DISCUSSION PAPER SERIES

DP17315

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PUBLIC ECONOMICS

CEPR

ISSN 0265-8003

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Discussion Paper DP17315
Published 19 May 2022
Submitted 18 May 2022

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www.cepr.org

Toward a General Theory of Peer Effects

Abstract

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JEL Classification: C31, D04, D85, Z13

Keywords: peer effects, Spillovers, Conformism, structural estimation, policies

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Acknowledgements
We thank the participants at the brown bag seminar, Monash University, at the Research Seminar, Johns Hopkins Carey Business School, and at the Labour Economics Seminar, Swedish Institute for Social Research (SOFI, Stockholm University), for all the very helpful comments.

Toward a General Theory of Peer Effects*†

Vincent Boucher‡ Michelle Rendall§ Philip Ushchev¶ Yves Zenou‖

May 18, 2022

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†This research uses data from AddHealth, a program directed by Kathleen Mullan Harris and designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris at the University of North Carolina at Chapel Hill and is funded by Grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from 23 other federal agencies and foundations. Special acknowledgment is given to Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Information on how to obtain AddHealth data files is available on the Add Health website (http://www.cpc.unc.edu/addhealth). No direct support was received from Grant P01-HD31921 for this research.

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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, program participation, obesity, environmentally friendly behavior, and tax evasion,[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. 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 theory 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.[2] Moreover, it is now well recognized that the LIM model can be equivalently microfounded by games assuming either conformist preferences or positive spillovers.[3]

In this paper, we develop a new and general model that provides a microfoundation for the LIM model that enables identification of the underlying behavioral foundation (conformism or spillovers) and relaxes the assumption that agents are *linearly* affected by the *mean* action of their peers. We show that these two models are of first-order importance for the policy implications of empirical studies of peer effects and that their policy implications are qualitatively (and quantitatively) different. We then structurally estimate this model and highlight the mistakes made by the planner in recommending policies if it wrongly assumes LIM instead of more general interactions.

First, we explore the differences between games of conformism and spillovers under the familiar linear context. We develop two different theoretical models, based either on *spillover*

[1]See, e.g., Calvó-Armengol et al. (2009) and Sacerdote (2011) for education, Patacchini and Zenou (2012), Damm and Dustmann (2014), and Lee et al. (2021) for crime, Dahl et al. (2014) for program participation, Christakis and Fowler (2007) for obesity, Gillingham and Bollinger (2021) and Kyriakopoulou and Xepapadeas (2021) for environmentally friendly behavior, and Fortin and Villeval (2007) for tax compliance and tax evasion.

[2]See, e.g., Patacchini and Zenou (2012), Blume et al. (2015), Boucher (2016), Kline and Tamer (2020) and Ushchev and Zenou (2020). For an overview of the network literature, see Jackson (2008), Jackson and Zenou (2015), Bramoullé and Kranton (2016), and Jackson et al. (2017).

[3]See, e.g., Blume et al. (2015) and Boucher (2016), among others.

effects or *conformism behavior*, that microfound the LIM model and show that they have very different policy implications. In the former, agents are positively affected by the spillovers that they receive from their neighbors. We show that, at the Nash equilibrium, agents make too little effort compared to the first best because they do not take into account the positive impact of their effort on that of others linked to them. In the conformist model, agents obtain negative utility from deviating from their neighbors' actions and thus want to minimize the difference between their action and that of their neighbors. We show that, at the Nash equilibrium, some agents provide positive externalities to their neighbors if the latter's effort is above their social norm while others provide negative externalities to their their neighbors if the latter's effort is below their social norm. Thus, the former exert too little effort compared to the first best while the latter exert too much effort. To restore the first best, in the spillover model, the planner always wants to subidize all agents, while in the conformist model, the planner wants to subsidize some agents (those who provide positive externalities) and tax others (those who provide negative externalities). This implies that one needs to know the behavioral foundation of the LIM model in order to derive adequate policies.

Second, 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 and mean peer behavior of the LIM model. Instead of defining the social norm of each agent by the average action of her peers, in this model, the social norm is defined by a CES function whose key parameter is β. When β is equal to 1, we revert to the LIM model. When β is very large, 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, they only care about the "least" active agents in their network.

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, 1990b; Vives, 1990a) and by studying the structure of the smallest and largest equilibria, we show that there always exists a unique Nash equilibrium.

Third, 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. 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, we simulate each activity and 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, and, in general, with the LIM model, the planner tends to uniformly tax/subsidize all agents in the network, while with the general model, it targets some key agents depending on whether the spillover or the conformist model dominates, and the value of β. Consider, for example, GPA, which is a spillover model for which β is much greater than 1, which 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 assume that the network is exogenous. Given the size of our sample (more than 70,000 individuals), this is a reasonable assumption, as it would be impossible to estimate a network formation model due to its computational unfeasibility. Moreover, the literature on peer effects with endogenous networks (Goldsmith-Pinkham and Imbens, 2013; Hsieh and Lee, 2016; König et al., 2019; Johnsson and Moon, 2021; Houndetoungan, 2022) has shown that correcting for the endogeneity of the network does not substantially change the estimation results. Houndetoungan (2022), who found the largest difference in the literature, showed that the peer effect coefficient was reduced by about 15 percent when he corrected for network endogeneity (from 0.306 (exogenous network) to 0.256 (endogenous network), a difference of 0.05; see his Tables 4 and 5). Furthermore, the aim of our study is to illustrate the restrictive nature of the LIM model when estimating peer effects. Even if we could control for network endogeneity, the resulting estimates will likely change across activities, albeit only marginally, and will certainly not all converge to the LIM model. Thus, the general conclusion from our policy exercises and the mistakes made by restricting the estimation to a simple reduced-form LIM model will remain unchanged.

Our study contributes to the literature on peer effects and on games on networks by providing 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). However, none of these papers have developed a general theoretical framework with different mechanisms (spillover or conformism) and different peer-group references and tested which model and which peer group matters the most. Our main conclusion confirms the fact that imposing the mean action as an individual social norm is misleading and leads to incorrect policy recommendations.

2 Theory

2.1 Linear-in-means models

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, $g_{ij} = 0$.[4] We assume that the network is *directed* (i.e., g_{ij} and g_{ji} are potentially different) 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, namely $d_i > 0$ for all i. We will relax this assumption in Section 3.[5] Consider the following class of best-response functions:

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

[4] We can easily generalize our results to directed and weighted networks.

[5] In the theory section, determining the best-reply functions for isolated individuals is straightforward. Thus, we leave this discussion to the structural estimation section.

where y_i is the effort or outcome in some activity (such as education), $\alpha_i = \mathbf{x}_i\boldsymbol{\gamma}+\epsilon_i$[6] captures the observable ($\mathbf{x}_i$) and unobservable (ϵ_i) characteristics of individual i, and $\overline{y}_{-i} := f(\mathbf{G}, \mathbf{y}_{-i})$ for some known function $f(.)$, with $\mathbf{y}_{-i} := (y_1, \ldots, y_{i-1}, y_{i+1}, \ldots, y_n)^T$ the vector of effort without the effort of agent i.

In (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 $\overline{y}_{-i} := f(\mathbf{G}, \mathbf{y}_{-i})$ in the population. One particular form is when $f(\cdot)$ represents the *average* effort of i's neighbors (excluding i). Formally,

$$\overline{y}_{-i} := f(\mathbf{G}, \mathbf{y}_{-i}) = \sum_{j=1}^{n} \widehat{g}_{ij} y_j. \tag{2}$$

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

The LIM model (3) corresponds to the best-response function of two, observationally equivalent, types of social preferences: spillover or conformism.[7]

The spillover model

In this model, each agent i chooses effort $y_i \in \mathbb{R}_+$ that maximizes the following utility function:

$$U_i^S(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \alpha_i y_i - \frac{1}{2}\, y_i^2 + \theta_1 y_i \overline{y}_{-i}, \tag{4}$$

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.

This utility function has two terms. First, $\alpha_i y_i - \frac{1}{2}\, y_i^2$ is i's utility of exerting effort y_i, independently of peer effects. Second, $\theta_1 y_i \overline{y}_{-i}$ captures the *peer-group pressure* faced by agent i or, equivalently, the *spillover effects* of the social norm on own utility (Binder and Pesaran, 2001; Brock and Durlauf, 2001; Glaeser and Scheinkman, 2002; Blanchflower et al., 2009; Boucher and Fortin, 2016; Reif, 2019).

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

[7] For the microfoundatons of the LIM model, there cannot be models other than the spillover and conformist models because of the linearity of the best-reply function, which imposes that the utility has to be linear-quadratic, and the fact that the average peers matter, which necessitates the social norm in the utility function to be the average action of one's neighbors.

Denote $\lambda_1 := \theta_1 < 1$. Then, the first-order condition is given by

$$y_i = \alpha_i + \lambda_1 \overline{y}_{-i} \tag{5}$$

or

$$y_i = \mathbf{x}_i \boldsymbol{\gamma} + \lambda_1 \sum_{j=1}^{n} \widehat{g}_{ij} y_j + \epsilon_i, \tag{6}$$

which corresponds to the LIM model (3).[8]

The conformist model

For this second type of social preferences, each agent i chooses effort $y_i \in \mathbb{R}_+$ that maximizes the following utility function:

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

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*.

As for the spillover model, this utility function has two terms. First, $\alpha_i y_i - \frac{1}{2} y_i^2$ gives the utility of exerting effort y_i, independently of peer effects. Second, $-\frac{1}{2}\theta_2 \left(y_i - \overline{y}_{-i}\right)^2$ is the price individual i has to pay in terms of utility when not *conforming* to her social norm $\overline{y}_{-i}$ (Akerlof, 1980, 1997; Kandel and Lazear, 1992; Bernheim, 1994; Fershtman and Weiss, 1998; Patacchini and Zenou, 2012; Boucher, 2016; Ushchev and Zenou, 2020). In other words, each agent i pays a utility cost of $\frac{\theta_2}{2} \left(y_i - \overline{y}_{-i}\right)^2$ for not conforming to the behavior of their neighbors.

In this formulation, $\theta_2 > 0$ is the taste for conformity. This implies that the *closer* i's effort is to her social norm, the higher i's utility is. In other words, while increasing the social norm $\overline{y}_{-i}$ decreases i's marginal cost of effort, the effect on i's utility is *non-monotonic*. When the social norm is higher than i's effort, such that $\overline{y}_{-i} > y_i$, increasing the social norm decreases i's utility, since i's effort moves further away from her social norm. When the social norm is smaller than i's effort, such that $\overline{y}_{-i} < y_i$, increasing the social norm increases i's utility.

[8] Since $\lambda_1 := \theta_1 < 1$, there exists a unique Nash equilibrium given by

$$\mathbf{y} = (\mathbf{I} - \lambda_1 \widehat{\mathbf{G}})^{-1} \boldsymbol{\alpha}, \tag{7}$$

where $\mathbf{y} := (y_1, y_2, \ldots, y_n)^T$ is the vector of efforts, $\mathbf{I}$ is the identity matrix, and $\boldsymbol{\alpha} := (\alpha_1, \alpha_2, \ldots, \alpha_n)^T$ is the vector of observable and unobservable characteristics.

The first-order condition is equal to

$$y_i = (1-\lambda_2)\alpha_i + \lambda_2 \overline{y}_{-i}, \tag{9}$$

where $\lambda_2 \equiv \frac{\theta_2}{(1+\theta_2)} < 1$. Using the fact that $\alpha_i = \mathbf{x}_i\boldsymbol{\gamma} + \epsilon_i$ and that $\overline{y}_{-i}$ is defined by (2), we can write this equation as

$$y_i = (1-\lambda_2)\mathbf{x}_i\boldsymbol{\gamma} + \lambda_2 \sum_{j=1}^{n} \widehat{g}_{ij} y_j + (1-\lambda_2)\epsilon_i, \tag{10}$$

which corresponds to the LIM model (3).[9]

Since $\boldsymbol{\gamma}$ is unknown, the predictions of the conformist model in (10) are observationally equivalent to that of the spillover model in (6). Importantly, as we will see in Section 2.3, the conformist model and the spillover model have very different policy implications.

