Heterogeneous peer effects and gender-based interventions for teenage obesity*

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Abstract

This paper explores the role of gender heterogeneity in the social diffusion of obesity among adolescents and its policy implications. We propose a linear social interaction model which allows for gender-dependent heterogeneity in peer effects through the channel of social synergy. We estimate the model using data on adolescent Body Mass Index and network-based interactions. Our approach allows us to account for network endogeneity. Our results show that peer effects are gender-dependent, and male students are particularly responsive to the weight of their female friends. According to simulations, reaching out to women results in an 8% increase in effectiveness in reducing overall BMI, based on the most conservative scenario. Thus, female-tailored interventions are likely to be more effective than a gender-neutral approach to fighting obesity in schools.

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1 Introduction

Obesity has reached epidemic proportions in children and adolescents in the United States, increasing from 5% in 1980 to over 19% in 2018 (Skinner et al. 2019; Fryar, Carroll, and Afful 2020). Mounting evidence suggests that the extra pounds often start children on the path to health problems such as cardiovascular diseases, diabetes, and cancer (Bendor et al. 2020). To explain such an alarming phenomenon, a large number of studies have focused on socio-economic factors such as growing unhealthy eating habits and the decline in time spent doing physical exercise (Papoutsi, Drichoutis, and Nayga 2013). Complementary to these views, health economists have also attempted to investigate the obesity epidemic from the perspective of social interactions (Christakis and Fowler 2007; Halliday and Kwak 2009; Trogdon, Nonnemaker, and Pais 2008; Yakusheva, Kapinos, and Eisenberg 2014; Cohen-Cole and Fletcher 2008; Fortin and Yazbeck 2015). Most of these studies document the presence of positive and significant peer effects which could increase the prevalence of obesity by changing reference norms for body image and/or by boosting the social transmission of unhealthy habits related to diet and physical activity.[1] Our paper follows the second strand of the literature by exploring the role of gender heterogeneity in the social diffusion of Body Mass Index (BMI) outcomes among teenagers, and its consequences in terms of anti-obesity interventions.[2]

Most studies on peer effects assume social interactions to be homogeneous (Manski 1993; Bramoullé, Djebbari, and Fortin 2009; Blume et al. 2015; De Paula 2017). This means that the effects of all peers are equal regardless of the particular type, such as race or gender. However, this assumption is restrictive and may not be realistic when speaking of the weight of adolescent students, arguably a period in life in which social interactions are important to structure an individual's body. In this context, heterogeneity in peer effects along gender lines could operate through different channels. One channel relates to the activities teenagers do together: for example, students may go to fast-food restaurants with peers of the same gender, or conversely, they may practice sport together with same-gender friends.[3] However, adolescents are also responsive to the BMI of opposite-gender friends for a variety of reasons related for instance to the influence of good eating habits and maturity of these peers. These examples reflect the presence of social spillover (or synergy) as a basic mechanism to explain peer effects.

This paper proposes an econometric model allowing for heterogeneous peer effects along gender lines, and estimates it using detailed network data on teenagers' friendship from the Add Health dataset. Simulations based on our results show that ignoring gender-based

[1] Despite some studies have pointed to a virus (Rogers et al. 2007), the standard channel of social propagation of obesity is thought to be related to complementarities in behavior and/or self-image.

[2] Although various methods exist to measure excess body fat, BMI (kg/m^2) is the most widely utilized measure of excess adiposity and risk for related diseases.

[3] Rees and Sabia (2010) document the heterogeneity in sport participation along gender lines, using the same Add Health data we use.

heterogeneity of peer effects may lead to inefficient health interventions to curb obesity. The present study contributes novel methodology, results, and policy insights to the existing literature, which we discuss in details below.

While the literature on dietary choices and weight outcomes of adolescents is sizable (Kapinos and Yakusheva 2011; Mora and Gil 2013; Corrado, Distante, and Joxhe 2019; Fortin and Yazbeck 2015; Angelucci et al. 2019), studies focusing on the heterogeneity of peer effects are rare. Some contributions suggest that female adolescents are more responsive than male ones to their peers' weight-related outcomes (Arduini, Iorio, and Patacchini 2019; Renna, Grafova, and Thakur 2008; Yakusheva, Kapinos, and Eisenberg 2014). However, to our knowledge, we are the first to model heterogeneity in between-gender peer effects. In our model, two types of individuals (*i.e.*, male *vs.* female students) interact within the same network (*i.e.*, a school). This defines an 'heterogeneous' model with two *within-gender* and two *between-gender* peer effects, with respect to the 'homogeneous' setting with one peer effect term. We characterize our model econometrically and theoretically. Our methodological approach is closely related to the ones developed by Hsieh and Lin (2017) and Arduini, Patacchini, and Rainone (2020), but with important differences. Hsieh and Lin (2017) model peer effects *via* Bayesian methods, and estimate them through Markov Chain Monte Carlo sampling techniques. Similarly to us, Arduini, Patacchini, and Rainone (2020) derive a set of identification conditions that generalize the standard linear model of Bramoullé, Djebbari, and Fortin (2009) to allow for heterogeneous peer effects. However, our paper emphasizes the theoretical foundation of our model by showing that it is micro-founded into an identifiable non-cooperative game of social synergy.

We illustrate our econometric model using the 1996's saturation sample of the National Longitudinal Study of Adolescent Health (Add Health) which provides census data on 16 selected schools. Respondents from the sample reported their height and weight (which we use to compute the BMI), and they were also asked to *name up to five male friends and up to five female friends within their school*, which allows us to map the friendship networks. We find that that peers' outcomes affect BMI in a way that is gender-specific. In particular, we find that the 'male-female' endogenous peer effect (that is, the effect on male students' BMI of the BMI of their female friends) is significantly larger than the other estimated peer effects (for male-male, female-male, female-female interactions, respectively). Our results are in line with Kooreman (2007) and Hsieh and Lin (2017) who find that the influence of female students on male students is generally larger than the reverse for a number of documented adolescent behaviors. This effect could be due to the fact that girls are more mature and presumably more influential than boys at the same age during childhood and adolescence. This hypothesis is consistent with recent studies in neuroscience (*e.g.,* Gong et al. 2009; Lenroot and Giedd 2010; Lim et al. 2015; Goyal et al. 2019) suggesting that girls tend to optimize brain connections earlier than boys.

One limitation of our benchmark model is that it implicitly assumes that the formation of links between students is exogenous once we account for observable attributes and school choice. However, as long as students self-select their peers partly based on unobserved factors that equally appear in the equation of interest (*i.e.*, the BMI equation), this will create an endogeneity problem. For instance, under homophily, that is, when individuals tend to bond with peers with similar preferences, a spurious correlation will arise between the individual's BMI and his/her peers' BMI. Thus, it is important to provide a robustness check of network exogeneity. While many approaches have been developed in recent years to test for network exogeneity (see the recent survey by Bramoullé, Djebbari, and Fortin 2020), we focus on the one proposed by Jochmans (2022), which we incorporate in our estimation framework.

Finally, we conduct a simulation exercise to study the impact of an intervention proposing one balanced meal per week in replacement of one fast-food type serving. On the basis of our most conservative findings, we conclude that the social spillovers of offering meal replacement to female students are 33% higher than the spillovers of males. This suggests that returns from (resources spent on treating) females are 8% larger than the ones from males in terms of overall BMI decrease in the student population. If we further assume that females are more responsive to the intervention, we conclude that the social spillovers from females are twice the spillovers from males, which translates into a 54% gain in terms of aggregate BMI decrease from reaching out to female students. Overall, our analysis indicates that acknowledging gender-based heterogeneity of peer effects may increase dramatically the efficiency of anti-obesity policies. More generally, while ex-ante evaluations based on structural models are common in other fields of economics (*e.g.*, Wolpin 2007), they are novel in the context of social interactions. By providing the infrastructure to evaluate how interventions interplay with heterogeneous social diffusion, our paper may be of interest in many contexts where peer effects differ along individual dimensions (*e.g.*, race, education).

The rest of the paper is organized as follows. In Section 2 we characterize our model. Section 3 introduces the data, Section 4 presents our results, and Section 5 describes the simulation exercise. Section 6 concludes. Appendix A illustrates the micro-foundation of our model. Appendix B formalizes the identification conditions and presents the estimation techniques in use.

2 Estimation Strategy

2.1 The model

We study a setting where n agents (*e.g.*, students) are distributed across R social networks (*e.g.*, schools), with $r = 1, \dots, R$. In a given network r of size n_r there are n_r^f female agents and n_r^m male agents ($n_r^f + n_r^m = n_r$).[4] These agents interact with both own-gender and other-gender peers and their outcome (*i.e.*, BMI) can be influenced by their behavior.[5]

[4]In what follows, we order all vector and matrices so that the first n_r^f rows correspond to female agents of network r, and the remaining n_r^m rows are for male agents in network r.

[5]The model could easily be extended to other types of peer heterogeneity such as race and education. However, for the sake of parsimony, we limit the analysis to gender-based heterogeneity.

For each network we define four fixed and known adjacency matrices: $\mathbb{A}_{z,r}(z = 1, \cdots, 4)$. The matrix $\mathbb{A}_{1,r}$ is such that $a_{1,r,ij} = 1$ if in network r the male student i is influenced by the male student j, and 0 otherwise.[6] The matrix $\mathbb{A}_{2,r}$ is such that $a_{2,r,ij} = 1$ if in network r the male student i is influenced by the female student j, and 0 otherwise. The matrices $\mathbb{A}_{3,r}$ and $\mathbb{A}_{4,r}$ are similarly defined for female students, that is, $\mathbb{A}_{3,r}$ represents the impact of female friends on female students, and $\mathbb{A}_{4,r}$ the impact of male friends on female students in network r. These matrices are directed: the fact that i influences j does not necessarily imply that j influences i (*e.g.*, we could have $a_{1,r,ij} \neq a_{1,r,ji}$).[7]

Let us call $n^m_{i,r}$ and $n^f_{i,r}$ the number of male and female individuals influencing i in the network r respectively. The social interaction matrix $\mathbb{G}_{z,r}$ is the weighted version of matrix $\mathbb{A}_{z,r}$ such that one has $g_{1,r,ij} = 1/(n^m_{i,r} + n^f_{i,r})$ if i is a male student in network r and is influenced by the male student j, and 0 otherwise. Since we allow for individuals to be 'isolated', that is, not influenced by anyone in their network (*i.e.*, $n^m_{i,r} = n^f_{i,r} = 0$), the $\mathbb{G}_{z,r}$'s matrices are not row-normalized (*i.e.*, not all matrix's rows sum up to one). Thus, the social interaction matrix for the whole population in network r could be written as $\mathbb{G}_r = \mathbb{G}_{1,r} + \mathbb{G}_{2,r} + \mathbb{G}_{3,r} + \mathbb{G}_{4,r}$. The heterogeneous peer effect model for the network r writes as

$$\begin{aligned}\mathbf{y_r} = \quad & \boldsymbol{\iota}_{n_r}\alpha_r + \beta_{mm}\mathbb{G}_{1,r}\mathbf{y}_r \ + \ \beta_{mf}\mathbb{G}_{2,r}\mathbf{y}_r \ + \ \beta_{ff}\mathbb{G}_{3,r}\mathbf{y}_r \ + \ \beta_{fm}\mathbb{G}_{4,r}\mathbf{y}_r \ + \\ & \gamma\ \mathbf{x}_r + \delta_{mm}\mathbb{G}_{1,r}\ \mathbf{x}_r \ + \ \delta_{mf}\mathbb{G}_{2,r}\ \mathbf{x}_r \ + \ \delta_{ff}\mathbb{G}_{3,r}\mathbf{x}_r \ + \ \delta_{fm}\mathbb{G}_{4,r}\ \mathbf{x}_r \ + \boldsymbol{\epsilon}_r, \end{aligned} \quad (1)$$

