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ABSTRACT

Towards a General Theory of Peer Effects*

There is substantial empirical evidence showing that peer effects matter in many activities. The workhorse model in empirical work on peer effects is the linear-in-means (LIM) model, whereby it is assumed that agents are linearly affected by the mean action of their peers. We develop a new general model of peer effects that relaxes the linear assumption of the best-reply functions and the mean peer behavior and that encompasses the spillover, conformist model, and LIM model as special cases. Then, using data on adolescent activities in the U.S., we structurally estimate this model. We find that for many activities, individuals do not behave according to the LIM model. We run some counterfactual policies and show that imposing the mean action as an individual social norm is misleading and leads to incorrect policy implications.

JEL Classification: C31, D04, D85, Z13

Keywords: peer effects, spillovers, conformism, policies

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KEYWORDS: spillovers, conformism, structural estimation, policies.

1. INTRODUCTION

Individuals interact in all kinds of ways. In particular, they imitate and learn from the behavior of others, especially those close to them, such as their friends, neighbors, and colleagues. The impact of these interactions on individual behavior is referred to as peer effects. The decisions individuals take in the presence of peer effects generate externalities, and thus inefficiencies. While there is substantial empirical evidence showing that peer effects matter in many contexts, such as education, crime, and program participation,[1] the overwhelming majority of research assumes that individuals are affected by a linear function of the mean behavior of their peers and are silent about the underlying behavioral foundation generating the estimated peer effects.

Indeed, most peer-effect studies use the standard linear-in-means (LIM) model.[2] For example, the criminal activity of an individual is assumed to depend on the average criminal activity of the neighborhood where she lives. In education, each student compares herself with the average performance of students in her classroom, and so forth. It is well-known that the game theoretic foundation of the LIM model is a network model such that the best-reply function of each agent is linear and proportional to the mean action of her peers.[3] Moreover, it is now well recognized that the LIM model can be equivalently microfounded by games assuming either conformist preferences or positive spillovers.[4]

In this paper, we develop a new general model of peer effects that encompasses the spillover and conformist models as special cases and relaxes the assumptions of linearity of the best-reply functions and the mean peer behavior of the LIM model. Instead of assuming that the social norm of each agent is given by the average action of her peers, we allow for more flexibility and define the social norm using a CES function with elasticity parameter

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[1] See, e.g., Calvó-Armengol et al. (2009), Sacerdote (2011), and Dahl et al. (2014), and Lee et al. (2021).

[2] Manski (1993) was among the first to highlight the identification issues in estimating the LIM model, in particular, the reflection problem.

[3] See, e.g., Patacchini and Zenou (2012), Blume et al. (2015), Boucher (2016), Kline and Tamer (2020) and Ushchev and Zenou (2020).

[4] See Blume et al. (2015) and Boucher and Fortin (2016). In particular, Boucher and Fortin (2016) have highlighted the fact that both the conformist and spillover models can microfound the LIM model; they also have suggested, but not implemented, a way to identify them separately using isolated individuals.

β. When β is equal to 1, we revert to the LIM model. When β is very large, we obtain the "max" model in which agents only care about the "most" active agents (i.e. the one exerting the most effort) in their network, while when β is very negative, the "min" model prevails in which agents only care about the "least" active agents in their network. The main advantage of providing a model in which the individual action/outcome is a function of a CES of peer actions is that it contains the LIM model, as well as the min and the max model, as special cases but provides flexibility in modeling, since the relevant peer group is estimated from the data.

We show that, contrary to the linear case, the best-response function for the general model with flexible β is not necessarily contracting. However, by relying on the literature on supermodular games (Milgrom and Roberts, 1990) and by studying the structure of the smallest and largest equilibria, we show that there always exists a unique Nash equilibrium. Our proof of existence and uniqueness of a Nash equilibrium applies to any social norm function that is homogeneous of degree one and increasing in individual action, which includes the CES function.

Then, using data on teenagers in the United States from the National Longitudinal Survey of Adolescent Health (AddHealth), we structurally estimate this general model. We proceed in two independent steps. First, for each activity, we estimate which LIM model (conformist, spillover, or general) matches best the data, by formalizing and operationalizing the intuition in Boucher and Fortin (2016). Second, we estimate the value of β to determine the relevant peer reference group. We find that for GPA, social clubs, self-esteem, and exercise, the spillover effect strongly dominates, while for risky behavior, study effort, fighting, smoking, and drinking, conformism plays a stronger role. We also find that for many activities, individuals do not behave according to the LIM model. Indeed, for GPA, self-esteem, exercise, and study effort, individuals have peer preferences skewed towards more "active" agents, while for trouble behavior at school, fighting, and drinking, the peers that matter are the "least" active agents. This confirms the fact that imposing the mean action as an individual social norm is misleading and may lead to incorrect policy implications.

In order to quantitatively evaluate the policy implications in the context of our data, for each activity, we simulate a counterfactual tax/subsidy policy that restores the first best. In particular, we contrast the differences between a planner that uses the LIM model and one that uses the general results obtained in our structural estimations. We show that the differences are large. In general, with the LIM model, the planner tends to uniformly tax/subsidize all agents in the network. In contrast, with the general model, it targets some key agents depending on whether the spillover or the conformist model dominates, and on the value of β. Consider, for example, GPA, which is a spillover model for which β is much greater than 1; this means that peer preferences are skewed toward students with the highest GPA. In contrast to the LIM model, we find in our policy simulations that in the general model, there is a large mass at zero because these individuals do not provide any positive spillover to their neighbors (they are not the more active friends), and there is therefore little social value in subsidizing them. We also show that some individuals obtain very large positive subsidies; this is when the social norm is made up of very low-performing students, and thus it becomes valuable to give large subsidies to the most active peers because they will generate large spillover effects.

We consider the baseline situation in which the network is exogenous and not affected by policy shocks. This allows us to focus on the impact of the behavioral foundations (conformism or spillovers) and non-linearity for public policies when the network is fixed. We find that the policy recommendations resulting from conformism or spillover effects differ wildly and that non-linearities have a huge influence on who should be targeted by the policies. We provide an estimator that allows us to identify the behavioral foundation and the non-linearity from the data.

Our main contribution is to provide a general structural framework to study peer effects in a context in which peers do not necessarily react to the average of their peers' behavior, and that enables identification of the behavioral foundation of the estimated peer effects. Even though the vast majority of papers have used the LIM model to estimate peer effects, some have considered the maximum peers, namely the leaders, shining lights, or high achievers (Carrell et al., 2010, Tao and Lee, 2014, Diaz et al., 2021, Islam et al., 2021), some have included the minimum peers, namely the bad apples or low-ability individuals (Bietenbeck, 2020, Hahn et al., 2020), and some have incorporated both (Hoxby and Weingarth, 2005, Tatsi, 2017).[5] However, none of these papers have developed a general

[5]See also Brock and Durlauf (2001b) who look at a variety of models of peer behavior and suggest some nonlinearities in some applications, and Blume et al. (2011) who classify these different peer effects.

theoretical framework with different mechanisms (spillover or conformism) and different peer-group references. In contrast, our proposed framework allows us to identify which mechanism and which peer group matter most. Our main conclusion confirms the fact that ex ante imposing the mean (max or min) action as an individual social norm is misleading and leads to incorrect policy recommendations.

2. THEORY

2.1. *Linear-in-means models*

Before presenting our general model, we describe our setup using the well known linear-in-means model. Our main specification is presented in Section 2.2. Consider $n \geq 2$ individuals who are embedded in a network $\mathbf{g}$. The adjacency matrix $\mathbf{G} = [g_{ij}]$ is an $(n \times n)$-matrix with $\{0, 1\}$ entries that keeps track of the direct connections in the network. By definition, agents i and j are directly connected if and only if $g_{ij} = 1$; otherwise, $g_{ij} = 0$. We assume that the network is directed (i.e., g_{ij} and g_{ji} are potentially different)[6] and has no self-loops (i.e. $g_{ii} = 0$). $\mathcal{N}_i = \{j \mid g_{ij} \in \mathbf{g}\}$ denotes the set of i's neighbors. The cardinal of $\mathcal{N}_i$ is d_i, the degree or the number of direct neighbors of individual i, so that $d_i := \sum_{j=1}^n g_{ij} = |\mathcal{N}_i|$. Finally, $\widehat{\mathbf{G}} = [\widehat{g}_{ij}]$ denotes the $(n \times n)$ row-normalized adjacency matrix defined by $\widehat{g}_{ij} := g_{ij}/d_i$ if $d_i > 0$ and $\widehat{g}_{ij} := 0$ otherwise.

Assume that each individual has at least one neighbor,[7] namely $d_i > 0$ for all i. Consider the following class of best-response functions:

$$y_i = \alpha_i + \lambda \overline{y}_{-i}, \tag{1}$$

where y_i is the effort or outcome in some activity (such as education); $\alpha_i = \mathbf{x}_i\boldsymbol{\gamma} + \epsilon_i > 0$[8] is a vector of individual characteristics that includes both the observable ($\mathbf{x}_i$) and unobservable (ϵ_i) characteristics of individual i; λ is the peer-effect propagation rate (common for

[6] We can easily generalize our results to undirected and weighted networks.

[7] We deal with isolated individuals in Section 2.1.1 below.

[8] $\mathbf{x}_i$ is a $(1 \times k)$ vector of k observable characteristics, and $\boldsymbol{\gamma}$ is a $(k \times 1)$ vector, so that $\mathbf{x}_i\boldsymbol{\gamma} = \sum_{l=1}^k x_l \gamma_l$.

all individuals in the group); and

$$\overline{y}_{-i} = \sum_{j=1}^{n} \widehat{g}_{ij} y_j. \tag{2}$$

is the average effort of i's neighbors (excluding i). In Equation (1), individuals choose their effort y_i as a function of their own characteristics α_i and also as a function of the effort of the other individuals $\overline{y}_{-i}$ in the population. The model in (1) with the norm $\overline{y}_{-i}$ defined in (2) is referred to as the linear-in-means (LIM) model and can thus be written as

$$y_i = \mathbf{x}_i \boldsymbol{\gamma} + \lambda \sum_{j=1}^{n} \widehat{g}_{ij} y_j + \epsilon_i. \tag{3}$$

2.1.1. *Microfoundations*

Before starting with the microfoundations of the LIM model, let us analyze what happens if individuals are isolated, that is, they have no friends. This is important because we will use isolated individuals in our identification strategy in Section 3.2. Define $\mathbf{y}_{-i} := (y_1, \ldots, y_{i-1}, y_{i+1}, \ldots, y_n)^T$ the vector of effort without the effort of agent i. The utility function of each isolated individual i is given by:

$$U_i^I(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \alpha_i y_i - \frac{1}{2} y_i^2. \tag{4}$$

There is a unique (Nash) equilibrium in dominant strategies such that each i makes the following effort

$$y_i = \alpha_i = \mathbf{x}_i \boldsymbol{\gamma} + \epsilon_i. \tag{5}$$

That is, by the nature of her isolation, i's effort only depends on her observable and unobservable characteristics.

Let us now go back to the model with peer effects so that each individual i has at least one neighbor. As highlighted by Boucher and Fortin (2016), the LIM model (3) corresponds to the best-response function of two, observationally equivalent, types of social preferences: spillover or conformism.

For the spillover model (Brock and Durlauf, 2001a, Glaeser and Scheinkman, 2002, Boucher and Fortin, 2016, Reif, 2019), each agent i chooses effort $y_i \in \mathbb{R}_+$ that maximizes the following utility function:

$$U_i^S(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \alpha_i y_i - \frac{1}{2} y_i^2 + \theta_1 y_i \overline{y}_{-i}, \tag{6}$$

where $\overline{y}_{-i}$ is defined in (2), $\alpha_i = \mathbf{x}_i \boldsymbol{\gamma} + \epsilon_i$ captures the productivity (observable and unobservable characteristics) of agent i, and $0 \leq \theta_1 < 1$ is the intensity of the spillover effect.

For the conformist model (Akerlof, 1997, Bernheim, 1994, Patacchini and Zenou, 2012, Boucher, 2016, Ushchev and Zenou, 2020), each agent i chooses effort $y_i \in \mathbb{R}_+$ that maximizes the following utility function:

$$U_i^C(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \alpha_i y_i - \frac{1}{2} y_i^2 - \frac{\theta_2}{2} \left(y_i - \overline{y}_{-i}\right)^2, \tag{7}$$

where $\theta_2 \geq 0$ is the taste for conformity, and $\overline{y}_{-i} : \mathbb{R}_+^n \to \mathbb{R}_+$ is defined by (2) and determines agent i's social norm.

2.2. *A model with general social norms*

So far, following the LIM model, we assumed that peers operate through a linear and an average effect, that is, the social norm $\overline{y}_{-i}$ is the average effort of i's peers. This is a strong assumption, especially for empirical applications. The empirical literature has been partially addressing this issue by not only looking at the effect of the average peer, but instead the minimum or maximum. In this section, we provide a more general and flexible structure of peer preferences. That is, we relax the assumption by considering a peer effect model that is not linear and for which an agent's peers are not necessarily the average effect.

2.2.1. *A general social norm*

For each individual i, we generalize the social norm $\overline{y}_{-i}$ given in (2) by considering the following CES social norm:[9]

$$\widetilde{y}_{-i}(\beta) = \left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta} \right)^{\frac{1}{\beta}}. \tag{8}$$

We can easily see that the social norm in the LIM model defined in (2) is a special case of (8) when $\beta = 1$, that is, $\overline{y}_{-i} \equiv \widetilde{y}_{-i}(1) = \sum_{j=1}^{n} \widehat{g}_{ij} y_j$. Our social norm is general, since (8) allows for any β, that is, $\beta \in [-\infty, +\infty]$. We argue that this parameter, β, captures peer preference. For example, if we set $\beta = +\infty$, (8) becomes

$$\lim_{\beta \to +\infty} \widetilde{y}_{-i}(\beta) = \max_{j \in \mathcal{N}_i} \{y_j\},$$

that is, the social norm is defined with respect to the "most active agent" in the network (e.g., criminal leaders in crime). Under $\beta = -\infty$, (8) becomes

$$\lim_{\beta \to -\infty} \widetilde{y}_{-i}(\beta) = \min_{j \in \mathcal{N}_i} \{y_j\},$$

that is, the social norm is defined with respect to the "least active agent" in the network. Other possible values of $\beta \in \mathbb{R}$ capture a rich spectrum of intermediate cases. When $\beta < 0$, the expression (8) reads as follows:

$$\widetilde{y}_{-i}(\beta) = \begin{cases} \left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta} \right)^{\frac{1}{\beta}}, & y_i > 0 \text{ for all } i = 1, 2, \ldots, n; \\ 0, & y_i = 0 \text{ for some } i = 1, 2, \ldots, n. \end{cases} \tag{9}$$

Moreover, we have:

$$\frac{\partial \widetilde{y}_{-i}(\beta)}{\partial y_j} = \widehat{g}_{ij} \left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta} \right)^{(\frac{1}{\beta} - 1)} y_j^{\beta - 1},$$

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[9] Observe that, in the theory, we focus (and provide conditions) on equilibria for which $y_i > 0$, for all i. Thus, Equation (8) is well-defined for all $y_i > 0$.

while, in the linear-in-means model with the social norm given by Equation (2), we have: $\frac{\partial \overline{y}_{-i}}{\partial y_j} = \widehat{g}_{ij}$.

The main advantage of providing a model in which the individual action is a function of a CES function of peer actions is that it contains the LIM, the min and max models and any combination of them as a special case.

2.2.2. *A general model*

Let us now provide a general model that nests the two previous models (spillover and conformist) as special cases. The utility function for each individual i is now given by

$$U_i(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \underbrace{\alpha_i y_i + \theta_1 y_i \widetilde{y}_{-i}(\beta)}_{\text{benefit}} - \underbrace{\frac{1}{2}\left[y_i^2 + \theta_2 \left(y_i - \widetilde{y}_{-i}(\beta)\right)^2\right]}_{\text{cost}}. \tag{10}$$

where the social norm $\widetilde{y}_{-i}(\beta)$ is defined in (8). Denote $\lambda_1 := \theta_1/(1+\theta_2)$ and $\lambda_2 := \theta_2/(1+\theta_2)$. Then, the first-order condition can be written as[10]

$$y_i = (1-\lambda_2)\alpha_i + (\lambda_1 + \lambda_2)\widetilde{y}_{-i}(\beta), \tag{11}$$

or equivalently

$$y_i = (1-\lambda_2)\alpha_i + (\lambda_1 + \lambda_2)\left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}\right)^{\frac{1}{\beta}}. \tag{12}$$

The main difference with the LIM model (where $\beta = 1$) is that the first-order conditions (12) are not linear anymore. Thus, when estimating (12), in particular, β, we can determine whether the correct model is the LIM (i.e., $\beta = 1$) and, if not, which peers matter. We have the following result.

PROPOSITION 1: *Assume that the utility function of each individual $i = 1, \ldots, n$ is given by (10), with $0 < \lambda_1 + \lambda_2 < 1$ and $0 < \lambda_1 < 1$, and her social norm $\widetilde{y}_{-i}(\beta)$ has the CES functional form (8). Then, there exists a unique Nash equilibrium.*

[10] Note that for isolated individuals, their utility is still given by Equation (4) and their equilibrium action by Equation (5).

The proof of Proposition 1 is given in Appendix A. It is is not obvious because, contrary to the LIM model, the best-reply functions are not linear and not always contracting. First, for the existence of equilibrium, we use the fact that the game is supermodular and solve for a fixed point theorem. To prove uniqueness, we use the fact that there always exist a maximum and a minimum equilibrium and show that they are equal. To achieve this, we need to differentiate between concave and convex norms and demonstrate this equality; thus, the equilibrium is unique. In fact, we show that the existence and uniqueness of the equilibrium of this game is true for more general norms than the CES one, since we only need to assume Assumption 1 (see the proof of Proposition 1 in Appendix A).

2.3. *Spillover versus conformist effects: Policy implications*

It is important to understand which model microfounds the estimation of (3), as the policy implications of the two models are different. In Online Appendix A, we determine the social optimum (first best) for the spillover and the conformist model in the framework of the LIM model.

For the spillover model, compared to the Nash equilibrium, the first best has an extra term, $\lambda_1 \sum_j \widehat{g}_{ij} y_j = \lambda_1 \overline{y}_{-i}$, which is always positive. This implies that agents exert too little effort at the Nash equilibrium as compared to the social optimum outcome. Equilibrium interaction effort is too low because each agent ignores the positive impact of her effort on the effort choices of others; that is, each agent ignores the positive externality she exerts on her neighbors due to complementarity in effort choices. As a result, the market equilibrium is inefficient.