2.1.2 A general model

Let us now provide a general model that embeds the two previous models as special cases. The utility function for each individual i is now given by

$$U_i(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \underbrace{\alpha_i y_i + \theta_1 y_i \overline{y}_{-i}}_{\text{benefit}} - \underbrace{\frac{1}{2}\left[y_i^2 + \theta_2\left(y_i - \overline{y}_{-i}\right)^2\right]}_{\text{cost}}. \tag{12}$$

The best reply function of individual i is given by

$$y_i = \frac{1}{(1+\theta_2)}\alpha_i + \frac{\theta_1}{(1+\theta_2)}\overline{y}_{-i} + \frac{\theta_2}{(1+\theta_2)}\overline{y}_{-i},$$

or equivalently

$$y_i = (1-\lambda_2)\alpha_i + (\lambda_1+\lambda_2)\overline{y}_{-i}, \tag{13}$$

where $\lambda_1 := \frac{\theta_1}{(1+\theta_2)}$ and $\lambda_2 \equiv \frac{\theta_2}{(1+\theta_2)}$, with $0 < \lambda_1 + \lambda_2 < 1$.[10] Using the fact that $\alpha_i = \mathbf{x}_i\boldsymbol{\gamma} + \epsilon_i$

[9] Since $\lambda_2 \equiv \frac{\theta_2}{(1+\theta_2)} < 1$, there exists a unique Nash equilibrium given by

$$\mathbf{y} = (1-\lambda_2)(\mathbf{I} - \lambda_2\widehat{\mathbf{G}})^{-1}\boldsymbol{\alpha}. \tag{11}$$

[10] There is a unique Nash equilibrium given by

$$\mathbf{y} = (1-\lambda_2)(\mathbf{I} - (\lambda_1+\lambda_2)\widehat{\mathbf{G}})^{-1}\boldsymbol{\alpha}. \tag{14}$$

and that $\overline{y}_{-i}$ is defined by (2), we can write this equation as

$$y_i = (1-\lambda_2)\mathbf{x}_i\boldsymbol{\gamma} + (\lambda_1+\lambda_2)\sum_{j=1}^{n}\widehat{g}_{ij}y_j + (1-\lambda_2)\epsilon_i. \tag{15}$$

When $\lambda_1 = 0$, we obtain the *conformist model* (see (9)), while when $\lambda_2 = 0$, we revert to the *spillover* model (see (6)). Without additional structure, λ_1 and λ_2 cannot be separately identified, since $\boldsymbol{\gamma}$ has to be estimated. As we show in Section 3, following Boucher and Fortin (2016), we use the isolated individuals (individuals who have no neighbor) to identify $\boldsymbol{\gamma}$, which in turn allows us to identify λ_1 and λ_2.

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 $\overline{y}_{-i} := f(\mathbf{G}, \mathbf{y}_{-i})$ given in (2) by considering the following social norm:

$$\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, \beta) = \left(\sum_{j=1}^{n}\widehat{g}_{ij}y_j^{\beta}\right)^{\frac{1}{\beta}}. \tag{16}$$

We can easily see that the social norm in the LIM model defined in (2) is a special case of (16) when $\beta = 1$, that is, $\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, \beta = 1) = \sum_{j=1}^{n}\widehat{g}_{ij}y_j$. Our social norm is general, since (16) allows for any β, that is, $\beta \in [-\infty, +\infty]$. We argue that this parameter, β, captures *peer preference*. For example, if we set $\beta = +\infty$, (16) becomes

$$\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, +\infty) = \max_{j\in\mathcal{N}_i}\{y_j\},$$

that is, the social norm is defined with respect to the "most active agent" in the network (e.g., criminal leaders in crime). Under $\beta = -\infty$, (16) becomes

$$\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, -\infty) = \min_{j \in \mathcal{N}_i} \{y_j\},$$

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. For example, when $\beta = 0$, the social norm is defined as a Cobb-Douglas function, since we have

$$\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, 0) = \prod_{j \in \mathcal{N}_i} y_j^{1/d_i} = \prod_{j=1}^{n} y_j^{\widehat{g}_{ij}}.$$

2.2.2 A general model

Consider our general model, whose utility is given by (12) and where the social norm is equal to (16). The first-order condition (13) can now be written as

$$y_i = (1 - \lambda_2)\alpha_i + (\lambda_1 + \lambda_2)\overline{y}(\mathbf{y}_{-i}, \beta), \tag{17}$$

or equivalently

$$y_i = (1 - \lambda_2)\alpha_i + (\lambda_1 + \lambda_2) \left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta} \right)^{\frac{1}{\beta}}. \tag{18}$$

The main difference with the LIM model (where $\beta = 1$) is that the first-order conditions (18) are *not* linear anymore. Thus, when estimating (18), 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.[11]

Proposition 1. *Assume that the utility function of each individual $i = 1, \cdots, n$ is given by (12), with $0 < \lambda_1 + \lambda_2 < 1$ and $0 < \lambda_1 < 1$, and her social norm $\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, \beta)$ has the CES functional form (16). Then, there exists a unique Nash equilibrium.*

The proof is not obvious because, contrary to the LIM model, the best-reply functions are *not* linear; thus, we cannot just invert a matrix. 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

[11]See Section A of the Online Appendix for a proof of Proposition 1, where we first demonstrate the existence (Section A.1) and then the uniqueness of equilibrium (Section A.2).

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, as the following corollary demonstrates:

Corollary 1. *Assume that the utility function of each individual i is given by (12), with $0 < \lambda_1 + \lambda_2 < 1$ and $0 < \lambda_1 < 1$, and her social norm $\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, \beta)$ is an increasing function of $\mathbf{y}$, is homogeneous of degree 1, and satisfies the inequality $||\overline{\mathbf{y}}(\mathbf{z})||_\infty \leq ||\mathbf{z}||_\infty$ for any $\mathbf{z}$. Then, there exists a unique Nash equilibrium.*

2.3 Spillover versus conformist effects: Policy implications

2.3.1 General results

It is important to understand which model microfounds the estimation of (3), as the policy implications of the two models are different. In Appendix A.3, 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 ((5)) as compared to the social optimum outcome (Equation (A.29)). 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 given by (A.27) and is neither exclusively larger or smaller than the Nash equilibrium effort, given by (9). 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.

In Appendix A.4, we study the policy implications of the spillover and the conformist model. In particular, in Appendix A.4.1 (for the LIM model where $\beta = 1$), 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 $S_i^S = \lambda_1 \sum_j \widehat{g}_{ij} y_j^o = \lambda_1 \overline{y}_{-i}^o$[12] 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.

In Appendix A.4.2, we generalize these results for the general model, 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 (see Equation (A.36)):

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

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. Let us illustrate this point when $\beta = 1$.

2.3.2 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

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

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 $y_2^N = y_3^N \gtreqless y_3^o = y_2^o \iff \lambda_2 \gtreqless 1/2$, 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[13]

$$\mathbf{S}^C = \frac{\lambda_2}{(1+4\lambda_2)} \begin{pmatrix} -2 \\ 1 \\ 1 \end{pmatrix}. \tag{19}$$

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

[13] 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.

that the subsidies that restore the first best are given by:

$$\mathbf{S}^S = \frac{\lambda_1}{(1-4\lambda_1^2)} \begin{pmatrix} 1+4\lambda_1 \\ 2+2\lambda_1 \\ 2+2\lambda_1 \end{pmatrix}. \tag{20}$$

To summarize, compared to the theoretical literature on peer/network effects, we have two contributions. First, we propose a general model that encompasses the spillover and the conformist model as special cases, having shown that the policy implications of these two models are very different. Second, and more importantly, we generalize the social norm so that the *mean* norm is a special 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 (*i*) test for which model (conformist or spillover) is the most appropriate in the data and (*ii*) 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 nesting of conformity and spillover effects and the non-linearity of the social norm. We are interested in structurally estimating (*i*) the peer preference (or elasticity of substitution between a friend's efforts, $\frac{1}{1-\beta}$, of an individual's social norm); (*ii*) the intensity of the spillover effect, λ_1; and (*iii*) the taste for conformity, λ_2.

We can formulate the equilibrium effort of individual i, y_i, by

$$y_{is} = (1-\lambda_2)\mathbf{x}_{is}\boldsymbol{\gamma} + (\lambda_1+\lambda_2)\overline{y}(\mathbf{y}_{-is}, \beta) + \zeta_s + \varepsilon_{is}. \tag{21}$$

Equation (21) is the equivalent of the first-order condition (17), where, as above, $\alpha_i := \mathbf{x}_i\boldsymbol{\gamma} + \epsilon_i$ and $\varepsilon_i := (1-\lambda_2)\epsilon_i$. As we have different schools in AddHealth, we added the subscript s to denote each school s in our data. Thus, compared to (17), we control for school fixed effects, ζ_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)),

$$y_{is} = \boldsymbol{x}_{is}\boldsymbol{\gamma} + \lambda\overline{y}_{-is} + \epsilon_{is}, \tag{22}$$

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, (22) 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 solve for $\boldsymbol{\theta} = [\boldsymbol{\gamma}', \lambda_1, \lambda_2, \beta]'$ by deriving the appropriate generalized method of moment (GMM) estimator. Let us provide some intuition for the estimation procedure. Equation (21) 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, and there is thus no social norm to consider in their actions. This separation allows us the 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 (21), namely

$$y_{is} = \mathbf{x}_{is}\boldsymbol{\gamma} + \zeta_s^{iso} + \varepsilon_{is}, \tag{23}$$

where ζ_s^{iso} is the school fixed effect specific to isolated individuals.[14] 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 terms, $\mathbb{E}\left(\varepsilon_{is}\mathbf{x}_{is}\right) = \mathbf{0}$.

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, $\mathbf{x}_{is}$, then, given λ_2, the identification of λ_1 comes from the moment $\overline{y}(\hat{\mathbf{y}}_{-is}, \beta)$ for non-isolated individuals—our second instrument. Finally, the identification of β comes from the derivative of the social norm with respect to β,

[14] Identification does not allow us to estimated separate $\boldsymbol{\gamma}$s for isolated and non-isolated students. However, we allowed the school fixed effect to differ for the two types of students.

$\frac{\partial \overline{y}(\hat{\mathbf{y}}_s,\beta)}{\partial \beta} = \overline{y}'(\hat{\mathbf{y}}_s,\beta)$—our last instrument.[15] 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 $\overline{y}'(\hat{\mathbf{y}}_s,\beta)$ as a moment condition is justified by the fact that $\overline{y}'(\hat{\mathbf{y}}_s,\beta)$ is equal to the first-order condition for the nonlinear least-squares estimator in Section 5.8.2 of Cameron and Trivedi (2005).[16] Thus, the set of instruments for all non-isolated individuals can be summarized by $\mathbf{z}_{is} = [\mathbf{x}_{is}, \overline{y}_{-is}(\hat{\mathbf{y}}_s,\beta), \overline{y}'_{-is}(\hat{\mathbf{y}}_s,\beta)]$, 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 $\bar{y}_{-i,s} = \max_{j:g_{ij,s}=1} y_{j,s}$. While $\bar{z}_{i,s} = \max_{j:g_{ij,s}=1} \hat{y}_{j,s}$ is likely a good predictor of $\bar{y}_{-i,s}$, 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 $\bar{y}_{-i,s}$. 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.[17]

We therefore have four moment conditions, one from isolated individuals ($\mathbb{E}\left(\varepsilon_{is}\mathbf{x}_{is}\right) = \mathbf{0}$) and three from non-isolated individuals ($\mathbb{E}(\varepsilon_{is}\mathbf{x}_{is}) = \mathbf{0}$, $\mathbb{E}(\varepsilon_{is}\overline{y}_{-is}(\hat{\mathbf{y}}_s,\beta)) = \mathbf{0}$, and $\mathbb{E}(\varepsilon_{is}\overline{y}'_{-is}(\hat{\mathbf{y}}_s,\beta)) = \mathbf{0}$). 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 considered 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.

[15] See Section A.5 of Appendix A for a formal derivation of $\frac{\partial \overline{y}(\hat{\mathbf{y}},\beta)}{\partial \beta}$ in the theoretical model.

[16] 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).

[17] The OLS predictor is simple and performs well in our context, but it is worth noting that more flexible predictors could also be used, i.e., $\hat{y}_{i,s} = \hat{f}(\mathbf{X}_s)$ for some function $\hat{f}$.

3.3 Data description

Our analysis is based on a well-known database on friendship networks from the National Longitudinal Survey of Adolescent Health (AddHealth). The AddHealth survey has been designed to study the impact of the social environment (i.e., friends, family, neighborhood, and school) on adolescents' behavior in the United States by collecting data on students in grades 7–12 from a nationally representative sample of more than 130 private and public schools in years 1994–1995. AddHealth provides a wealth of information regarding student's 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.[18]

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 limitation 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. We do so due to the large computational burden of controlling for network endogeneity and the negligible effect it should have on illustrating our theory. Indeed, as stated in the introduction, most peer/network effect papers find that the difference between controlling and not controlling for network endogeneity is small.

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.[19] 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 1.

[18]The precise sample size varies by activity; for exact numbers, see Table 1.

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

Table 1: 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 Appendix C.

Table 1 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 risky behavior reflects an increased level of activity; a higher value for self-esteem reflects an increased levels of self-esteem; a higher value for exercise reflects a greater frequency of exercise. Importantly, 14–15 percent of students did not report any friends, and we labeled them *isolated*.[20] Lastly, the activity or outcome values reported in Table 1 often included an outcome of zero (e.g., non-smokers never smoke). Equation (16) 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.[21]

3.4 Empirical results

We proceed in two independent steps. First, we test which LIM model (conformist, spillover, or general) is the most appropriate one for each activity in the data. Second, we estimate the value of β to determine the relevant peer reference group. 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 as described in Section 3.3.