where $\mathbf{y}_r$ is the BMI vector and $\boldsymbol{\iota}_{n_r}$ is a $n_r \times 1$ vector of ones. α_r stands for a fixed effect specific to network r, which takes into account the unobserved factors which commonly influence the BMI of all students within a school. The βs coefficients represent the 'endogenous' peer effects (*i.e.*, the effect of peers' outcomes) which are heterogeneous. For instance, β_{mm} measures the effect of the outcome of male peers on (the BMI of) male students. In the same way, β_{mf} stands for the effect of the outcomes of female peers on male students, β_{ff} of female peers on female students, and β_{fm} of male peers on female students. We also allow for heterogeneous contextual effects δs that account for the effect of the characteristics of peers on student's outcomes and reads the same way (*e.g.*, δ_{mm} measures the effect of the characteristics of male peers on the outcome of male students). Finally, if we observe $R > 1$ distinct networks, we can stack up the data and write the heterogeneous model succinctly as

$$\mathbf{y} = \bar{\mathbb{G}}(\boldsymbol{\beta})\mathbf{y} + \gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota}\boldsymbol{\alpha} + \boldsymbol{\epsilon} \quad (2)$$

where $\mathbf{y} = (\mathbf{y}'_1, ..., \mathbf{y}'_R)'$, $\mathbf{x} = (\mathbf{x}'_1, ..., \mathbf{x}'_R)'$, $\boldsymbol{\iota} = D(\boldsymbol{\iota}_{n_1}, ..., \boldsymbol{\iota}_{n_R})$, $\boldsymbol{\alpha} = (\alpha_1, ..., \alpha_R)'$, $\boldsymbol{\epsilon} = (\boldsymbol{\epsilon}'_1, ..., \boldsymbol{\epsilon}'_R)'$, $\boldsymbol{\beta} = (\beta_{mm}, \beta_{mf}, \beta_{ff}, \beta_{fm})'$, $\boldsymbol{\delta} = (\delta_{mm}, \delta_{mf}, \delta_{ff}, \delta_{fm})'$, $\bar{\mathbb{G}}_z = D(\mathbb{G}_{z,1}, ..., \mathbb{G}_{z,R})$,

[6] The student i is excluded from his/her own reference group.

[7] This is because in our illustration we use information on social links as declared by respondents and the two reports may not coincide within a pair. Nevertheless, our estimation strategy is also compatible with undirected network data.

$\bar{\mathbb{G}}(\boldsymbol{\beta}) = \beta_{mm}\bar{\mathbb{G}}_1 + \beta_{mf}\bar{\mathbb{G}}_2 + \beta_{ff}\bar{\mathbb{G}}_3 + \beta_{fm}\bar{\mathbb{G}}_4$ and $\bar{\mathbb{G}}(\boldsymbol{\delta}) = \delta_{mm}\bar{\mathbb{G}}_1 + \delta_{mf}\bar{\mathbb{G}}_2 + \delta_{ff}\bar{\mathbb{G}}_3 + \delta_{fm}\bar{\mathbb{G}}_4$, and D indicates a block diagonal matrix.

In order to eliminate the fixed effects $\boldsymbol{\iota\alpha}$ avoiding the incidental parameters problem, we perform a global transformation on equation (2).[8] For that purpose we define the global transformation matrix $\mathbf{J} = D(\mathbf{J}_1, ..., \mathbf{J}_R)$ where $\mathbf{J}_r = (\mathbf{I}_r - \frac{\boldsymbol{\iota}_r\boldsymbol{\iota}_r'}{n_r})\ \forall\ r \in \{1, ..., R\}$, such that $\mathbf{J}\boldsymbol{\iota\alpha} = \mathbf{0}$, and obtain a transformed model that writes succinctly as

$$\mathbf{Jy} = \mathbf{JZ}\boldsymbol{\theta} + \mathbf{J}\boldsymbol{\epsilon}, \tag{3}$$

where $\mathbf{Z} = \left[\bar{\mathbb{G}}_1\mathbf{y}, \bar{\mathbb{G}}_2\mathbf{y}, \bar{\mathbb{G}}_3\mathbf{y}, \bar{\mathbb{G}}_4\mathbf{y}, \mathbf{X}\right]$, $\mathbf{X} = \left[\mathbf{x}, \bar{\mathbb{G}}_1\mathbf{x}, \bar{\mathbb{G}}_2\mathbf{x}, \bar{\mathbb{G}}_3\mathbf{x}, \bar{\mathbb{G}}_4\mathbf{x}\right]$, $\boldsymbol{\theta} = (\boldsymbol{\beta}, \gamma, \boldsymbol{\delta})'$.

Note that if we impose $\beta_{mm} = \beta_{mf} = \beta_{ff} = \beta_{fm} = \beta_h$ and $\delta_{mm} = \delta_{mf} = \delta_{ff} = \delta_{fm} = \delta_h$ in equation (2), we obtain the so-called 'homogeneous' model

$$\mathbf{y} = \beta_h\bar{\mathbb{G}}\mathbf{y} + \gamma\mathbf{x} + \delta_h\bar{\mathbb{G}}\mathbf{x} + \boldsymbol{\iota\alpha} + \boldsymbol{\epsilon}. \tag{4}$$

This corresponds to the specification by Bramoullé, Djebbari, and Fortin (2009) with fixed effects and will be used as benchmark for our empirical analysis in Section 4.

In Appendix A we show that Equation 2 can be micro-founded in a non-cooperative model where peer effects work through the channel of 'social synergy' in BMI. The latter assumption is plausible in our context, because body size can only be indirectly chosen through effort, that is, healthy life habits (*e.g.*, good dietary behavior, physical exercise). We show that we can identify all parameters of the utility function, provided that we have a proxy for individuals' effort, and discuss the relevance of it in terms of policy evaluation.

2.2 Identification

Let us assume for now that the social interaction matrices are 'conditionally' exogenous, that is, they are exogenous once we control for individual attributes and school-level fixed effects.[9] As long as the matrix $\mathbf{S}(\boldsymbol{\beta}) = (\mathbf{I} - \bar{\mathbb{G}}(\boldsymbol{\beta}))$, where $\mathbf{I}$ is the identity matrix, is invertible,[10] we can write the reduced form of equation (2) as

$$\mathbf{y} = \mathbf{S}(\boldsymbol{\beta})^{-1}\left[\gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota\alpha}\right] + \mathbf{S}(\boldsymbol{\beta})^{-1}\boldsymbol{\epsilon}, \tag{5}$$

which allows us to rewrite

$$\bar{\mathbb{G}}_z\mathbf{y} = \mathbf{W}_z(\boldsymbol{\beta})\left[\gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota\alpha}\right] + \mathbf{W}_z(\boldsymbol{\beta})\boldsymbol{\epsilon},$$

[8] The incidental parameters problem, which is discussed at length in Lancaster (2000), occurs whenever the data available for each group or network are finite. This transformation captures the selection bias stemming from the fact that individuals in the same network face a common environment.

[9] Formally, the conditional exogeneity assumption writes as $\mathbb{E}(\boldsymbol{\epsilon}|\mathbf{x}, \iota\alpha, \bar{\mathbb{G}}_{z=1,\cdots,4}) = 0$.

[10] A sufficient condition for this assumption to hold is that $|\beta_{mm}| < 1$, $|\beta_{mf}| < 1$, $|\beta_{ff}| < 1$ and $|\beta_{fm}| < 1$. This condition also implies that the matrix $\mathbf{S}(\boldsymbol{\beta})$ is uniformly bounded in absolute value.

where $\mathbf{W}_z(\boldsymbol{\beta}) = \bar{\mathbb{G}}_z\mathbf{S}(\boldsymbol{\beta})^{-1}$ and $z = 1, \cdots, 4$. This shows that the right-hand side terms in equation (2) is endogenous ($\mathbb{E}\left[(\mathbf{W}_z(\boldsymbol{\beta})\boldsymbol{\epsilon})'\boldsymbol{\epsilon}\right] \neq 0$), and thus that the model cannot be consistently estimated by OLS. This type of endogeneity is frequent in social interaction models and it stems from the simultaneous determination of outcomes among peers.

Proposition 1 below states the identification condition of equation (2), which extends the conditions by Bramoullé, Djebbari, and Fortin (2009) to the case of peer effects heterogeneity.[11] For the proof and a detailed discussion, we remand to Appendix B.

Proposition 1 *Suppose model (2) holds. Suppose that* $\mathbf{S}(\boldsymbol{\beta})$ *is invertible and that* $(\delta_{mm} + \gamma\beta_{mm}) \neq 0$, $(\delta_{ff} + \gamma\beta_{ff}) \neq 0$, $(\delta_{mf} + \gamma\beta_{mf}) \neq 0$ *and* $(\delta_{fm} + \gamma\beta_{fm}) \neq 0$. *If vector columns of matrix* $\mathbf{Q}_K$ *are linearly independent, then social effects are identified.*

One immediate consequence of Proposition 1 is that equation (2) can be estimated with instrumental variable techniques, and that any set $\mathbf{Q}_K$ containing products of interaction matrices of arbitrary order and individual attributes is a valid set of instruments for $\bar{\mathbb{G}}_z\mathbf{y}$. This is a extension of the lagged-friend instrumental strategy which has been widely used in presence of network data (Calvo-Armengol, Patacchini, and Zenou 2009; Kelejian and Prucha 1998; Patacchini and Zenou 2012). For instance, the instrument set of all matricial products up to the second order (which we use in Section 4) is[12]

$$\mathbf{Q_K} = \mathbf{J}\left[\bar{\mathbb{G}}_1^2\mathbf{x}, \bar{\mathbb{G}}_3^2\mathbf{x}, \bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\mathbf{x}, \bar{\mathbb{G}}_2\bar{\mathbb{G}}_3\mathbf{x}, \bar{\mathbb{G}}_2\bar{\mathbb{G}}_4\mathbf{x}, \bar{\mathbb{G}}_3\bar{\mathbb{G}}_4\mathbf{x}, \bar{\mathbb{G}}_4\bar{\mathbb{G}}_1\mathbf{x}, \bar{\mathbb{G}}_4\bar{\mathbb{G}}_2\mathbf{x}\right]. \tag{6}$$

2.3 The endogeneity of social interactions

Endogeneity stemming from network assortativity may arise whenever individual-level unobservables simultaneously determine social interactions and outcome (*i.e.*, BMI). This type of endogeneity is usually associated with homophily, that is, the well-documented tendency to create links with individuals with some similar preferences or characteristics. In our context, this means that the instrumentation strategy of Section 2.2 is valid as long as students do not make friends based on some unobservable characteristics also affecting BMI, once we control for their observable attributes and school choice. This means that the network is stochastic but exogenous. However, there could be instances where this assumption is violated. In what follows we discuss an alternative estimation method that is robust to network endogeneity of this kind.

Several methodological papers have recently tackled network endogeneity (see the recent survey by Bramoullé, Djebbari, and Fortin 2020). The majority of them adopt a control function approach where the network formation equation is specified parametrically (*e.g.*, Goldsmith-Pinkham and Imbens 2013; Patacchini and Rainone 2017; Hsieh and Lee 2016)

[11] This resembles the conditions derived by Arduini, Patacchini, and Rainone (2020).

[12] Recall that the matrix ordering leads by construction to the following identities: $\bar{\mathbb{G}}_1\bar{\mathbb{G}}_4 = 0_{n_r}$, $\bar{\mathbb{G}}_3\bar{\mathbb{G}}_2 = 0_{n_r}$, $\bar{\mathbb{G}}_1\bar{\mathbb{G}}_3 = 0_{n_r}$, $\bar{\mathbb{G}}_3\bar{\mathbb{G}}_1 = 0_{n_r}\bar{\mathbb{G}}_2\bar{\mathbb{G}}_1 = 0_{n_r}$, $\bar{\mathbb{G}}_4\bar{\mathbb{G}}_3 = 0_{n_r}$,$\bar{\mathbb{G}}_2^2 = 0_{n_r}$,$\bar{\mathbb{G}}_4^2 = 0_{n_r}$.

or non-parametrically (*e.g.*, Johnsson and Moon 2021). We tackle the issue adopting the instrumental-variable method proposed by Jochmans (2022). In our context, this approach has two advantages: it remains relatively agnostic with respect to the peer selection process, and it suits data on small (and possibly sparse) networks as the school-level networks we observe in Add Health. Also, it can be easily integrated into our estimation strategy as we explain below.

