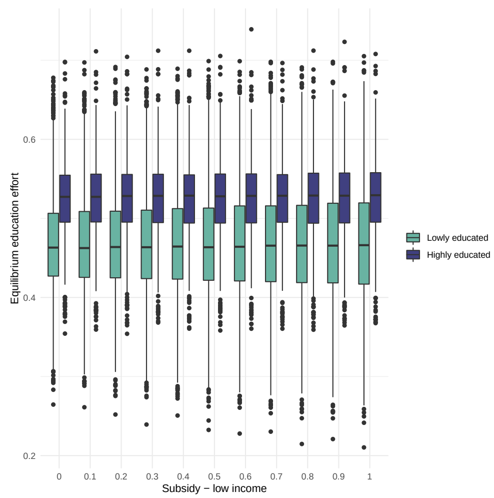
Figure 4: Increasing social interactions of students from low-educated families



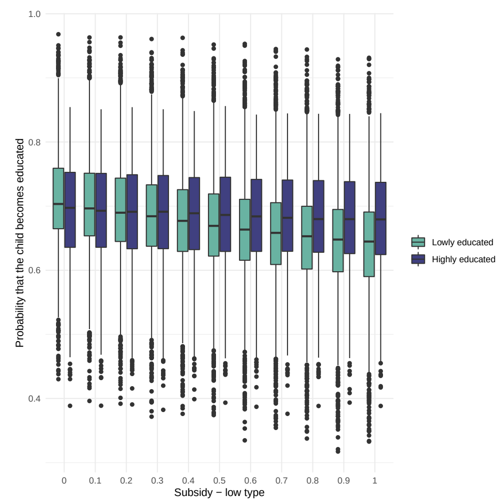
(a) Socialization effort (s_i)



(b) Fraction of same-type friends (h_i^t)



(c) Education effort (τ_i^t)



(d) Probability that the child becomes educated (π_i^{tH})

Notes: Counterfactual policy simulations for the main outcomes of the model. The policy corresponds to a uniform shift in b_i for all i such that the variable *Type* is equal to 0: $b_i \rightarrow b_i + policy$ for all $i : Type_i = 0$, where *policy* ranges from zero to one standard deviation of s_i in the data ($\sqrt{Var(s_i)}$), by increments of $0.1\sqrt{Var(s_i)}$. Box plots show the 25th, 50th, and 75th percentiles.

Thus, our results suggest that *school-based policies*, such as, for example, those that promote students' interactions by facilitating project-based learning or other approaches favoring teamwork, may not be as successful as expected in terms of educational outcomes. Other policies that directly affect social-mixing (*place-based policies*) could be more effective in increasing education outcomes. A prominent example of such policies is the Moving to Opportunity (MTO) program (Katz et al., 2001; Kling et al., 2007; Ludwig et al., 2013), which provides housing assistance (i.e., vouchers and certificates) to low-income families when they relocate to better and richer neighborhoods. This policy tends to favor interactions between children of different backgrounds. However, it has been shown that there is a significant and positive long-term effect of neighborhoods on education (college attendance) and earnings *only* for children who move when they are younger than 13 years old (Chetty et al., 2016). The main explanation of this result is that when the MTO program moves people (mostly low-educated families) from poor areas to richer areas, they do not interact much with their "new neighbors" but instead with their "old neighbors," who are their real peers. For example, de Souza Briggs et al. (2010) document the fact that many African American families who moved to richer areas thanks to the MTO program did not interact with their new neighbors because they felt rejected. In particular, on Sundays, they were still going to the church in their previous neighborhood, even though it was located very far away from their current residence. However, when young children (under 13) move to a new area, they have time to build a new network of friends; therefore, their new neighbors can become their peers and have a positive impact on their education outcomes.

The question of which policy is best for improving the educational outcomes of children is very difficult. In this paper, we have highlighted one dimension related to the role of children's socialization and homophily behavior and of parents' effort in education outcomes. We believe that a successful education policy should therefore take into account its impact on children's social networks and on parents' education transmission.

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APPENDIX

A Theory

We look for an upper-bound $\bar{s}$ such that

$$\mathbf{b} - \bar{s}\mathbf{1} + \bar{s}\frac{\phi}{c}\mathbf{D}\mathbf{1} < 0$$

such that the first derivative of the utility function is negative for all children. Let $c = \bar{s}^2 \geq d_{ij}s_i s_j$. It is then sufficient to look for $\bar{s}$ such that:

$$\bar{s}\bar{b} - \bar{s}^2 + \phi(n-1) < 0,$$

where $\bar{b} = \max_i b_i$. It is therefore sufficient to have:

$$\bar{s} \geq \left(\bar{b} + \sqrt{\bar{b}^2 + 4\phi(n-1)}\right)/2,$$

and, as such, a sufficient condition of c is $c \geq \left(\bar{b} + \sqrt{\bar{b}^2 + 4\phi(n-1)}\right)^2/4$.

B Empirical Application

B.1 Constructed variables

To measure the *socialization effort* s_i of each child i, we take the average of three types of interactions of student i and then normalize them between 0 and 1 (log scale). These three types of interactions are as follows:

1. *The number of extracurricular (or after-school) activities* in which the student participates (normalized between 1 and 2, after censoring outliers). These activities are: dance, music, any kind of sports, writing or editing the school newspaper, honors club, foreign language clubs, participating in the school council, and other clubs.

2. *Involvement in daily activities*: The average value of the answer to the question: "During the past week, how many times did you hang out with friends?". Range between 0 and 3.

3. *Average neighborhood participation*: The average of the two following binary variables:

"You know most of the people in your neighborhood and if, during the month before the interview, they stopped on the street to talk to someone they knew " (answer 0 or 1) and "Do you use a physical fitness or recreation center in your neighborhood?" (answer 0 or 1).

To measure the *education effort* τ_i^t of a parent i of type $t = H, L$, we average all the answers to questions asked to students regarding their relationship with their parents and to parents regarding their relation with their kids concerning school activities. These three types of questions are as follows:

1. *Decision variables*: The average of the answers from the child to the following questions: "Do your parents let you make your own decisions about..." (for each question, the answer is either 0 or 1).

2. *Caring*: The average of the answer from the child to the following question: "How much do you think she/he cares about you?" (range between 0 and 5).

3. *Activities related to school*: We take the average of three questions that were asked to the parents about the following topics: (*i*) whether they talked to the child about his or her grades, (*ii*) whether they helped the child with a school project, (*iii*) whether they talked to the child about other things he or she did at school.

B.2 Bootstrap procedure for parental effort models

The standard errors are bootstrapped as follows:

1. A parameter $\tilde{\boldsymbol{\theta}}$ is drawn from the multivariate normal distribution $N(\hat{\boldsymbol{\theta}}, \hat{\mathbf{V}}_{\boldsymbol{\theta}})$, where $\hat{\boldsymbol{\theta}}$ and $\hat{\mathbf{V}}_{\boldsymbol{\theta}}$ are the estimator and estimated variance-covariance matrix for the joint likelihood (19).

2. Given $\tilde{\boldsymbol{\theta}}$, we compute the predicted probabilities from (21). We then simulate $\bar{h}_{i,r}^H$ using 500 network draws.

3. We take a bootstrap sample of $\{\tau_{i,r}^t, \mathbf{w}_{i,r}, \bar{h}_{i,r}^H\}_{i,r}$.

4. We estimate (20) for $t = L, H$.

5. We repeat 1–4 499 times.