3.4.1 Spillover, conformism, or general: Linear-in-means model

We start with the GMM results of (21), whereby we impose the social norm of the *average peer*, $\beta = 1$. Henceforth, we refer to this as the *general LIM* model. Table 2 presents the results for the λ's of our 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 (22)). 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, $2(N^k + N)(Q^k(\lambda) - Q(\lambda_1, \lambda_2))$, with $k = C, S$, comparing the two separate models (spillover and conformist) to the general LIM model.[22] This

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

[21]For comparability, we did this for all activities. Results without adding 1 in instances where $\beta > 1$ are comparable and available upon request.

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

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 A1–A4 in Appendix C.

Table 2 shows a clear distinction between the two models (conformist vs. spillover), with one model usually preforming 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 (21)); 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.

Table 2 also reveals substantial heterogeneity in the varying magnitude of peer effects across different model specifications. To illustrate, we can compare the total peer effect in the general LIM model, $(\lambda_1 + \lambda_2)$, versus the peer effect in the reduced form model, λ. For GPA, self esteem, fighting, and smoking, the total peer effect across the general LIM model and the reduced-form LIM model are almost identical. For the remaining activities, the estimate of λ in the reduced form and $(\lambda_1 + \lambda_2)$ in the general LIM model differ by various degrees: (*i*) roughly 10 percent for social clubs, exercise, and trouble behavior; (*ii*) roughly 30 percent for risky behavior; (*iii*) roughly 40 percent for study effort; and (*iv*) roughly 190 percent for drinking. However, as shown in Section 2.3, the policy implications of each model significantly differ between the conformism and the spillover model. Thus, simply comparing the total peer effects, $(\lambda_1 + \lambda_2)$, can be misleading. We return to this point in Section 4.

3.4.2 Peer preferences with general social norms

Table 3 shows the results for the general model with estimated peer preferences, the βs. For comparison purposes, the table also shows the general LIM model and reduced-form estimates from Table 2. While we estimate all three versions: (*i*) the general model, (*ii*) the general model only with spillovers imposing $\lambda_2 = 0$, and (*iii*) the general model only with conformism imposing $\lambda_1 = 0$ for exposition purposes, we only show the model with the "best fit" (lowest objective value) under the assumption of an unconstrained β.[23]

[23]Full results for spillover and conformism versions of the model are available upon request. Full results for the general model can be found in Table A5 of Appendix C.

Table 2: Structural estimation versus reduced form: Linear-in-means model

	General model with $\beta = 1$			Spillover			Conformism			Reduced form
Activity	$\boldsymbol{\lambda}_1$	$\boldsymbol{\lambda}_2$	**Obj. Value**	$\boldsymbol{\lambda}_1$	**Obj. Value**	**L-R test**	$\boldsymbol{\lambda}_2$	**Obj. Value**	**L-R test**	$\boldsymbol{\lambda}$
GPA	0.388	0.190	0.0026	0.519	0.0035	122.1	0.406	0.0085	814.4	0.589
	(0.062)	(0.042)		(0.019)			(0.019)			(0.019)
Clubs	0.349	0.344	0.0023	0.612	0.0030	109.9	0.529	0.0040	259.0	0.638
	(0.104)	(0.070)		(0.034)			(0.030)			(0.033)
Self-esteem	0.252	0.027	0.0027	0.270	0.0028	5.7	0.154	0.0035	110.9	0.289
	(0.108)	(0.072)		(0.035)			(0.034)			(0.035)
Risky	-0.185	0.492	0.0017	0.079	0.0067	752.9	0.467	0.0023	83.3	0.235
	(0.069)	(0.032)		(0.037)			(0.029)			(0.034)
Exercise	0.181	0.021	0.0017	0.193	0.0017	2.8	0.094	0.0029	168.1	0.177
	(0.060)	(0.038)		(0.021)			(0.020)			(0.022)
Study effort	-0.017	0.322	0.0010	0.125	0.0027	258.6	0.315	0.0011	10.0	0.216
	(0.084)	(0.043)		(0.040)			(0.034)			(0.041)
Fight	0.062	0.188	0.0013	0.172	0.0021	117.4	0.209	0.0013	10.6	0.254
	(0.075)	(0.043)		(0.031)			(0.028)			(0.031)
Smoke	0.130	0.624	0.0009	0.442	0.0055	686.6	0.675	0.0013	66.6	0.732
	(0.067)	(0.035)		(0.031)			(0.028)			(0.031)
Drink	-0.177	0.626	0.0019	0.102	0.0084	964.5	0.601	0.0026	110.2	0.156
	(0.072)	(0.029)		(0.044)			(0.029)			(0.043)
Trouble	0.225	0.251	0.0007	0.391	0.0012	61.8	0.374	0.0012	74.5	0.521
	(0.115)	(0.073)		(0.041)			(0.039)			(0.042)

Notes: *General Model* results are for estimation of (21), *Spillover* are results for (21) 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 $\boldsymbol{\gamma}$ can be found in Appendix C.

Just two of the ten activities have marginal cases regarding the most appropriate general model choice (spillover, conformism, or both). More specifically, consistent with the results of the general LIM model, although the objective value is, by construction, always lowest for the general model with both spillovers and conformism, the LR-ratio statistics between the general model and the general model with only spillovers are 1.1 for self-esteem and 0.8 for exercise, respectively. As the coefficient on λ_2 for self-esteem and exercise are statistically zero, the general model exclusively estimates spillover effects. Correspondingly, estimates of λ_1 and β for the general model with only spillovers are very similar to the general model reported here.

Table 3 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 $\beta = 1$.

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 (20 percent), (*iv*) exercise (30 percent), and (V) self-esteem, risky behavior, exercise and smoking (10 percent).[24,25] Only for social clubs and self-esteem the total peer effects remain unchanged.

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

[25]For some instances, differences are even larger when compared to the reduced-form estimation. Comparing the general model peer effect to the reduced form and comparing between the two general models, the differences for (*i*) drinking are 280 and 30 percent, (*ii*) study effort are 70 and 20 percent, (*iii*) risky behavior are 40 and 10 percent, (*iv*) exercise are 30 and 10 percent, (*v*) GPA 40 and 30 percent, and (*vi*) smoking 20 and 10 percent, respectively.

Table 3: 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	0.320	0.058	370.781	0.0014	0.388	0.190	0.0026	179.5	0.589
	(0.061)	(0.046)	(114.860)		(0.062)	(0.042)			(0.019)
Clubs	0.331	0.333	1.398	0.0022	0.349	0.344	0.0023	19.1	0.638
	(0.108)	(0.071)	(0.167)		(0.104)	(0.070)			(0.033)
Self esteem	0.284	0.010	22.282	0.0020	0.252	0.027	0.0027	110.1	0.289
	(0.112)	(0.073)	(8.103)		(0.108)	(0.072)			(0.035)
Risky	-0.162	0.497	0.757	0.0016	-0.185	0.492	0.0017	9.6	0.235
	(0.081)	(0.032)	(0.359)		(0.069)	(0.032)			(0.034)
Exercise	0.210	0.012	8.143	0.0008	0.181	0.021	0.0017	122.2	0.177
	(0.060)	(0.038)	(3.447)		(0.060)	(0.038)			(0.022)
Study effort	0.021	0.340	3.904	0.0008	-0.017	0.322	0.0010	39.8	0.216
	(0.087)	(0.042)	(1.389)		(0.084)	(0.043)			(0.041)
Fight	-0.081	0.123	73.578	0.0011	0.062	0.188	0.0013	19.1	0.254
	(0.054)	(0.044)	(14.866)		(0.075)	(0.043)			(0.031)
Smoke	0.208	0.649	0.692	0.0006	0.130	0.624	0.0009	40.7	0.732
	(0.091)	(0.035)	(0.139)		(0.067)	(0.035)			(0.031)
Drink	-0.052	0.640	0.362	0.0018	-0.177	0.626	0.0019	14.5	0.156
	(0.104)	(0.029)	(0.233)		(0.072)	(0.029)			(0.043)
Trouble	0.291	0.000	-414.969	0.0005	0.225	0.251	0.0007	34.4	0.521
	(0.708)	(0.166)	(148.975)		(0.115)	(0.073)			(0.042)

Notes: Results under *Peer preferences* are for estimation of (21). We only report the best fit, namely the general model. We also report the best fit of the general LIM model ($\beta = 1$) and the reduced form from Table 2 for comparison. All results control for school fixed effects. Standard errors are reported in parentheses. In the case of the LIM model, likelihood ratio tests, $2(N^{LIM} + N)(Q^{LIM}(\lambda_1, \lambda_2) - Q(\lambda_1, \lambda_2))$, 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 Appendix C.

Furthermore, comparing spillover versus conformism effects, across the general model (GM) and the general LIM model shows substantial differences. For example, as peer preference increases towards the most active agent for GPA (i.e., $\beta = 371$), the conformism effect mostly 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. The same is true for trouble behavior, for which conformism plays no role, and there is a skewed peer preference towards the least active agents instead.

To illustrate the effect of the size of β on each social norm, Figure 1 shows the density distribution of social norms for non-isolated individuals from the standard LIM model and our general social norm (see Equation (16)) with estimates of β from Table 3. The figures provide a graphical illustration of the above 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., $\overline{y}(\mathbf{y}_{-i}, \beta)$) (see left panels of Figure 1) 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., $(\lambda_1 + \lambda_2)\overline{y}(\mathbf{y}_{-i}, \beta)$) (see right panels of Figure 1). Estimates of β and λ's for the general model are from the left-hand side of Table 3. Estimates of β and λ's for the general LIM model are from the right-hand side of Table 3. Finally, estimates for λ for the LIM model are from the column of the extreme right of Table 3.

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 can be found in Appendix C.

The first row of Figure 1 shows the results for risky behavior, which has an estimate of peer preference close to the average peer, namely $\beta = 0.757$. As the coefficient is close to one, the density distribution of the individuals' social norm is similar to the LIM model (panel (a)). The right panel (panel (b)) also shows the result of varying estimates on the intensity of the peer effect. Theses estimates differ substantially for the general model, compared to the reduced form LIM model, which has considerably more mass to the left.

The second row shows the social norm for study effort, for which the coefficient is now above one (i.e., $\beta = 3.904$). This leads to a slight skewedness towards the right for the general model (panel (c)), but it is still small. However, unlike the result for risky behavior, the *total peer effect* ($\lambda\overline{y}_{-i}$) shows large variance across the three models, with the general model strongly skewed toward higher peer effect outcomes (panel (d)).

Lastly, the third row shows an example where peer preference is highly skewed towards active agents (i.e., $\beta = 370.781$) for GPA outcomes. The distribution of the social norm is skewed toward the right, with several distinct peaks, but still far from the "most" active agents (panel (e)). 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 is perfectly hump-shaped following the average peer social norm. Panel (f) shows that the intensity of peer preference across the three models greatly exacerbates differences between the general model and the LIM models.

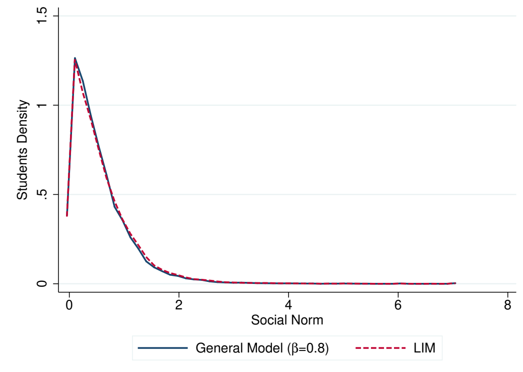
These three different examples highlight the importance of moving towards a general theory of peer effects. There is a large range of peer preference estimates (i.e., the βs). These differences translate into vastly different social norms that cannot be approximated by either the average, the most active 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

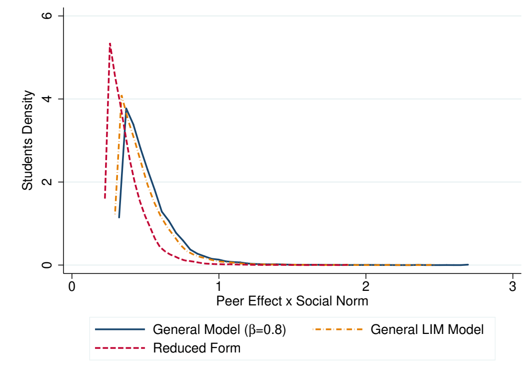
Returning to the discussion of policy implications from Section 2.3, we now illustrate the importance of microfounding a model of peer effects through our estimated activities. We proceed in two steps. First, following the general estimation procedure, we simulate the Nash equilibrium and the social 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 2, we display the (kernel) density of the subsidies required for all non-isolated individuals to reach the first best for each model (see Equation (A.36) in Appendix A). We use the same three activities as in Figure 1; the results for all the other activities can be found in Appendix C. In the left panels of Figure 2, 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).