Jochmans (2022) devises instrumental variables with close resemblance to the estimator of Bramoullé, Djebbari, and Fortin (2009). This method is based on two all-embracing conditional moment restrictions: (i) that link decisions that involve a given individual are not all independent of one another, but (ii) that they are independent of the link decisions made between other pairs of individuals that are located sufficiently far away in the network.[13] For each individual i and for $z = 1, \cdots, 4$, Jochmans (2022) defines the so-called 'leave-own-out network' $\bar{\mathbb{Q}}_{z,i}$ as the sub-network obtained from $\bar{\mathbb{G}}_z$ by setting to zero all links involving agent i. Under the two restrictions above, this leave-own-out network is exogenous to i's link behavior (because it contains link decisions that do not involve i) but it also contains predictive information about it (since link decisions between any triple of individuals are informative about each other). Therefore, linear combinations of these leave-own-out networks can serve as instruments for $\bar{\mathbb{G}}_z\mathbf{y}$ and $\bar{\mathbb{G}}_z\mathbf{x}$ in equation (2) in analogy with the standard lagged-friend strategy.[14] For the purpose of our study, it boils down to replacing the instrumental variable set in equation (6) with

$$\mathbf{Q_K} = \mathbf{J}\left[\bar{\mathbb{Q}}_1\mathbf{x}, \bar{\mathbb{Q}}_2\mathbf{x}, \bar{\mathbb{Q}}_3\mathbf{x}, \bar{\mathbb{Q}}_4\mathbf{x}, \bar{\mathbb{Q}}_1^2\mathbf{x}, \bar{\mathbb{Q}}_3^2\mathbf{x}, \bar{\mathbb{Q}}_1\bar{\mathbb{Q}}_2\mathbf{x}, \bar{\mathbb{Q}}_2\bar{\mathbb{Q}}_3\mathbf{x}, \bar{\mathbb{Q}}_2\bar{\mathbb{Q}}_4\mathbf{x}, \bar{\mathbb{Q}}_3\bar{\mathbb{Q}}_4\mathbf{x}, \bar{\mathbb{Q}}_4\bar{\mathbb{Q}}_1\mathbf{x}, \bar{\mathbb{Q}}_4\bar{\mathbb{Q}}_2\mathbf{x}\right], \tag{7}$$

where $\bar{\mathbb{Q}}_z$ indicate the average over i for the leave-own-out networks z.

3 Data

3.1 Add Health

The National Longitudinal Study of Adolescent Health (Add Health) is a panel study of a nationally representative sample of adolescents in grades 7-12 in the United States, conducted by the Carolina Population Center. It combines information on respondents' social, economic, psychological and physical well-being with data on family, neighborhood, community, school, friendships, peer groups, and romantic relationships. The richness of this information puts Add Health among the largest and most comprehensive longitudinal surveys of adolescents ever undertaken.

[13] For a discussion on how these restrictions accommodate most (cooperative and non-cooperative) peer selection patterns and nest several control-function methods, see Jochmans (2022).

[14] Note that, if we relax conditional exogeneity of the network, the contextual peer effects $\bar{\mathbb{G}}_z\mathbf{x}$ become endogeneous.

Wave I of Add Health consists of an In-school questionnaire that was filled out by 90,118 students in 145 schools and 80 communities during the 1994-1995 school year. A subset of these students was then chosen for an in-depth survey: Wave II, which was held in 1996, includes a detailed In-Home questionnaire that was completed overall by 14,738 students out of the original Wave I pupils. Students who were selected for the In-Home survey were asked for information on their height and weight, which can be used to compute body mass indices (BMI). Along with other notable socio-economic covariates, Wave II also provides information on social interactions, because respondents are asked to *name up to five male friends and up to five of their female friends within their school*.

For the purpose of our analysis, we use the saturated sample of Wave II that focuses on 16 selected schools. Every student attending these 16 schools answered the In-Home questionnaire, thus providing information on BMI and social links. We construct student BMI according to the formula: BMI = (weight in kilograms)/(height in meters)^2.[15] Having a census of the schools' population (rather than a random sample of students within a given school) is crucial for our study, since our estimation strategy crucially relies on observing the whole network topology.

3.2 Descriptive statistics

Our estimation sample consists of 2307 students. The sample is balanced across gender (1146 females and 1161 males). It also includes 'isolated' students, that is, students who do not mention any friends within the school.[16] Table (1) provides descriptive statistics of the variable of interest. Average BMI is 23.13 with a standard deviation of 4.71. This reveals that on average, the population considered is *normal* in terms of weight. In terms of relevant individual characteristics, we can see that mean age is about 16. White students are more represented (61%) than the other racial communities. The percentage of Black is 16%, and the omitted category includes Hispanic, Asian and American Indian students. 63% of students in our sample attend grade 11 or 12 and 26% are in grade 9 or 10 (grade 7 or 8 is omitted). 43% of mothers have college-level education (or above) compared to 36% for fathers of the students in our sample.

Our interaction matrices represent *directed* links (*e.g.*, $g_{ij} > 0$ if student i is influenced by student j, but not necessarily *vice versa*). Statistics about the directed network point to more links with same-gender friends: males have on average 1.46 links with males and 0.83 with females, while females have 1.44 links with females and 0.88 with males. This shows that the number of same-gender *vs.* other-gender friends is remarkably comparable for male and female students. The fact that students declare 2.3 friends on average suggests that the constraint put in the number of friends by the Add Health study (up to 5 males

[15] We do not use self-declared body mass indices, although declared BMIs are shown to reflect real variables in the context of Add Health.

[16] 548 students do not nominate any friend, and 309 of them were also nominated by no one.

and 5 females) is not binding.[17]

4 Results

This section presents the estimates of our peer effects model using Add Health data. This could be consistently estimated with 2SLS or GMM techniques with the instruments described in Section 2. We use the GMM estimator by Liu and Lee (2010) whose quadratic moments exploit the correlations between the error term of the reduced peer-effect form model. This estimator provides more precise estimates of social interaction models compared to the traditional 2SLS method. For details on the associated weighting matrix we remand to Appendix B.

4.1 Homogenous peer effects and BMI

Table (2) presents the GMM estimates from the homogeneous peer effects model of equation (4), which serves as a benchmark. The set of characteristics $\mathbf{x}$ comprises: student attributes (age, race, grade), and education level of mother and father respectively.[18] We instrument the term $\bar{\mathbb{G}}\mathbf{y}$ with lagged-friends characteristics of the second degree, that is, the (average) attributes of friends of friends $\bar{\mathbb{G}}^2\mathbf{x}$. This boils down to assuming that social interactions are exogenous conditionally on observables and school-level effects (see Footnote 9).

Results indicate that the coefficient associated with the endogenous peer effect ($\bar{\mathbb{G}}\mathbf{y}$) is significant at 1%. Its estimated magnitude suggests that, *ceteris paribus*, a 1-unit increase in the average BMI of peers induces an increase of 0.22 units in the student's BMI. This is aligned with the recent literature reporting evidence of positive but small endogenous peer effects on weight. We also remark that several individual and peer attributes appear to influence one's BMI. The first two columns report the estimates and standard errors of individual own characteristics $\mathbf{x}$, and columns 3 and 4 refer to the contextual effects, that is, effects of friends' characteristics $\bar{\mathbb{G}}\mathbf{x}$. We notice that for students in lower grades and whose father has college education have lower BMI. Regarding contextual effects, having older friends and/or friends whose father has a college education reduces a student's BMI, which may indicate transmission of information *via* learning good health habit.

Table (3) re-estimate the homogeneous peer effects model allowing for endogenous social interactions (Section 2.3). For the homogeneous model, this consists in instrumenting $\bar{\mathbb{G}}\mathbf{y}$ and $\bar{\mathbb{G}}\mathbf{x}$ with $\bar{\mathbb{Q}}\mathbf{x}$ and $\bar{\mathbb{Q}}^2\mathbf{x}$. Results from Table (3) show that estimates remain overall

[17] This alleviates the concern that the network may be only partially observed. Also, it is worth noting that censoring leads to an underestimation of the magnitude of peer effects, as shown by Griffith (Forthcoming) using Add Health data. This is reassuring in our context where peer-effect estimates are significantly positive.

[18] The omitted category for race includes Hispanic, Asian and American Indian respondents, while the omitted category for grade is "7 or 8". The parent education dummy equals one if the mother/father has some education at the college level or above.

stable (the endogenous peer effect is now at 0.23).[19] This suggests that the fixed-effect instrumentation strategy is rather efficient in reducing the selection bias associated with confounding correlates. This finding is in line with several recent papers concluding against a severe assortativity bias in Add Health data (Goldsmith-Pinkham and Imbens 2013; Boucher 2016; Badev 2021).[20]

4.2 Gender heterogeneity and BMI

In this subsection, we present the estimates from the model allowing for within- and between-gender heterogeneity in peer effects. Table (4) provides the results from the GMM estimation of equation (2), under the assumption that social interactions are conditionally exogenous. This consists in instrumenting the four endogenous peer-effect terms with the set of instruments spelled out in Equation (6), that is, all exogenous attributes of friends at distance 2, per category: $\bar{\mathbb{G}}_1^2\mathbf{x}$ and $\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\mathbf{x}$ (the attributes of males/female friends of males friends of male students); $\bar{\mathbb{G}}_2\bar{\mathbb{G}}_4\mathbf{x}$ and $\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3\mathbf{x}$ (the attributes of males/female friends of females friends of male students); $\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1\mathbf{x}$ and $\bar{\mathbb{G}}_4\bar{\mathbb{G}}_2\mathbf{x}$ (the attributes of males/female friends of males friends of female students), $\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4\mathbf{x}$ and $\bar{\mathbb{G}}_3^2\mathbf{x}$ (the attributes of males/female friends of females friends of female students). The upper panel provides the four endogenous peer effects coefficients (standard errors of the estimates are reported in the adjacent columns), namely: the effects of male peers' BMI on the BMI of male students ($m-m$, columns 3 and 4), the effects of female peers' BMI on the BMI of male students ($m-f$, columns 5 and 6), the effects of female peers' BMI on the BMI of female students ($f-f$, columns 7 and 8) and the effects of male peers' BMI on the BMI of female students ($f-m$, columns 9 and 10).

As in the case of the homogeneous model, the endogenous peer effect estimates are positive and highly significant, suggesting that interaction with peers of all types influences a student's BMI. The within-gender point estimates (0.226 and 0.197 for the $m-m$ and $f-f$ coefficients respectively) are comparable for magnitude to the $f-m$ coefficient (0.229) which represents the effect of the average BMI of male peers on female student's BMI. On the other hand, the estimated coefficient for the between-gender effect from females to males is noticeably larger (0.465).[21] This suggests that males respond more to the average BMI of their female friends that the reverse, a result which is also obtained by Kooreman (2007) and Hsieh and Lin (2017) for several adolescent behaviors. As mentioned in the introduction, in our context this may be partly related to the fact that girls become mature and their brain reaches their peak volume earlier than boys in the adolescence.[22]

[19] Using the Durbin-Wu-Hausman test we do not reject the exogeneity of the endogenous peer effect.

[20] Boucher and Fortin (2016) suggest that with a rich set of control variables as those that can be used in our data set, the impact of homophily may be small. Other studies using different data sets and different outcomes reach the opposite conclusion (*e.g.*, Carrell, Sacerdote, and West (2013) and Hsieh et al. (2020)).

[21] All pairwise Wald test statistics reject the equality of the $m-f$ coefficient with the other three peer-effect estimates (with significance at 10% or below).