For the conformist model, we show that the first best is neither exclusively larger or smaller than the Nash equilibrium effort. Indeed, compared to the Nash equilibrium, the first best has an extra term, $\lambda_2 \sum_j \widehat{g}_{ij}(y_j - \overline{y}_{-j}) = \lambda_2(\overline{y}_{-i} - \overline{y}_{-j})$, which could be positive or negative. This means that, at the Nash equilibrium, when deciding her individual effort, each agent does not take into account the effect of her effort on the social norm of her peers, which creates an externality that can be positive or negative. Indeed, if individual i has friends for whom $y_j > \overline{y}_{-j}$ (resp. $y_j < \overline{y}_{-j}$), then when she exerts her effort, she does not take into account the fact that she positively affects $\overline{y}_{-j}$, the norm of her friends, which increases (decreases) the utility of their neighbors. In that case, compared to the first best, individual i underinvests (overinvests) in effort, because she exerts positive (negative) externalities on her friends.

We also study the policy implications of the spillover and the conformist model. We show that the policy implications of the spillover and the conformist model are very different for the LIM model. Indeed, consider a two-stage model where, in the first stage, the planner gives a per-effort subsidy S_i^m ($m = S$ for the spillover model and $m = C$ for the conformist model) to each agent i in the network, while in the second stage, the agents play the game described above. If $S_i^S = \lambda_1 \sum_j \widehat{g}_{ij} y_j^o = \lambda_1 \overline{y}_{-i}^o$[11] for the spillover model and $S_i^C = \frac{\lambda_2}{1-\lambda_2} \sum_j \widehat{g}_{ij} (y_j^o - \overline{y}_{-j}^o) = \frac{\lambda_2}{1-\lambda_2} (\overline{y}_{-i}^o - \overline{y}_{-j}^o)$ for the conformist model, then, in the second stage, each player will play her first-best effort instead of the Nash-equilibrium effort. Thus, the first best is restored. This implies that, in the spillover model, the planner needs to subsidize all agents in the network while, in the conformist model, the planner will only subsidize agents whose neighbors' effort is above the average effort of their neighbors but will tax agents whose neighbors' effort is below the average effort of their neighbors. This implies, in particular, that the planner is more likely to tax central agents (since their neighbors are more likely to have a lower effort) and to subsidize less central agents. Thus, the planner needs to target agents in the network to restore the first best.

In Online Appendix A, we generalize these results for the general model (10), for which β can take any value. We show that to restore the first best, the planner needs to give to each agent i the following subsidy:

$$S_i^G = \frac{y_i^o - y_i^N}{1-\lambda_2} = \frac{1}{1-\lambda_2}\left[\lambda_1 \sum_j y_j^o \frac{\partial \widetilde{y}_{-i}^o(\beta)}{\partial y_i^o} + \lambda_2 \sum_j (y_j^o - \widetilde{y}_{-i}^o(\beta)) \frac{\partial \widetilde{y}_{-i}^o(\beta)}{\partial y_i^o}\right]. \tag{13}$$

We show that the policy implications in terms of tax/subsidies derived for the LIM model can be qualitatively extended for the general case. For instance, in a star network, in the conformist model, the planner will tax the star agent, while in the spillover model, she will subsidize this agent (see Section A.2.2 of Online Appendix A).

To summarize, compared to the theoretical literature on peer/network effects, our main contribution is to generalize the social norm in a way such that the mean norm is a special

[11] A variable with the superscript o denotes its optimal value while a variable with the superscript N denotes its Nash-equilibrium value.

case of ours. This implies that the reference group can be the most active, the least active, the mean peer, or any combination of them. In the following section, we will test for which model (conformist or spillover) is the most appropriate in the data and estimate the value of β to determine the relevant reference group. We will implement these estimations for different outcomes.

3. STRUCTURAL ESTIMATION

3.1. *Empirical Strategy*

The model has two main components: the non-linearity of the social norm, and the nesting of conformity and spillover effects. We are interested in structurally estimating (i) the intensity of the spillover effect, λ_1; (ii) the taste for conformity, λ_2; and (iii) the peer preference, β. We can formulate the equilibrium effort of individual i by

$$y_{is} = (1-\lambda_2)\mathbf{x}_{is}\boldsymbol{\gamma} + (\lambda_1+\lambda_2)\widetilde{y}_{-is}(\beta) + \zeta_s + \varepsilon_{is}. \tag{14}$$

Equation (14) is the equivalent of the first-order condition (11), where, as above, $\alpha_{is} := \mathbf{x}_{is}\boldsymbol{\gamma} + \xi_s + \epsilon_{is}$ captures the observable and unobservable characteristics of i as well as the school fixed effects ξ_s, where $\zeta_s := (1-\lambda_2)\xi_s$, and $\varepsilon_i := (1-\lambda_2)\epsilon_i$. Indeed, as we discuss in Section 3.3 below, students in the data are assumed to interact within their school. We therefore added the subscript s to denote each school s in our data. Thus, compared to (11), we control for school fixed effects, ξ_s, which will absorb any factor that is common to all students within a given school, including the effect of the school itself. We assume that ε_{is}, the error term, is such that $\mathbb{E}(\varepsilon_{is}|\mathbf{X},\mathbf{G}) = 0$ for all i, implying an exogenous network.

For comparison purposes, we will also provide results for the reduced-form LIM model (Equation (3)),

$$y_{is} = \boldsymbol{x}_{is}\boldsymbol{\gamma} + \lambda\overline{y}_{-is} + \epsilon_{is}, \tag{15}$$

where y_{is} is the effort or outcome in some activity (e.g., GPA), and $\overline{y}_{-is}$ is the average effort of i's neighbors (excluding i), instrumented by their friends' characteristics, x_{-is}. That is, (15) is estimated using instrumental variable, where the instruments for the social norm are agents' characteristics, x_{-is} (Bramoullé et al., 2009).

3.2. *Identification*

We show in Appendix B how to formally estimate $\boldsymbol{\theta} = [\boldsymbol{\gamma}', \lambda_1, \lambda_2, \beta]'$ by deriving the appropriate generalized method of moment (GMM) estimator. Let us provide some intuition for the estimation procedure. Equation (14) does not allow us to separately identify λ_2 from $\boldsymbol{\gamma}$ or λ_1. However, we can consider two types of individuals in the data: (a) isolated and (b) non-isolated individuals. Isolated individuals are individuals without friends. This separation allows us to break the estimation problem into two parts and consequently identify λ_2 and $\boldsymbol{\gamma}$ separately.

First, note that isolated individuals have a simplified version of the general first-order condition (14), given by Equation (5) in the theory section, namely,

$$y_{is} = \mathbf{x}_{is}\boldsymbol{\gamma}^{iso} + \xi_s^{iso} + \varepsilon_{is}, \tag{16}$$

where ξ_s^{iso}, the school fixed effect specific to isolated individuals, has been added. This equation is independent of any social norm and, therefore, of β, λ_1 and λ_2. Thus, in our specification, the identification of $\boldsymbol{\gamma}$ can be obtained from isolated individuals, under the independence assumption of the error term, $\mathbb{E}\left(\varepsilon_{is}\mathbf{x}_{is}\right) = \mathbf{0}$. Note, identification does not allow us to estimate separately $\boldsymbol{\gamma}$s for isolated and non-isolated students. However, we allow the school fixed effect to differ between the two types of students. We acknowledge that assuming $\boldsymbol{\gamma}$ to be identical for isolated and non-isolated individuals can be a strong assumption. In Online Appendix B.2, we consider a number of robustness exercises to this assumption. In general, our results of peer preference are robust to alternative assumptions using non-isolated individuals only and estimates of β are consistently different from the average peer (see, in particular, Table A2 and Figures A1 and A2). Note that only the identification of the conformist effect in the general model hinges on isolated individuals. Thus, when estimating a model that does not nest the conformist and spillover model, the peer preference parameter β can be estimated without isolated individuals.

Second, to identify $\tilde{\boldsymbol{\theta}} = [\lambda_1, \lambda_2, \beta]$, we require three further moment conditions. Let us define three instruments, $\mathbf{z}_{is}$ for non-isolated individuals that satisfy the moment conditions, $\mathbb{E}\left(\varepsilon_{is}\mathbf{z}_{is}\right) = \mathbf{0}$. First, we can identify $(1 - \lambda_2)\boldsymbol{\gamma}$, and thus λ_2, given the result of $\boldsymbol{\gamma}$ from the solution of isolated individuals. Consequently, our first instrument is the set of covariates, $\mathbf{x}_{is}$. Secondly, if $\hat{\mathbf{y}}_s$ is the OLS predictor of $\mathbf{y}_s$, on the covariates, $\mathbf{x}_{is}$,[12] then, given λ_2, the identification of λ_1 comes from the moment $\widetilde{y}_{-is}(\hat{\mathbf{y}}_s, \beta)$ for non-isolated individuals—our second instrument. Finally, the identification of β comes from the derivative of the social norm with respect to β, $\frac{\partial \widetilde{y}_{-is}(\hat{\mathbf{y}}_s, \beta)}{\partial \beta} = \widetilde{y}'_{-is}(\hat{\mathbf{y}}_s, \beta)$—our last instrument. The intuition behind this instrument is that the slope of the social norm with respect to β should inform the directional movement of search for the parameter that minimizes the objective function during the numerical simulation. Also note that the choice of $\widetilde{y}'_{-is}(\hat{\mathbf{y}}_s, \beta)$ as a moment condition is justified by the fact that $\widetilde{y}'_{-is}(\hat{\mathbf{y}}_s, \beta)$ is equal to the first-order condition for the nonlinear least-squares estimator of a model in which $\tilde{y}_{is}(\beta)$ is substituted by $\tilde{y}_{is}(\hat{\mathbf{y}}_s, \beta)$.[13] Thus, the set of instruments for all non-isolated individuals can be summarized by $\mathbf{z}_{is} = [\mathbf{x}_{is}, \widetilde{y}_{-is}(\hat{\mathbf{y}}_s, \beta), \widetilde{y}'_{-is}(\hat{\mathbf{y}}_s, \beta)]$, with the assumption that $\mathbb{E}(\varepsilon_{is}\mathbf{z}_{is}) = \mathbf{0}$.

Note that our additional moment conditions are evaluated at $\hat{\mathbf{y}}_s$, the OLS predictor of $\mathbf{y}_s$. While it is standard to use the entire matrix of observable characteristics as instruments, namely $\hat{\mathbf{G}}\mathbf{X}$ (Bramoullé et al., 2009) when $\beta = 1$, this approach is not suitable for the general model when β could be substantially different to 1. Indeed, suppose that $\beta = +\infty$, so that $\widetilde{y}_{-is} = \max_{j:g_{ij,s}=1} y_{j,s}$. While $\bar{z}_{i,s} = \max_{j:g_{ij,s}=1} \hat{y}_{j,s}$ is likely a good predictor of $\widetilde{y}_{-i,s}$, it may well be the case that none of the maximum of characteristics of i's friends, taken individually (i.e., $\max_{j:g_{ij,s}=1} x^l_{j,s}$, $l = 1, ..., k$), would be a good predictor of $\widetilde{y}_{-i,s}$. Evaluating the instruments at $\hat{\mathbf{y}}_s$ is therefore a simple and effective way to ensure strong instruments, irrespective of the value of β.

We therefore have four sets of moment conditions, one from isolated individuals (i.e. $\mathbb{E}\left(\varepsilon_{is}\mathbf{x}_{is}\right) = \mathbf{0}$) and three from non-isolated individuals (i.e. $\mathbb{E}(\varepsilon_{is}\mathbf{x}_{is}) = \mathbf{0}$, $\mathbb{E}(\varepsilon_{is}\widetilde{y}_{-is}(\hat{\mathbf{y}}_s, \beta)) = \mathbf{0}$, and $\mathbb{E}(\varepsilon_{is}\widetilde{y}'_{-is}(\hat{\mathbf{y}}_s, \beta)) = \mathbf{0}$). Notice that the moment conditions for $\boldsymbol{\gamma}$ and for $(\lambda_1, \lambda_2, \beta)$, are not based on the same number of observations. The first set of moments characterizes isolated individuals (N_1), while the second set of moments characterizes non-isolated individuals (N_2). As such, the two sets of moments can be con-

[12]Because y_{is} is potentially endogenous, we estimate the reduced form of y_{is} on $\mathbf{x}_{is}$ to obtain the predicted $\hat{\mathbf{y}}_s$ for each i. Thus, $\hat{\mathbf{y}}_s$ is an exogenous predictor and independent of β. While we use a simple OLS predictor for simplicity, any predictor of y_i (potentially non-parametric) that is based on the exogeneous variables $\mathbf{X}$ would be admissible.

[13]For a textbook treatment of the nonlinear least-squares estimator, see Section 5.8.2 in Cameron and Trivedi (2005). For an in-depth discussion of the optimal moment conditions for non-linear GMM, see also Section 6.3.7 in Cameron and Trivedi (2005).

sidered to be coming from two different data sets (Angrist and Krueger, 1992, Arellano and Meghir, 1992). Thus, the estimations for isolated and non-isolated individuals are performed jointly using the sum of the GMM objective functions for both sets of moments, leading to an observation-weighted average of the two sets of moment conditions (Arellano and Meghir, 1992). For details, see Appendix B. Lastly, since the first-order condition is linear in $\boldsymbol{\gamma}$, we can use the model and the objective function to derive $\boldsymbol{\gamma}$ as a function of the three remaining parameters $[\lambda_1, \lambda_2, \beta]$ for both isolated and non-isolated individuals (see Appendix B for details). This allows us to concentrate the objective function around these remaining three parameters, $\tilde{\boldsymbol{\theta}} = [\lambda_1, \lambda_2, \beta]$, which are numerically estimated.

3.3. *Data description*

Our analysis is based on a well-known database of 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 more than 130 private and public schools in years 1994–1995. AddHealth provides a wealth of information regarding students' activities and outcomes. We extracted a large number of the activities available in the in-school interview sample to test our theory. For the purpose of studying peer effects, AddHealth data also record friendship information, which is based upon actual friends' nominations. Pupils were asked to identify their best friends from a school roster (up to five males and five females). Our estimation sample comprised over 70,000 students, from 134 schools.[14]

We use AddHealth data because it is one of the few datasets that provides both the exact network of all students and has multiple activities, so we can illustrate our theory with different values of β and consider their policy implications. Nonetheless, we acknowledge that AddHealth poses some limitations in terms of network endogeneity. However, our aim is methodological, as we want to illustrate the importance of having a microfoundation in estimating peer effect models. Thus, we assume that the network $\mathbf{G}$ is conditional exogenous.

[14]The precise sample size varies by activity; for exact numbers, see Table C.I in Appendix C.

In Section 3.4, we report the estimation results for 10 activities: (1) grade point average (GPA), (2) social clubs, (3) self-esteem, (4) risky behavior, (5) exercise, (6) study effort, (7) fighting, (8) smoking, (9) drinking, and (10) trouble behavior.[15] We also use a series of students' individual characteristics, such as age, gender, racial group, and mother's education and occupation. Summary statistics are presented in Table C.I in Appendix C.

Table C.I shows that activities are reported consistently across schools, with summary statistics similar across standard demographic characteristics (e.g., age, gender, race). All activities are based on increasing activity levels; for example, a higher value for self-esteem reflects an increased level of self-esteem. Importantly, 14–15 percent of students did not report any friends, and we labeled them isolated.[16,17]

3.4. *Empirical results*

For each activity in the data, we estimate the value of β to determine the relevant peer reference group, and we test which model (conformist or spillover) is the most appropriate one. The aim here is not to study the quantitative impact of specific peer effects, but rather to illustrate the importance of using a generalised theory of peer effects when trying to estimate their economic impact and, consequently, design adequate policies that improve agents' outcomes. Thus, to provide a broad view of our theory, we pick from a wide range of activities documented in AddHealth. That is, we provide estimation results for $\tilde{\boldsymbol{\theta}} = [\lambda_1, \lambda_2, \beta]$ for the 10 activities described in Section 3.3.

Table I shows the GMM results of (14) for the general model with estimated peer preferences, that is, the βs. For comparison purposes, the table also shows the general LIM model, whereby we impose the social norm of the average peer (i.e., $\beta = 1$), and reduced-form es-

[15] For an exact definition of each variable and further details on the variable construction, see Appendix C.

[16] We follow Boucher and Houndetoungan (2021) in dropping individuals who are potentially falsely classified as having no friends.

[17] Lastly, the activity or outcome values reported in Table C.I often included an outcome of zero (e.g., nonsmokers never smoke). Equation (8) is not defined for values of zero if peer preference is skewed to the least active agent, $\beta < 0$. To avoid this computational error, we have added in the estimation a value of 1 for each activity or outcome. For comparability, we did this for all activities. Results without adding 1 in instances where $\beta > 1$ are comparable and available upon request.

timates from Equation (15).[18] Lastly, the table reports two ways of testing the validity of the general model relative to the LIM model; (1) we report the significance of the hypothesis test of $H_0 : \beta \neq 1$, and (2) we report the objective value of each GMM procedure, as well as the likelihood-ratio statistic, $2N(Q^{LIM}(\lambda_1, \lambda_2) - Q(\lambda_1, \lambda_2))$, comparing it to the general LIM model. This latter measure is a simple way of establishing the relevant peer preference in the estimation, as it compares the goodness of fit for a model with $\beta \neq 1$ and $\beta = 1$.[19]

Just two of the ten activities have marginal cases regarding the most appropriate general model choice (spillover, conformism, or both). As the coefficient on λ_2 for self-esteem and exercise are statistically zero, the general model exclusively estimates spillover effects. As the objective value is, by construction, always lowest for the general model with both spillovers and conformism, we report it as our baseline.[20]

Table I also shows that activities have varying degrees of peer preference. Overall we find a wide range of values for $\beta = [-415, 371]$. Thus, peer preference does not necessarily conform to the average peer, as per the assumption in the commonly used LIM model. For example, GPA, self esteem, exercise, and study effort, have peer preferences skewed towards more "active" agents. However, with the exception of GPA, peer preferences are still far from the "most" active agent, defined by $\beta = +\infty$. Trouble behavior at school, fighting and drinking are skewed towards the "least" active agents, $\beta = -\infty$, while social clubs, risky behavior, and smoking are close to the LIM assumption of $\beta = 1$. However, only for risk behavior we cannot reject that $\beta = 1$.

With varying degrees of peer preference, the resulting estimates on total peer effects, as well as the magnitudes of spillover versus conformism effects, change in non-negligible ways across activities. We find that the difference in total peer effects $(\lambda_1 + \lambda_2)$ between the general model (GM) and the general LIM model to be large for (i) trouble behavior at school (40 percent), (ii) GPA and drinking (30 percent), (iii) study effort and fighting

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[18]Table A1 in Online Appendix B, in addition, displays the GMM results of (14) for the spillover LIM model and conformist LIM model, separately. The spillover LIM model refers to the case when $\lambda_2 = 0$ and $\beta = 1$, whereas the conformism LIM model refers to the case when $\lambda_1 = 0$ and $\beta = 1$.