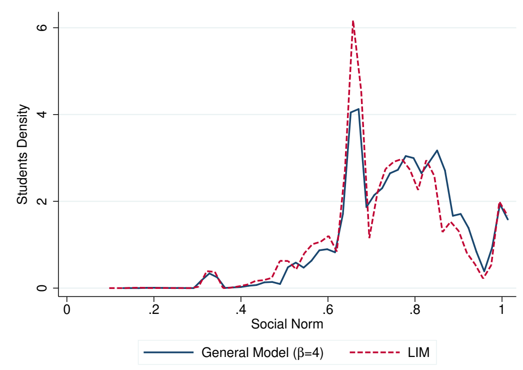
Figure 1: *Social norms and peer effects (Examples)*



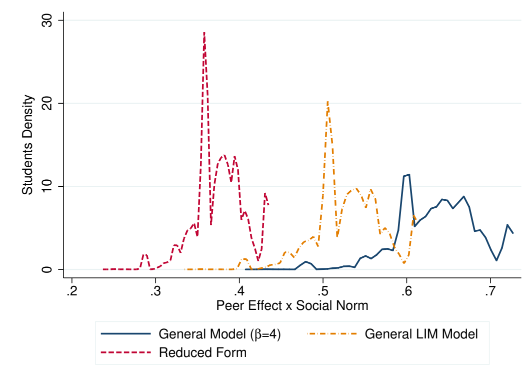
(a) Social Norm (Risky Behavior)



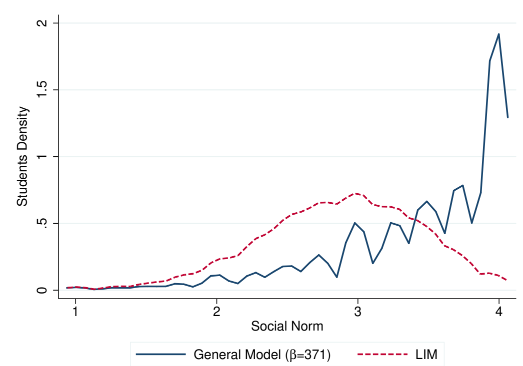
(b) Peer Effect (Risky Behavior)



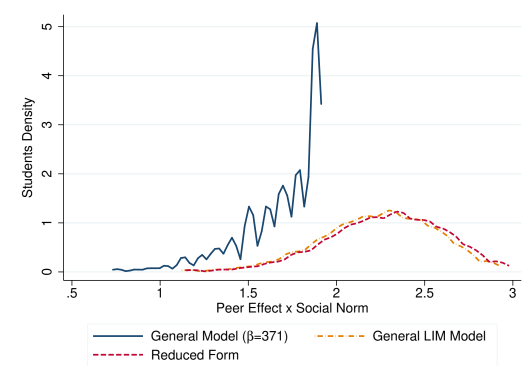
(c) Social Norm (Study Effort)



(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 3. Estimates of β and λ's for the general LIM model are from the right-hand side of Table 3. Estimates for λ for the linear-in-means model are from the right-most column of Table 2.

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 2 and 3.[26] 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 (A.36). 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 unbounded 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 Appendix A.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 microfoundation. Consider the left panels in Figure 2, 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 (red dashed line in left panels of Figure 2), while GPA is almost exclusively driven by spillover effects (blue solid line). However, picking between the conformism (right dashed line) and spillover (blue 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 2, 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.[27] 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).

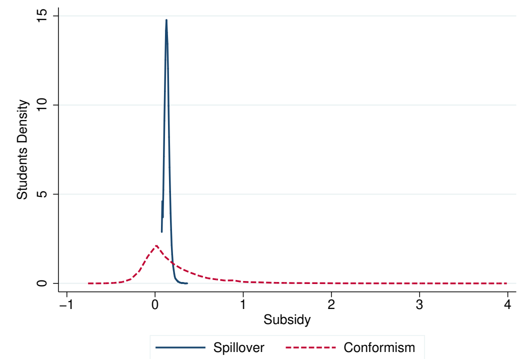
[26] Errors come from the same normal distribution with mean zero, but truncation is individual specific, based on the natural bounds of each outcome (e.g., the outcomes for GPA lie between 1 and 4.

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

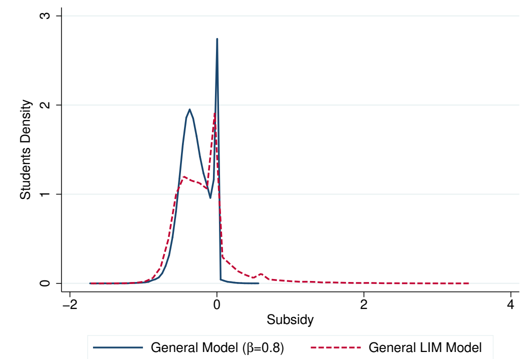
More specifically, in panel (b), for risky behavior, since peer preferences are close to 1 ($\beta = 0.757$), the general model policy implications seem to be similar to that of the general LIM model. There is, however, one subtle difference: The general model mostly taxes individuals, while the general 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 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., $\beta = 3.904$), the social planner can implement more *targeted polices* 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.

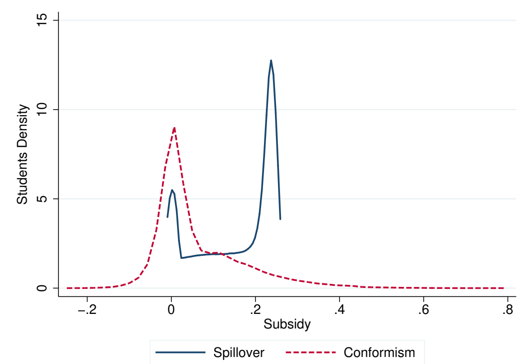
Figure 2: *First-best subsidies (Examples)*



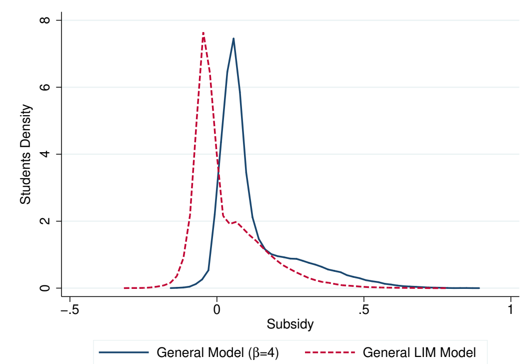
(a) LIM (Risky Behavior)



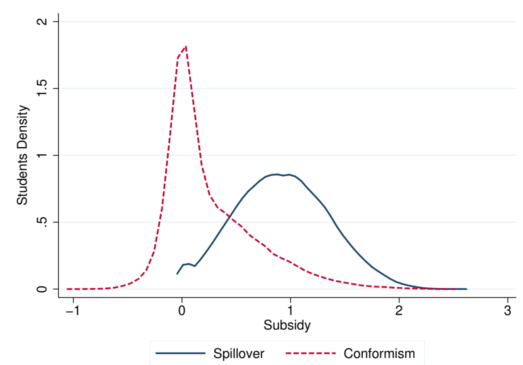
(b) Peer Preference (Risky Behavior)



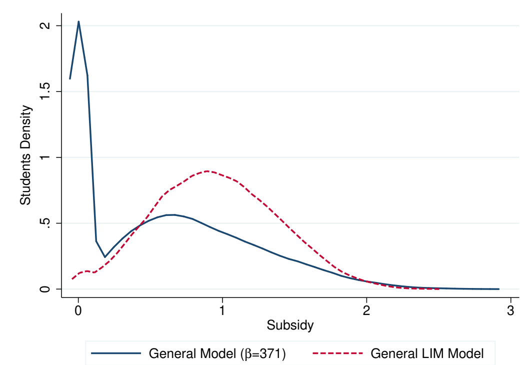
(c) LIM (Study Effort)



(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 2; and (*ii*) the general model and general LIM model using estimates from the right-hand panel of Table 3.

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 (see (A.33)). In contrast, in the general model, since peer preferences are skewed towards the most active agents (i.e., $\beta = 370.781$), 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 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 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*.

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 shown that two possible models, one based on spillover effects and the other on conformist behavior, can provide a microfoundation of the LIM model, and that the policy implications of these models are drastically different. We have also developed a general model that embeds these two models as special cases 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 most 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.

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Appendix

A Theory

A.1 Existence of Nash equilibrium

Define the social norm mapping $\overline{\mathbf{y}} : \mathbb{R}_+^n \to \mathbb{R}_+^n$ as follows:[28]

$$\overline{\mathbf{y}}(\mathbf{y}) \equiv \begin{pmatrix} \overline{y}_1(\mathbf{y}) \\ \overline{y}_2(\mathbf{y}) \\ \vdots \\ \overline{y}_n(\mathbf{y}) \end{pmatrix}. \tag{A.1}$$

As stated in the main text, the main technical complication compared to the standard *linear* local-average model is that, in our model, the mapping $\mathbf{y} \to \overline{\mathbf{y}}$ of efforts into norms is non-linear.

In what follows, we adopt the following notations:

$$y_{\min}(\mathbf{y}) \equiv \min\{y_i, y_2, \dots, y_n\}, \qquad y_{\max}(\mathbf{y}) \equiv \max\{y_1, y_2, \dots, y_n\},$$

$$\overline{y}_{\min}(\mathbf{y}) \equiv \min\{\overline{y}_1(\mathbf{y}), \overline{y}_2(\mathbf{y}), \dots, \overline{y}_n(\mathbf{y})\}, \quad \overline{y}_{\max}(\mathbf{y}) \equiv \max\{\overline{y}_1(\mathbf{y}), \overline{y}_2(\mathbf{y}), \dots, \overline{y}_n(\mathbf{y})\}.$$

Lemma 2. *For any $\mathbf{y} \in \mathbb{R}_+^n$, the following inequalities hold:*

$$y_{\min}(\mathbf{y}) \leq \overline{y}_{\min}(\mathbf{y}) \leq \overline{y}_{\max}(\mathbf{y}) \leq y_{\max}(\mathbf{y}). \tag{A.2}$$

Proof. Observe that (i) the social norm mapping $\overline{\mathbf{y}}(\cdot)$ defined by (16) is monotone increasing over $\mathbb{R}_+^n$, and (ii) $\overline{\mathbf{y}}(t\mathbf{1}) = t\mathbf{1}$ for any scalar $t \geq 0$. Hence:

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

which is equivalent to (A.2). This completes the proof. □

We now provide two different proofs for the existence of equilibrium. The first one uses the standard Brower fixed point theorem. The second one use monotonicity argument from supermodular games (Milgrom and Roberts, 1990a; Vives, 1990b).

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

A.1.1 Existence of equilibrium: A topological proof

For any $\theta > 0$, we have: $\theta = \lambda/(1-\lambda)$, with $\lambda \in (0,1)$. The best-reply (BR) mapping in the game is given by (see (13)):

$$\mathbf{y} = \mathbf{b}(\mathbf{y}) \equiv (1-\lambda_2)\boldsymbol{\alpha} + (\lambda_1+\lambda_2)\overline{\mathbf{y}}(\mathbf{y}). \tag{A.3}$$

where $\mathbf{b}(\mathbf{y})$ denote the vector of best-reply functions. Let $\mu := \lambda_1 + \lambda_2 \in (0,1)$. For each $i = 1, 2, \ldots, n$, define

$$\widetilde{\alpha}_i := \frac{1-\lambda_2}{1-\mu}\alpha_i \qquad \text{and} \qquad \widetilde{\boldsymbol{\alpha}} := (\widetilde{\alpha}_1, \widetilde{\alpha}_2, \ldots, \widetilde{\alpha}_n)\,. \tag{A.4}$$

Then, the BR mapping (A.3) can be rewritten as follows:

$$\mathbf{y} = \mathbf{b}(\mathbf{y}) := (1-\mu)\widetilde{\boldsymbol{\alpha}} + \mu\overline{\mathbf{y}}(\mathbf{y}). \tag{A.5}$$

Let $\widetilde{\alpha}_{\min}$ and $\widetilde{\alpha}_{\max}$ be the productivity levels of the least productive agent and the most productive agent, respectively, that is,

$$\widetilde{\alpha}_{\min} := \min\{\widetilde{\alpha}_1, \widetilde{\alpha}_2, \ldots, \widetilde{\alpha}_n\}, \qquad \widetilde{\alpha}_{\max} := \max\{\widetilde{\alpha}_1, \widetilde{\alpha}_2, \ldots, \widetilde{\alpha}_n\}.$$

Define a compact n-dimensional cube $C \subset \mathbb{R}^n_{++}$ by

$$C \equiv \left\{\mathbf{y} \in \mathbb{R}^n_+ : \widetilde{\alpha}_{\min}\mathbf{1} \leq \mathbf{y} \leq \widetilde{\alpha}_{\max}\mathbf{1}\right\}. \tag{A.6}$$

Lemma 3. *The best-reply mapping* $\mathbf{b}(\cdot)$ *defined in* (A.5) *maps the compact cube* C *defined by* (A.6) *into itself:*

$$\mathbf{y} \in C \quad \Longrightarrow \quad \mathbf{b}(\mathbf{y}) \in C. \tag{A.7}$$