[22] According to a neuroscience study by Lim et al. (2015), the optimizing of brain connectivity usually

We report the estimates and standard errors related to individual characteristics in columns 1-2, and the ones for contextual effects (within- and between- gender) in columns 3 to 9. Grade 9-10 and 11-12 students are the ones who report a higher BMI (in line with the results from the homogeneous model). The other coefficients for the individual effects do not appear significant. Our results also reveal an important number of differences in the estimates of contextual effects depending on the nature (within- or between-gender) of social interactions. However, some regularities emerge in line with the results of the homogeneous model. For instance, the age of friends has a negative impact on a student's BMI. Furthermore, having male peers whose father holds some college degree negatively affects male students' BMI.[23]

Table (5) re-estimates the heterogeneous peer effects model allowing for endogenous social interactions (Section 2.3). This consists in instrumenting $\bar{\mathbb{G}}_z\mathbf{y}$ and $\bar{\mathbb{G}}_z\mathbf{x}$ for $z = 1, ...4$ with the set of instruments in Equation (7). Results from Table (5) show that estimates remain overall stable, as in the homogeneous peer effect model.[24] In particular, the estimate for the between-gender effect from females to males remains much larger than the other three coefficients. One thus concludes that gender heterogeneity is the appropriate hypothesis in our context. This result has potentially important consequences in terms of public policy evaluation, which we illustrate in the next section through a simulation exercise.

5 Gender-based Policy Evaluation

Interventions to curb obesity among teenagers may take various forms, aiming at improving health habits through action (*i.e.*, by changing the cafeteria menu, subsidizing gym access, *etc.*) or information (*i.e.*, educational campaigns about nutrition and healthy lifestyle). Below we provide a simulation exercise that demonstrates the importance of incorporating gender diversity in peer effects when designing effective interventions. We first show how to calculate the total treatment effect of an intervention when peer effects are heterogeneous along gender lines. We then describe the simulation procedure and discuss its results under different hypotheses regarding the intervention's design and response.

5.1 Treatment effect with Gender Heterogeneity

We aim at assessing the effect of an intervention designed to curb obesity among a target population of teenage students connected in a social network. The intervention's allocation

occurs during ages 10-12 in girls and 15-20 in boys. Girls also mature faster than boys on a physical level: girls undergo puberty earlier than boys by about 1-2 years and generally finish the stages of puberty quicker than males.

[23]We also perform a robustness analysis of our results when using the zBMI instead of absolute BMI, and the GMM estimation strategies reveals similar patterns.

[24]Using the Durbin-Wu-Hausman test we do not reject the exogeneity of the endogenous peer effects.

is represented by the intent-to-treat vector $\boldsymbol{itt}$, where $itt_i = 1$ if student i is offered the intervention. We assume that the intervention induces a gender-dependent shift in the BMI intercept, as in[25]

$$\mathbf{y} = \boldsymbol{\iota\alpha} + \gamma \boldsymbol{itt} + \bar{\mathbb{G}}(\boldsymbol{\beta})\mathbf{y} + \boldsymbol{\epsilon} \tag{8}$$

and that the coefficients $\boldsymbol{\gamma} = (\gamma_f, \gamma_m)$ representing the response to the intervention of (male, female) students could be modeled as

$$\gamma_g = impact_g * compliance_g \quad for\ g = m, f \tag{9}$$

where *impact* represents the gender-specific impact of the intervention (*e.g.*, the intervention could induce different changes on females' body size for reasons related to nutrition and biology), and *compliance* represents the propensity of students to comply with the intervention which may also depend on gender (*e.g.*, females could be more or less likely to comply with the intervention).[26]

In a linear intent-to-treat model without peer effects ($\boldsymbol{\beta} = 0$), the total treatment effect would be given by the coefficients $\boldsymbol{\gamma}$. In models with social lags in the dependent variable, the interpretation of the estimated parameters is complicated by the fact that the treatment status of an individual affects not only his own outcome (the *direct* effect), but also the outcome of others (the *indirect* effect). To define a measure of the treatment effect for equation (8), we start from its reduced form

$$\mathbf{y} = \mathbf{S}(\boldsymbol{\beta})^{-1}[\boldsymbol{\iota\alpha} + \gamma \boldsymbol{itt}] + \mathbf{S}(\boldsymbol{\beta})^{-1}\boldsymbol{\epsilon}, \tag{10}$$

where $\mathbf{S}(\boldsymbol{\beta}) = [\boldsymbol{I} - \bar{\mathbb{G}}(\boldsymbol{\beta})]$, and derive the closed-form of the $N \times N$ matrix of partial derivatives with respect to the intervention, which we call $\frac{\partial E(\mathbf{y}|\boldsymbol{itt})}{\partial \boldsymbol{itt}}$. The k^{th} column of $\frac{\partial E(\mathbf{y}|\boldsymbol{itt})}{\partial \boldsymbol{itt}}$ is an $N \times 1$ vector that represents the effect of the treatment of individual k on the outcomes of all other individuals and writes

$$\frac{\partial E\left(\mathbf{y}|\boldsymbol{itt}\right)}{\partial \boldsymbol{itt}_k} = \mathbf{S}(\boldsymbol{\beta})^{-1}[\gamma \mathbf{e}_k], \tag{11}$$

where $\mathbf{e}_k$ is an $N \times 1$ vector with 1 at the k^{th} element and 0 elsewhere. Following the practice in spatial and network econometrics (Hsieh and Lee 2016; LeSage and Page 2009; Comola and Prina 2021), we compute the treatment effect of the intervention as follows: the *direct* treatment effect is the average of the elements in $\frac{\partial E(\mathbf{y}|\boldsymbol{itt})}{\partial \boldsymbol{itt}}$. The *indirect* treatment effect, which operates through the change in the treatment status of peers, is the average of the

[25]The only individual attribute included is one's treatment status, and contextual peer effects are ruled out. This latter condition implies that the treatment status of peers only impacts own BMI through the changes in peers' BMI. Imposing positive contextual peer effects would further increase the estimates of social spillovers in Table (6).

[26]For the sake of simplicity, we are ruling out complications related to non-random attrition.

column (or row) sums of the non-diagonal elements of $\frac{\partial E(\mathbf{y}|\boldsymbol{itt})}{\partial \boldsymbol{itt}}$.[27] The *total* treatment effect is then calculated as the sum of the direct and indirect effects.[28] Note that the formula of equation (11) also applies to the homogeneous peer effect model of equation (4), once we replace $\beta_{mm} = \beta_{mf} = \beta_{ff} = \beta_{fm} = \beta_h$ in $\mathbf{S}(\boldsymbol{\beta})$.

5.2 Simulation Procedure

For given values of $\boldsymbol{\gamma}, \boldsymbol{\beta}$ our simulation routine consists in the following five steps:

1. Generate a dataset with N nodes, equally distributed between males and females, and multiple intent-to-treat vectors $\boldsymbol{itt^k}$ for $k = 1, ..., K$;
2. generate the interaction matrices as follows: first, we draw the binary matrices $\mathbb{A}_z$ for $z = 1, ..., 4$ as random graphs where each link exists independently with a probability p_z (Erdös and Rényi 1959). We then row-standardized $\mathbb{A}_z$ to obtain $\mathbb{G}_z$;
3. compute the (direct, indirect, total) treatment effect using equation (11) for: all students, males, females;[29]
4. compute the aggregate decrease in BMI associated to each treatment vector itt_k;
5. repeat the procedure of steps (1) to (4) for $s = 1, ..., 500$ times.

To carry out the steps above, we must calibrate the values for $\boldsymbol{\gamma}, \boldsymbol{\beta}$ and the population parameters, which we do as follows. As for $\boldsymbol{\gamma}$ we think of an intervention that replaces one fast-food type serving option with one balanced meal. This follows a large experimented tradition of school-level and firm-level initiatives, such as weekly vegetarian menus in cafeterias.[30] We rely on the estimates of the weight production function by Fortin and Yazbeck (2015), which are computed using longitudinal data from Add Health. Their estimate suggest that if a student eats one fast-food meal less per week, his/her BMI decreases by 0.85 in the long term in absence of social interactions.[31] Our first set of results assumes

[27] The row sum represents the impact of changing the treatment status of all other individuals on the outcome of one particular individual, while the column sum represents the impact of changing the treatment status of one particular individual on the outcome of all other individuals. These two quantities coincide.

[28] Note that the estimates of both the direct and indirect effects result from complex interactions between the parameters and the social-interaction structure. For instance, an arbitrary diagonal element may not equal the estimated γ, because the former also includes feedback loops (where observation i affects observation j, and observation j also affects observation i) and longer paths that might go from observation i to j to k and back to i. This is because the series expansion of $\mathbf{S}(\beta)^{-1}$ contains terms $(\mathbb{G})^k$ that, for $k \geqslant 2$, have non-zero elements on the diagonal.

[29] Note that the randomness of the network structure generate variation in these quantities of interest.

[30] One famous campaign in this spirit is the Meatless Monday, launched in the 2000s in collaboration with the Johns Hopkins Bloomberg School of Public Health.

[31] Controlling for lagged BMI, Fortin and Yazbeck (2015) find that an extra day of fast food restaurant visit per week increases zBMI (that is, the BMI standardized for gender and age) by 0.02 points in the long term. This is also consistent with the results by Niemeier et al. 2006. Since the average zBMI in our sample is 0.55, we have transposed their result in our metric as $(23.1 * 0.02)/0.55 \approx 0.85$.

that the impact of the intervention is the same for males and females, and all individuals comply with the intervention, which gives $\gamma_f = \gamma_m = -0.85$. In our second set of results, we assume that $\gamma_f > \gamma_m$, which could be rationalized either with a differential impact (i.e. one fast-food type serving may have a larger impact on females because of hormonal differences, metabolism and portion size) or with differential compliance by gender (i.e. females may be more likely choose the healthy meal rather than looking for fast-food options within or outside the cafeteria, a point that will be discussed below).

The remaining parameters are calibrated on the Add Health sample and our estimation results. We fix $N = 120$, $p_1 = p_3 = 0.03$ and $p_2 = p_4 = 0.015$, which gives the same expected number of within- and between-gender links as the estimation sample of Section (4) (1.8 and 0.9 respectively). Finally, we calibrate the peer effect parameters for the heterogeneous model to equal the estimates from Table (5), and we set β_h accordingly.[32]

5.3 Simulation Results

5.3.1 Gender-neutral response

Panel A of Table (6) reports the results from the simulation exercise assuming $\gamma_f = \gamma_m = \gamma = -0.85$, *i.e.*, full compliance and same impact across gender. The upper part of the panel reports the treatment effect (direct, indirect, total) for all students together and by gender, for the homogeneous and heterogeneous model respectively (mean and standard deviation over 500 draws).

The estimate of the direct effect is -0.85 throughout, meaning that one less fast-food meal per week has a long-term 'direct' effect of decreasing student's own BMI by 0.85 units. This is the same as the response parameter γ in absence of the intervention.[33] The estimate is stable across models (homogeneous and heterogeneous) and across gender (males and females) as it is expected to be.

The indirect treatment effect represents the social spillover through network lines. Its estimate for the homogeneous model is -0.31 for all students confounded, males and females. This means that treating a randomly chosen student has on average an indirect effect of -0.31 units on the BMI of the others, given the existing social synergies. This indirect effect is sizable, as it represents approximately a 37% increase with respect to the direct effect. That is, on the basis of the evidence from Add Health, we conclude that social interactions amplify the impact of the intervention by about 37% with respect to the benchmark scenario of no social interactions and/or no social synergies among students.

When we turn to the heterogeneous model (columns 4-6) we notice that the overall indirect coefficient is still -0.31, but this is actually a weighted average of an estimated effect of -0.26 for males vs. -0.35 for females. This suggests that, once gender-based het-

[32] β_h is the weighted average of the four estimates for the heterogeneous model, which ensures internal consistency (i.e. the two models deliver comparable outcome vectors y for any arbitrary α).

[33] Although these two quantities do not need to coincide precisely (footnote 28), they often do.

erogeneity is accounted for, the social spillovers (in term of BMI decrease among peers) of the intervention on female students are 33% higher than the corresponding social spillovers from males.