[19]Complete results, including estimates for γ, are presented in Tables A3–A4 in Online Appendix B.

[20]For the two instances of self-esteem and exercise, the corresponding estimates of λ_1 and β for the general model with only spillovers are very similar to the general model reported here.

(20 percent), (iv) exercise (30 percent), and (V) self-esteem, risky behavior, exercise and smoking (10 percent).[21] Only for social clubs and self-esteem the total peer effects remain unchanged.

Thus, estimating the general model compared to imposing the reduced form model has implications on behavior through changing (i) the shape of the distribution of individuals' social norms, and/or (ii) the distribution of individuals' total peer effect exposure. We illustrate this further with three distinct examples, risky behavior, study effort and GPA outcomes.[22]

As for risky behavior, the estimated peer preference is close to one while the density distribution of social norms is similar in the general model and LIM model. However, given the sizable difference between the estimates on λ in the reduced form and $(\lambda_1 + \lambda_2)$ in the general model, the distribution of peer effects interacted with individuals' social norms in the reduced form has considerably more mass to the left.

The distribution of the social norm of study effort, for which the coefficient is above one (i.e., $\beta = 3.9$), shows a slight skewedness towards the right for the general model. Moreover, even stronger than for risky behavior, the *total peer effect* $(\lambda \overline{y}_{-i})$ or $(\lambda \tilde{y}_{-i})$, has large variance across the three models, with the general model strongly skewed toward higher peer effect outcomes.

Lastly, GPA outcomes serves as an example where peer preference is highly skewed towards active agents (i.e., $\beta = 371$). Thus, the distribution of the social norm in the general model is skewed toward the right, with several distinct peaks, but still far from the "most" active agents. Peaks appear because individuals might naturally have peers who do not achieve the highest (4.0) GPA, but something just below it, such as from 3.0 to 4.0. In comparison, the LIM model will have a perfectly hump-shaped distribution following the average peer social norm. The intensity of peer preference across the models greatly exacerbates differences between the general model and the LIM model. As peer preference increases towards the most active agent in the general model, the conformism effect mostly

[21]Formally, the difference in peer preference reported is $\left|1 - \frac{\lambda_1^{GM} + \lambda_2^{GM}}{\lambda_1^{LIM} + \lambda_2^{LIM}}\right|$.

[22]Figure A3 in Online Appendix B provides a graphical illustration of the below examples by graphing (i) the density of the average social norm commonly used in the LIM (i.e., $\overline{y}_{-i}$) and the social norm resulting from the general model (i.e., $\widetilde{y}_{-i}(\beta)$) and (ii) the distribution of peer effects in the LIM model (i.e., $\lambda \overline{y}_{-i}$), the general LIM model (i.e., $(\lambda_1 + \lambda_2)\overline{y}_{-i}$), and the general model (i.e., $(\lambda_1 + \lambda_2)\widetilde{y}_{-i}(\beta)$).

disappears. That is, for GPA, the friends with the best academic success will influence one's outcomes through positive spillovers, while friends with average academic outcomes will have no effect. Moreover, individuals do not try or succeed in conforming to their peers' academic outcomes.

These three different examples highlight the importance of moving towards a general theory of peer effects. There is a large range of peer preference estimates. These differences

TABLE I

STRUCTURAL ESTIMATION: PEER PREFERENCES (β)

	Peer preferences with general β				**$\beta = 1$**				**Reduced form**
Activity	$\boldsymbol{\lambda_1}$	$\boldsymbol{\lambda_2}$	$\boldsymbol{\beta}$	**Obj. Value**	$\boldsymbol{\lambda_1}$	$\boldsymbol{\lambda_2}$	**Obj. Value**	**L-R test**	$\boldsymbol{\lambda}$
GPA	0.32 (0.06)	0.06 (0.05)	370.8 $^{(a)}$ (114.9)	0.0014	0.39 (0.06)	0.19 (0.04)	0.0026	179.5	0.59 (0.02)
Clubs	0.33 (0.11)	0.33 (0.07)	1.4 $^{(b)}$ (0.2)	0.0022	0.35 (0.10)	0.34 (0.07)	0.0023	19.1	0.64 (0.03)
Self esteem	0.28 (0.11)	0.01 (0.07)	22.3 $^{(a)}$ (8.1)	0.0020	0.25 (0.11)	0.03 (0.07)	0.0027	110.1	0.29 (0.04)
Risky	-0.16 (0.08)	0.50 (0.03)	0.8 (0.4)	0.0016	-0.19 (0.07)	0.49 (0.03)	0.0017	9.6	0.24 (0.03)
Exercise	0.21 (0.06)	0.01 (0.04)	8.1 $^{(b)}$ (3.4)	0.0008	0.18 (0.06)	0.02 (0.04)	0.0017	122.2	0.18 (0.02)
Study effort	0.02 (0.09)	0.34 (0.04)	3.9 $^{(b)}$ (1.4)	0.0008	-0.02 (0.08)	0.32 (0.04)	0.0010	39.8	0.22 (0.04)
Fight	-0.08 (0.05)	0.12 (0.04)	73.6 $^{(a)}$ (14.9)	0.0011	0.06 (0.07)	0.19 (0.04)	0.0013	19.1	0.25 (0.03)
Smoke	0.21 (0.09)	0.65 (0.04)	0.7 $^{(b)}$ (0.1)	0.0006	0.13 (0.07)	0.62 (0.04)	0.0009	40.7	0.73 (0.03)
Drink	-0.05 (0.10)	0.64 (0.03)	0.4 $^{(a)}$ (0.2)	0.0018	-0.18 (0.07)	0.63 (0.03)	0.0019	14.5	0.16 (0.04)
Trouble	0.29 (0.71)	0.00 (0.17)	-415.0 $^{(a)}$ (149.0)	0.0005	0.22 (0.12)	0.25 (0.07)	0.0007	34.4	0.52 (0.04)

Notes: We report the general model (Equation (14)), the general LIM model ($\beta = 1$), and the reduced form (Equation (15)). All results control for school-fixed effects. Standard errors are reported in parentheses. For the general model, we report the significance of the hypothesis test, $H_0 : \beta \neq 1$ with (a) $p < 0.01$, (b) $p < 0.05$, (c) $p < 0.1$. In the case of the LIM model, likelihood ratio tests, $2N(Q^{LIM}(\lambda_1, \lambda_2) - Q(\lambda_1, \lambda_2))$, are also reported comparing the general LIM model with $\beta = 1$ with the *peer preference* outcome, $\beta \neq 1$. Results for $\boldsymbol{\gamma}$ can be found in Online Appendix B.3.

translate into vastly different social norms that cannot be consistently approximated by either the average, the most active or the least active agents. That is, moving from the reduced form to a general LIM model (with both spillover and conformism behavior) but without relaxing the functional form of the social norm is not enough to provide a general theory of peer effects.

4. POLICY IMPLICATIONS

Returning to the discussion of policy implications from Section 2.3, we now illustrate the importance of microfounding a model of peer effects through our estimated activities. We proceed in two steps. First, following the general estimation procedure, we simulate the Nash equilibrium and the social optimum (first best) for the LIM spillover and conformist model. Second, we simulate the Nash and social optimum for the general LIM model and the general model.

In Figure 1, we display the (kernel) density of the subsidies required for all non-isolated individuals to reach the first best for each model (see Equation (13) and Online Appendix A for details). We use the same three activities as above for illustration, that is, risky behavior, study effort and GPA outcomes; the results for all the other activities are available upon request. In the left panels of Figure 1, we show the subsidies in the LIM spillover and conformist models, while in the right panels, we show the subsidies in the general LIM model (i.e., $\beta = 1$) and the general model (i.e., β can take any value).

Technically, we simulate the best-response outcomes y_i for all students within each school based on their individual characteristics, estimated school fixed effects, and a truncated normally distributed error term using the parameter estimates from Tables I and A1.[23] We then proceed in steps to find the social optimal outcome and subsidy. First, we guess an initial value of the first best subsidy, $\hat{S}_0$, based on the Nash outcome using (13). Second, we compute the *subsidised* Nash outcome y_i with subsidy $\hat{S}_0$. Third, we recompute the first best subsidy $\hat{S}_1$ based on this new *subsidised* Nash outcome. Fourth, we repeat the second and third steps until we have convergence of the first best subsidy. In the spillover model, with positive peer effects, subsidies can potentially become un-

[23]Errors come from the same normal distribution with mean zero, but truncation is individual specific, based on the natural bounds of each outcome (e.g., the outcomes for GPA lie between 1 and 4.

bounded if the cost of exerting effort is smaller than the peer effect. To avoid such an issue, we limit the amount of subsidy such that the first best outcomes never exceed the highest outcome observed in the data. Thus, subsidies are bounded for each individual by $S_i \in \left[\min\left\{y_i^{data}\right\}_i - y_i^N, \max\left\{y_i^{data}\right\}_i - y_i^N\right]$.

From the theory (see Section 2.3), we know that the spillover model requires only positive subsidies, while, in the conformist model, the planner can tax or subsidize agents. Consequently, policy prescriptions are vastly different depending on the selected micro-foundation. Consider the left panels in Figure 1, where we compare the subsidies/taxes in the LIM spillover and LIM conformist model. As predicted by the theory, to reach the first best (social optimum) in the conformism model, the planner subsidizes some agents and taxes others, while in the spillover model, all agents are subsidized. For both risky behavior and study effort, peer effects are all driven by conformism (dashed line in left panels of Figure 1), while GPA is almost exclusively driven by spillover effects (solid line). However, picking between the conformism (right dashed line) and spillover (solid line), subsidy schedules do not necessarily reflect the correct policy intervention, as we have so far ignored the degree of peer preference.

Let us now focus on the right panels of Figure 1, in which we compare the policy that restores the first best for the general LIM model (imposing $\beta = 1$) and the general model with flexible peer preferences.[24] We observe a wide range of results, which is consistent with the large variation we obtained in the peer-preference estimates of β in Section 3.4. An activity that has peer preferences close to the average peer (i.e., $\beta = 1$) displays similar subsidy schedules between the general model and general LIM model (i.e., risky behavior). As peer preferences skew towards more active or less active agents, policy prescriptions start to differ more (e.g., study effort, GPA).

More specifically, in panel (b), for risky behavior, since peer preferences are close to 1 ($\beta = 0.8$), the general model policy implications seem to be similar to that of the general LIM model. There is, however, one subtle difference: The general model mostly taxes individuals, while the general LIM model does also subsidize a share of individuals, some of them with relatively large subsidies. Indeed, since for risky behavior, the conformist model is the most prominent one, and since peer preferences are slightly skewed toward the least

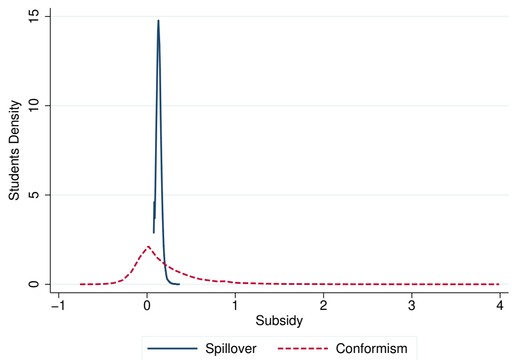
[24]Note the general LIM model represents the full effect (spillover, conformism, or both) from the left panel.

active agents, namely those agents who do not engage in risky activities, there is little use in subsidizing individuals to increase their risky behavior. In other words, all individuals have a tendency to put more weight on their least active peers, $\beta < 1$, when forming their social norm in the general model. These least active agents already engage in no risky behavior. Therefore, to reach the first best outcomes, it is optimal to tax the most risk-loving agents because it will induce them to decrease their risky behavior. In contrast, in the general LIM model, as the social planner tries to move individuals closer to their *average* peers' risky behavior, it is beneficial to increase some individuals' risky behavior, as each friend's behavior has an equal impact on one's social norm. Thus, the planner finds it optimal to subsidize some individuals to engage in more risky behavior.

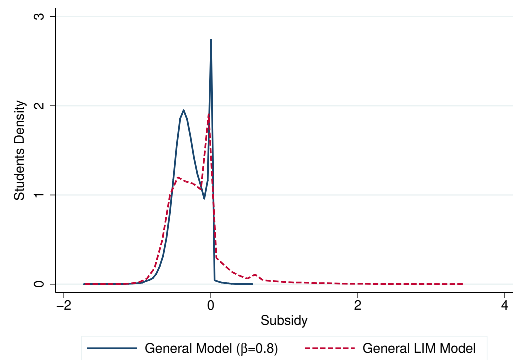
In panel (d), study effort requires, in general, greater levels of subsidy to reach the social optimum (the mean of the distribution of subsidies is larger for the general model). In the LIM model, since study effort is driven by conformism, the social planner needs to tax high-effort students. However, in the general model, since peer preferences are skewed towards the right (i.e., $\beta = 4$), the social planner can implement more targeted policies that require less taxation and overall higher utility outcomes. Thus, in the general model, while the social planner still taxes some of the highest-effort students, the number of students who need to be taxed to reach the first best are fewer while the number of students receiving a subsidy increases. This results in higher overall study effort and also higher utility.

Lastly, in panel (f), since GPA is driven by spillover effects, for the general LIM model, the social planner gives every individual $\lambda\overline{y}_{-i}$, namely the social norm times the peer effect. In contrast, in the general model, since peer preferences are skewed towards the most active agents (i.e., $\beta = 371$), there is a large mass at zero because these individuals do not have any positive spillover effect (they are not the most active friends), and there is therefore little social value in subsidising them. The general model also has some instance of very large positive subsidies, which are cases where the social norm is made up of very low-performing students. Indeed, from the social planner's perspective, it is valuable to greatly subsidize the most active peers, even if they are low-performing students. This is because, within their friendship group, being the highest performer will generate large spillover effects for their poorly performing peers. For example, take two groups, one where all peers have a GPA between 3.3 and 3.8 and one where all peers have a GPA between 1.2 and 1.5. For both of these groups, the social planner will give most subsidies to the peers

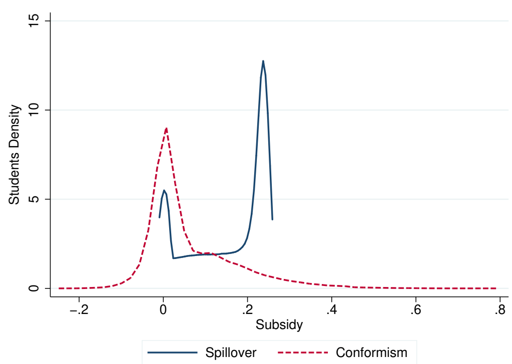
FIGURE 1.—*First-best subsidies (Examples)*



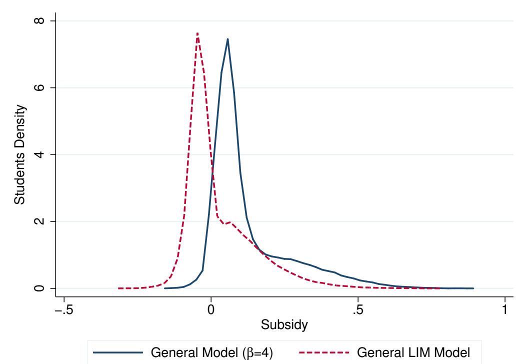
(a) LIM (Risky Behavior)



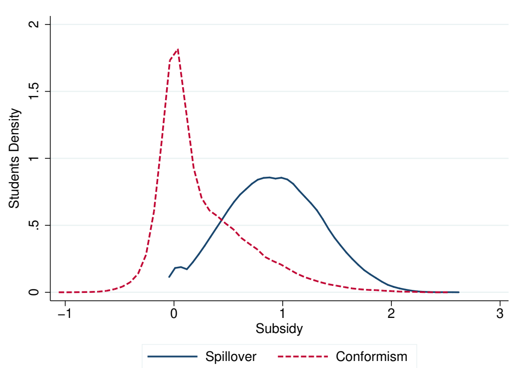
(b) Peer Preference (Risky Behavior)



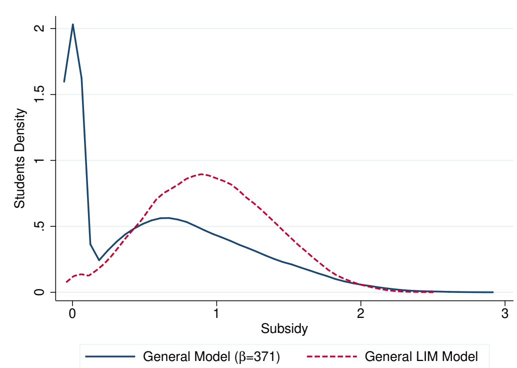
(c) LIM (Study Effort)



(d) Peer Preference (Study Effort)



(e) LIM (GPA)



(f) Peer Preference (GPA)

Notes: Kernel density distribution of non-isolated individuals of the subsidy required to reach the social optimum for (i) the linear-in-means (LIM) spillover and conformist model using estimates from the left-hand panel of Table A1; and (ii) the general model and general LIM model using estimates from the right-hand panel of Table I.

with the highest GPA because peer preferences are skewed toward the most active agents. A student with a lower GPA (1.5) in the second group will receive a considerably higher subsidy than a student with a higher GPA (3.8) in the first group. This is mechanical since subsidies are capped by the natural limit of 4.0 (the highest achievable GPA). Observe that since the model has mostly spillover effects, no agent is taxed. More generally, policies are very different between the LIM and the general model. In particular, compared to the LIM model, with the general model, the planner gives no subsidy to a large share of agents because they do not have the highest GPA in their peer group but she does give larger subsidies; that is, the curve is flatter but more spread for the general model, compared to the LIM model. In other words, with peer preferences skewed toward high-GPA students, the most effective way of reaching the social optimum in the general model is by subsidizing only a selected number of individuals.

We acknowledge that, as an applied exercise, there are shortcomings in our policy implications (in particular, potential network endogeneity). We therefore do not recommend to take the exact estimates at face value. However, we urge researchers to acknowledge that individuals do not necessarily respond to the mean of the peer group action and it is likely a function of whether a conformism or spillover game is at play. These have important policy implications that can be tested, since nonlinearity and behavioral foundations can be inferred from data.

5. CONCLUSION

Most papers that estimate peer effects use the LIM model, which assumes that impact on outcomes is linear and that the mean peers' outcomes matter. In this paper, we have argued that to prescribe adequate policies, one needs to know which model microfounds the LIM model and determine the correct peer reference group (or social norm). We have developed a general model that embeds the spillover and the conformist model and a general social norm for which the LIM model is a special case.