Proof. Observe that (i) the best reply mapping (A.5) is monotone increasing over $\mathbb{R}^n_+$, and (ii) $\overline{\mathbf{y}}(t\mathbf{1}) = t\mathbf{1}$ for any scalar $t \geq 0$. Hence, for any $\mathbf{y}$ such that $\widetilde{\alpha}_{\min}\mathbf{1} \leq \mathbf{y} \leq \widetilde{\alpha}_{\max}\mathbf{1}$, the following inequalities hold:

$$\widetilde{\alpha}_{\min}\mathbf{1} \leq (1-\mu)\widetilde{\boldsymbol{\alpha}} + \mu\widetilde{\alpha}_{\min}\mathbf{1} = (1-\mu)\widetilde{\boldsymbol{\alpha}} + \mu\overline{\mathbf{y}}\left(\widetilde{\alpha}_{\min}\mathbf{1}\right) = \mathbf{b}\left(\widetilde{\alpha}_{\min}\mathbf{1}\right) \leq \mathbf{b}(\mathbf{y}),$$

$$\mathbf{b}(\mathbf{y}) \leq \mathbf{b}\left(\widetilde{\alpha}_{\max}\mathbf{1}\right) = (1-\mu)\boldsymbol{\alpha} + \mu\overline{\mathbf{y}}\left(\widetilde{\alpha}_{\max}\mathbf{1}\right) = (1-\mu)\widetilde{\boldsymbol{\alpha}} + \mu\widetilde{\alpha}_{\max}\mathbf{1} \leq \widetilde{\alpha}_{\max}\mathbf{1}.$$

Thus, we have:

$$\widetilde{\alpha}_{\min}\mathbf{1} \leq \mathbf{y} \leq \widetilde{\alpha}_{\max}\mathbf{1} \quad \Longrightarrow \quad \widetilde{\alpha}_{\min}\mathbf{1} \leq \mathbf{b}(\mathbf{y}) \leq \widetilde{\alpha}_{\max}\mathbf{1},$$

which, by the definition (A.6) of C, is equivalent to (A.7). This completes the proof. □

Proposition 4. *For any $\boldsymbol{\alpha} \in \mathbb{R}_{++}$, any $\lambda \in (0,1)$, any $\beta \in [-\infty, +\infty]$, and any network $\mathbf{g}$, there exists an interior Nash equilibrium $\mathbf{y}^*$.*

Proof. Observe first that C is a convex compact subset of $\mathbb{R}^n$, while $\mathbf{b}(\cdot)$ is continuous over C. Combining this with Lemma 3 and using Brower's fixed point theorem, we conclude that $\mathbf{b}(\cdot)$ has a fixed point $\mathbf{y}^* \in C$. That $\mathbf{y}^*$ is a Nash equilibrium follows immediately from the fact that $\mathbf{y} = \mathbf{b}(\mathbf{y}) \Longleftrightarrow \partial U_i(y_i, \mathbf{y}_{-i})/\partial y_i = 0$ for all $i = 1, 2, \ldots, n$. Furthermore, because each utility function $U_i(y_i, \mathbf{y}_{-i})$ is quadratic and strictly concave in the own choice variable y_i, the second-order conditions hold automatically. Finally, because $C \subset \mathbb{R}^n_{++}$ by construction, $\mathbf{y}^* \in C$ is an interior equilibrium. This completes the proof. □

A.1.2 Existence of equilibrium: A monotonicity-based proof

Let us provide an alternative proof of Proposition 4 based on supermodular games.

For each $k = 0, 1, 2, \ldots$, define $\mathbf{x}_k \in \mathbb{R}^n_+$ and $\mathbf{z}_k \in \mathbb{R}^n_+$ as follows:

$$\mathbf{x}_0 := \widetilde{\alpha}_{\min}\mathbf{1}, \qquad \mathbf{x}_{k+1} := \mathbf{b}(\mathbf{x}_k), \qquad k = 0, 1, 2, \ldots \tag{A.8}$$

$$\mathbf{z}_0 := \widetilde{\alpha}_{\max}\mathbf{1}, \qquad \mathbf{z}_{k+1} \equiv \mathbf{b}(\mathbf{z}_k), \qquad k = 0, 1, 2, \ldots \tag{A.9}$$

The following Lemma states that the smallest and largest Nash equilibria can be obtained by iterating the best reply mapping $\mathbf{b}(\cdot)$.

Lemma 5. *The smallest Nash equilibrium $\mathbf{y}^*$ and the largest Nash equilibrium $\mathbf{y}^{**} \geq \mathbf{y}^*$ are given, respectively, by:*

$$\mathbf{y}^* = \lim_{k\to\infty} \mathbf{x}_k, \qquad \mathbf{y}^{**} = \lim_{k\to\infty} \mathbf{z}_k, \tag{A.10}$$

where $\mathbf{x}_k$ and $\mathbf{z}_k$ are defined, respectively, by (A.8) and (A.9).

Proof. It suffices to prove that: (*i*) both limits, $\mathbf{y}^*$ and $\mathbf{y}^{**}$, exist; (*ii*) both $\mathbf{y}^*$ and $\mathbf{y}^{**}$ are Nash equilibria; and (*iii*) for any Nash equilibrium $\widetilde{\mathbf{y}}$, we have: $\mathbf{y}^* \leq \widetilde{\mathbf{y}} \leq \mathbf{y}^{**}$.

Step 1: The limits $\mathbf{y}^*$ and $\mathbf{y}^{**}$ exist.

Let us prove by induction that, for any $k = 0, 1, 2, \ldots$, the following inequalities hold:

$$\mathbf{x}_k \leq \mathbf{x}_{k+1} \leq \widetilde{\alpha}_{\max}\mathbf{1}, \qquad \mathbf{z}_k \geq \mathbf{z}_{k+1} \geq \widetilde{\alpha}_{\min}\mathbf{1}. \tag{A.11}$$

Basis: For $k = 0$, we have:

$$\widetilde{\alpha}_{\min}\mathbf{1} = \mathbf{x}_0 \leq \mathbf{x}_1 = (1-\mu)\widetilde{\boldsymbol{\alpha}} + \mu\widetilde{\alpha}_{\min}\mathbf{1} \leq \widetilde{\alpha}_{\max}\mathbf{1},$$

$$\widetilde{\alpha}_{\max}\mathbf{1} = \mathbf{z}_0 \geq \mathbf{z}_1 = (1-\lambda)\widetilde{\boldsymbol{\alpha}} + \lambda\widetilde{\alpha}_{\max}\mathbf{1} \geq \widetilde{\alpha}_{\min}\mathbf{1}.$$

In the second line we use that $\overline{\mathbf{y}}\,(t\mathbf{1}) = t\mathbf{1}$ for any scalar $t \geq 0$, which is implied by (16).

Induction step: Assume that (A.11) holds for some integer k (for example, we have just shown that they hold for $k = 0$). Then, using the monotonicity of $\mathbf{b}(\cdot)$, we have:

$$\mathbf{x}_{k+1} = \mathbf{b}(\mathbf{x}_k) \leq \mathbf{b}(\mathbf{x}_{k+1}) \leq \mathbf{b}(\widetilde{\alpha}_{\max}\mathbf{1}) \leq \widetilde{\alpha}_{\max}\mathbf{1},$$

$$\mathbf{z}_{k+1} = \mathbf{b}(\mathbf{z}_k) \geq \mathbf{b}(\mathbf{z}_{k+1}) \geq \mathbf{b}(\widetilde{\alpha}_{\min}\mathbf{1}) \geq \widetilde{\alpha}_{\min}\mathbf{1}.$$

Combining this with (A.8)–(A.9) yields

$$\mathbf{x}_{k+1} \leq \mathbf{x}_{k+2} \leq \widetilde{\alpha}_{\max}\mathbf{1}, \qquad \mathbf{z}_{k+1} \geq \mathbf{z}_{k+2} \geq \widetilde{\alpha}_{\min}\mathbf{1}.$$

Hence, if (A.11) holds for some integer k, the same is true for $k+1$. This completes the induction step and proves that (A.11) holds for all $k = 0, 1, 2, \ldots$

The inequalities (A.11) imply that $\{\mathbf{x}_k\}$ is an ascending sequence bounded from above, while $\{\mathbf{z}_k\}$ is a descending sequence bounded from below. Hence, both $\{\mathbf{x}_k\}$ and $\{\mathbf{z}_k\}$ must converge. This proves the existence of the limits $\mathbf{y}^*$ and $\mathbf{y}^{**}$.

Step 2: $\mathbf{y}^*$ and $\mathbf{y}^{**}$ are Nash equilibria.

By the continuity of $\mathbf{b}(\cdot)$, we have:

$$\mathbf{y}^* = \lim_{k\to\infty} \mathbf{x}_k = \lim_{k\to\infty} \mathbf{x}_{k+1} = \lim_{k\to\infty} \mathbf{b}\left(\mathbf{x}_k\right) = \mathbf{b}\left(\mathbf{y}^*\right),$$

$$\mathbf{y}^{**} = \lim_{k\to\infty} \mathbf{z}_k = \lim_{k\to\infty} \mathbf{z}_{k+1} = \lim_{k\to\infty} \mathbf{b}\left(\mathbf{z}_k\right) = \mathbf{b}\left(\mathbf{y}^{**}\right).$$

Hence, both $\mathbf{y}^*$ and $\mathbf{y}^{**}$ are fixed points of $\mathbf{b}(\cdot)$. Thus, they are Nash equilibria (see proof of Proposition 4 above).

Step 3: $\mathbf{y}^* =$ smallest equilibrium, $\mathbf{y}^{**} =$ largest equilibrium.

As implied by Step 2, the set of Nash equilibria is non-empty. So, let $\widetilde{\mathbf{y}}$ be some Nash equilibrium. We need to show that $\mathbf{y}^* \leq \widetilde{\mathbf{y}} \leq \mathbf{y}^{**}$. Due to (A.10), it suffices to prove instead that, for any $k = 0, 1, 2, \dots$, we have:

$$\mathbf{x}_k \leq \widetilde{\mathbf{y}} \leq \mathbf{z}_k. \tag{A.12}$$

We proceed by induction.

Basis: we first prove (A.12) for $k = 0$. Because $\widetilde{\mathbf{y}}$ is a Nash equilibrium, it must satisfy (A.3). Applying the function $y_{\min}(\cdot)$ to both parts of (A.12), and using the Jensen's inequality for concave functions and Lemma 2, we get:

$$y_{\min}(\widetilde{\mathbf{y}}) \geq (1-\mu)\widetilde{\alpha}_{\min} + \mu \overline{y}_{\min}(\widetilde{\mathbf{y}}) \geq (1-\mu)\widetilde{\alpha}_{\min} + \mu y_{\min}(\widetilde{\mathbf{y}}).$$

Similarly, applying the function $y_{\max}(\cdot)$ to both parts of (A.12), and using Jensen's inequality for convex functions and Lemma 2, we get:

$$y_{\max}(\widetilde{\mathbf{y}}) \leq (1-\mu)\widetilde{\alpha}_{\max} + \mu \overline{y}_{\max}(\widetilde{\mathbf{y}}) \leq (1-\mu)\widetilde{\alpha}_{\max} + \mu y_{\max}(\widetilde{\mathbf{y}}).$$

Hence, we have: $y_{\min}(\widetilde{\mathbf{y}}) \geq \widetilde{\alpha}_{\min}$ and $y_{\max}(\widetilde{\mathbf{y}}) \leq \widetilde{\alpha}_{\max}$. This, in turn, implies that $\widetilde{\alpha}_{\min} \leq \widetilde{y}_i \leq \widetilde{\alpha}_{\max}$ for all $i = 1, 2, \dots, n$, or, equivalently:

$$\mathbf{x}_0 = \widetilde{\alpha}_{\min}\mathbf{1} \leq \widetilde{\mathbf{y}} \leq \widetilde{\alpha}_{\max}\mathbf{1} = \mathbf{z}_0. \tag{A.13}$$

This proves (A.12) for $k = 0$. Note also that (A.13) implies that any Nash equilibrium belongs to the cube C defined by (A.6).

Induction step: Let (A.12) hold for some integer k (for example, this is true for $k = 0$). Applying the best reply mapping $\mathbf{b}(\cdot)$ to all terms in (A.12) and using monotonicity of $\mathbf{b}(\cdot)$, we get:

$$\mathbf{b}(\mathbf{x}_k) \leq \mathbf{b}(\widetilde{\mathbf{y}}) \leq \mathbf{b}(\mathbf{z}_k).$$

Because $\widetilde{\mathbf{y}}$ is a Nash equilibrium, we have: $\mathbf{b}(\widetilde{\mathbf{y}}) = \widetilde{\mathbf{y}}$. Combining this with (A.8) – (A.9), we get:

$$\mathbf{x}_{k+1} \leq \widetilde{\mathbf{y}} \leq \mathbf{z}_{k+1},$$

which proves that (A.12) holds for $k+1$, hence for all $k = 0, 1, 2 \ldots$ This completes the induction step, the proof of (A.12), Step 3, and thus the whole proof of Lemma 5.