The bottom part of panel A reports the aggregate effect on BMI of three intent-to-treat vectors representing different partial-intervention designs. $\boldsymbol{itt^1}$ depicts a scenario where 50% of students were randomly selected for the obesity-curbing intervention, regardless of their gender. $\boldsymbol{itt^2}$ represents a scenario where only female students were selected for the intervention, while in $\boldsymbol{itt^3}$ only male students were selected. In all three scenarios, the expected number of treated students stays the same (i.e. 60 out of 120). The aggregate effect reported in Column 4 ('without PE') does not take into account the social spillovers driven by peer effects.[34] Columns 5 and 6 ('with PE') report the aggregate effect on BMI accounting for social spillovers. Since the intent-to-treat vectors are drawn independently for each simulated network, we report both the average BMI decrease (column 5) and its standard deviation (column 6) over the 500 simulations.

The estimated decrease in BMI without social spillovers is the same across all treatment vectors (51 BMI points throughout column 4). Once we account for social spillovers, results from $\boldsymbol{itt^1}$ suggest that treating 50% of students at random (i.e. regardless of gender) decreases aggregate BMI by 69.34 points.[35] This corresponds to a decrease of 0.58 BMI points per student, or 12.3% of BMI standard deviation in Add Health. However, the magnitude of the impact is larger (-72.1 BMI points) when we treat female students only in $\boldsymbol{itt^2}$. Conversely, the magnitude of the impact is smaller (-66.8 BMI points) when we treat male students only in $\boldsymbol{itt^3}$. These numbers represent a 'natural' metric of efficiency in the context of our policy evaluation exercise: aggregate returns from treating females are 8% larger than returns from treating males. In other words, investing monetary resources in females results in an overall reduction in BMI that is 8% greater than the reduction achieved by treating males.

To summarize, even in the 'neutral' scenario of Panel A where all students are affected by the intervention to the same extent, we find that social spillovers from females are about 33% larger than the ones from males, which results in an additional 8% returns from treating females in terms of aggregate BMI decrease. This result serves as a lower benchmark as it is entirely driven by the heterogeneity of peer effects along gender lines.

5.3.2 Gender-heterogeneous response

Panel B of Table (6) explores a scenario where females are more responsive to the intervention at hand, that is, $\gamma_f > \gamma_m$. This could be due to the fact that the intervention is more effective on female compliers, or to the fact that compliance is higher among females – a point to be discussed below. In particular, we have calibrated a mean-preserving spread

[34] This boils down to summing up the direct effect over treated individuals.

[35] This statistics is by construction the same for the homogeneous peer-effect model under any intent-to-treat vector.

of $\gamma_f = 1; \gamma_m = 0.7$ so that the resulting BMI vector across the student population is comparable to panel A.

Results from Panel B for Column (1) (homogeneous model, all students confounded) are comparable to Column (1) in Panel A, as expected. Columns (2) and (3) report the estimates of the homogeneous peer effect model for females and males respectively: the estimated direct effects are now unsurprisingly -1 and -0.7, but the indirect effects are now -0.36 and -0.25 respectively for females and males: even if peer effects are homogeneous within and across gender, females now have a larger impact on their peers because they experience a larger BMI decrease following the intervention. As before, the estimated effect of -0.31 in Column (1) is a weighted average of the gender-specific effects in columns (2) and (3).

When we turn to the heterogeneous model (columns 4 to 6) we see that all three estimates of the direct effect are comparable to the ones for the homogeneous model, as expected. However, we can see that the gap in indirect effect estimates across gender lines becomes even wider. The indirect effect for females is now almost double that the one for males, -0.41 in Column (5) versus -0.22 in Column (6). This is due to the fact that when $\gamma_f > \gamma_m$ and peer effects are allowed to be heterogeneous across gender, females loose more weight *and also* influence more their peers. The weighted average of these estimates is still 0.31 (as in Column 1), meaning that if we consider a random sample of students regardless of their gender, we expect an indirect effect of 0.31 on average. However, this hides a large disparity across gender lines, as the expected social spillovers from females are double the ones from males.

The bottom part of Panel B reports the effect of the intervention on aggregate BMI. Results show that treating 50% of students at random induces an aggregate decrease of -69.74 BMI points under $\boldsymbol{itt^1}$, which hinders a large disparity between the aggregate BMI decrease from treating females only (-84.82 under $\boldsymbol{itt^2}$) and the corresponding value from treating males only (-55.03 under $\boldsymbol{itt^3}$). This suggests that, because of social synergies, keeping the budget constant, the returns from treating females only are 54% larger than returns from treating males (from -55.03 to -84.82 BMI points).

To summarize, we had seen in Panel A that the heterogeneity of peer effects along gender lines has tangible consequences even in a benchmark setting where all students respond in the same way to the intervention. If we further assume that female students are more responsive to the intervention under scrutiny (Panel B), the estimated spillovers generated by females are twice as large as those generated by males. This translate into a 54% gains in aggregate BMI decrease from reaching out to female students.

5.4 Discussion

Results from Table (6) show that interventions are most effective when targeted to the group generating higher social spillovers. This suggests that incorporating gender-based peer effects could improve the efficacy of policy interventions. In fact, failing to consider such heterogeneity overlooks critical information that could aid in optimizing the allocation process, especially when resources are scarce. The last two decades have witnessed the implementation of a large variety of policy instruments aimed at curbing obesity among teenagers in western countries. Those include interventions administered remotely (*e.g.*, online nutrition education program, email nudges with tailored dieting advice or steps/day goal) and offline (*e.g.*, face-to-face discussion groups, interactive action planning, supply of fruits and vegetables, supply of wearable sport activity trackers). Evidence from the literature on nutrition science suggests that young adults respond differently to interventions depending on their gender (Poobalan et al. 2010; Sharkey et al. 2020).[36] In particular, females appear more motivated to undertake dietary changes, while males are generally more responsive to incentives related to physical activity. Since interventions are often constrained in terms of budget, one way to allocate resources efficiently could be to design policy instruments implicitly tailored to address the motivation and barrier of one specific gender. On the basis of our results above, it is *ceteris paribus* preferable to invest in interventions aimed at educating teenagers towards better dietary patterns, because the higher direct impact on the female population could in turn spills over more effectively to their male peers. Such policy instruments are easy to implement, and they do not aim at impacting the structure of social interactions directly.[37]

Finally, it is worth noting that, throughout the exercise above, we have modeled the response to the intervention as a shift in the BMI. This assumption allows us to be relatively agnostic with respect to the precise mechanism at work. However, policy makers may have alternative assumptions, based on their knowledge of the policy under scrutiny: for instance, they can hypothesize that the intervention affects the way peers influence the marginal utility of own BMI. In order to do a policy-evaluation exercise on the basis of alternative assumptions, one could rely on the theoretical framework developed in Appendix A.

6 Conclusion

This paper explores gender heterogeneity in the social transmission of BMI among teenagers, and its policy consequences. We propose a model where social interactions allow for between- and within-gender heterogeneity, and the Body Mass Index (BMI) results from social synergy among peers in a way that is micro-founded in a non-cooperative manner. We characterize the model econometrically, showing how identification conditions generalize those of the homogeneous model by Bramoullé, Djebbari, and Fortin (2009).

[36] In an extensive meta-analysis, Sharkey et al. 2020 find that gender-targeted programs are more effective to tackle youth obesity, but the results are not statistically significant due to the small sample size.

[37] According to our results, an increase in the frequency of between-gender links could also magnify the effect of the anti-obesity campaign. However, interventions aimed at manipulating directly social links (Goette, Huffman, and Meier 2012; Fafchamps and Quinn 2018) are widely seen as difficult to implement and scale up.

We estimate the model using data on BMI and social interactions of adolescents in the Add Health dataset, controlling for the endogeneity of declared links. Comparing the GMM estimates of a standard homogeneous model with our heterogeneous model, we show that Add Health data display significant gender-dependent heterogeneity in peer effects. In particular, results suggest that male students are more affected by the average BMI of their female friends that the reverse.

One interest in our approach is to design interventions on the basis of the heterogeneity in social interaction patterns. We illustrate this point with a simulation exercise where we evaluate an intervention replacing one fast-food type serving with one balanced meal per week. Results from our simulations show that, in the most conservative scenario where all students are affected by the intervention to the same extent, the social spillovers stemming from female students are 33% higher than the spillovers from males. This result is entirely driven by the heterogeneity of peer effects along gender lines, and it translates into an 8% gain in terms of aggregate BMI decrease from reaching out to females rather than males. If we further assume that female students respond more to the kind of intervention under scrutiny (as the literature on nutrition science seems to suggest), we conclude that social spillovers from females are twice as large as male-generated spillovers and that resources spent on females generate a decrease of aggregate BMI which is 54% above the one generated by resources spent on males.

References

Angelucci, Manuela et al. (2019). "Incentives and Unintended Consequences: Spillover Effects in Food Choice". In: *American Economic Journal: Economic Policy* 11.4, pp. 66–95.

Arduini, Tiziano, Daniela Iorio, and Eleonora Patacchini (2019). "Weight, Reference Points, and the Onset of Eating Disorders". In: *Journal of Health Economics* 65, pp. 170–188.

Arduini, Tiziano, Eleonora Patacchini, and Edoardo Rainone (2020). "Identification and Estimation of Network Models with Heterogeneous Interactions". In: *Advances in Econometrics*. Ed. by A. de Paula, E. Tamer, and M. Voia. Vol. 42.

Badev, Anton (2021). "Nash equilibria on (un)stable networks". In: *Econometrica* 89.3, pp. 1179–1206.

Bendor, Cole D. et al. (2020). "Cardiovascular morbidity, diabetes and cancer risk among children and adolescents with severe obesity". In: *Cardiovascular diabetology* 19.1, pp. 1–14.

Blume, Lawrence E. et al. (2015). "Linear Social Interactions Models". In: *Journal of Political Economy* 123.2, pp. 444–496.

Boucher, Vincent (2016). "Conformism and self-selection in social networks". In: *Journal of Public Economics* 136, pp. 30 –44.

Boucher, Vincent and Bernard Fortin (2016). "Some challenges in the empirics of the effects of networks". In: *The Oxford handbook of the economics of networks*, pp. 277–302.

Boucher, Vincent et al. (2022). "Toward a General Theory of Peer Effects". In: *CEPR Discussion Paper No. DP17315.*

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin (2009). "Identification of peer effects through social networks". In: *Journal of Econometrics* 150.1, pp. 41–55.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin (2020). "Peer effects in networks: a survey". In: *Annual Review of Economics* 12.1, pp. 603–629.

Calvo-Armengol, Antoni, Eleonora Patacchini, and Yves Zenou (2009). "Peer Effects and Social Networks in Education". In: *Review of Economic Studies* 76.4, pp. 1239–1267.

Carrell, Scott E., Bruce I. Sacerdote, and James E. West (2013). "From natural variation to optimal policy? The importance of endogenous peer group formation". In: *Econometrica* 81.3, pp. 855–882.

Christakis, Nicholas A. and James H. Fowler (2007). "The Spread of Obesity in a Large Social Network over 32 Years". In: *The New England Journal of Medicine* 357.4, pp. 370–379.

Cohen-Cole, Ethan and Jason M. Fletcher (2008). "Is obesity contagious?: social networks vs. environmental factors in the obesity epidemic". In: *Journal of Health Economics* 27.5, pp. 1143–1406.

Comola, Margherita and Silvia Prina (2021). "Treatment Effect Accounting for Network Changes". In: *The Review of Economics and Statistics* 103.3, pp. 597–604.

Corrado, Luisa, Roberta Distante, and Majlinda Joxhe (2019). "Body mass index and social interactions from adolescence to adulthood". In: *Spatial Economic Analysis* 14.4, pp. 425–445.

De Paula, Áureo (2017). "Econometrics of Network Models, in Advances in Economics and Econometrics: Theory and Applications". In: ed. by M. Piazzesi B. Honore A. Pakes and L. Samuelson. Cambridge University Press.

Erdös, Paul and Alfréd Rényi (1959). "On Random Graphs I". In: *Publicationes Mathematicae Debrecen* 6, pp. 290–297.