We structurally estimated this model for ten different activities and showed which model mattered the most for each activity. We found that, for most activities, individuals did not behave according to the LIM model; that is, their social norm was not the average outcome of their peers. For example, for GPA, self-esteem, exercise, and study effort, we found that individuals cared mostly about the more "active" agents among their peers, while for trouble behavior, fighting and drinking, the peers that mattered were the "less" active individuals. We then implemented some counterfactual policies; that is, we determined for each activity the taxes/subsidies that would restore the first best. We found that in most cases, it was optimal to target some individuals in the network. For example, for GPA, the most effective way of reaching the social optimum would be to only subsidize a selected number of individuals while, in the LIM model, the planner should give the same subsidy to all individuals. This implies that by imposing the LIM model, the policy recommendations may be very wrong and lead to inefficient outcomes.

More generally, our aim in this study was mainly methodological, as we wanted to show the potential mistakes made by using the (reduced-form) LIM model. While we considered a tax/subsidy policy that would restore the first best, other policies could be implemented. For example, we could consider a policy for which the planner would either maximize (for positive activities such as GPA or self-esteem) or minimize (for negative activities such as risky behavior or drinking) total outcome (instead of welfare) under a budget constraint. Since in our estimations, we show that the peer reference group greatly varies between different activities and very rarely corresponds to the mean peers' outcomes, the discrepancy between the LIM and our general model in terms of policy recommendations would still be very large.

The takeaway from our study is that a tighter link between theory, econometric methods, and data is necessary to deeply understand how peer effects work and which policy to recommend.

APPENDIX A: THEORY: EXISTENCE AND UNIQUENESS OF EQUILIBRIUM (PROPOSITION 1)

A.1. *Existence of Nash equilibrium*

Define the social norm mapping $\widetilde{\mathbf{y}} : \mathbb{R}_+^n \to \mathbb{R}_+^n$ as follows:[25]

$$\widetilde{\mathbf{y}}(\mathbf{y}) := (\widetilde{y}_1(\mathbf{y}), \widetilde{y}_2(\mathbf{y}), \ldots, \widetilde{y}_n(\mathbf{y}))\,. \tag{17}$$

[25] For the ease of the presentation, the social norm of individual i is denoted by $\widetilde{y}_i(\mathbf{y}) \equiv \widetilde{y}_{-i}(\beta) \equiv \widetilde{y}_{-i}(\mathbf{y}_{-i}, \beta)$.

ASSUMPTION 1: *For all $i = 1, 2, \ldots, n$, agent i's social norm $\widetilde{y}_i(\mathbf{y}) : \mathbb{R}^n_+ \to \mathbb{R}_+$, is monotone increasing, continuous, linear homogeneous, and normalized:* $\widetilde{y}_i(\mathbf{1}) = 1$.[26]

Clearly, the CES norm (8) satisfies Assumption 1 for any $\beta \in [-\infty, +\infty]$. The best-reply (BR) mapping is given by (11) or, in matrix form:

$$\mathbf{y} = \mathbf{b}(\mathbf{y}) := (1 - \lambda_2)\boldsymbol{\alpha} + (\lambda_1 + \lambda_2)\widetilde{\mathbf{y}}(\mathbf{y}). \tag{18}$$

Let $\mu := (\lambda_1 + \lambda_2) \in (0, 1)$. For each $i = 1, 2, \ldots, n$, define

$$\widetilde{\alpha}_i := \frac{1 - \lambda_2}{1 - \mu}\alpha_i \qquad \text{and} \qquad \widetilde{\boldsymbol{\alpha}} := (\widetilde{\alpha}_1, \widetilde{\alpha}_2, \ldots, \widetilde{\alpha}_n). \tag{19}$$

Then, the BR mapping (18) can be written as follows:

$$\mathbf{y} = \mathbf{b}(\mathbf{y}) := (1 - \mu)\widetilde{\boldsymbol{\alpha}} + \mu\,\widetilde{\mathbf{y}}(\mathbf{y}). \tag{20}$$

For any n-dimensional vector $\mathbf{x} = (x_1, x_2, \ldots, x_n)$, define:

$$x_{\min} := \min_{1 \le i \le n} \{x_i\}, \quad x_{\max} := \max_{1 \le i \le n} \{x_i\}.$$

LEMMA 2: *Under Assumption 1, the following inequalities hold for any* $\mathbf{y} \in \mathbb{R}^n_+$*:*

$$y_{\min} \le \widetilde{y}_{\min}(\mathbf{y}) \le \widetilde{y}_{\max}(\mathbf{y}) \le y_{\max}. \tag{21}$$

PROOF: By Assumption 1, $\widetilde{\mathbf{y}}(\cdot)$ is increasing over $\mathbb{R}^n_+$. Furthermore, linear homogeneity and the normalization together imply that $\widetilde{\mathbf{y}}(c\mathbf{1}) = c\mathbf{1}$ for any scalar $c \ge 0$. Hence:

$$y_{\min}(\mathbf{y})\mathbf{1} = \widetilde{\mathbf{y}}\left(y_{\min}(\mathbf{y})\mathbf{1}\right) \le \widetilde{\mathbf{y}}\left(\mathbf{y}\right) \le \widetilde{\mathbf{y}}\left(y_{\max}(\mathbf{y})\mathbf{1}\right) = y_{\max}(\mathbf{y})\mathbf{1},$$

which is equivalent to (21). This completes the proof. *Q.E.D.*

PROPOSITION 3: *For any $\widetilde{\boldsymbol{\alpha}} \in \mathbb{R}_{++}$, any $\mu \in (0, 1)$, any network $\mathbf{g}$, and any norm satisfying Assumption 1, the set of Nash equilibria is non-empty and contains a minimum equilibrium $\mathbf{y}^*$ and a maximum equilibrium $\mathbf{y}^{**}$.*

[26] Here, and everywhere below, $\mathbf{1}$ stands for the n-dimensional vector of ones.

PROOF: Consider a game with payoffs (10), social norms (17), and each agent's strategy space $[\widetilde{\alpha}_{\min} - \varepsilon, \widetilde{\alpha}_{\max} + \varepsilon]$, where $\varepsilon > 0$ is small. Clearly, it is a supermodular game.[27] Hence, the set of Nash equilibria of the restricted game contains a minimum equilibrium $\mathbf{y}^*$ and a maximum equilibrium $\mathbf{y}^{**}$ (Topkis, 1998, Theorem 4.2.1). Also, the set of Nash equilibria in the original game is the same as in the restricted game. To see this, using the BR (20), concavity of the $\min$-function (resp., convexity of the $\max$-function), and Lemma 2, for any agent i, we find that

$$
\begin{aligned}
&b_i(\mathbf{y}^*) \geq \min\nolimits_{1\leq i\leq n}\{(1-\mu)\widetilde{\alpha}_i + \mu\widetilde{y}_i(\mathbf{y}^*)\} \geq (1-\mu)\widetilde{\alpha}_{\min} + \mu\widetilde{y}_{\min}(\mathbf{y}^*) \\
&\geq (1-\mu)\widetilde{\alpha}_{\min} + \mu y^*_{\min} \implies b_i(\mathbf{y}^*) \geq \widetilde{\alpha}_{\min}; \\
&b_i(\mathbf{y}^*) \leq \max\nolimits_{1\leq i\leq n}\{(1-\mu)\widetilde{\alpha}_i + \mu\widetilde{y}_i(\mathbf{y}^*)\} \leq (1-\mu)\widetilde{\alpha}_{\max} + \mu\widetilde{y}_{\max}(\mathbf{y}^*) \\
&\leq (1-\mu)\widetilde{\alpha}_{\min} + \mu y^*_{\max} \implies y^*_{\max} \geq \widetilde{\alpha}_{\max}.
\end{aligned}
$$

Thus, every Nash equilibrium in both the restricted game and the unrestricted game is interior and satisfies $\widetilde{\alpha}_{\min} \leq y_i^* \leq \widetilde{\alpha}_{\max}$ for all $i = 1, 2, \ldots, n$. Hence, restricting the strategy space of each player to $[\widetilde{\alpha}_{\min} - \varepsilon, \widetilde{\alpha}_{\max} + \varepsilon]$ does not change the set of Nash equilibria. This completes the proof. *Q.E.D.*

A.2. *Uniqueness of Nash equilibrium*

A.2.1. *Uniqueness of Nash equilibrium for convex norms*

ASSUMPTION 2: *The social norm mapping $\widetilde{\mathbf{y}} : \mathbb{R}^n_+ \to \mathbb{R}^n_+$ is globally convex, that is, the inequality $\widetilde{\mathbf{y}}((1-\gamma)\mathbf{x} + \gamma\mathbf{z}) \leq (1-\gamma)\widetilde{\mathbf{y}}(\mathbf{x}) + \gamma\widetilde{\mathbf{y}}(\mathbf{z})$ holds for any $\gamma \in [0,1]$ and for any $\mathbf{x}, \mathbf{z} \in \mathbb{R}^n_+$*

PROPOSITION 4: *Let the social norm mapping $\widetilde{\mathbf{y}} : \mathbb{R}^n_+ \to \mathbb{R}^n_+$ satisfy Assumptions 1 and 2. Then, (20), and hence (18), has a unique fixed point.*

PROOF: Let $\|\cdot\|_\infty$ be the standard sup-norm over $\mathbb{R}^n$, that is,

$$\|\mathbf{z}\|_\infty := \max_{i=1,2,\ldots,n} |z_i|, \qquad \text{for all } \mathbf{z} = (z_1, z_2, \ldots, z_n) \in \mathbb{R}^n.$$

[27] A game with strategies in $\mathbb{R}$ is a supermodular game if (i) each player's strategy space is compact; (ii) each player's utility is upper semi-continuous; (iii) each player's utility function has increasing differences.

For all $\mathbf{x}, \mathbf{z} \in \mathbb{R}^n_+$, the following relations are readily verified:[28]

$$\|\mathbf{z}-\mathbf{x}\|_\infty = \|\mathbf{x} \vee \mathbf{z} - \mathbf{x} \wedge \mathbf{z}\|_\infty; \tag{22}$$

$$-\mathbf{z} \le \mathbf{x} \le \mathbf{z} \quad \Longrightarrow \quad \|\mathbf{x}\|_\infty \le \|\mathbf{z}\|_\infty; \tag{23}$$

$$\|\widetilde{\mathbf{y}}(\mathbf{z})\|_\infty \le \|\mathbf{z}\|_\infty. \tag{24}$$

From the monotonicity of the BR mapping (20), we have:

$$\mathbf{b}(\mathbf{x} \wedge \mathbf{z}) - \mathbf{b}(\mathbf{x} \vee \mathbf{z}) \le \mathbf{b}(\mathbf{z}) - \mathbf{b}(\mathbf{x}) \le \mathbf{b}(\mathbf{x} \vee \mathbf{z}) - \mathbf{b}(\mathbf{x} \wedge \mathbf{z}).$$

Using consecutively (23), (20), the homogeneity and convexity of $\widetilde{\mathbf{y}}(\cdot)$, (24), and (22), we obtain:

$$\begin{aligned}
\|\mathbf{b}(\mathbf{z}) - \mathbf{b}(\mathbf{x})\|_\infty \le \|\mathbf{b}(\mathbf{x} \vee \mathbf{z}) - \mathbf{b}(\mathbf{x} \wedge \mathbf{z})\|_\infty &= \mu \|\widetilde{\mathbf{y}}(\mathbf{x} \vee \mathbf{z}) - \widetilde{\mathbf{y}}(\mathbf{x} \wedge \mathbf{z})\|_\infty \\
&= \mu \|\widetilde{\mathbf{y}}(\mathbf{x} \wedge \mathbf{z} + \mathbf{x} \vee \mathbf{z} - \mathbf{x} \wedge \mathbf{z}) - \widetilde{\mathbf{y}}(\mathbf{x} \wedge \mathbf{z})\|_\infty \\
&= \mu \left\| 2\widetilde{\mathbf{y}}\left(\tfrac{1}{2}\mathbf{x} \wedge \mathbf{z} + \tfrac{1}{2}(\mathbf{x} \vee \mathbf{z} - \mathbf{x} \wedge \mathbf{z})\right) - \widetilde{\mathbf{y}}(\mathbf{x} \wedge \mathbf{z}) \right\|_\infty \\
&\le \mu \|\widetilde{\mathbf{y}}(\mathbf{x} \wedge \mathbf{z}) + \widetilde{\mathbf{y}}(\mathbf{x} \vee \mathbf{z} - \mathbf{x} \wedge \mathbf{z}) - \widetilde{\mathbf{y}}(\mathbf{x} \wedge \mathbf{z})\|_\infty \\
&= \mu \|\widetilde{\mathbf{y}}(\mathbf{x} \vee \mathbf{z} - \mathbf{x} \wedge \mathbf{z})\|_\infty \le \mu \|\mathbf{x} \vee \mathbf{z} - \mathbf{x} \wedge \mathbf{z}\|_\infty = \mu \|\mathbf{z} - \mathbf{x}\|_\infty,
\end{aligned}$$

i.e., for all $\mathbf{x}, \mathbf{z} \in \mathbb{R}^n_+$, the following inequality holds: $\|\mathbf{b}(\mathbf{z}) - \mathbf{b}(\mathbf{x})\|_\infty \le \mu \|\mathbf{z} - \mathbf{x}\|_\infty$. Therefore, as $\mu \in (0,1)$, $\mathbf{b}(\cdot)$ is a contraction over the complete metric space $\left(\mathbb{R}^n_+, \rho\right)$, with the distance $\rho(\mathbf{x}, \mathbf{z}) := \|\mathbf{x} - \mathbf{z}\|_\infty$ for all $\mathbf{x}, \mathbf{z} \in \mathbb{R}^n_+$. By the contraction mapping theorem, $\mathbf{b}(\cdot)$ has a unique fixed point $\mathbf{y}^* \in \mathbb{R}^n_+$. This completes the proof. *Q.E.D.*

[28]We use standard notation of lattice theory: for all $\mathbf{x}, \mathbf{z} \in \mathbb{R}^n$,

$$\begin{aligned}
\mathbf{x} \vee \mathbf{z} &:= (\max\{x_1, z_1\}, \max\{x_2, z_2\}, \ldots, \max\{x_n, z_n\}), \\
\mathbf{x} \wedge \mathbf{z} &:= (\min\{x_1, z_1\}, \min\{x_2, z_2\}, \ldots, \min\{x_n, z_n\}).
\end{aligned}$$

Observe that the inequality (24) is an immediate implication of Lemma 2.

A.2.2. *Uniqueness of Nash equilibrium for concave norms*

ASSUMPTION 3: *The social norm mapping $\widetilde{\mathbf{y}}:\mathbb{R}^n_+ \to \mathbb{R}^n_+$ is globally concave, that is, the inequality $\widetilde{\mathbf{y}}((1-\gamma)\mathbf{x}+\gamma\mathbf{z}) \geq (1-\gamma)\widetilde{\mathbf{y}}(\mathbf{x})+\gamma\widetilde{\mathbf{y}}(\mathbf{z})$ holds for any $\gamma \in [0,1]$ and for any $\mathbf{x},\mathbf{z} \in \mathbb{R}^n_+$*

PROPOSITION 5: *Let the social norm mapping $\widetilde{\mathbf{y}}:\mathbb{R}^n_+ \to \mathbb{R}^n_+$ satisfy Assumptions 1 and 3. Then, (20), and hence (18), has a unique fixed point.*

PROOF: We proceed by contradiction. From Proposition 3, there exist the minimum equilibrium $\mathbf{y}^*$ and the maximum equilibrium $\mathbf{y}^{**}$. Assume that $\mathbf{y}^{**} \neq \mathbf{y}^*$, so that the set $\mathcal{I} := \{i \,|\, y_i^{**} > y_i^*\}$ of agents is non-empty. For each $i \in \mathcal{I}$, define τ_i by

$$\tau_i y_i^{**} + (1-\tau_i)y_i^* = 0 \quad \Longrightarrow \quad \tau_i := 1 - \frac{y_i^{**}}{y_i^*} < 0.$$

Pick $j \in \mathcal{I}$ such that $\tau_j = \max\{\tau_i \,|\, i \in \mathcal{I}\}$. It is readily verified that[29]

$$\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^* \geq \mathbf{0} \implies b_j\left(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*\right) \geq b_j\left(\mathbf{0}\right) > 0. \tag{25}$$

From (25), and by definition of τ_j, we get:[30]

$$\begin{aligned} &b_j\left(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*\right) > 0 = \tau_j y_j^{**} + (1-\tau_j) y_j^* \Longrightarrow \\ &b_j\left(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*\right) > \tau_j b_j(\mathbf{y}^{**}) + (1-\tau_j) b_j(\mathbf{y}^*). \end{aligned} \tag{26}$$

However, applying $b_j(\cdot)$ to both parts of the identity, we obtain:

$$\mathbf{y}^* = \frac{-\tau_j}{1-\tau_j}\mathbf{y}^{**} + \frac{1}{1-\tau_j}\left(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*\right),$$

and using concavity of $b_j(\cdot)$, we get:

$$b_j\left(\mathbf{y}^*\right) \geq \frac{-\tau_j}{1-\tau_j} b_j\left(\mathbf{y}^{**}\right) + \frac{1}{1-\tau_j} b_j\left(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*\right) \quad \Longrightarrow$$

---

[29]Here $b_j(\cdot)$ is the jth component of (20). We use monotonicity of $b_j(\cdot)$ and $b_j(\mathbf{0}) = (1-\mu)\widetilde{\alpha}_i > 0$.

[30]Because $\mathbf{y}^*$ and $\mathbf{y}^{**}$ are Nash equilibria, $\tau_j b_j(\mathbf{y}^{**}) + (1-\tau_j) b_j(\mathbf{y}^*) = \tau_j y_j^{**}(1-\tau_j) y_j^*$.

$$b_j\left(\tau_j \mathbf{y}^{**}+(1-\tau_j)\mathbf{y}^*\right) \leq (1-\tau_j) b_j\left(\mathbf{y}^*\right)+\tau_j b_j\left(\mathbf{y}^{**}\right),$$

which contradicts (26). This completes the proof. *Q.E.D.*

It is now straightforward to prove Proposition 1.

Case 1: $\beta \in (1,+\infty]$. In this case, the social norm mapping $\widetilde{\mathbf{y}}:\mathbb{R}_+^n \to \mathbb{R}_+^n$ is convex. The existence and uniqueness result follows from Proposition 4.

Case 2: $\beta \in (1,+\infty]$. In this case, the social norm mapping $\widetilde{\mathbf{y}}:\mathbb{R}_+^n \to \mathbb{R}_+^n$ is concave. The existence and uniqueness result follows from Proposition 5.