□

Lemma 5 is very useful. Indeed, unlike the topological proof based on Brower's fixed point theorem, Lemma 5 allows to compute equilibria by iterating the best-reply mapping under parameter values estimated from the data. Furthermore, we will see below that the best-reply mapping $\mathbf{b}(\cdot)$ is a contraction mapping over the whole $\mathbb{R}_+^n$; hence the equilibrium is unique ($\mathbf{y}^* = \mathbf{y}^{**}$) and can be obtained by successive iterations of $\mathbf{b}(\cdot)$ no matter where we start.

Corollary 2. *If all the agents have the same productivity level $\alpha > 0$, i.e., if $\alpha_1 = \alpha_2 = \ldots = \alpha_n = \alpha$, then the equilibrium is unique and is given by*

$$\mathbf{y}^* = \widetilde{\alpha}\mathbf{1} = \mathbf{y}^{**},$$

where $\widetilde{\alpha} := \frac{1-\lambda_2}{1-\mu}\alpha$.

Proof. Using (A.8)–(A.9) and the identities $\overline{\mathbf{y}}(\alpha\mathbf{1}) = \alpha\overline{\mathbf{y}}(\mathbf{1}) = \alpha\mathbf{1}$, it is readily verified that, when $\boldsymbol{\alpha} = \alpha\mathbf{1}$, we have: $\mathbf{x}_k = \alpha\mathbf{1} = \mathbf{z}_k$ for all $k \geq 2$. Taking the limit on both sides under $k \to \infty$ proves the result. □

A.2 Uniqueness of Nash equilibrium

A.2.1 Uniqueness of Nash equilibrium for convex norms

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

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

We first prove a general uniqueness result for convex social norms, which does *not* require a CES functional form (16) of the social norm mapping $\overline{\mathbf{y}}(\cdot)$.

Proposition 6. *Let the social norm mapping $\overline{\mathbf{y}} : \mathbb{R}_+^n \to \mathbb{R}_+^n$ be any function which is (i) convex, i.e., the inequality $\overline{\mathbf{y}}((1-\gamma)\mathbf{x} + \gamma\mathbf{z}) \leq (1-\gamma)\overline{\mathbf{y}}(\mathbf{x}) + \gamma\overline{\mathbf{y}}(\mathbf{z})$ holds for any $\gamma \in [0,1]$ and for any $\mathbf{x}, \mathbf{z} \in \mathbb{R}_+^n$; (ii) positive homogeneous of degree 1, i.e., the equality $\overline{\mathbf{y}}(t\mathbf{z}) = t\overline{\mathbf{y}}(\mathbf{z})$ holds for any $t \in \mathbb{R}_+$ and for any $\mathbf{z} \in \mathbb{R}_+^n$; and (iii) satisfies the inequality $||\overline{\mathbf{y}}(\mathbf{z})||_\infty \leq ||\mathbf{z}||_\infty$ for any $\mathbf{z} \in \mathbb{R}_+^n$. Then, (A.5), and hence (A.3), has a unique fixed point.*

Proof. Consider again the consecutive approximations, $\mathbf{x}_k$ and $\mathbf{z}_k$, $k = 0, 1, 2, \ldots$, to the minimum equilibrium and the maximum equilibrium. Recall that $\mathbf{x}_k$ and $\mathbf{z}_k$ are defined by (A.8) and (A.9), respectively. It suffices to prove that $\lim_{k\to\infty}(\mathbf{z}_k - \mathbf{x}_k) = \mathbf{0}$, which will imply $\mathbf{y}^* = \mathbf{y}^{**}$, and hence uniqueness of equilibrium.

Using consecutively (A.8)–(A.9), (A.5), Jensen's inequality (i) for convex functions, and positive homogeneity (ii), we have for any $k = 0, 1, 2, \ldots$:

$$\begin{aligned}\mathbf{0} \leq \mathbf{z}_{k+1} - \mathbf{x}_{k+1} &= \mu\left(\overline{\mathbf{y}}(\mathbf{z}_k) - \overline{\mathbf{y}}(\mathbf{x}_k)\right) = \mu\left(\overline{\mathbf{y}}(\mathbf{x}_k + \mathbf{z}_k - \mathbf{x}_k) - \overline{\mathbf{y}}(\mathbf{x}_k)\right) \\ &= \mu\left[2\overline{\mathbf{y}}\left(\tfrac{1}{2}\mathbf{x}_k + \tfrac{1}{2}(\mathbf{z}_k - \mathbf{x}_k)\right) - \overline{\mathbf{y}}(\mathbf{x}_k)\right] \\ &\leq \mu\left[\overline{\mathbf{y}}\left(\mathbf{x}_k\right) + \overline{\mathbf{y}}\left(\mathbf{z}_k - \mathbf{x}_k\right) - \overline{\mathbf{y}}(\mathbf{x}_k)\right] = \mu\overline{\mathbf{y}}\left(\mathbf{z}_k - \mathbf{x}_k\right).\end{aligned}$$

By combining this with the monotonicity of the sup-norm, we obtain:

$$\mathbf{z} \geq \mathbf{x} \Longrightarrow ||\mathbf{z}||_\infty \geq ||\mathbf{x}||_\infty \quad \text{for any } \mathbf{x}, \mathbf{z} \in \mathbb{R}^n_+.$$

This, with assumption (iii) of the Proposition, we get:

$$||\mathbf{z}_{k+1} - \mathbf{x}_{k+1}||_\infty \leq \mu||\mathbf{z}_k - \mathbf{x}_k||_\infty,$$

which, in turn, implies by induction:

$$||\mathbf{z}_k - \mathbf{x}_k||_\infty \leq \mu^k||\mathbf{z}_0 - \mathbf{x}_0||_\infty = \mu^k(\alpha_{\max} - \alpha_{\min}) \underset{k\to\infty}{\longrightarrow} 0.$$

Equivalently, we have: $\lim_{k\to\infty}(\mathbf{z}_k - \mathbf{x}_k) = \mathbf{0}$, hence, $\mathbf{y}^* = \mathbf{y}^{**}$. This completes the proof. □

A.2.2 Uniqueness of Nash equilibrium for concave norms

We now prove a second general uniqueness result for concave social norms, which also does *not* require a CES functional form (16) of the social norm mapping $\overline{\mathbf{y}}(\cdot)$.

Proposition 7. *Let the social norm mapping* $\overline{\mathbf{y}} : \mathbb{R}^n_+ \to \mathbb{R}^n_+$ *be any concave function, i.e., the inequality* $\overline{\mathbf{y}}((1-\gamma)\mathbf{x} + \gamma\mathbf{z}) \geq (1-\gamma)\overline{\mathbf{y}}(\mathbf{x}) + \gamma\overline{\mathbf{y}}(\mathbf{z})$ *holds for any* $\gamma \in [0, 1]$ *and for any* $\mathbf{x}, \mathbf{z} \in \mathbb{R}^n_+$. *Then,* (A.3) *has a unique fixed point.*

Proof. Assume that, on the contrary, $\mathbf{y}^{**} \neq \mathbf{y}^*$. Define

$$\mathcal{I} \equiv \{i \,|\, y_i^{**} > y_i^*\}. \tag{A.14}$$

Because $\mathbf{y}^{**} \neq \mathbf{y}^*$ and $\mathbf{y}^{**} \geq \mathbf{x}^*$, it must be true that $\mathcal{I}$ is non-empty.

For each $i \in \mathcal{I}$, denote by τ_i the unique solution (in τ) to the equation:

$$\tau y_i^{**} + (1-\tau) y_i^* = 0. \tag{A.15}$$

Observe that $\tau_i < 0$ for all $i \in \mathcal{I}$.

Let $j \in \mathcal{I}$ be such that $\tau_j = \max\{\tau_i \,|\, i \in \mathcal{I}\}$. We have:

$$\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^* \geq \mathbf{0}. \tag{A.16}$$

To prove (A.16), assume first that $i \in \mathcal{I}$. Then, because the left-hand side of (A.15) is increasing in τ and because $\tau_j \geq \tau_i$ for all $i \in \mathcal{I}$, we have:

$$\tau_j y_i^{**} + (1-\tau_j) y_i^* \geq \tau_i y_i^{**} + (1-\tau_i) y_i^* = 0.$$

Assume now that $i \in \{1, 2, \ldots, n\} \setminus \mathcal{I}$. Then, $y_i^* = y_i^{**}$, and we have:

$$\tau_j y_i^{**} + (1-\tau_j) y_i^* = y_i^{**} = y_i^* \geq 0.$$

This proves (A.16). By definition of τ_j, we also have:

$$\tau_j y_j^{**} + (1-\tau_j) y_j^* = 0. \tag{A.17}$$

Let $b_j(\cdot)$ be the jth component of the best-reply mapping defined by (A.3). Because $\mathbf{y}^*$ and $\mathbf{y}^{**}$ are both Nash equilibria, we have:

$$b_j(\mathbf{y}^*) = y_j^*, \qquad b_j(\mathbf{y}^{**}) = y_j^{**}. \tag{A.18}$$

Because the social norm mapping is concave, so is $b_j(\cdot)$. Consider the following identity:

$$\mathbf{y}^* = \frac{-\tau_j}{1-\tau_j}\mathbf{y}^{**} + \frac{1}{1-\tau_j}\left(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*\right). \tag{A.19}$$

Because $\tau_j < 0$, the coefficients $\frac{-\tau_j}{1-\tau_j}$ and $\frac{1}{1-\tau_j}$ in the right-hand side of (A.19) are non-negative and sum up to one. Combining this with concavity of $b_j(\cdot)$ and using Jensen's inequality for concave functions, we get:

$$b_j(\mathbf{y}^*) \geq \frac{-\tau_j}{1-\tau_j} b_j(\mathbf{y}^{**}) + \frac{1}{1-\tau_j} b_j(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*),$$

or, equivalently,

$$b_j(\tau_j \mathbf{x}^{**} + (1-\tau_j)\mathbf{x}^*) \leq (1-\tau_j) b_j(\mathbf{x}^*) + \tau_j b_j(\mathbf{x}^{**}).$$

Using consecutively (A.18) and (A.17), we get:

$$b_j(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*) \leq (1-\tau_j) y_j^* + \tau_j y_j^{**} = 0. \tag{A.20}$$

However, using (A.16), the monotonicity of $b_j(\cdot)$, and the definition (A.3) of the best-reply mapping, we obtain:

$$b_j(\tau_j \mathbf{y}^{**} + (1-\tau_j)\mathbf{y}^*) \geq b_j(\mathbf{0}) = (1-\lambda)\alpha_j > 0,$$

which contradicts (A.20). This completes the proof. □

It is now straightforward to prove Proposition 1, i.e., the uniqueness of the Nash equilibrium of the game for which the utility function of each individual $i = 1, \cdots, n$ is given by (12) and her social norm $\overline{\mathbf{y}}_i$ has the CES functional form (16).

Consider first the case when $\beta \in (1, +\infty]$. In that case, the social norm mapping $\overline{\mathbf{y}} : \mathbb{R}_+^n \to \mathbb{R}_+^n$ is a *convex function*. Proposition 6 shows that there exists a unique fixed point of the best-reply functions (A.5), and hence (A.3), for any convex social norm mapping, which includes the CES social norm when $\beta \in (1, +\infty]$. This, clearly, implies that there exists a unique Nash equilibrium of this game for $\beta \in (1, +\infty]$.

Consider now the case when $\beta \in [-\infty, 1]$. In that case, the social norm mapping $\overline{\mathbf{y}} : \mathbb{R}_+^n \to \mathbb{R}_+^n$ is a *concave function*. Proposition 7 shows that there exists a unique fixed point of the best-reply functions (A.5), and hence (A.3), for any concave social norm mapping, which includes the CES social norm when $\beta \in [-\infty, 1]$. This, clearly, implies that there exists a unique Nash equilibrium of this game for $\beta \in [-\infty, 1]$.

A.3 Social optimum (first-best) for the spillover and the conformist 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.