Fafchamps, Marcel and Simon Quinn (2018). "Networks and Manufacturing Firms in Africa: Results from a Randomized Field Experiment". In: *The World Bank Economic Review* 32.3, 656–675.

Fortin, Bernard and Myra Yazbeck (2015). "Peer effects, fast food consumption and adolescent weight gain". In: *Journal of Health Economics* 42, pp. 125–138.

Fryar, Cheryl D., Margaret D. Carroll, and Joseph Afful (2020). "Prevalence of overweight, obesity, and severe obesity among children and adolescents aged 2–19 years: United States, 1963–1965 through 2017–2018." In: *National Center for Health Statistics: Health E-Stats.*

Goette, Lorenz, David Huffman, and Stephan Meier (2012). "The Impact of Social Ties on Group Interactions: Evidence from Minimal Groups and Randomly Assigned Real Groups". In: *American Economic Journal: Microeconomics* 4.1, 101–115.

Goldsmith-Pinkham, Paul and Guido W Imbens (2013). "Social networks and the identification of peer effects". In: *Journal of Business and Economic Statistics* 31.3, pp. 253 –264.

Gong, Gaolang et al. (2009). "Age- and Gender-Related Differences in the Cortical Anatomical Network". In: *Journal of Neuroscience* 29.50, pp. 15684–15693.

Goyal, Manu S et al. (2019). "Persistent metabolic youth in the aging female brain". In: *Proceedings of the National Academy of Sciences* 116.8, pp. 3251–3255.

Griffith, Alan (Forthcoming). "Name Your Friends, but Only Five? The Importance of Censoring in Peer Effects Estimates using Social Network Data". In: *Journal of Labor Economics*.

Halliday, Timothy J. and Sally Kwak (2009). "Weight gain in adolescents and their peers". In: *Economics & Human Biology, Elsevier* 7.2, pp. 181–190.

Hsieh, Chih-Sheng and Lung-Fei Lee (2016). "A Social Interactions Model with Endogenous Friendship Formation and Selectivity". In: *Journal of Applied Econometrics* 31.2, pp. 301–319.

Hsieh, Chih-Sheng and Xu Lin (2017). "Gender and Racial Peer Effects with Endogenous Network Formation". In: *Regional Science and Urban Economics* 67, pp. 135–147.

Hsieh, Chih-Sheng et al. (2020). *Collaboration in bipartite networks, with an application to coauthorship networks*. Tech. rep. Working Paper 2020-030A, Federal Reserve Bank of St-Louis.

Jochmans, Koen (2022). "Peer Effects and Endogenous Social Interactions". In: *Journal of Econometrics*. URL: `https://doi.org/10.1016/j.jeconom.2022.10.004`.

Johnsson, Ida and Hyungsik Roger Moon (2021). "Estimation of peer effects in endogenous social networks: control function approach". In: *Review of Economics and Statistics* 103.2, pp. 328–345.

Kapinos, Kandice and Olga Yakusheva (2011). "Environmental influences on young adult weight gain: evidence from a natural experiment". In: *Journal of Adolescent Health* 48.1, pp. 52–58.

Kelejian, Harry H. and Ingmar Prucha (1998). "A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances". In: *The Journal of Real Estate Finance and Economics* 17.1, pp. 99–121.

Kooreman, Peter (2007). "Time, money, peers, and parents; some data and theories on teenage behavior". In: *Journal of Population Economics* 20.1, pp. 9–33.

Lancaster, Tony (2000). "The incidental parameter problem since 1948". In: *Journal of econometrics* 95.2, pp. 391–413.

LeSage, James and Kelley Page (2009). *Introduction to Spatial Econometrics*. CRC Press, Taylor and Francis.

Lenroot, Rhoshel K and Jay N Giedd (2010). "Sex differences in the adolescent brain." In: *Brain and cognition* 72.1, pp. 46–55.

Lim, Sol et al. (2015). "Preferential Detachment During Human Brain Development: Age- and Sex-Specific Structural Connectivity in Diffusion Tensor Imaging (DTI) Data, Cerebral Cortex". In: *Cerebral Cortex* 25.6, pp. 1477–1489.

Liu, Xiaodong and Lung-fei Lee (2010). "GMM estimation of social interaction models with centrality". In: *Journal of Econometrics* 159.1, pp. 99–115.

Manski, Charles F. (1993). "Identification of endogenous social effects: The reflection problem". In: *The Review of Economic Studies* 60.3, pp. 531–542.

Mora, Toni and Joan Gil (2013). "Peer Effects In Adolescent BMI: Evidence From Spain". In: *Health Economics* 22.5, pp. 501–516.

Niemeier, Heather M. et al. (2006). "Fast food consumption and breakfast skipping: predictors of weight gain from adolescence to adulthood in a nationally representative sample". In: *Journal of Adolescent Health* 39.6, pp. 842–849.

Papoutsi, Georgia S, Andreas C Drichoutis, and Rodolfo M Nayga (2013). "The causes of childhood obesity: A survey". In: *Journal of Economic Surveys* 27.4, pp. 743–767.

Patacchini, Eleonora and Edoardo Rainone (2017). "Social Ties and the Demand for Financial Services". In: *Journal of Financial Services Research* 52, pp. 35–88.

Patacchini, Eleonora and Yves Zenou (2012). "Juvenile delinquency and conformism". In: *Journal of Law, Economics, and Organization* 28.1, pp. 1–31.

Poobalan, Aucott et al. (2010). "Weight loss interventions in young people (18 to 25 year olds): a systematic review." In: *Obesity Review* 11(8), pp. 580–92.

Rees, Daniel and Joseph Sabia (2010). "Sports participation and academic performance: Evidence from the National Longitudinal Study of Adolescent Health". In: *Economics of Education Review* 29.5, pp. 751–759.

Renna, Francesco, Irina B. Grafova, and Nidhi Thakur (2008). "The effect of friends on adolescent body weight". In: *Economics & Human Biology* 6.3, pp. 377–387.

Rogers, Pamela M. et al. (2007). "Human adenovirus Ad-36 induces adipogenesis via its E4 orf-1 gene". In: *International Journal of Obesity* 32.3, pp. 397–406.

Sharkey, Thomas et al. (2020). "Effectiveness of gender-targeted versus gender-neutral interventions aimed at improving dietary intake, physical activity and/or overweight/obesity in young adults (aged 17–35 years): a systematic review and meta-analysis". In: *Nutrition Journal* 19.1, pp. 1–20.

Skinner, Ashley Cockrell et al. (2019). "Prevalence of Obesity and Severe Obesity in US Children, 1999–2016". In: *Pediatrics* 145.5, pp. 34–59.

Trogdon, Justin G., James Nonnemaker, and Joanne Pais (2008). "Peer effects in adolescent overweight". In: *Journal of Health Economics* 27.5, pp. 1388 –1399.

Wolpin, Kenneth I. (2007). "Ex Ante Policy Evaluation, Structural Estimation, and Model Selection". In: *The American Economic Review* 97.2, pp. 48–52.

Yakusheva, Olga, Kandice A Kapinos, and Daniel Eisenberg (2014). "Estimating Heterogeneous and Hierarchical Peer Effects on Body Weight Using Roommate Assignments as a Natural Experiment". In: *Journal of Human Resources* 49.1, pp. 234–261.

Tables and Figures

Table 1: Descriptive statistics

	Mean	s.d.	Min	Max
Weight Status				
BMI	23.13	4.71	12.98	46.07
Males' BMI	23.54	4.64	15.12	44.63
Females' BMI	22.73	4.75	12.98	46.07
Regressors				
Age	16.38	1.44	13	20
White	0.61	0.49	0	1
Black	0.16	0.36	0	1
Grades 9-10	0.26	0.44	0	1
Grades 11-12	0.63	0.48	0	1
Mother: some college education	0.43	0.49	0	1
Father: some college education	0.36	0.48	0	1
Network Statistics				
Number of friends	2.30	2.10	0	10
Males: Number of male friends	1.46	1.34	0	5
Males: Number of female friends	0.83	1.12	0	5
Females: Number of male friends	0.88	1.18	0	5
Females: Number of female friends	1.44	1.31	0	5

N = 2307

Table 2: Estimation of homogeneous peer effects (exogenous network)

	(1)	(2)	(3)	(4)
	Individual Effects		*Contextual Effects*	
	coef.	*s.e.*	*coef.*	*s.e.*
Endogenous Peer Effects	0.220***	0.022	-	-
Age	0.124	0.086	-0.305***	0.044
White	-0.189	0.233	0.183	0.290
Black	-0.253	0.286	0.472	0.378
Grade 9-10	1.114***	0.423	0.097	0.520
Grade 11-12	1.830***	0.483	0.053	0.555
Mother: some college education	0.169	0.150	-0.121	0.244
Father: some college education	-0.260*	0.153	-0.506**	0.242

N=2307. School-level fixed effects included.

Table 3: Estimation of homogeneous peer effects (endogenous network)

	(1)	(2)	(3)	(4)
	Individual Effects		*Contextual Effects*	
	coef.	*s.e.*	*coef.*	*s.e.*
Endogenous Peer Effects	0.234***	0.035	-	-
Age	0.079	0.091	-0.281***	0.094
White	-0.111	0.368	-0.531	1.676
Black	0.267	0.802	-0.642	2.027
Grade 9-10	1.371**	0.663	-0.339	0.976
Grade 11-12	1.791**	0.699	0.263	1.122
Mother: some college education	0.170	0.177	-0.694	1.045
Father: some college education	-0.267	0.208	-0.165	0.994

N=2307. School-level fixed effects included.

Table 4: Estimation of heterogeneous peer effects (exogenous network)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Individual Effects		*Contextual Effects*							
			m - m		m - f		f - m		f - f	
	coef.	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*
Endogenous Peer Effects			0.226***	0.044	0.465***	0.125	0.229***	0.031	0.197**	0.079
Age	0.067	0.087	-0.318***	0.075	-0.427**	0.192	-0.481***	0.074	-0.219	0.138
White	-0.205	0.234	-0.308	0.452	-1.162*	0.680	1.535***	0.454	0.215	0.777
Black	-0.321	0.289	-1.038	0.654	0.393	0.904	1.644***	0.559	1.372	0.992
Grade 9-10	1.231***	0.428	0.738	0.738	-2.951**	1.161	1.341	0.891	-0.178	1.064
Grade 11-12	2.013***	0.488	0.937	0.793	-1.65	1.255	1.654*	0.967	-1.934*	1.110
Mother: some college education	0.215	0.151	0.447	0.419	-0.345	0.640	-0.362	0.400	-0.502	0.670
Father: some college education	-0.244	0.154	-1.1***	0.399	0.03	0.685	-0.347	0.404	-0.207	0.679

N=2307. School-level fixed effects included.

Table 5: Estimation of heterogeneous peer effects (endogenous network)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Individual Effects		*Contextual Effects*							
			m - m		*m - f*		*f - m*		*f - f*	
	coef.	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*
Endogenous Peer Effects			0.261***	0.069	0.424**	0.210	0.223***	0.039	0.272***	0.092
Age	0.015	0.096	-0.278**	0.142	-0.521	0.317	-0.314**	0.149	-0.245	0.259
White	0.09	0.301	-1.786	1.734	0.221	2.521	-0.572	1.435	-2.30	2.839
Black	0.149	0.627	-2.582	2.256	0.608	3.223	0.738	1.702	-2.632	3.301
Grade 9-10	1.591**	0.68	0.473	1.256	-3.863*	2.266	-1.156	1.864	1.310	2.243
Grade 11-12	2.057***	0.724	0.844	1.654	0.409	2.452	-0.494	1.982	0.916	2.350
Mother: some college education	0.128	0.169	-0.194	1.368	-1.853	1.747	0.299	1.245	-1.933	1.930
Father: some college education	-0.361**	0.184	-0.942	1.137	1.877	2.047	0.583	1.247	-2.150	2.085

N=2307. School-level fixed effects included.