APPENDIX B: ADDITIONAL DETAILS STRUCTURAL ESTIMATION

Weighted Average GMM

Given the moment conditions are based on two distinct groups, we follow the estimation strategy of Arellano and Meghir (1992). Formally, let $\hat{\mathbf{y}}$ be the OLS predictor of $\mathbf{y}$ (or any exogenous predictor of $\mathbf{y}$, that is, an object that is only a function of $\mathbf{x}$), and let $\widetilde{y}'_{-is}(\hat{\mathbf{y}}_s,\beta)$ denote the derivative of $\widetilde{y}_{-is}(\hat{\mathbf{y}}_s,\beta)$ with respect to β. Further, define the set of instruments as $\mathbf{z}_i = [\mathbf{x}_i, \widetilde{y}_{-is}(\hat{\mathbf{y}}_s,\beta), \widetilde{y}'_{-is}(\hat{\mathbf{y}}_s,\beta)]$. There are two orthogonality assumptions on the error term: (1) $\mathbb{E}\left(\varepsilon_i \mathbf{z}_i\right)=\mathbf{0}$ for all non-isolated individuals, and (2) $\mathbb{E}\left(\varepsilon_i \mathbf{x}_i\right)=\mathbf{0}$ for all isolated individuals. The orthogonality conditions follows directly from the assumption that $\mathbb{E}\left(\varepsilon_i|\mathbf{Z},\mathbf{G}\right)=0$ for all i as $\hat{y}$ is only a function of $\mathbf{x}$. Then, the method of moments estimator $\boldsymbol{\theta}=[\boldsymbol{\gamma}',\lambda_1,\lambda_2,\beta]'$ is the solution of,

$$Q(\boldsymbol{\theta}) = h_1(\boldsymbol{\theta})\mathbf{W}_1 h_1'(\boldsymbol{\theta}) + h_2(\boldsymbol{\theta})\mathbf{W}_2 h_2'(\boldsymbol{\theta}),$$

where

$$h_1(\boldsymbol{\theta}) = \frac{1}{N_1}\sum_{i=1}^{N_1}[y_i - (1-\lambda_2)\boldsymbol{x}_i\boldsymbol{\gamma} - (\lambda_1+\lambda_2)\widetilde{y}_{-is}(\mathbf{y}_{-is},\beta))]\mathbf{z}_i$$

and

$$h_2(\boldsymbol{\theta}) = \frac{1}{N_2}\sum_{i=1}^{N_2}[y_i - \boldsymbol{x}_i\boldsymbol{\gamma}]\mathbf{x}_i$$

for non-isolated and isolated individuals, respectively. Note, N_1 is the number of non-isolated individuals and N_2 is the number of isolated individuals . Note, the identification of $\boldsymbol{\theta}$ relies on both moment conditions so we need to ensure that both are asymptotically not-negligible, i.e. $\lim_{N_1+N_2\to\infty}\frac{N_1}{N_1+N_2}=r_1\in(0,1)$ (which is equivalent to $\lim_{N_1+N_2\to\infty}\frac{N_2}{N_1+N_2}=r_2\in(0,1)$).

Concentrated GMM

For estimation purposes, as the moment functions are linear in $\boldsymbol{\gamma}$, we can concentrate the objective function around $[\lambda_1,\lambda_2,\beta]$. Taking the first order condition of $Q(\boldsymbol{\theta})$ with respect to $\boldsymbol{\gamma}$, we obtain (after long, but straightforward algebra):

$$\begin{aligned}\hat{\boldsymbol{\gamma}}(\lambda_1,\lambda_2,\beta)=&\left[\frac{(1-\lambda_2)^2}{N_1^2}\mathbf{X}_1'\mathbf{Z}_1\mathbf{W}_1\mathbf{Z}_1'\mathbf{X}_1+\frac{1}{N_2^2}\mathbf{X}_2'\mathbf{X}_2\mathbf{W}_2\mathbf{X}_2'\mathbf{X}_2\right]^{-1}\times\\&\left[\frac{(1-\lambda_2)}{N_1^2}\mathbf{X}_1'\mathbf{Z}_1\mathbf{W}_1\mathbf{Z}_1'(\mathbf{y}_1-(\lambda_1+\lambda_2)\boldsymbol{\phi}_1(\mathbf{y}_{-i},\beta))+\frac{1}{N_2^2}\mathbf{X}_2'\mathbf{X}_2\mathbf{W}_2\mathbf{X}_2'\mathbf{y}_2\right]^{-1},\end{aligned}$$

where for any (row) vector $\mathbf{a}_i=(\mathbf{x}_i,\mathbf{z}_i,\mathbf{w}_i,\mathbf{y}_i)$, the matrix $\mathbf{A}_1=(\mathbf{X}_1,\mathbf{Z}_1,\mathbf{W}_1)$ is obtained by staking $\mathbf{a}_i$ for all non-isolated individual i, and $\mathbf{A}_2=(\mathbf{X}_2,\mathbf{Z}_2,\mathbf{W}_2)$ is obtained by staking $\mathbf{a}_i$ for all isolated individual i.

The concentrated objective function is therefore $\tilde{Q}(\tilde{\boldsymbol{\theta}})=\tilde{Q}([\lambda_1,\lambda_2,\beta])=Q([\hat{\boldsymbol{\gamma}}'(\lambda_1,\lambda_2,\beta),\lambda_1,\lambda_2,\beta])$, where $\tilde{\boldsymbol{\theta}}=[\lambda_1,\lambda_2,\beta]$. The function is minimized numerically in Section 3.4.

APPENDIX C: ADDITIONAL DATA DETAILS

AddHealth provides a wealth of information regarding student's activities and outcomes. We extract a large number of the activities available in the in-school interview sample to test our theory. In total, we are left with 10 activities that have potential testable peer effects and peer preferences: (1) grade point average (GPA), (2) social clubs, (3) self esteem, (4) risky behavior, (5) exercise, (6) study effort, (7) fighting, (8) smoking, (9) drinking, and (10) trouble behavior. These variables are constructed as follows,

1. GPA is the average across four disciplines: English, Mathematics, History, and Science (questions S10a-S10d). The lowest possible GPA is 1.0 and the highest is 4.0.

2. Social clubs refers to the number of social clubs a student belongs to at school (question S44A1-S44A33). The data list up to 33 possible clubs a student can join.
3. Self esteem is based on the average of six questions asking the individual how much they agree or disagree with a certain statement. The selected statements are, (1) "I have a lot of good qualities" (question S62h); (2) "I have a lot to be proud of" (question S62k); (3) "I like myself just the way I am" (question S62m); (4) "I feel like I am doing everything just right" (question S62n); (5) "I feel socially accepted" (question S62o); and (6) "I feel loved and wanted" (question S62p). We code statements from zero to 1 corresponding to no to strong self-esteem.
4. Risky behavior is based on the average of seven statements regarding risky behavior in the past 12 months. These questions are, (1) "smoke cigarettes?" (question S59a); (2) "drink beer, wine, or liquor?" (question S59b); (3) "get drunk" (question S59c); (4) "race on a bike, on a skateboard or roller blades, or in a boat or car?" (question S59d); (5) "do something dangerous because you were dared to?" (question S59e); (6) "lie to your parents or guardians?" (question S59f); and (7) "skip school without an excuse" (question S59g). The variable reflects average usual frequency of all events during a given week. Values range from 0 to 6 in the data, we recode these to frequency measures from zero to 7 (nearly everyday).
5. Exercise refers to the number of times per week the student exercises to a sweat (question S63). Values range from 0 to 4 in the data, we recode these to frequency measures from zero to 7.5 (more than 7 times).
6. Study effort is in regards to how hard a students tries to do her school work well (question S48). We code statements from zero to 1 corresponding to no effort to trying hard.
7. Fighting is in regards to the number of times the student got into a physical fight in the past 12 months (question S64). Values range from 0 to 4 in the data, we recode these to frequency measures from zero to 7.5 (more than 7 times).
8. Smoking asks the number of times the student smoked in the past 12 months (question S59a). Values range from 0 to 6 in the data, we recode these to frequency measures from zero to 7 (nearly everyday).

TABLE C.I

SUMMARY STATISTICS

Activity	*GPA*	*Clubs*	*Self-esteem*	*Risky*	*Exercise*	*Study effort*	*Fight*	*Smoke*	*Drink*	*Trouble*
Activity	2.816	2.199	0.712	0.611	4.536	0.739	1.357	0.958	0.421	1.178
	(0.807)	(2.621)	(0.190)	(0.982)	(2.445)	(0.231)	(2.143)	(2.224)	(1.152)	(1.391)
Age	15.073	15.029	15.088	15.055	15.092	15.049	15.093	15.059	15.059	15.046
	(1.686)	(1.710)	(1.689)	(1.701)	(1.688)	(1.701)	(1.688)	(1.699)	(1.699)	(1.702)
Female	0.512	0.505	0.514	0.510	0.513	0.509	0.513	0.511	0.511	0.510
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Hispanic	0.163	0.173	0.156	0.163	0.156	0.165	0.156	0.163	0.163	0.165
	(0.369)	(0.378)	(0.363)	(0.370)	(0.363)	(0.371)	(0.363)	(0.369)	(0.369)	(0.371)
White	0.652	0.633	0.657	0.646	0.656	0.644	0.657	0.647	0.647	0.645
	(0.476)	(0.482)	(0.475)	(0.478)	(0.475)	(0.479)	(0.475)	(0.478)	(0.478)	(0.479)
Black	0.165	0.175	0.164	0.169	0.164	0.170	0.164	0.168	0.168	0.170
	(0.371)	(0.380)	(0.370)	(0.374)	(0.370)	(0.375)	(0.371)	(0.374)	(0.374)	(0.375)
Asian	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069
	(0.254)	(0.254)	(0.254)	(0.254)	(0.254)	(0.253)	(0.254)	(0.254)	(0.254)	(0.253)
Mother Ed. less than HS.	0.169	0.178	0.168	0.173	0.167	0.174	0.167	0.173	0.173	0.174
	(0.375)	(0.382)	(0.374)	(0.378)	(0.373)	(0.379)	(0.373)	(0.378)	(0.378)	(0.379)
Mother Ed. more than HS	0.425	0.412	0.425	0.419	0.425	0.418	0.425	0.420	0.420	0.418
	(0.494)	(0.492)	(0.494)	(0.493)	(0.494)	(0.493)	(0.494)	(0.493)	(0.493)	(0.493)
Mother Ed. none	0.098	0.106	0.099	0.102	0.100	0.102	0.100	0.102	0.101	0.101
	(0.297)	(0.308)	(0.299)	(0.303)	(0.300)	(0.303)	(0.300)	(0.302)	(0.302)	(0.302)
Mother Professional	0.207	0.202	0.208	0.205	0.209	0.205	0.209	0.206	0.206	0.205
	(0.405)	(0.402)	(0.406)	(0.404)	(0.406)	(0.404)	(0.406)	(0.404)	(0.404)	(0.404)
Mother Other Job	0.443	0.436	0.440	0.439	0.440	0.439	0.440	0.439	0.440	0.439
	(0.497)	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)
Mother No Job	0.140	0.150	0.141	0.145	0.142	0.145	0.141	0.144	0.144	0.144
	(0.347)	(0.357)	(0.348)	(0.352)	(0.349)	(0.352)	(0.348)	(0.351)	(0.351)	(0.351)
Isolated Individuals	0.145	0.155	0.145	0.147	0.147	0.147	0.147	0.146	0.146	0.144
	(0.352)	(0.362)	(0.352)	(0.354)	(0.354)	(0.354)	(0.354)	(0.353)	(0.353)	(0.351)
Observations	69961	78735	71511	75149	71462	75799	71381	74584	74436	75847

Notes: Mean of variable by activity with standard deviations (in parenthesis) are reported. Excluded racial groups are "Native American" and "Other." For details on the activity and outcome variables, see Online Appendix C.

9. Drinking is in regards to the number of times the student drank in the past 12 months (question S59b). Values range from 0 to 6 in the data, we recode these to frequency measures from zero to 7 (nearly everyday).
10. Trouble behavior is based on the average of 4 statements of "Since school started this year, how often have you had trouble:" (1) "getting along with your teachers?" (question S46a); (2) "paying attention in school?" (question S46b); (3) "getting your homework done?" (question S46c); and (4) "getting along with other students?" (question S46d). The variable is recode from zero to five equivalent to an answer of "never" to "everyday" at school.

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Online Appendix

APPENDIX A: THEORY: POLICY IMPLICATIONS

A.1. *Social optimum (first-best) for the general model*

Consider a standard welfare function $\mathcal{W}^m(\mathbf{y},\mathbf{g}) = \sum_i U_i^m(y_i,\mathbf{y}_{-i},\mathbf{g})$, for $m = S$ (spillover model) and $m = C$ (conformist model). For the general model, we denote the total welfare by $\mathcal{W}(\mathbf{y},\mathbf{g}) = \sum_i U_i(y_i,\mathbf{y}_{-i},\mathbf{g})$. The planner chooses the actions $y_1, y_2, ..., y_n$ of each of the n agents that maximizes $\mathcal{W}^m(\mathbf{y},\mathbf{g})$ or $\mathcal{W}(\mathbf{y},\mathbf{g})$. This is the first best.

Let us solve the general model in which agents' utility is given by (10). The first best is equal to:

$$y_i^o = (1-\lambda_2)\alpha_i + (\lambda_1+\lambda_2)\widetilde{y}_{-i}(\beta) + \lambda_1 \sum_j y_j \frac{\partial \widetilde{y}_{-i}(\beta)}{\partial y_i} + \lambda_2 \sum_j (y_j - \widetilde{y}_{-j}(\beta)) \frac{\partial \widetilde{y}_{-i}(\beta)}{\partial y_i}, \tag{A.1}$$

where $\lambda_1 := \frac{\theta_1}{(1+\theta_2)}$, $\lambda_2 := \frac{\theta_2}{(1+\theta_2)}$,

$$\widetilde{y}_{-j}(\beta) = \begin{cases} \sum_{k=1}^n \widehat{g}_{jk} y_k & \text{if } \beta = 1 \\ \left(\sum_{k=1}^n \widehat{g}_{jk} y_k^\beta\right)^{\frac{1}{\beta}} & \text{if } \beta \in]-\infty, +\infty[, \end{cases} \tag{A.2}$$

and

$$\frac{\partial \widetilde{y}_{-j}(\beta)}{\partial y_i} = \begin{cases} \widehat{g}_{ji} = \widehat{g}_{ij} & \text{if } \beta = 1 \\ \widehat{g}_{ji} \left(\sum_{k=1}^n \widehat{g}_{jk} y_k^\beta\right)^{(\frac{1}{\beta}-1)} y_i^{\beta-1} > 0 & \text{if } \beta \in]-\infty, +\infty[. \end{cases} \tag{A.3}$$

The next proposition shows the existence and uniqueness of the first best outcome.

PROPOSITION 6: *Assume that $\lambda_1 + \lambda_2 < 1$. Then, the first best outcome is unique.*

PROOF: To rend the notations more explicit, denote $\widetilde{y}_{-i}(\beta) \equiv \widetilde{y}_{-i}(\mathbf{z},\beta)$. Let us restate (A.1) in vector-matrix form:

$$\mathbf{y} = (1-\lambda_2)\boldsymbol{\alpha} + \lambda_1 \mathbf{F}(\mathbf{y}) + \lambda_2 \mathbf{G}(\mathbf{y}), \tag{A.4}$$

where the mappings $\mathbf{F}(\mathbf{y}) = (F_1(\mathbf{y}), F_2(\mathbf{y}), \ldots, F_n(\mathbf{y}))$ and $\mathbf{G}(\mathbf{y}) = (G_1(\mathbf{y}), G_2(\mathbf{y}), \ldots, G_n(\mathbf{y}))$ are defined, respectively, as follows:

$$F_i(\mathbf{y}) := \widetilde{y}_{-i}(\mathbf{y}_{-i}, \beta) + \sum_j y_j(\mathbf{y}_{-j}) \frac{\partial \widetilde{y}_{-i}(\mathbf{y}_{-j}, \beta)}{\partial y_i},$$

$$G_i(\mathbf{y}) := \widetilde{y}_{-i}(\mathbf{y}_{-i}, \beta) + \sum_j (y_j - \widetilde{y}_{-i}(\mathbf{y}_{-j}, \beta)) \frac{\partial \widetilde{y}_{-i}(\mathbf{y}_{-j}, \beta)}{\partial y_i}.$$

At the extreme case of $\lambda_1 = \lambda_2 = 0$, the fixed point condition (A.4) has a unique solution $\mathbf{y}^O = \boldsymbol{\alpha}$. Furthermore, since the right-hand side of (A.4) is continuously differentiable with respect to λ_1, λ_2, and at $(\lambda_1, \lambda_2, \mathbf{y}) = (0, 0, \boldsymbol{\alpha})$, by the implicit function theorem, there exist threshold values $\widehat{\lambda}_1 > 0$ and $\widehat{\lambda}_2 > 0$ of λ_1 and λ_2 respectively, such that (A.4) defines a single-valued function $\mathbf{y}^O(\lambda_1, \lambda_2)$ for all $(\lambda_1, \lambda_2) \in \left[(0,0); (\widehat{\lambda}_1, \widehat{\lambda}_2)\right]$. Moreover, we need to impose that $\lambda_1 + \lambda_2 < 1$ for each model to be well-defined, which implies that $0 < \widehat{\lambda}_1 + \widehat{\lambda}_2 < 1$. It remains to prove that $\mathbf{y}^O(\lambda_1, \lambda_2)$ is a unique solution to (A.4). We proceed by contradiction. Assume that there exists a sequence $(\lambda_1^k, \lambda_2^k) \to 0$, such that, for any $(\lambda_1^k, \lambda_2^k)$ there exists $\widehat{\mathbf{y}}(\lambda_1^k, \lambda_2^k) \neq \mathbf{y}^O(\lambda_1^k, \lambda_2^k)$. Two cases may arise.

Case 1: the sequence $\widehat{\mathbf{y}}(\lambda_1^k, \lambda_2^k)$ converges to $\boldsymbol{\alpha}$. This case is impossible, since it implies the existence of two distinct branches of the fixed-point correspondence defined by (A.4), which violates the implicit function theorem.

Case 2: the sequence $\widehat{\mathbf{y}}(\lambda_1^k, \lambda_2^k)$ has a subsequence, which does not converge to $\boldsymbol{\alpha}$ but converges to some $\boldsymbol{\xi} \neq \boldsymbol{\alpha}$. This leads to a contradiction, since both the left-hand side and the right-hand side of (A.4) are continuous with respect to $(\lambda_1, \lambda_2, \mathbf{y})$ at $(\lambda_1, \lambda_2, \mathbf{y}) = (0, 0, \boldsymbol{\xi})$. Taking the limit on both sides of (A.4) under $(\lambda_1^k, \lambda_2^k, \widehat{\mathbf{y}}(\lambda_1^k, \lambda_2^k)) \to (0, 0, \boldsymbol{\xi})$, we conclude that $\mathbf{y} = \boldsymbol{\xi}$ must be a solution to (A.4) in the extreme case of $\lambda_1 = \lambda_2 = 0$. But we have assumed $\boldsymbol{\xi} \neq \boldsymbol{\alpha}$, and (A.4) clearly has no solutions other than $\boldsymbol{\alpha}$, a contradiction.