A.3.1 The general model

Let us first solve the general model in which agents' utility is given by (12). The first best is equal to:

$$y_i = (1 - \lambda_2)\alpha_i + (\lambda_1 + \lambda_2)\overline{y}_{-i} + \lambda_1 \sum_j y_j \frac{\partial \overline{y}_{-j}}{\partial y_i} + \lambda_2 \sum_j (y_j - \overline{y}_{-j}) \frac{\partial \overline{y}_{-j}}{\partial y_i}, \tag{A.21}$$

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

$$\overline{y}_{-j} = \begin{cases} \sum_{k=1}^n \widehat{g}_{jk} y_k & \text{if } \beta = 1 \\ \left(\sum_{k=1}^n \widehat{g}_{jk} y_k^\beta\right)^{\frac{1}{\beta}} & \text{if } \beta \in]-\infty, +\infty[, \end{cases} \tag{A.22}$$

and

$$\frac{\partial \overline{y}_{-j}}{\partial y_i} = \begin{cases} \widehat{g}_{ji} = \widehat{g}_{ij} & \text{if } \beta = 1 \\ \widehat{g}_{ji} \left(\sum_{k=1}^n \widehat{g}_{jk} y_k^\beta\right)^{(\frac{1}{\beta}-1)} y_i^{\beta-1} > 0 & \text{if } \beta \in]-\infty, +\infty[. \end{cases} \tag{A.23}$$

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

Proposition 8. *Assume λ_1 and λ_2 are not too large. Then, the first best outcome is unique.*

Proof. Let us restate (A.21) in vector-matrix form:

$$\mathbf{y} = (1 - \lambda_2)\boldsymbol{\alpha} + \lambda_1 \mathbf{F}(\mathbf{y}) + \lambda_2 \mathbf{G}(\mathbf{y}), \tag{A.24}$$

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:

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

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

At the extreme case of $\lambda_1 = \lambda_2 = 0$, the fixed point condition (A.24) has a unique solution $\mathbf{y}^O = \boldsymbol{\alpha}$. Furthermore, since the right-hand side of (A.24) 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.24) defines a single-valued function $\mathbf{y}^O(\lambda_1, \lambda_2)$ for all $(\lambda_1, \lambda_2) \in \left[(0,0); (\widehat{\lambda}_1, \widehat{\lambda}_2)\right]$. It remains to prove that $\mathbf{y}^O(\lambda_1, \lambda_2)$ is a unique solution to (A.24). 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 $\widetilde{\mathbf{y}}(\lambda_1^k, \lambda_2^k) \neq \mathbf{y}^O(\lambda_1^k, \lambda_2^k)$. Two cases may arise.

Case 1: the sequence $\widetilde{\mathbf{y}}(\lambda_1^k, \lambda_2^k)$ 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.24), which violates the implicit function theorem.

Case 2: the sequence $\widetilde{\mathbf{y}}(\lambda_1^k, \lambda_2^k)$ 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.24) 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.24) under $(\lambda_1^k, \lambda_2^k, \widetilde{\mathbf{y}}(\lambda_1^k, \lambda_2^k)) \to (0, 0, \boldsymbol{\xi})$, we conclude that $\mathbf{y} = \boldsymbol{\xi}$ must be a solution to (A.24) in the extreme case of $\lambda_1 = \lambda_2 = 0$. But we have assumed $\boldsymbol{\xi} \neq \boldsymbol{\alpha}$, and (A.24) clearly has no solutions other than $\boldsymbol{\alpha}$, a contradiction.

This completes the proof. □

The linear-in-means model ($\beta = 1$)

Consider the special case of the LIM model ($\beta = 1$). Then, using the fact that $\widehat{g}_{ji} = \widehat{g}_{ij}$ and $\sum_j \widehat{g}_{ij} = 1$, the first best is given by

$$y_i = (1 - \lambda_2)\alpha_i + 2(\lambda_1 + \lambda_2)\overline{y}_{-i} - \lambda_2 \overline{y}_{-j}, \qquad \text{(A.25)}$$

where $\overline{y}_{-i} = \sum_j \widehat{g}_{ij} y_j$.

The general social norm

When the social norm $\overline{y}_{-i} \equiv \overline{y}(\mathbf{y}_{-i}, \beta)$ is given by (16), the first best is equal to:

$$\begin{aligned} y_i &= (1-\lambda_2)\alpha_i + (\lambda_1+\lambda_2)\left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}\right)^{\frac{1}{\beta}} + \lambda_1 \sum_j \widehat{g}_{ij}\ y_j \left(\sum_{k=1}^{n} \widehat{g}_{jk} y_k^{\beta}\right)^{(\frac{1}{\beta}-1)} y_i^{\beta-1} \\ &+ \lambda_2 \sum_j \widehat{g}_{ij}\left(y_j - \left(\sum_{k=1}^{n} \widehat{g}_{jk} y_k^{\beta}\right)^{\frac{1}{\beta}}\right)\left(\sum_{k=1}^{n} \widehat{g}_{jk} y_k^{\beta}\right)^{(\frac{1}{\beta}-1)} y_i^{\beta-1}. \end{aligned} \tag{A.26}$$

A.3.2 The conformist model

Let us consider the conformist model in which the agents' utility is given by (8).

The linear-in-means model ($\beta = 1$)

By assuming that $\lambda_1 = 0$ in (A.25), we obtain:

$$y_i = (1-\lambda_2)\alpha_i + 2\lambda_2 \sum_j \widehat{g}_{ij} y_j - \lambda_2 \sum_k \widehat{g}_{jk} y_k. \tag{A.27}$$

The general social norm

By assuming that $\lambda_1 = 0$ in (A.26), we obtain:

$$y_i = (1-\lambda_2)\alpha_i + \lambda_2\left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}\right)^{\frac{1}{\beta}} + \lambda_2 \sum_j \widehat{g}_{ij}\left(y_j - \left(\sum_{k=1}^{n} \widehat{g}_{jk} y_k^{\beta}\right)^{\frac{1}{\beta}}\right)\left(\sum_{k=1}^{n} \widehat{g}_{jk} y_k^{\beta}\right)^{(\frac{1}{\beta}-1)} y_i^{\beta-1}. \tag{A.28}$$

A.3.3 The spillover model

Let us now consider the spillover model in which the agents' utility is given by (4).

The linear-in-means model ($\beta = 1$)

By assuming that $\lambda_2 = 0$ in (A.25), we obtain:

$$y_i = \alpha_i + 2\lambda_1 \sum_j \widehat{g}_{ij} y_j. \tag{A.29}$$

The general social norm

By assuming that $\lambda_2 = 0$ in (A.26), we obtain:

$$y_i = \alpha_i + \lambda_1\left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}\right)^{\frac{1}{\beta}} + \lambda_1 \sum_j \widehat{g}_{ij}\ y_j \left(\sum_{k=1}^{n} \widehat{g}_{jk} y_k^{\beta}\right)^{(\frac{1}{\beta}-1)} y_i^{\beta-1}. \tag{A.30}$$

A.4 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 (12)):

$$U_i(y_i, \mathbf{y}_{-i}, \mathbf{g}) = (\alpha_i + S_i)\, y_i + \theta_1 y_i \overline{y}_{-i} - \frac{1}{2}\left[y_i^2 + \theta_2 \left(y_i - \overline{y}_{-i}\right)^2\right]. \tag{A.31}$$

A.4.1 Comparing the spillover and the conformist model for the linear-in-means model ($\beta = 1$)

The spillover model

In (A.29), we show that 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.

As stated above, to restore the first best, the planner could subsidize the efforts of all agents. Consider the utility (A.31) for the spillover model, that is, when $\theta_2 = 0$. We obtain:

$$U_i^S(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \left(\alpha_i + S_i^S\right) y_i + \lambda_1 y_i \overline{y}_{-i} - \frac{1}{2} y_i^2. \tag{A.32}$$

where $\lambda_1 := \theta_1$ and S_i^S denotes the optimal subsidy per effort in the spillover model. If[29]

$$S_i^S = \lambda_1 \sum_j \widehat{g}_{ij} y_j^o = \lambda_1 \overline{y}_{-i}^o, \tag{A.33}$$

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.27), which is neither 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. Ths 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

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

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.31) for the conformist model, that is, when $\theta_1 = 0$. We obtain:

$$U_i^C(y_i, \mathbf{y}_{-i}, \mathbf{g}) = \left(\alpha_i + S_i^C\right) y_i - \frac{1}{2}\left[y_i^2 + \theta_2\left(y_i - \overline{y}_{-i}\right)^2\right]. \tag{A.34}$$

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

$$S_i^C = \frac{\lambda_2}{1-\lambda_2}\sum_j \widehat{g}_{ij}(y_j^o - \overline{y}_{-j}^o) = \frac{\lambda_2}{1-\lambda_2}(\overline{y}_{-i}^o - \overline{y}_{-j}^o), \tag{A.35}$$

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.4.2 Comparing the spillover and the conformist model for the general model

Consider now the general model where β can take any value and the utility of each individual i is given by (A.31). 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 (17), i.e,

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

while the first best is equal to (A.21), i.e,

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

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.31). It is straightforward to see that the subsidy given to each individual i that restores the first best is:

$$S_i^G = \frac{y_i^o - y_i^N}{1-\lambda_2} = \frac{1}{1-\lambda_2}\left[\lambda_1 \sum_j y_j^o \frac{\partial \overline{y}^o_{-j}}{\partial y_i^o} + \lambda_2 \sum_j (y_j^o - \overline{y}^o_{-j}) \frac{\partial \overline{y}^o_{-j}}{\partial y_i^o}\right]. \tag{A.36}$$

In particular, for the spillover model ($\lambda_2 = 0$), we have:

$$S_i^{G,S} = \lambda_1 \sum_j y_j^o \frac{\partial \overline{y}^o_{-j}}{\partial y_i^o}, \tag{A.37}$$

while, for the conformist model ($\lambda_1 = 0$), we obtain:

$$S_i^{G,C} = \frac{\lambda_2}{1-\lambda_2} \sum_j (y_j^o - \overline{y}^o_{-j}) \frac{\partial \overline{y}^o_{-j}}{\partial y_i^o}. \tag{A.38}$$

Since $\frac{\partial \overline{y}^o_{-j}}{\partial y_i^o} > 0$ (see (A.23)), 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 $\overline{y}^o_{-j}$. 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.

A.5 Derivative of the social norm with respect to β

Let us calculate $\frac{\partial \overline{y}(\mathbf{y}_{-i},\beta)}{\partial \beta}$. Remember that general social norm is defined as (see also Equation (16)),

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

Denote by $Y(\beta) := \sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}$. We have (assuming that $Y(\beta) \neq 1$),

$$\left(\sum_{j=1}^{n} \widehat{g}_{ij} z_j^{\beta}\right)^{\frac{1}{\beta}} := Y(\beta)^{\frac{1}{\beta}} = \exp\left([\ln Y(\beta)] \frac{1}{\beta}\right).$$

Thus,

$$\begin{aligned}
\frac{\partial \overline{y}(\mathbf{y}_{-i}, \beta)}{\partial \beta} &= \frac{\partial}{\partial \beta}\left[Y(\beta)^{\frac{1}{\beta}}\right] \\
&= \frac{\partial}{\partial \beta}\left[\exp\left([\ln Y(\beta)] \frac{1}{\beta}\right)\right] \\
&= \exp\left([\ln Y(\beta)] \frac{1}{\beta}\right) \frac{1}{\beta}\left(\frac{\partial [\ln Y(\beta)]}{\partial \beta} - \frac{\ln Y(\beta)}{\beta}\right).
\end{aligned}$$

Observe that $\ln Y(\beta) = \ln \sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}$, so that

$$\frac{\partial [\ln Y(\beta)]}{\partial \beta} = \frac{\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta} \ln y_j}{\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}}.$$

Thus

$$\begin{aligned}
\frac{\partial \overline{y}(\mathbf{y}_{-i}, \beta)}{\partial \beta} &= \exp\left([\ln Y(\beta)] \frac{1}{\beta}\right) \frac{1}{\beta}\left(\frac{\partial [\ln Y(\beta)]}{\partial \beta} - \frac{\ln Y(\beta)}{\beta}\right) \\
&= Y(\beta)^{\frac{1}{\beta}} \frac{1}{\beta}\left(\frac{\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta} \ln y_j}{\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}} - \frac{\ln \sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}}{\beta}\right) \\
&= \frac{1}{\beta}\left(\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}\right)^{\frac{1}{\beta}} \left(\frac{\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta} \ln y_j}{\sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}} - \frac{\ln \sum_{j=1}^{n} \widehat{g}_{ij} y_j^{\beta}}{\beta}\right).
\end{aligned}$$

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 $\mathbf{y}$, i.e., an object that is only a function of $\mathbf{x}$), and let $\overline{y}'_{is}$ denote the derivative of $\overline{y}_{is}$ with respect to β. Further, define the set of instruments as $\mathbf{z}_i = [\mathbf{x}_i, \overline{y}_{is}(\hat{\mathbf{y}}, \beta), \overline{y}'_{is}(\hat{\mathbf{y}}, \beta)]$. Given the two orthogonality assumptions on the error term: (1) $\mathbb{E}(\varepsilon_i \mathbf{z}_i) = \mathbf{0}$ for all non-isolated individuals, and (2) $\mathbb{E}(\varepsilon_i \mathbf{x}_i) = \mathbf{0}$ for all isolated individuals. The orthogonality conditions follows directly from the assumption that $\mathbb{E}(\varepsilon_i|\mathbf{Z}, \mathbf{G}) = 0$ 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

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

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):

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

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.

C Data and Results

C.1 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).

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.

C.2 Detailed Estimation Results

The following provides detailed estimation results for all estimations presented in Tables 2 and 3.

Table A1: 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 2 and 3. 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 A2: 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 2. 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 A3: 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 2. 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: 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 2. 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 $\boldsymbol{\gamma}$.