Table 6: Simulation results

Panel A: $\gamma_f = \gamma_m = -0.85$						
model:	homogeneous PE			heterogeneous PE		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	females	males	all	females	males
TE: direct	-0.85	-0.85	-0.85	-0.85	-0.85	-0.85
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TE: indirect	-0.31	-0.31	-0.31	-0.31	-0.35	-0.26
	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
TE: total	-1.16	-1.16	-1.16	-1.16	-1.20	-1.11
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)
Aggregate effect on BMI				without PE	with PE	
$\boldsymbol{itt^1}$: 50% students at random				-51	-69.34	(6.35)
$\boldsymbol{itt^2}$: 50% students, females only				-51	-72.10	(1.65)
$\boldsymbol{itt^3}$: 50% students, males only				-51	-66.82	(1.19)
Panel B: $\gamma_f = -1, \gamma_m = -0.7$						
model:	homogeneous PE			heterogeneous PE		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	females	males	all	females	males
TE: direct	-0.85	-1	-0.7	-0.85	-1	-0.7
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TE: indirect	-0.31	-0.36	-0.25	-0.31	-0.41	-0.22
	(0.01)	(0.03)	(0.02)	(0.01)	(0.03)	(0.02)
TE: total	-1.16	-1.37	-0.95	-1.17	-1.41	-0.92
	(0.01)	(0.03)	(0.02)	(0.01)	(0.03)	(0.02)
Aggregate effect on BMI				without PE	with PE	
$\boldsymbol{itt^1}$: 50% students at random				-51	-69.74	(6.51)
$\boldsymbol{itt^2}$: 50% students, females only				-60	-84.82	(1.94)
$\boldsymbol{itt^3}$: 50% students, males only				-42	-55.03	(0.98)

Note: average values computed over 500 draws. Standard errors in parentheses.

Appendix A

We now develop a non-cooperative model to micro-found our estimating equation through the channel of strategic complementarity ('social synergy') in BMI within the social network. We develop the theoretical model for one network of non-isolated students where heterogeneous peer effects only work through the 'endogenous' channel (*i.e.*, δs are set to zero). This is done to simplify the notation, and is aligned with the simulation exercise of section 5. However, the discussion can be trivially extended to the most general case. Also, we ignore the network formation endogeneity as our results remain stable when we take it into account.

Let us consider one population of students ($n^m + n^f = n$), interacting among them. The student i's reference group is non-empty: $n_{i,m} + n_{i,f} > 0$ for each i.[38] The friendship network is defined by four fixed and known binary adjacency matrices $\mathbb{A}_z(z = 1, \cdots, 4)$, and their weighted version $\mathbb{G}_z(z = 1, \cdots, 4)$, defined as above. Every individual maximizes a gender-dependent quadratic utility function which is separable in private and social sub-utilities, subject to a linear production function for the BMI. The maximization program of a type-m individual i is:

$$\max_{y_{i,m}, e_{i,m}} \quad U_{i,m}(e_{i,m}, \mathbf{y}) = -y_{i,m} - \frac{e_{i,m}^2}{2} + \psi_{mm} y_{i,m} \mathbf{g}'_{1i} \mathbf{y}_m + \psi_{mf} y_{i,m} \mathbf{g}'_{2i} \mathbf{y}_f, \tag{12}$$

$$s.t. \quad y_{i,m} = \alpha_0 - \alpha_1 e_{i,m} + \alpha_2 x_{i,m} + \eta_{i,m}, \tag{13}$$

where $y_{i,m}$ is the outcome (*i.e.*, BMI) of individual i in category m, $\mathbf{y}_m$ is the vector of outcomes in m category, $\mathbf{y}_f$ is the vector of outcomes in f category, $\mathbf{y}$ is the concatenated vector of outcomes in f and m categories, e_i stands for the effort of i, $\mathbf{g}'_{zi}$ is the i^{th} row of the social interaction matrix $\mathbb{G}_z$, and x_i and $\eta_{i,m}$ denote observable and unobservable individual characteristics. The first two terms in the utility function describe the private sub-utility: the first term assumes that an increase in BMI reduces the individual i's utility.[39] The second term $\frac{e_{i,m}^2}{2}$ represents the cost of effort to reduce weight and assumes that the marginal cost of effort is increasing with effort. The social sub-utility corresponds to the two last terms in the utility function: we assume that social interactions influence preferences through the channel of social synergy in BMI between a student and his reference group of each type (Fortin and Yazbeck 2015).[40]

[38] Note that the empirical illustration relaxes this assumption, allowing for isolated students.

[39] We are ignoring here a situation where very low weight negatively affects health (*e.g.*, anorexia).

[40] This framework is also consistent with a mechanism of *pure conformity* in social interactions. In that case, an individual's utility is positively affected by the degree to which he conforms with his peers' outcome or characteristics due for instance to the presence of social norms. However, while in a model such as ours, the channels of social synergy and pure conformity are observationally equivalent (Blume et al. 2015; Boucher and Fortin 2016; Boucher et al. 2022), it seems plausible to assume that social synergy is

The maximization program of type-f individuals can be written using a similar utility function, where social interaction parameters can differ from those of type-m ones. Hence, a type-f individual solves the following program:

$$\max_{y_{i,f},e_{i,f}} \quad U_f(e_{i,f},\mathbf{y}) = -y_{i,f} - \frac{e_{i,f}^2}{2} + \psi_{ff} y_{i,f} \mathbf{g}'_{3i} \mathbf{y}_f + \psi_{fm} y_{i,f} \mathbf{g}'_{4i} \mathbf{y}_m \tag{14}$$

$$s.t. \quad y_{i,f} = \alpha_0 - \alpha_1 e_{i,f} + \alpha_2 x_{i,f} + \eta_{i,f} \tag{15}$$

The first order conditions of the type-m maximization program lead to

$$\mathbf{y}_m = \alpha \boldsymbol{\iota}_m + \beta_{mm} \mathbb{G}_1 \mathbf{y}_m + \beta_{mf} \mathbb{G}_2 \mathbf{y}_f + \alpha_2 \mathbf{x}_m + \boldsymbol{\epsilon}_m \tag{16}$$

where $\alpha = \alpha_0 - \mu$, $\beta_{mm} = \mu\psi_{mm}$, $\beta_{mf} = \mu\psi_{mf}$, and $\boldsymbol{\epsilon}_m = \boldsymbol{\eta}_m$, where $\mu = \alpha_1^2$ represents the squared marginal productivity of effort on weight level. Similarly, the first order conditions for type-f individuals lead to

$$\mathbf{y}_f = \alpha \boldsymbol{\iota}_f + \beta_{ff} \mathbb{G}_3 \mathbf{y}_f + \beta_{fm} \mathbb{G}_4 \mathbf{y}_m + \alpha_2 \mathbf{x}_f + \boldsymbol{\epsilon}_f \tag{17}$$

where $\beta_{ff} = \mu\psi_{ff}$, $\beta_{fm} = \mu\psi_{fm}$, and $\boldsymbol{\epsilon}_f = \boldsymbol{\eta}_f$. Assuming that the absolute value of the β's is less than one, if we concatenate Equations (16) and (17), we obtain the following best-response functions for the whole population of students, given the others' weight level (Nash equilibrium):

$$\mathbf{y} = \alpha \boldsymbol{\iota} + \beta_{mm} \mathbb{G}_1 \mathbf{y} + \beta_{mf} \mathbb{G}_2 \mathbf{y} + \beta_{ff} \mathbb{G}_3 \mathbf{y} + \beta_{fm} \mathbb{G}_4 \mathbf{y} + \alpha_2 \mathbf{x} + \boldsymbol{\epsilon}, \tag{18}$$

which coincides with equation (2). Notice that homogeneity implies that all ψ's are equal $(= \psi)$, and thus $\beta_{mm} = \beta_{mf} = \beta_{ff} = \beta_{fm} = \beta$ (equation (4)).

This theoretical result has a practical relevance for the evaluation of exogenous shocks and interventions (Section 5). In fact, the conditions above imply that we can separately identify all the parameters of the utility function provided that we have a proxy for effort. While effort is generally not observed, it is possible to find a good proxy for effort in observational databases at the individual level (*e.g.*, a measure of eating habits, physical exercise, *etc.*). When no such data are available, one can always recover the parameters of the preferences and the production function, *for a given level of* μ. Indeed, each of the four social sub-utility parameters (the ψ's) are proportional to its corresponding β, the proportionality coefficient being μ^{-1}.

Finally, throughout the simulation exercise of section 5 we have assumed that the intervention shifts the intercept α_0 of the BMI production function in equation (13) . This

the mechanism at play in peer effects. Indeed, it means that an increase in the peers' average BMI of a given gender positively influences the marginal utility of his own BMI ($\psi_{fm} > 0; \psi_{mf} > 0$). Heterogeneity in social interactions is reflected by the fact that ψ_{fm} and ψ_{mf} can be different. For instance, as mentioned earlier, since girls are in general more mature and influencial than boys at the same age, it is natural to assume that the former have more influence on the latter's marginal utility than the reverse.

is a benchmark assumption which allows us to be relatively agnostic with respect to the underlying mechanism. However, we could have alternative hypotheses about the channels through which the intervention affects the BMI in the population of interest: for instance, policy makers may have good reasons to believe that the intervention affects either the marginal productivity of effort (α_1) of directly the way peers' BMI influences the marginal utility of own BMI (ψ's). These different scenarios yield different conclusions in terms of policy evaluation, and the amplitude of these discrepancies could be evaluated by an appropriate calibration of the model above, following the footsteps of section (5).

Appendix B

Proof of proposition 1

To prove our proposition, we assume that $\mathbf{S}(\boldsymbol{\beta})$ is invertible (see footnote 10 for sufficient conditions) and we use the formula of the inverse of matrix established using the Newton Binomial formula. The following steps are necessary to prove our proposition:

1. Let $k = 1, 2, 3, 4, ...$ and derive the expression of $\mathbf{S}_k(\boldsymbol{\beta})^{-1}$ using:[41]

$$\mathbf{S}_k(\boldsymbol{\beta}) = \sum_{i=0}^{k\geq 1} \binom{k}{i} \left[(\beta_{mm}\bar{\mathbb{G}}_1)^{k-i} + (k-i)\beta_{mf}(\beta_{mm}\bar{\mathbb{G}}_1)^{k-i-1}\bar{\mathbb{G}}_2\right] . \left[(\beta_{ff}\bar{\mathbb{G}}_3)^{i} + i\beta_{fm}(\beta_{ff}\bar{\mathbb{G}}_3)^{i-1}\bar{\mathbb{G}}_4\right]$$

2. Sum over all k's and re-write $\mathbf{S}(\boldsymbol{\beta})^{-1}$ such that $\mathbf{S}(\boldsymbol{\beta})^{-1} = \mathbf{I} + \sum_{k=1}^{\infty} \mathbf{S}_k(\boldsymbol{\beta})$.

3. Using the latter expression, derive an expression of $\mathbf{W}_i(\boldsymbol{\beta}) = \bar{\mathbb{G}}_i\mathbf{S}(\boldsymbol{\beta})^{-1}$ and $\mathbf{W}_i(\boldsymbol{\beta})\bar{\mathbb{G}}(\boldsymbol{\delta})$ $\forall i \in \{1, 2, 3, 4\}$.

4. Write $\{\mathbf{W_i}(\boldsymbol{\beta}) \left[\gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota\alpha}\right]\}_{\{i=1,2,3,4\}}$ as a function of instruments and extract intruments and the associated restrictions on the parameters of the model, pre-multiplied by matrix $\mathbf{J}$.