This completes the proof. *Q.E.D.*

A.2. *Policy implications of the spillover and the conformist model*

Let us now determine the subsidies that the planner can give to each agent i in order to restore the first best. For that, we add one stage before the effort game is played in which the planner will announce the optimal subsidy S_i to each agent i such that (using the general utility (10)):

$$U_i(y_i, \mathbf{y}_{-i}, \mathbf{g}) = (\alpha_i + S_i)\, y_i + \theta_1 y_i \widetilde{y}_{-i}(\beta) - \frac{1}{2}\left[y_i^2 + \theta_2 \left(y_i - \widetilde{y}_{-i}(\beta)\right)^2\right]. \tag{A.5}$$

A.2.1. *Comparing the spillover and the conformist model for the linear-in-means model ($\beta = 1$)*

The spillover model

The first best is given by (A.1) when $\lambda_2 = 0$ and the norm is $\widetilde{y}_{-i}(\beta) = \overline{y}_{-i}$. In the spillover model, there is too little effort at the Nash equilibrium as compared to the social optimum outcome (first best). Equilibrium interaction effort is too low because each agent ignores the positive impact of her effort on the effort choices of others, that is, each agent ignores the positive externality arising from complementarity in effort choices. As a result, the market equilibrium is not efficient.

To restore the first best, the planner could subsidize the efforts of all agents. Consider the utility (A.5) for the spillover model, that is, when $\theta_2 = 0$. We obtain:

$$U_i^S(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \left(\alpha_i + S_i^S\right) y_i + \lambda_1 y_i \overline{y}_{-i} - \frac{1}{2} y_i^2. \tag{A.6}$$

where $\lambda_1 := \theta_1$ and S_i^S denotes the optimal subsidy per effort in the spillover model. If[31]

$$S_i^S = \lambda_1 \sum_j \widehat{g}_{ij} y_j^o = \lambda_1 \overline{y}_{-i}^o, \tag{A.7}$$

or in matrix form $\mathbf{S}^S = \lambda_1 \mathbf{G} \mathbf{y}^o$, then it is easily verified that, in the second stage, each player will play her first-best effort instead of the Nash-equilibrium effort. Thus, the first best is restored.

The conformist model

The first best is given by (A.1) when $\lambda_1 = 0$ and the norm is $\widetilde{y}_{-i}(\beta) = \overline{y}_{-i}$, which is neither larger or smaller than the Nash equilibrium effort. Indeed, compared to the Nash

[31]All variables with the superscript o denote their optimal values, that is, the variables that maximize social welfare.

equilibrium, the first best has an extra term, $\lambda_2 \sum_j \widehat{g}_{ij}(y_j - \overline{y}_{-j}) = \lambda_2(\overline{y}_{-i} - \overline{y}_{-j})$, which could be positive or negative. This means that, at the Nash equilibrium, when deciding her individual effort, each agent does not take into account the effect of her effort on the social norm of her peers, which creates an externality that can be positive or negative. Indeed, if individual i has friends for whom $y_j > \overline{y}_{-j}$ (resp. $y_j < \overline{y}_{-j}$), then when she exerts her effort, she does not take into account the fact that she positively affects $\overline{y}_{-j}$, the norm of her friends, which increases (decreases) the utility of their neighbors. In that case, compared to the first best, individual i underinvests (overinvests) in effort, because she exerts positive (negative) externalities on her friends.

Contrary to the spillover model, the planner does not want to subsidize all agents in the network. Consider the utility (A.5) for the conformist model, that is, when $\theta_1 = 0$. We obtain:

$$U_i^C(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \left(\alpha_i + S_i^C\right) y_i - \frac{1}{2}\left[y_i^2 + \theta_2\left(y_i - \overline{y}_{-i}\right)^2\right]. \tag{A.8}$$

where S_i^C denotes the optimal subsidy per effort in the spillover model. Denote $\lambda_2 \equiv \frac{\theta_2}{(1+\theta_2)}$. Then, if

$$S_i^C = \frac{\lambda_2}{1-\lambda_2}\sum_j \widehat{g}_{ij}(y_j^o - \overline{y}_{-j}^o) = \frac{\lambda_2}{1-\lambda_2}(\overline{y}_{-i}^o - \overline{y}_{-j}^o), \tag{A.9}$$

or in matrix form $\mathbf{S}^C = \lambda_2 \widehat{\mathbf{G}}^T(\mathbf{I} - \widehat{\mathbf{G}})\mathbf{y}^o$, in the second stage, each player will play her first-best effort instead of the Nash-equilibrium effort. Thus, the first best is restored. This implies that the planner restores the first best and subsidizes (taxes) agents whose neighbors make efforts above (below) their social norms. In other words, it is necessary to subsidize agents who exert effort below that of their neighbors and to tax those who exert effort above that of their neighbors.

Consequently, the policy implications of the two models are very different. In the spillover model, the planner subsidizes all agents in the network. In the conformist model, the planner subsidizes only agents whose neighbors' effort is above the average effort of their neighbors but taxes agents whose neighbors' effort is below the average effort of their neighbors. This implies, in particular, that the planner is more likely to tax central agents (since their neighbors are more likely to have a lower effort) and to subsidize less central agents.

A.2.2. *An example*

Consider a star network in which $n = 3$ and agent $i = 1$ is the star. Set $\alpha_1 = 2$, $\alpha_2 = \alpha_3 = 1$, so that the star is the most productive agent in the network.

The conformist model: Since $\alpha_1 = 2 > 1 = (\alpha_2 + \alpha_3)/2$, it is easily verified that the Nash equilibrium in efforts is not optimal. Assume that $\lambda_2 < 1$; we have

$$\mathbf{y}^N = \frac{1}{(1+\lambda_2)}\begin{pmatrix} 2+\lambda_2 \\ 1+2\lambda_2 \\ 1+2\lambda_2 \end{pmatrix}, \qquad \mathbf{y}^o = \frac{1}{(1+4\lambda_2)}\begin{pmatrix} 2+5\lambda_2 \\ 1+6\lambda_2 \\ 1+6\lambda_2 \end{pmatrix},$$

where $\mathbf{y}^N$ and $\mathbf{y}^o$ correspond to the Nash equilibrium and the social optimum, respectively. The star agent overinvests compared to the first best $\left(y_1^N > y_1^o\right)$. Indeed, since $y_2^N = y_3^N < \overline{y}_{-2}^N = \overline{y}_{-3}^N = y_1^N$, the externality term $\lambda_2 \sum_{j=1}^n \widehat{g}_{ij}\left(y_j - \overline{y}_{-j}\right)$ is negative, and the star, when deciding her effort level, does not take into account the negative externalities she exerts on agents 2 and 3. For the peripheral agents 2 or 3, we obtain $y_2^N = y_3^N \gtreqqless y_3^o = y_2^o \iff \lambda_2 \gtreqqless 1/2$, so that they may overinvest or underinvest in effort, depending on the value of λ_2. However, the externality term is always positive, since $y_1^N > \overline{y}_{-1}^N$, and thus agents 2 and 3 always exert positive externalities on agent 1. As a result, to restore the first best, the planner should tax agent 1 (the most central agent) and subsidize agents 2 and 3 (the less central agents). Since $y_2 = y_3$, it is easily verified that the subsidies per unit of effort are equal to $S_1^C = \frac{2\lambda_2}{(1-\lambda_2)}(y_2^o - y_1^o) < 0$ and $S_2^C = S_3^C = \frac{\lambda_2}{(1-\lambda_2)}(y_1^o - y_2^o) > 0$. The subsidies or taxes exactly correct for the externalities exerted by the agents. We obtain[32]

$$\mathbf{S}^C = \frac{\lambda_2}{(1+4\lambda_2)}\begin{pmatrix} -2 \\ 1 \\ 1 \end{pmatrix}. \tag{A.10}$$

[32]Clearly, this result strongly depends on the productivity values. For example, if $\alpha_1 = 0.5$ and $\alpha_2 = \alpha_3 = 1$ so that the productivity of the central agent is the lowest, then to restore the first best, the planner now needs to subsidize agent 1 (the star) and to tax agents 2 and 3 (the peripheral agents), since the former now exerts positive externalities on agents 2 and 3, while the latter exert negative externalities on agent 1.

The spillover model: We obtain

$$\mathbf{y}^N = \frac{1}{(1-\lambda_1^2)}\begin{pmatrix} 2+\lambda_1 \\ 1+2\lambda_1 \\ 1+2\lambda_1 \end{pmatrix}, \qquad \mathbf{y}^o = \frac{1}{(1-4\lambda_1^2)}\begin{pmatrix} 2(1+\lambda_1) \\ 1+4\lambda_1 \\ 1+4\lambda_1 \end{pmatrix},$$

where we assume that $\lambda_1 < 1/2$. We see that, at the Nash equilibrium, all agents make too little effort compared to the first best; that is, $y_i^N < y_i^o$, for all $i = 1, 2, 3$. It is easily verified that the subsidies that restore the first best are given by:

$$\mathbf{S}^S = \frac{\lambda_1}{(1-4\lambda_1^2)}\begin{pmatrix} 1+4\lambda_1 \\ 2+2\lambda_1 \\ 2+2\lambda_1 \end{pmatrix}. \tag{A.11}$$

A.2.3. *Comparing the spillover and the conformist model for the general model*

Consider now the general model where β can take any value, the social norm is $\widetilde{y}_{-i}(\beta)$, and the utility of each individual i is given by (A.5). We can perform the same exercise and determine the optimal subsidies that restore the first best. In the general model, the Nash equilibrium in effort is given by (11), i.e,

$$y_i^N = (1-\lambda_2)\alpha_i + (\lambda_1+\lambda_2)\widetilde{y}_{-i}(\beta),$$

while the first best is equal to (A.1), i.e,

$$y_i^o = (1-\lambda_2)\alpha_i + (\lambda_1+\lambda_2)\widetilde{y}_{-i}(\beta) + \lambda_1 \sum_j y_j \frac{\partial \widetilde{y}_{-i}(\beta)}{\partial y_i} + \lambda_2 \sum_j (y_j - \overline{y}_{-j}) \frac{\partial \widetilde{y}_{-i}(\beta)}{\partial y_i}.$$

As above, let us add one stage before the effort game is played in which the planner will announce the optimal subsidy S_i to each agent i such that the utility is given by (A.5). It is straightforward to see that the subsidy given to each individual i that restores the first best is:

$$S_i^G = \frac{y_i^o - y_i^N}{1-\lambda_2} = \frac{1}{1-\lambda_2}\left[\lambda_1 \sum_j y_j^o \frac{\partial \widetilde{y}_{-i}^o(\beta)}{\partial y_i^o} + \lambda_2 \sum_j (y_j^o - \widetilde{y}_{-i}^o(\beta)) \frac{\partial \widetilde{y}_{-i}^o(\beta)}{\partial y_i^o}\right]. \tag{A.12}$$

In particular, for the spillover model ($\lambda_2 = 0$ and the social norm is $\widetilde{y}_{-i}(\beta) = \overline{y}_{-i}$), we have:

$$S_i^{G,S} = \lambda_1 \sum_j y_j^o \frac{\partial \overline{y}_{-j}^o}{\partial y_i^o}, \tag{A.13}$$

while, for the conformist model ($\lambda_1 = 0$ and $\widetilde{y}_{-i}(\beta) = \overline{y}_{-i}$), we obtain:

$$S_i^{G,C} = \frac{\lambda_2}{1-\lambda_2} \sum_j (y_j^o - \overline{y}_{-j}^o) \frac{\partial \overline{y}_{-j}^o}{\partial y_i^o}. \tag{A.14}$$

Since $\frac{\partial \overline{y}_{-j}^o}{\partial y_i^o} > 0$ (see (A.3)), for the spillover model, the planner wants to subsidize all agents in the network. For the conformist model, this is not always true since it depends on the difference between y_j^o and $\overline{y}_{-j}^o$. This implies that the planner will subsidize agents who exert effort below that of their neighbors and tax those who exert effort above that of their neighbors. Thus, the policy implications from the previous section qualitatively extend to the case when β can take any value.

APPENDIX B: ADDITIONAL RESULTS

B.1. *Spillover, conformism, or general: Linear-in-means model*

Here we expand on our main results, when imposing the social norm of the *average peer*, $\beta = 1$ in Equation (14). Table A1 presents the results for the λ's of four models, (i) the general LIM model, (ii) the spillover LIM model, (iii) the conformist LIM model, and (iv) the reduced-form LIM model (see Equation (15)). The spillover LIM model refers to the case when $\lambda_2 = 0$ and $\beta = 1$, whereas the conformism LIM model refers to the case when $\lambda_1 = 0$ and $\beta = 1$. The table also reports the objective value of each GMM procedure, as well as the likelihood-ratio statistic, $2(Q^k(\lambda) - Q(\lambda_1, \lambda_2))$, with $k = C, S$, comparing the two separate models (spillover and conformist) to the general LIM model.[33] This measure is a simple way of establishing the dominant drivers, spillover, conformism or both in the estimation, as it compares the goodness of fit for a model with only one driver (conformism or spillover) with the general LIM model that includes both effects. Complete results, including estimates for $\boldsymbol{\gamma}$, are presented in Tables A4–A5 in Online Appendix C.

[33]The test statistic is (approximately) distributed χ^2.

TABLE A1

STRUCTURAL ESTIMATION VERSUS REDUCED FORM: LINEAR-IN-MEANS MODEL

	General model with $\beta = 1$			Spillover			Conformism			Reduced form
Activity	λ_1	λ_2	**Obj. Value**	λ_1	**Obj. Value**	**L-R test**	λ_2	**Obj. Value**	**L-R test**	λ
GPA	0.388 (0.062)	0.190 (0.042)	0.0026	0.519 (0.019)	0.0035	122.1	0.406 (0.019)	0.0085	814.4	0.589 (0.019)
Clubs	0.349 (0.104)	0.344 (0.070)	0.0023	0.612 (0.034)	0.0030	109.9	0.529 (0.030)	0.0040	259.0	0.638 (0.033)
Self-esteem	0.252 (0.108)	0.027 (0.072)	0.0027	0.270 (0.035)	0.0028	5.7	0.154 (0.034)	0.0035	110.9	0.289 (0.035)
Risky	-0.185 (0.069)	0.492 (0.032)	0.0017	0.079 (0.037)	0.0067	752.9	0.467 (0.029)	0.0023	83.3	0.235 (0.034)
Exercise	0.181 (0.060)	0.021 (0.038)	0.0017	0.193 (0.021)	0.0017	2.8	0.094 (0.020)	0.0029	168.1	0.177 (0.022)
Study effort	-0.017 (0.084)	0.322 (0.043)	0.0010	0.125 (0.040)	0.0027	258.6	0.315 (0.034)	0.0011	10.0	0.216 (0.041)
Fight	0.062 (0.075)	0.188 (0.043)	0.0013	0.172 (0.031)	0.0021	117.4	0.209 (0.028)	0.0013	10.6	0.254 (0.031)
Smoke	0.130 (0.067)	0.624 (0.035)	0.0009	0.442 (0.031)	0.0055	686.6	0.675 (0.028)	0.0013	66.6	0.732 (0.031)
Drink	-0.177 (0.072)	0.626 (0.029)	0.0019	0.102 (0.044)	0.0084	964.5	0.601 (0.029)	0.0026	110.2	0.156 (0.043)
Trouble	0.225 (0.115)	0.251 (0.073)	0.0007	0.391 (0.041)	0.0012	61.8	0.374 (0.039)	0.0012	74.5	0.521 (0.042)

Notes: *General Model* results are for estimation of (14), *Spillover* are results for (14) but with restricting $\lambda_2 = 0$, and *Conformism* are results when restricting $\lambda_1 = 0$. In addition, all three models are estimated with the average social norm, the restriction $\beta = 1$. All results control for school fixed effects. Standard errors are reported in parentheses. In the case of the two LIM model likelihood ratio tests, $2(N^k + N)(Q^k(\lambda) - Q(\lambda_1, \lambda_2))$ with $k = C, S$, are also reported. Results for γ can be found in Online Appendix B.3.

Table A1 shows a clear distinction between the two models (conformist vs. spillover), with one model usually performing clearly better, as measured by the objective value. The general LIM model, as it embeds both effects, spillovers, and conformism, has always the lowest objective value. However, for GPA, social clubs, self-esteem, and exercise, the spillover effect dominates. For risky behavior, study effort, fighting, smoking, and drinking, conformism plays a strong role in determining outcomes. Lastly, for trouble behavior at school, neither effect dominates. Also note, a negative spillover effect, $\lambda_1 < 0$, is a dampening effect on the total peer effect $(\lambda_1 + \lambda_2)$ (see also Equation (14)); that is, it must not be interpreted as a *negative* spillover effect, as long as $\lambda_1 + \lambda_2 > 0$, which is always the case.

B.2. *The role of isolated individuals in the estimation of peer effects*

To illustrate the validity of our assumption of using isolated individuals to identify a common $\boldsymbol{\gamma}$, we run two separate exercises. First, we estimate a model with general social norms, but with only one type of peer effect (spillover or conformism) without isolated individuals. Second, we consider how our estimates of peer preference, β, change for the joint model when we allow for different assumptions on the $\boldsymbol{\gamma}$.

B.2.1. *General restricted model without isolated individuals*

Without distinguishing between spillover and conformism, Equation (14) simplifies to

$$y_{is} = \mathbf{x}_{is}\boldsymbol{\gamma}^{niso} + \lambda\widetilde{y}_{-is}(\beta) + \xi_s + \epsilon_{is}, \tag{B.1}$$

where the superscript $niso$ refers to non-isolated individuals. Identification of $\tilde{\boldsymbol{\theta}} = [\lambda, \beta]$ comes exclusively from non-isolated individuals. Table A2 shows the results of estimating Equation (B.1) by GMM without isolated individuals compared to the benchmark results.

The results confirm that, for all activities, the average peer model is rejected, that is β is not equal to one. Moreover, for the majority of activities, the peer preference, β, is similar to the general model, although the precision of estimates is generally weaker. This confirms the fact that relying on both isolated and non-individuals for the estimation of β is not crucial for our results.