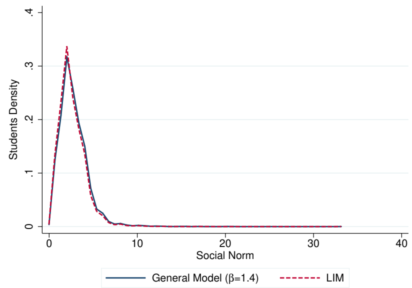
Table A5: General Model Estimation

	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

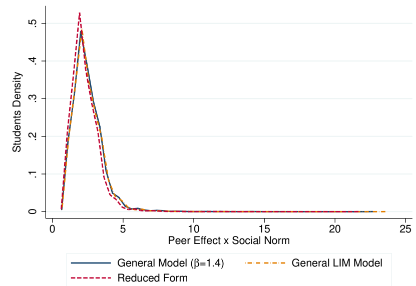
Notes: Detailed estimation results for the general model presented in Table 3. Age, female, hispanic, white, black, asian, mother's education less than high school, mother's education more than high school, mother's education non, mother professional occupation, mother other job, mother no job make up the covariates, x_i for estimating $\boldsymbol{\gamma}$.

C.3 Additional Figures

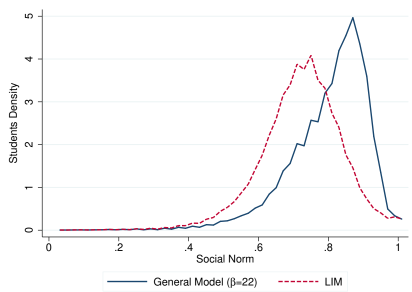
The following provides all additional examples of Figures 1 and 2 that are omitted in the main text.



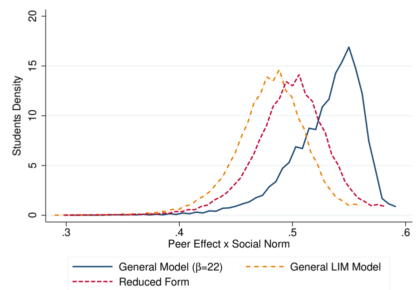
(g) Social Clubs Social Norm



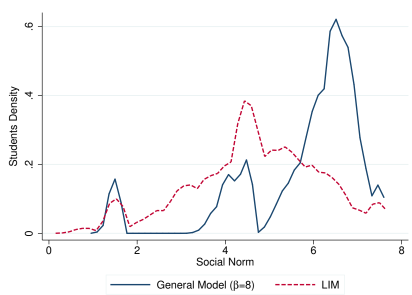
(h) Social Clubs Peer Effect



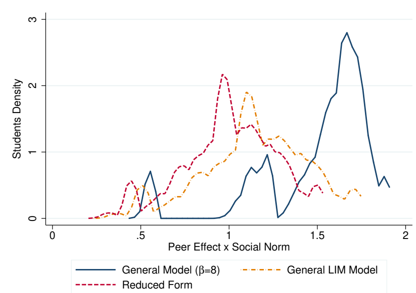
(i) Social Norm (Self Esteem)



(j) Peer Effect (Self Esteem)



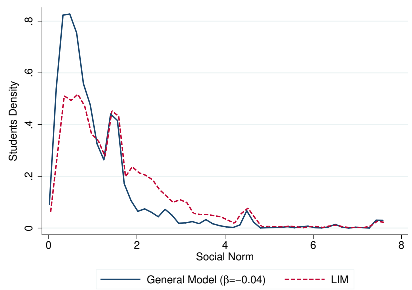
(k) Exercise Social Norm



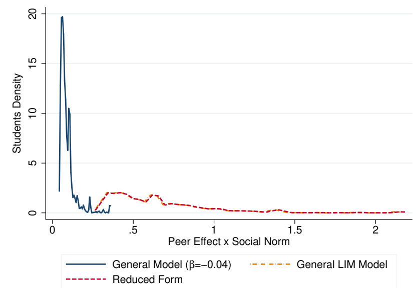
(l) Exercise Peer Effect

Notes: See notes in Figure 1

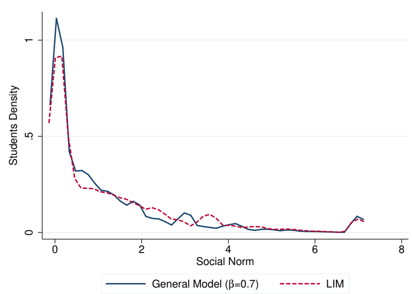
Figure A1: *Social Norms and Peer Effects (2)*



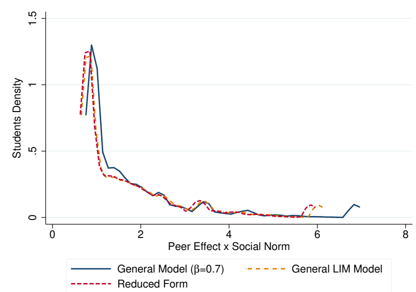
(a) Fighting Social Norm



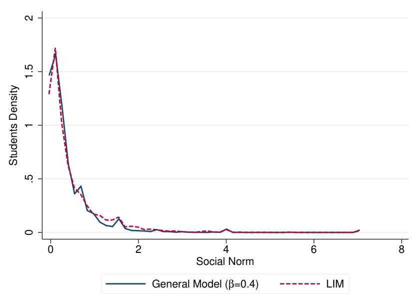
(b) Fighting Peer Effect



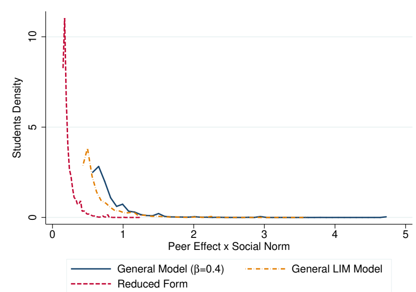
(c) Smoking Social Norm



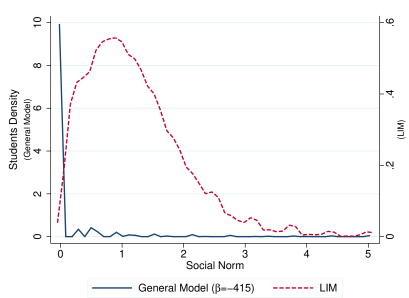
(d) Smoking Peer Effect



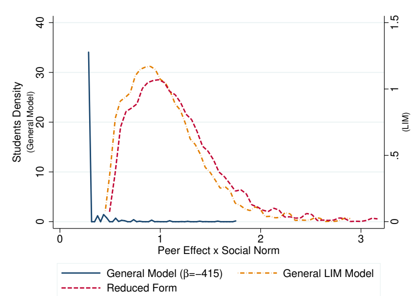
(e) Drinking Social Norm



(f) Drinking Peer Effect



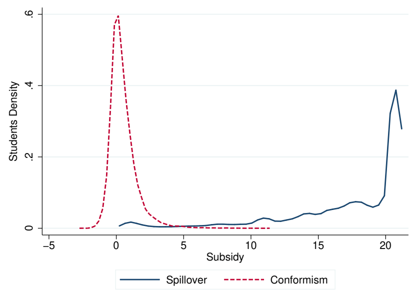
(g) Trouble Behavior Social Norm



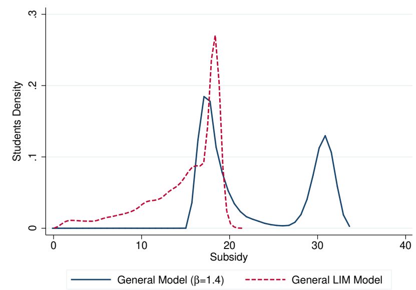
(h) Trouble Behavior Peer Effect

Notes: See notes in Figure 1

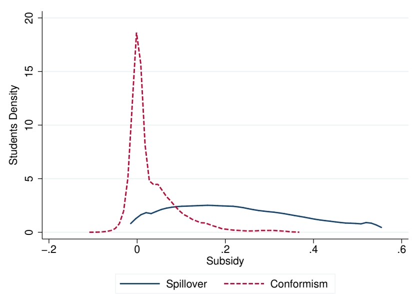
Figure A2: *First Best Subsidies (1)*



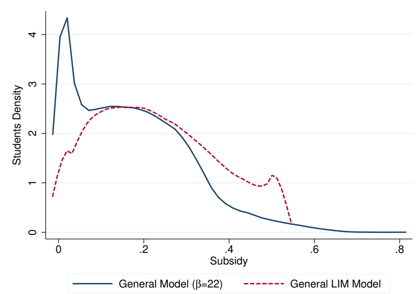
(a) Social Clubs LIM



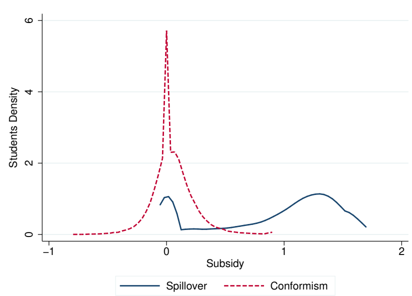
(b) Social Clubs Preference Effect



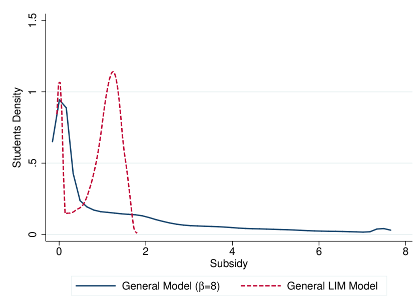
(c) LIM (Self Esteem)



(d) Peer Preference (Self Esteem)



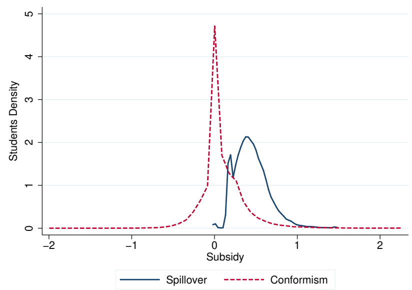
(e) Exercise LIM



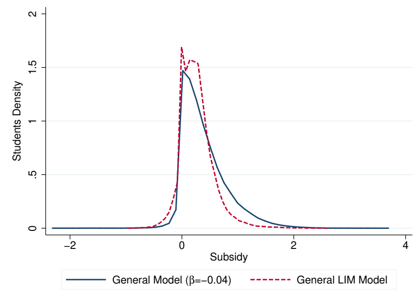
(f) Exercise Peer Preference Effect

Notes: See notes in Figure 2

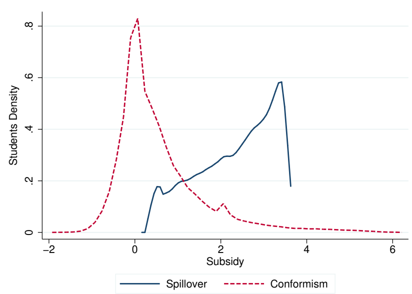
Figure A3: *First Best Subsidies (2)*



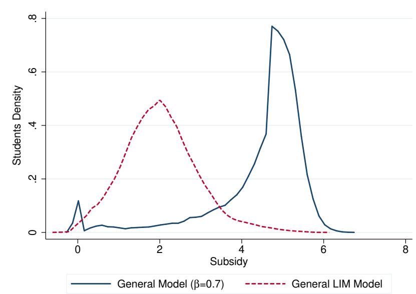
(a) Fighting LIM



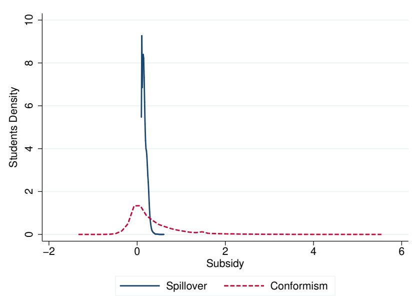
(b) Fighting Peer Preference Effect



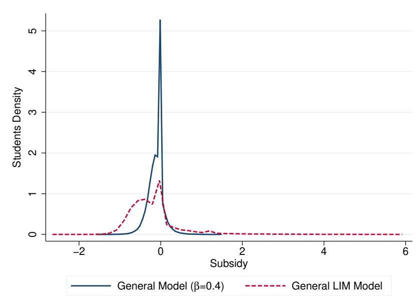
(c) Smoking LIM



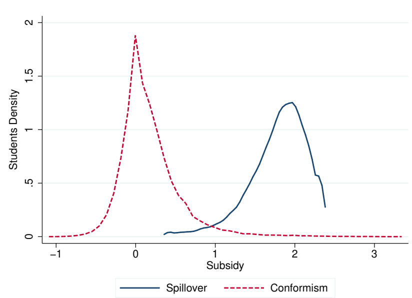
(d) Smoking Peer Preference Effect



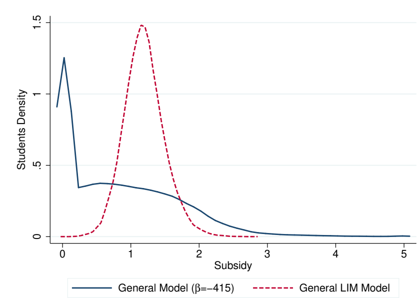
(e) Drinking LIM



(f) Drinking Peer Preference Effect



(g) Trouble Behavior LIM



(h) Trouble Behavior Peer Preference Effect

Notes: See notes in Figure 2