TABLE A2

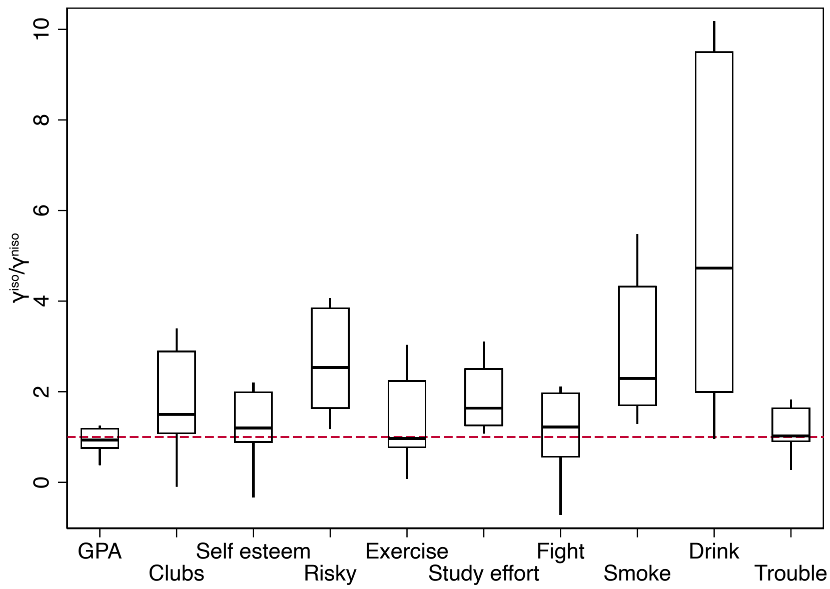
STRUCTURAL ESTIMATION: PEER PREFERENCES (β)

Activity	Benchmark λ_1	Benchmark λ_2	Benchmark β	Non-isolated only λ	Non-isolated only β
GPA	0.32	0.06	370.8 $^{(a)}$	0.36	$+\infty$
	(0.06)	(0.05)	(114.9)	(0.01)	-
Clubs	0.33	0.33	1.4 $^{(b)}$	0.62	1.55 $^{(a)}$
	(0.11)	(0.07)	(0.2)	(0.04)	(0.18)
Self esteem	0.28	0.01	22.3 $^{(a)}$	0.31	21.78 $^{(a)}$
	(0.11)	(0.07)	(8.1)	(0.04)	(7.83)
Risky	-0.16	0.50	0.8	0.22	1.40
	(0.08)	(0.03)	(0.4)	(0.05)	(0.56)
Exercise	0.21	0.01	8.1 $^{(b)}$	0.19	49.63
	(0.06)	(0.04)	(3.4)	(0.02)	(60.85)
Study effort	0.02	0.34	3.9 $^{(b)}$	0.24	5.34 $^{(c)}$
	(0.09)	(0.04)	(1.4)	(0.05)	(2.28)
Fight	-0.08	0.12	73.6 $^{(a)}$	0.03	$+\infty$
	(0.05)	(0.04)	(14.9)	(0.01)	-
Smoke	0.21	0.65	0.7 $^{(b)}$	0.74	0.95
	(0.09)	(0.04)	(0.1)	(0.05)	(0.16)
Drink	-0.05	0.64	0.4 $^{(a)}$	0.09	4.32
	(0.10)	(0.03)	(0.2)	(0.05)	(3.21)
Trouble	0.29	0.00	-415.0 $^{(a)}$	0.29	$-\infty$
	(0.71)	(0.17)	(149.0)	(0.03)	-

Notes: We report the general model (Equation (14)), and the general restricted model (Equation (B.1)). All results control for school-fixed effects. Standard errors are reported in parentheses. We report the significance of the hypothesis test, $H_0 : \beta \neq 1$ with (a) $p < 0.01$, (b) $p < 0.05$, (c) $p < 0.1$. For the case of $\pm\infty$ the hypothesis test is omitted.

We can further compare the coefficients of γ^{niso} from Equation (B.1) for non-isolated individuals to the OLS estimated coefficients, γ^{iso}, of Equation (16) for isolated individuals only. Figure A1 summarizes this as a comparison of the ratio of $\frac{\gamma^{iso}}{\gamma^{niso}}$, where the numerator is estimated by OLS from Equation (16) and the denominator is the estimation results of the general restricted model in Equation (B.1). The further away this ratio is from one, the more likely we should have identified $\lambda_2 > 0$, as by our imposed assumption, we would expect $\gamma^{niso} = \gamma^{iso}(1 - \lambda_2)$. As can be seen from Figure A1, the results are consistent with conformism in drinking, smoking, risky behavior, and also, to a smaller degree, effort, and the number of clubs. In contrast, when this ratio is close to one, we should find no conformism, e.g., for GPA, trouble, exercise, and self-esteem. These groupings between conformism and spillover are consistent with the results of the paper (see Table I).

FIGURE A1.—*Observable characteristics: Isolated versus non-isolated individuals*



Notes: Boxplot of the ratio of γ^{iso} from Equation (16) and γ^{niso} from the GMM of Equation (B.1) for each activity.

B.2.2. *Further robustness exercises*

The estimation of $\tilde{\boldsymbol{\theta}} = [\lambda_1, \lambda_2, \beta]$ and $\boldsymbol{\gamma}$ can be separated into two parts. We can estimate $\boldsymbol{\gamma}$ in a first-stage OLS regression, then use these estimates in our general model (Equation (14)) to estimate $\tilde{\boldsymbol{\theta}} = [\lambda_1, \lambda_2, \beta]$ through GMM by using only the sample of non-isolated individuals. Using variations of Equation (16), we consider three different first-stage specifications to estimate $\boldsymbol{\gamma}$.

1. Using only isolated individuals, we estimate:

$$y_{is} = \mathbf{x}_{is}\boldsymbol{\gamma}^{iso} + \xi_s^{iso} + \varepsilon_{is}. \tag{B.2}$$

2. Using all individuals (both isolated and non-isolated), we estimate:

$$y_{is} = \mathbf{x}_{is}\boldsymbol{\gamma}^{all} + \xi_s^{iso} + \xi_s^{niso} + \varepsilon_{is}, \tag{B.3}$$

where ξ_s^{niso} is the school fixed effects for non-isolated individuals.

3. Using all individuals (both isolated and non-isolated), but allowing for $\boldsymbol{\gamma}$ to differ between isolated and non-isolated individuals, we estimate:

$$y_{is} = \mathbf{x}_{is}\boldsymbol{\gamma}^{niso} + \mathbf{x}_{is}\boldsymbol{\gamma}^{iso} + \xi_s^{iso} + \xi_s^{niso} + \varepsilon_{is}. \tag{B.4}$$

Figure A2 graphically summarizes our benchmark results (in red) with the 95 percent confidence interval (Tables I and A3) and the estimates resulting from the three scenarios described above for our three representative activities: risky behavior, study effort and GPA (in blue). For both study effort and GPA the results on $\boldsymbol{\gamma}$ and more importantly β are close irrespective of the specification.

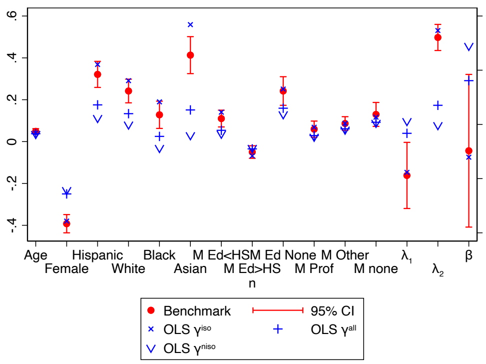
For risky behavior, we observe a larger variance in $\boldsymbol{\gamma}$ estimates across the three specifications and, thus, also a larger variance among the β and λ estimates. The new estimates are in line with the estimates obtained from the pure spillover model in the above section. While for GPA or study effort, both isolated and non-isolated individuals are influenced in similar ways through parental characteristics, this is not necessarily true for risky behavior, where, for example, isolated individuals with mothers of less than high school education engage in more risky behavior than non-isolated peers.

In summary, the estimation of $\boldsymbol{\gamma}$ using isolated individuals does not drive the main results regarding the estimation of β; in most activities, individuals are not affected by the average behavior of their peers. In general, the estimation does not hinge on isolated individuals. It is only when both conformism and spillover effects are nested into a general model that we need a set of individuals that are not affected by the local social norm.

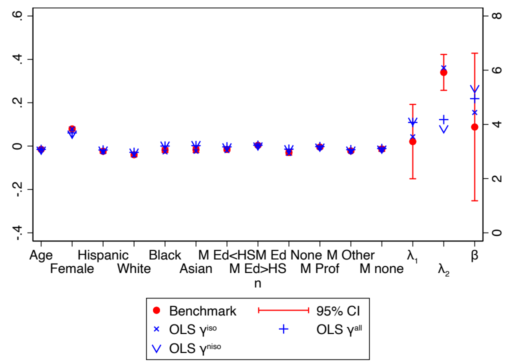
B.3. *General results: Social norms and total peer effects*

To illustrate the effect of the size of β on each social norm discussed in the paper, Figure A3 shows the density distribution of social norms for non-isolated individuals from the

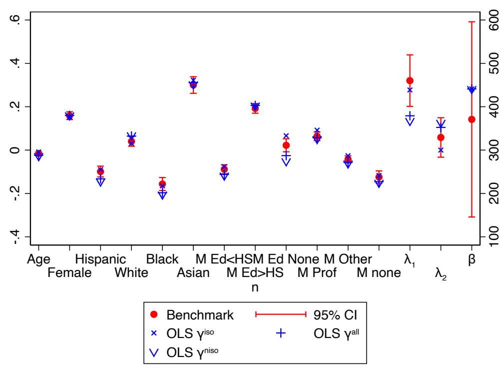
FIGURE A2.—*Robustness Exercise Estimates*



(a) Risky Behavior



(b) Study Effort

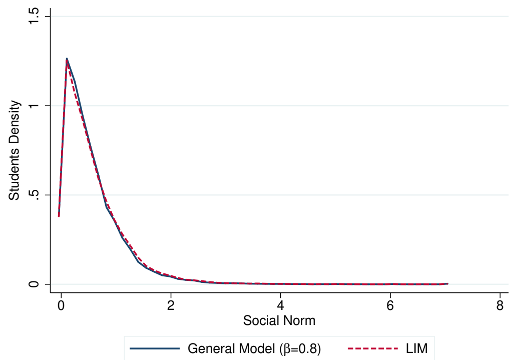


(c) GPA

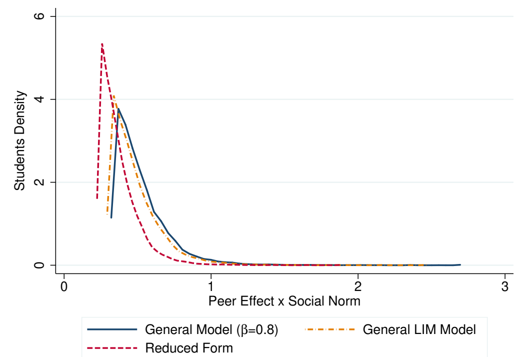
Notes: Estimates of $\boldsymbol{\gamma}$ and $\tilde{\boldsymbol{\theta}} = [\lambda_1, \lambda_2, \beta]$ with the 95 percent confidence interval (in red) are from the benchmark GMM of Tables I and A3. In addition, figures also show, for each coefficient, the estimate for the two-stage estimation procedure where $\boldsymbol{\gamma}$ is estimated by OLS (in blue) according to Equations (B.2)-(B.4) and $\tilde{\boldsymbol{\theta}} = [\lambda_1, \lambda_2, \beta]$ are estimated on non-isolated individuals only through GMM by Equation (14). All coefficients, but for β are graphed on the primary (left side) y-axis.

standard LIM model and our general social norm (see Equation (8)) with estimates of β from Table I. The figures provide a graphical illustration of the findings by comparing (i) the density of the average social norm commonly used in the LIM (i.e., $\overline{y}_{-i}$) and the social norm resulting from the general model (i.e., $\tilde{y}(\mathbf{y}_{-i}, \beta)$) (see left panels of Figure A3) and (ii) the distribution of peer effects in the LIM model (i.e., $\lambda\overline{y}_{-i}$), the general LIM model (i.e., $(\lambda_1 + \lambda_2)\overline{y}_{-i}$), and the general model (i.e., $(\lambda_1 + \lambda_2)\tilde{y}(\mathbf{y}_{-i}, \beta)$) (see right panels of Figure A3). Estimates of β and λ's for the general model are from the left-hand side of Table I. Estimates of β and λ's for the general LIM model are from the right-hand side

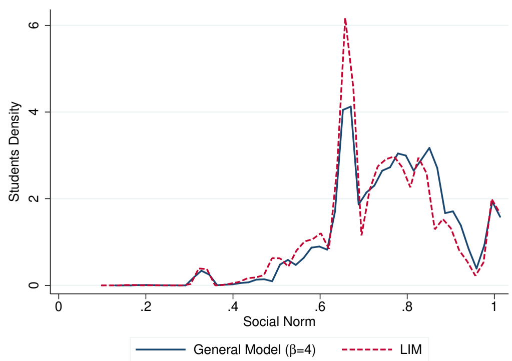
FIGURE A3.—*Social norms and peer effects (Examples)*



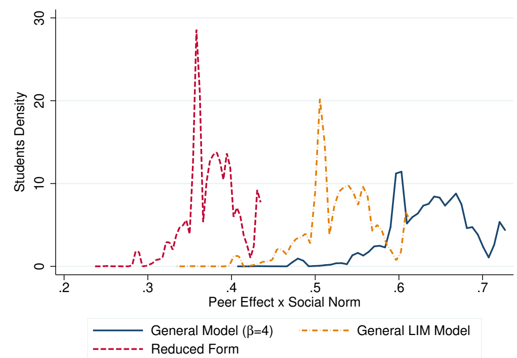
(a) Social Norm (Risky Behavior)



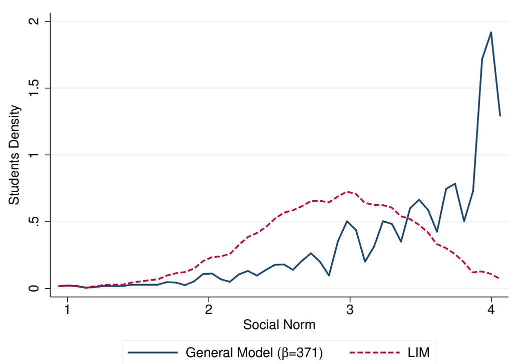
(b) Peer Effect (Risky Behavior)



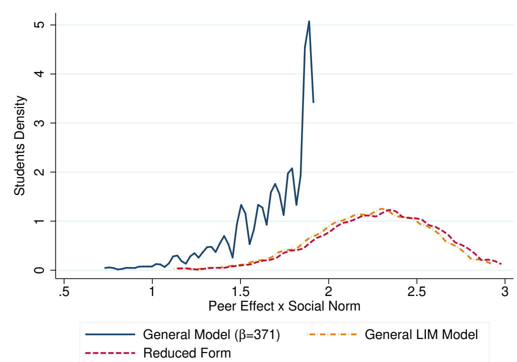
(c) Social Norm (Study Effort)



(d) Peer Effect (Study Effort)



(e) Social Norm (GPA)



(f) Peer Effect (GPA)

Notes: Kernel density distribution of non-isolated individuals of (a) the social norms for the general model, $\overline{y}(\mathbf{y}_{-i}, \beta)$, and the linear-in-means model, $\overline{y}_{-i}$, on the left-hand panel; and (b) peer effect from the general model, $(\lambda_1 + \lambda_2)\overline{y}_{-i}(\mathbf{y}_{-i}, \beta)$, the general LIM model, $(\lambda_1 + \lambda_2)\overline{y}_{-i}$, and the linear-in-means model, $\lambda\overline{y}_{-i}$, on the right-hand panel. Estimates of β and λ's for the general model are from the left-hand side of Table I. Estimates of β and λ's for the general LIM model are from the right-hand side of Table I. Estimates for λ for the linear-in-means model are from the right-most column of Table I.

of Table I. Finally, estimates for λ for the LIM model are from the column of the extreme right of Table I.

We illustrate this with three activities of varying peer preference and peer effects, namely risky behavior, study effort, and GPA. The full set of figures with all 10 activities is available upon request.

TABLE A3

GENERAL MODEL ESTIMATION

	GPA	*Clubs*	*Self esteem*	*Risky*	*Exercise*	*Study effort*	*Fight*	*Smoke*	*Drink*	*Trouble*
	GPA	*Clubs*	*Self esteem*	*Risky*	*Exercise*	*Study effort*	*Fight*	*Smoke*	*Drink*	*Trouble*
Age	-0.015	-0.007	-0.002	0.049	-0.131	-0.015	-0.077	0.176	0.104	-0.016
	(0.003)	(0.013)	(0.001)	(0.007)	(0.009)	(0.001)	(0.009)	(0.016)	(0.012)	(0.005)
Female	0.159	0.128	-0.046	-0.392	-1.404	0.079	-0.903	-0.058	-0.383	-0.152
	(0.009)	(0.028)	(0.003)	(0.022)	(0.050)	(0.004)	(0.043)	(0.036)	(0.026)	(0.016)
Hispanic	-0.099	0.466	-0.003	0.321	-0.100	-0.024	0.394	0.126	0.381	0.155
	(0.013)	(0.078)	(0.003)	(0.032)	(0.036)	(0.005)	(0.041)	(0.060)	(0.045)	(0.024)
White	0.040	0.196	-0.010	0.242	0.215	-0.040	-0.004	0.523	0.192	-0.101
	(0.011)	(0.062)	(0.003)	(0.029)	(0.034)	(0.005)	(0.036)	(0.064)	(0.040)	(0.021)
Black	-0.156	0.576	0.034	0.128	-0.099	-0.019	0.264	-0.342	0.226	0.172
	(0.015)	(0.089)	(0.004)	(0.033)	(0.041)	(0.006)	(0.044)	(0.068)	(0.050)	(0.028)
Asian	0.300	1.250	-0.037	0.413	-0.333	-0.017	0.170	0.393	0.541	0.177
	(0.020)	(0.143)	(0.004)	(0.045)	(0.047)	(0.007)	(0.048)	(0.083)	(0.066)	(0.031)
Mother Ed. less than HS.	-0.088	-0.026	-0.026	0.110	-0.117	-0.015	0.105	0.147	0.122	0.086
	(0.011)	(0.040)	(0.003)	(0.020)	(0.029)	(0.004)	(0.030)	(0.054)	(0.031)	(0.019)
Mother Ed. more than HS	0.192	0.488	0.008	-0.050	0.181	0.003	-0.186	-0.216	-0.037	-0.114
	(0.011)	(0.053)	(0.002)	(0.015)	(0.024)	(0.003)	(0.024)	(0.045)	(0.023)	(0.021)
Mother Ed. none	0.022	0.376	-0.009	0.242	-0.143	-0.029	0.203	0.417	0.304	0.045
	(0.015)	(0.079)	(0.004)	(0.035)	(0.045)	(0.006)	(0.048)	(0.082)	(0.050)	(0.034)
Mother Professional	0.064	0.294	0.001	0.059	0.082	-0.005	0.074	0.068	0.129	-0.024
	(0.010)	(0.050)	(0.002)	(0.020)	(0.029)	(0.004)	(0.029)	(0.054)	(0.031)	(0.017)
Mother Other Job	-0.043	0.108	-0.008	0.086	-0.021	-0.022	0.117	0.238	0.074	0.041
	(0.008)	(0.036)	(0.002)	(0.017)	(0.024)	(0.003)	(0.024)	(0.046)	(0.025)	(0.018)
Mother No Job	-0.125	-0.031	-0.021	0.130	-0.005	-0.014	0.245	0.176	0.055	0.135
	(0.015)	(0.063)	(0.004)	(0.029)	(0.040)	(0.005)	(0.043)	(0.072)	(0.042)	(0.050)
$1-\lambda_2$	0.942	0.667	0.990	0.503	0.988	0.660	0.877	0.351	0.360	1.000
	(0.046)	(0.071)	(0.073)	(0.032)	(0.038)	(0.042)	(0.044)	(0.035)	(0.029)	(0.166)
$\lambda_1+\lambda_2$	0.379	0.664	0.294	0.336	0.222	0.361	0.041	0.857	0.588	0.291
	(0.014)	(0.037)	(0.039)	(0.049)	(0.023)	(0.045)	(0.010)	(0.056)	(0.074)	(0.542)
β	370.781	1.398	22.282	0.757	8.143	3.904	73.578	0.692	0.362	-414.969
	(114.860)	(0.167)	(8.103)	(0.359)	(3.447)	(1.389)	(14.866)	(0.139)	(0.233)	(148.975)
Observations	69961	78735	71511	75149	71462	75799	71381	74584	74436	75847

Notes: Detailed estimation results for the general model presented in Table I. Age, female, hispanic, white, black, asian, mother's education less than high school, mother's education more than high school, mother's education non, mother professional occupation, mother other job, mother no job make up the covariates, x_i for estimating $\boldsymbol{\gamma}$.

TABLE A4

GENERAL LIM MODEL ESTIMATION

	GPA	*Clubs*	*Self esteem*	*Risky*	*Exercise*	*Study effort*	*Fight*	*Smoke*	*Drink*	*Trouble*
Age	-0.018	-0.010	-0.002	0.049	-0.129	-0.016	-0.072	0.180	0.108	-0.009
	(0.003)	(0.013)	(0.001)	(0.006)	(0.009)	(0.001)	(0.009)	(0.016)	(0.011)	(0.006)
Female	0.167	0.127	-0.046	-0.392	-1.404	0.079	-0.912	-0.050	-0.381	-0.167
	(0.010)	(0.029)	(0.003)	(0.022)	(0.050)	(0.004)	(0.043)	(0.033)	(0.026)	(0.019)
Hispanic	-0.089	0.471	-0.004	0.318	-0.100	-0.023	0.393	0.123	0.378	0.165
	(0.014)	(0.079)	(0.003)	(0.031)	(0.036)	(0.005)	(0.043)	(0.058)	(0.044)	(0.028)
White	0.041	0.197	-0.009	0.239	0.214	-0.039	-0.001	0.516	0.190	-0.103
	(0.013)	(0.063)	(0.003)	(0.029)	(0.034)	(0.005)	(0.038)	(0.061)	(0.039)	(0.026)
Black	-0.150	0.577	0.033	0.123	-0.108	-0.017	0.254	-0.342	0.220	0.182
	(0.017)	(0.090)	(0.004)	(0.033)	(0.041)	(0.005)	(0.047)	(0.065)	(0.048)	(0.032)
Asian	0.294	1.254	-0.037	0.405	-0.331	-0.015	0.194	0.378	0.530	0.200
	(0.021)	(0.144)	(0.004)	(0.044)	(0.048)	(0.006)	(0.051)	(0.078)	(0.063)	(0.037)
Mother Ed. less than HS.	-0.089	-0.026	-0.027	0.108	-0.122	-0.014	0.092	0.154	0.121	0.094
	(0.012)	(0.040)	(0.003)	(0.020)	(0.030)	(0.004)	(0.032)	(0.051)	(0.030)	(0.023)
Mother Ed. more than HS	0.188	0.486	0.008	-0.050	0.181	0.003	-0.180	-0.198	-0.038	-0.114
	(0.012)	(0.053)	(0.002)	(0.015)	(0.024)	(0.003)	(0.026)	(0.042)	(0.023)	(0.019)
Mother Ed. none	0.022	0.380	-0.010	0.241	-0.147	-0.028	0.201	0.431	0.301	0.045
	(0.017)	(0.080)	(0.004)	(0.035)	(0.046)	(0.006)	(0.051)	(0.079)	(0.049)	(0.033)
Mother Professional	0.067	0.295	0.001	0.058	0.088	-0.004	0.087	0.067	0.128	-0.030
	(0.011)	(0.050)	(0.002)	(0.019)	(0.030)	(0.004)	(0.031)	(0.051)	(0.030)	(0.022)
Mother Other Job	-0.040	0.111	-0.008	0.086	-0.017	-0.022	0.120	0.237	0.075	0.043
	(0.009)	(0.036)	(0.002)	(0.016)	(0.025)	(0.003)	(0.026)	(0.044)	(0.024)	(0.019)
Mother No Job	-0.124	-0.029	-0.022	0.131	-0.004	-0.013	0.241	0.178	0.057	0.142
	(0.016)	(0.063)	(0.004)	(0.029)	(0.041)	(0.005)	(0.045)	(0.068)	(0.041)	(0.032)
$1 - \lambda_2$	0.810	0.656	0.973	0.508	0.979	0.678	0.812	0.376	0.374	0.749
	(0.042)	(0.070)	(0.072)	(0.032)	(0.038)	(0.043)	(0.043)	(0.035)	(0.029)	(0.073)
$\lambda_1 + \lambda_2$	0.577	0.694	0.279	0.307	0.202	0.305	0.250	0.754	0.449	0.476
	(0.020)	(0.035)	(0.036)	(0.037)	(0.022)	(0.041)	(0.032)	(0.032)	(0.042)	(0.043)
β	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	-	-	-	-	-	-	-	-	-	-
Observations	69961	78735	71511	75149	71462	75799	71381	74584	74436	75847

Notes: Detailed estimation results for the general LIM model presented in Tables I and A1. Age, female, hispanic, white, black, asian, mother's education less than high school, mother's education more than high school, mother's education non, mother professional occupation, mother other job, mother no job make up the covariates, x_i for estimating γ.

TABLE A5

REDUCED FORM ESTIMATION

	GPA	*Clubs*	*Self esteem*	*Risky*	*Exercise*	*Study effort*	*Fight*	*Smoke*	*Drink*	*Trouble*
Age	-0.025	-0.022	-0.003	0.033	-0.146	-0.013	-0.056	0.095	0.076	0.004
	(0.002)	(0.008)	(0.001)	(0.003)	(0.009)	(0.001)	(0.008)	(0.008)	(0.004)	(0.005)
Female	0.147	0.219	-0.052	-0.216	-1.392	0.054	-0.758	0.010	-0.171	-0.143
	(0.006)	(0.019)	(0.002)	(0.007)	(0.022)	(0.002)	(0.018)	(0.016)	(0.009)	(0.012)
Hispanic	-0.074	0.259	-0.001	0.108	-0.081	-0.014	0.186	0.021	0.120	0.094
	(0.012)	(0.036)	(0.003)	(0.013)	(0.037)	(0.003)	(0.033)	(0.030)	(0.016)	(0.022)
White	0.044	0.094	-0.009	0.072	0.220	-0.023	-0.096	0.164	0.037	-0.089
	(0.011)	(0.033)	(0.003)	(0.012)	(0.035)	(0.003)	(0.031)	(0.029)	(0.015)	(0.021)
Black	-0.100	0.236	0.027	-0.011	-0.035	0.005	0.141	-0.148	0.028	0.080
	(0.014)	(0.040)	(0.004)	(0.015)	(0.042)	(0.004)	(0.038)	(0.037)	(0.018)	(0.025)
Asian	0.194	0.555	-0.027	0.056	-0.269	0.006	-0.045	0.075	0.025	0.103
	(0.015)	(0.047)	(0.004)	(0.018)	(0.048)	(0.004)	(0.043)	(0.040)	(0.021)	(0.028)
Mother Ed. less than HS.	-0.081	-0.058	-0.019	0.031	-0.072	-0.001	0.100	0.070	0.006	0.065
	(0.010)	(0.030)	(0.002)	(0.011)	(0.030)	(0.003)	(0.027)	(0.025)	(0.013)	(0.018)
Mother Ed. more than HS	0.138	0.351	0.005	-0.017	0.181	0.002	-0.094	-0.004	-0.010	-0.078
	(0.008)	(0.025)	(0.002)	(0.009)	(0.024)	(0.002)	(0.022)	(0.020)	(0.011)	(0.015)
Mother Ed. none	-0.043	0.216	-0.007	0.123	-0.031	-0.010	0.243	0.274	0.080	0.055
	(0.015)	(0.045)	(0.004)	(0.017)	(0.047)	(0.004)	(0.041)	(0.038)	(0.020)	(0.027)
Mother Professional	0.034	0.212	0.003	0.024	0.115	-0.001	0.041	0.037	0.018	-0.003
	(0.010)	(0.031)	(0.003)	(0.011)	(0.031)	(0.003)	(0.028)	(0.026)	(0.013)	(0.019)
Mother Other Job	-0.046	0.049	-0.007	0.050	0.012	-0.014	0.074	0.099	0.040	0.026
	(0.008)	(0.025)	(0.002)	(0.009)	(0.026)	(0.002)	(0.023)	(0.021)	(0.011)	(0.015)
Mother No Job	-0.109	-0.035	-0.019	0.077	0.011	-0.009	0.172	0.088	0.049	0.139
	(0.013)	(0.040)	(0.003)	(0.015)	(0.042)	(0.004)	(0.037)	(0.035)	(0.018)	(0.025)
λ	0.589	0.638	0.289	0.235	0.177	0.216	0.254	0.732	0.156	0.521
	(0.019)	(0.033)	(0.035)	(0.034)	(0.022)	(0.041)	(0.031)	(0.031)	(0.043)	(0.042)
Observations	69961	78735	71511	75149	71462	75799	71381	74584	74436	75847

Notes: Detailed estimation results for the reduced form presented in Table I and A1. Age, female, hispanic, white, black, asian, mother's education less than high school, mother's education more than high school, mother's education non, mother professional occupation, mother other job, mother no job make up the covariates, x_i for estimating $\boldsymbol{\gamma}$.

TABLE A6

SPILLOVER LIM MODEL ESTIMATION

	GPA	*Clubs*	*Self esteem*	*Risky*	*Exercise*	*Study effort*	*Fight*	*Smoke*	*Drink*	*Trouble*
Age	-0.018	-0.015	-0.002	0.039	-0.128	-0.014	-0.069	0.154	0.085	-0.008
	(0.002)	(0.009)	(0.001)	(0.003)	(0.008)	(0.001)	(0.007)	(0.008)	(0.005)	(0.005)
Female	0.151	0.136	-0.046	-0.275	-1.390	0.066	-0.828	-0.005	-0.236	-0.149
	(0.006)	(0.018)	(0.002)	(0.007)	(0.020)	(0.002)	(0.018)	(0.015)	(0.008)	(0.011)
Hispanic	-0.083	0.336	-0.003	0.210	-0.099	-0.020	0.356	0.089	0.234	0.146
	(0.011)	(0.045)	(0.003)	(0.016)	(0.035)	(0.003)	(0.034)	(0.029)	(0.019)	(0.021)
White	0.040	0.149	-0.009	0.152	0.213	-0.033	-0.004	0.360	0.109	-0.093
	(0.011)	(0.042)	(0.003)	(0.015)	(0.033)	(0.003)	(0.032)	(0.029)	(0.017)	(0.020)
Black	-0.137	0.406	0.033	0.050	-0.106	-0.010	0.234	-0.292	0.114	0.160
	(0.013)	(0.052)	(0.003)	(0.018)	(0.040)	(0.004)	(0.039)	(0.033)	(0.022)	(0.024)
Asian	0.269	0.927	-0.036	0.217	-0.329	-0.008	0.154	0.202	0.231	0.176
	(0.015)	(0.070)	(0.004)	(0.022)	(0.046)	(0.005)	(0.043)	(0.037)	(0.026)	(0.027)
Mother Ed. less than HS.	-0.084	-0.039	-0.026	0.066	-0.120	-0.009	0.092	0.115	0.041	0.083
	(0.009)	(0.028)	(0.002)	(0.011)	(0.029)	(0.003)	(0.027)	(0.024)	(0.013)	(0.017)
Mother Ed. more than HS	0.169	0.390	0.008	-0.034	0.179	0.003	-0.160	-0.119	-0.020	-0.101
	(0.007)	(0.023)	(0.002)	(0.009)	(0.023)	(0.002)	(0.020)	(0.020)	(0.010)	(0.014)
Mother Ed. none	0.011	0.295	-0.010	0.179	-0.145	-0.022	0.199	0.348	0.172	0.046
	(0.014)	(0.051)	(0.004)	(0.019)	(0.045)	(0.004)	(0.042)	(0.038)	(0.021)	(0.026)
Mother Professional	0.057	0.229	0.001	0.034	0.088	-0.003	0.069	0.038	0.049	-0.023
	(0.009)	(0.029)	(0.002)	(0.011)	(0.029)	(0.003)	(0.025)	(0.023)	(0.013)	(0.017)
Mother Other Job	-0.038	0.077	-0.008	0.059	-0.016	-0.018	0.104	0.165	0.047	0.037
	(0.008)	(0.024)	(0.002)	(0.009)	(0.024)	(0.002)	(0.021)	(0.020)	(0.011)	(0.014)
Mother No Job	-0.115	-0.031	-0.021	0.101	-0.004	-0.012	0.217	0.155	0.052	0.131
	(0.013)	(0.044)	(0.003)	(0.016)	(0.040)	(0.004)	(0.037)	(0.033)	(0.018)	(0.024)
λ_1	0.519	0.612	0.270	0.079	0.193	0.125	0.172	0.442	0.102	0.391
	(0.019)	(0.034)	(0.035)	(0.037)	(0.021)	(0.040)	(0.031)	(0.031)	(0.044)	(0.041)
β	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	-	-	-	-	-	-	-	-	-	-
Observations	69961	78735	71511	75149	71462	75799	71381	74584	74436	75847

Notes: Detailed estimation results for the spillover LIM model presented in Table A1. Age, female, hispanic, white, black, asian, mother's education less than high school, mother's education more than high school, mother's education non, mother professional occupation, mother other job, mother no job make up the covariates, x_i for estimating $\boldsymbol{\gamma}$.

TABLE A7

CONFORMISM LIM MODEL ESTIMATION

	GPA	*Clubs*	*Self esteem*	*Risky*	*Exercise*	*Study effort*	*Fight*	*Smoke*	*Drink*	*Trouble*
Age	-0.019	-0.009	-0.002	0.045	-0.142	-0.016	-0.075	0.186	0.099	-0.012
	(0.004)	(0.017)	(0.001)	(0.006)	(0.008)	(0.001)	(0.008)	(0.015)	(0.009)	(0.006)
Female	0.185	0.121	-0.050	-0.377	-1.489	0.078	-0.928	-0.053	-0.372	-0.179
	(0.010)	(0.034)	(0.002)	(0.018)	(0.028)	(0.003)	(0.029)	(0.036)	(0.024)	(0.017)
Hispanic	-0.110	0.545	-0.004	0.309	-0.107	-0.023	0.402	0.122	0.368	0.178
	(0.017)	(0.087)	(0.003)	(0.029)	(0.038)	(0.005)	(0.041)	(0.061)	(0.042)	(0.029)
White	0.048	0.260	-0.010	0.227	0.230	-0.039	-0.001	0.535	0.180	-0.113
	(0.016)	(0.077)	(0.003)	(0.027)	(0.036)	(0.004)	(0.039)	(0.062)	(0.038)	(0.028)
Black	-0.184	0.710	0.037	0.125	-0.119	-0.016	0.261	-0.359	0.210	0.203
	(0.019)	(0.098)	(0.004)	(0.032)	(0.044)	(0.005)	(0.046)	(0.067)	(0.047)	(0.033)
Asian	0.341	1.504	-0.041	0.401	-0.345	-0.014	0.194	0.384	0.515	0.212
	(0.021)	(0.132)	(0.004)	(0.043)	(0.050)	(0.006)	(0.052)	(0.083)	(0.061)	(0.039)
Mother Ed. less than HS.	-0.098	-0.034	-0.030	0.101	-0.130	-0.014	0.096	0.153	0.110	0.102
	(0.014)	(0.051)	(0.003)	(0.019)	(0.031)	(0.004)	(0.032)	(0.055)	(0.029)	(0.025)
Mother Ed. more than HS	0.226	0.578	0.009	-0.041	0.194	0.003	-0.186	-0.217	-0.030	-0.128
	(0.011)	(0.044)	(0.002)	(0.014)	(0.025)	(0.003)	(0.025)	(0.045)	(0.022)	(0.020)
Mother Ed. none	0.041	0.416	-0.011	0.235	-0.152	-0.028	0.201	0.427	0.294	0.042
	(0.021)	(0.095)	(0.004)	(0.033)	(0.048)	(0.006)	(0.051)	(0.083)	(0.047)	(0.037)
Mother Professional	0.087	0.355	0.002	0.058	0.091	-0.004	0.088	0.068	0.120	-0.036
	(0.014)	(0.056)	(0.003)	(0.019)	(0.032)	(0.004)	(0.031)	(0.055)	(0.029)	(0.025)
Mother Other Job	-0.043	0.125	-0.009	0.080	-0.018	-0.022	0.124	0.245	0.070	0.048
	(0.012)	(0.044)	(0.002)	(0.015)	(0.026)	(0.003)	(0.026)	(0.046)	(0.023)	(0.021)
Mother No Job	-0.140	-0.040	-0.023	0.125	-0.008	-0.013	0.247	0.184	0.055	0.150
	(0.019)	(0.080)	(0.004)	(0.028)	(0.043)	(0.005)	(0.045)	(0.072)	(0.039)	(0.034)
λ_2	0.406	0.529	0.154	0.467	0.094	0.315	0.209	0.675	0.601	0.374
	(0.019)	(0.030)	(0.034)	(0.029)	(0.020)	(0.034)	(0.028)	(0.028)	(0.029)	(0.039)
β	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	-	-	-	-	-	-	-	-	-	-
Observations	69961	78735	71511	75149	71462	75799	71381	74584	74436	75847

Notes: Detailed estimation results for the conformism LIM model presented in Table A1. Age, female, hispanic, white, black, asian, mother's education less than high school, mother's education more than high school, mother's education non, mother professional occupation, mother other job, mother no job make up the covariates, x_i for estimating γ.