For sake of simplicity, let susbscripts mm, mf, ff and fm in $\boldsymbol{\beta}$ be replaced by $1, 2, 3, 4$ respectively. Using the steps enumerated above and developing for $k \in 1, 2, 3, 4$, one can write $\mathbf{S}_k(\boldsymbol{\beta})$ using the expression below:

$$\mathbf{S}_1(\boldsymbol{\beta}) = \left[\beta_1\bar{\mathbb{G}}_1 + \beta_2\bar{\mathbb{G}}_2\right] \times \left[\beta_3\bar{\mathbb{G}}_3 + \beta_4\bar{\mathbb{G}}_4\right]$$

$$\mathbf{S}_2(\boldsymbol{\beta}) = \left[\beta_1^2\bar{\mathbb{G}}_1^2 + 2\beta_1\beta_2\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\right] + 2\left[\beta_1\bar{\mathbb{G}}_1 + \beta_2\bar{\mathbb{G}}_2\right] \times \left[\beta_3\bar{\mathbb{G}}_3 + \beta_4\bar{\mathbb{G}}_4\right] + \left[\beta_3^2\bar{\mathbb{G}}_3^2 + 2\beta_3\beta_4\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4\right]$$

[41]Recall that we order all matrices so that the first n_r^f rows correspond to type-f individuals of network r, and the remaining n_r^m rows are for type-m individuals in network r. This leads by construction to the following identities: $\mathbb{G}_{1,r}.\mathbb{G}_{4,r} = 0_{n_r}$, $\mathbb{G}_{3,r}.\mathbb{G}_{2,r} = 0_{n_r}$, $\mathbb{G}_{1,r}.\mathbb{G}_{3,r} = 0_{n_r}$, $\mathbb{G}_{3,r}.\mathbb{G}_{1,r} = 0_{n_r}$, $\mathbb{G}_{2,r}^{k\geq 2} = 0_{n_r}$, $\mathbb{G}_{4,r}^{k\geq 2} = 0_{n_r}$, $\mathbb{G}_{4,r}.\mathbb{G}_{3,r} = 0_{n_r}$ and $\mathbb{G}_{2,r}.\mathbb{G}_{1,r} = 0_{n_r}$.

$$\begin{aligned}\mathbf{S}_3(\boldsymbol{\beta}) = \quad & \left[\beta_1^3\bar{\mathbb{G}}_1^3 + 3\beta_1^2\beta_2\bar{\mathbb{G}}_1^2\bar{\mathbb{G}}_2\right] + 3\left[\beta_1^2\bar{\mathbb{G}}_1^2 + 2\beta_1\beta_2\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\right] \times \left[\beta_3\bar{\mathbb{G}}_3 + \beta_4\bar{\mathbb{G}}_4\right] \\ + \quad & 3\left[\beta_1\bar{\mathbb{G}}_1 + \beta_2\bar{\mathbb{G}}_2\right] \times \left[\beta_3^2\bar{\mathbb{G}}_3^2 + 2\beta_3\beta_4\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4\right] + \left[\beta_3^3\bar{\mathbb{G}}_3^3 + 3\beta_3^2\beta_4\bar{\mathbb{G}}_3^2\bar{\mathbb{G}}_4\right]\end{aligned}$$

$$\begin{aligned}\mathbf{S}_4(\boldsymbol{\beta}) = \quad & \left[\beta_1^4\bar{\mathbb{G}}_1^4 + 4\beta_1^3\beta_2\bar{\mathbb{G}}_1^3\bar{\mathbb{G}}_2\right] + 4\left[\beta_1^3\bar{\mathbb{G}}_1^3 + 3\beta_1^2\beta_2\bar{\mathbb{G}}_1^2\bar{\mathbb{G}}_2\right] \times \left[\beta_3\bar{\mathbb{G}}_3 + \beta_4\bar{\mathbb{G}}_4\right] \\ + \quad & 6\left[\beta_1^2\bar{\mathbb{G}}_1^2 + 2\beta_1\beta_2\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\right] \times \left[\beta_3^2\bar{\mathbb{G}}_3^2 + 2\beta_3\beta_4\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4\right] + 4\left[\beta_1\bar{\mathbb{G}}_1 + \beta_2\bar{\mathbb{G}}_2\right] \\ \times \quad & \left[\beta_3^3\bar{\mathbb{G}}_3^3 + 3\beta_3^2\beta_4\bar{\mathbb{G}}_3^2\bar{\mathbb{G}}_4\right] + \left[\beta_3^4\bar{\mathbb{G}}_3^4 + 4\beta_3^3\beta_4\bar{\mathbb{G}}_3^3\bar{\mathbb{G}}_4\right]\end{aligned}$$

We then write $\mathbf{S}^{-1}(\boldsymbol{\beta}) = \mathbf{I} + \mathbf{S}_1(\boldsymbol{\beta}) + \mathbf{S}_2(\boldsymbol{\beta}) + \mathbf{S}_3(\boldsymbol{\beta}) + \mathbf{S}_4(\boldsymbol{\beta}) + \sum_{k=5}^{\infty}\mathbf{S}_k(\boldsymbol{\beta})$ using the expressions of $\mathbf{S}_k(\boldsymbol{\beta})$ given above. We are then able to write, $\forall i \in \{1,2,3,4\}$, $\mathbf{W_i}(\boldsymbol{\beta})\left[\gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota\alpha}\right]$ as:

$$\begin{aligned}\mathbf{W_1}(\boldsymbol{\beta})\left[\gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota\alpha}\right] = \gamma\bar{\mathbb{G}}_1\mathbf{x} \quad & + \quad (\gamma\beta_1 + \delta_1)\left[\bar{\mathbb{G}}_1^2 + \beta_1\bar{\mathbb{G}}_1^3 + \beta_1^2\bar{\mathbb{G}}_1^4 + \beta_1^5\bar{\mathbb{G}}_1^2\right]\mathbf{x} \\ & + \quad (\gamma\beta_2 + \delta_2)\left[\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\right]\mathbf{x} + \beta_1(2\gamma\beta_2 + \delta_2)\left[\bar{\mathbb{G}}_1^2\bar{\mathbb{G}}_2\right]\mathbf{x} \\ & + \quad \beta_2(2\gamma\beta_3 + \delta_3)\left[\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3\right]\mathbf{x} + \beta_2(2\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\bar{\mathbb{G}}_4\right]\mathbf{x} \\ & + \quad \left[\bar{\mathbb{G}}_1 + \beta_1\bar{\mathbb{G}}_1^2 + \beta_2\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2 + \beta_1^2\bar{\mathbb{G}}_1^3 + 2\beta_1\beta_2\bar{\mathbb{G}}_1^2\bar{\mathbb{G}}_2 + ...\right]\boldsymbol{\iota\alpha} \\ & + \quad \bar{\mathbb{G}}_1\sum_{k=5}^{\infty}\mathbf{S}_k(\boldsymbol{\beta})\left[(\gamma + \bar{\mathbb{G}}(\boldsymbol{\delta}))\mathbf{x} + \boldsymbol{\iota\alpha}\right]\end{aligned}$$

$$\begin{aligned}\mathbf{W_2}(\boldsymbol{\beta})\left[\gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota\alpha}\right] = \gamma\bar{\mathbb{G}}_2\mathbf{x} \quad & + \quad (\gamma\beta_3 + \delta_3)\left[\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3 + \beta_3\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^2 + \beta_3^2\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^3 + \beta_3^3\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^3\right]\mathbf{x} \\ & + \quad (\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_2\bar{\mathbb{G}}_4\right]\mathbf{x} + \beta_3(2\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4\right]\mathbf{x} \\ & + \quad \beta_3^2(3\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^2\bar{\mathbb{G}}_4\right]\mathbf{x} + \beta_3^3(4\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^3\bar{\mathbb{G}}_4\right]\mathbf{x} \\ & + \quad \left[\bar{\mathbb{G}}_2 + \beta_3\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3 + \beta_3^2\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^2 + 2\beta_3\beta_4\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4 + ...\right]\boldsymbol{\iota\alpha} \\ & + \quad \bar{\mathbb{G}}_2\sum_{k=5}^{\infty}\mathbf{S}_k(\boldsymbol{\beta})\left[(\gamma + \bar{\mathbb{G}}(\boldsymbol{\delta}))\mathbf{x} + \boldsymbol{\iota\alpha}\right]\end{aligned}$$

$$\begin{aligned}\mathbf{W_3}(\boldsymbol{\beta})\left[\gamma\mathbf{x} + \bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x} + \boldsymbol{\iota\alpha}\right] = \gamma\bar{\mathbb{G}}_3\mathbf{x} \quad & + \quad (\gamma\beta_3 + \delta_3)\left[\bar{\mathbb{G}}_3^2 + \beta_3\bar{\mathbb{G}}_3^3 + \beta_3^2\bar{\mathbb{G}}_3^4 + \beta_3^3\bar{\mathbb{G}}_3^5\right]\mathbf{x} \\ & + \quad (\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4\right]\mathbf{x} + \beta_3(2\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_3^2\bar{\mathbb{G}}_4\right]\mathbf{x} \\ & + \quad \beta_3^2(3\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_3^3\bar{\mathbb{G}}_4\right]\mathbf{x} + \beta_3^3(4\gamma\beta_4 + \delta_4)\left[\bar{\mathbb{G}}_3^4\bar{\mathbb{G}}_4\right]\mathbf{x} \\ & + \quad \left[\bar{\mathbb{G}}_3 + \beta_3\bar{\mathbb{G}}_3^2 + \beta_4\bar{\mathbb{G}}_3\bar{\mathbb{G}}_4 + 2\beta_3\beta_4\bar{\mathbb{G}}_3^2\bar{\mathbb{G}}_4 + ...\right]\boldsymbol{\iota\alpha} \\ & + \quad \bar{\mathbb{G}}_3\sum_{k=5}^{\infty}\mathbf{S}_k(\boldsymbol{\beta})\left[(\gamma + \bar{\mathbb{G}}(\boldsymbol{\delta}))\mathbf{x} + \boldsymbol{\iota\alpha}\right]\end{aligned}$$

$$
\begin{aligned}
\mathbf{W_4}(\boldsymbol{\beta})\left[\gamma\mathbf{x}+\bar{\mathbb{G}}(\boldsymbol{\delta})\mathbf{x}+\boldsymbol{\iota\alpha}\right]=\gamma\bar{\mathbb{G}}_4\mathbf{x} \quad &+\quad (\gamma\beta_1+\delta_1)\left[\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1+\beta_1\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1^2+\beta_1^2\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1^3+\beta_1^3\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1^4\right]\mathbf{x}\\
&+\quad (\gamma\beta_2+\delta_2)\left[\bar{\mathbb{G}}_4\bar{\mathbb{G}}_2\right]\mathbf{x}+\beta_1(2\gamma\beta_2+\delta_2)\left[\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\right]\mathbf{x}\\
&+\quad \beta_2(2\gamma\beta_3+\delta_3)\left[\bar{\mathbb{G}}_4\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3\right]\mathbf{x}+\beta_2(2\gamma\beta_4+\delta_4)\left[\bar{\mathbb{G}}_4\bar{\mathbb{G}}_2\bar{\mathbb{G}}_4\right]\mathbf{x}\\
&+\quad \left[\bar{\mathbb{G}}_4+\beta_1\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1+\beta_2\bar{\mathbb{G}}_4\bar{\mathbb{G}}_2+\beta_1^2\bar{\mathbb{G}}_4\bar{\mathbb{G}}_1^2+\dots\right]\boldsymbol{\iota\alpha}\\
&+\quad \bar{\mathbb{G}}_4\sum_{k=5}^{\infty}\mathbf{S}_k(\boldsymbol{\beta})\left[(\gamma+\bar{\mathbb{G}}(\boldsymbol{\delta}))\mathbf{x}+\boldsymbol{\iota\alpha}\right]
\end{aligned}
$$

The above expressions provide sufficient conditions of identification of our parameters using the IV method. These conditions extend the ones obtained in Bramoullé, Djebbari, and Fortin (2009) regarding the independence of the interaction matrices of our model and restrictions on our parameters.

Specifically, considering the expressions given above, we can see that naturally occuring intruments of our endogenous variables include different order of our interaction matrices and interactions of different orders of these matrices. For example, instruments of our first endogenous variable include $\mathbf{JG_1x}$, $\mathbf{J{G_1}^2x}$, $\mathbf{J{G_1}^3x}$ and higher degrees of the matrix $\mathbf{JG}_1$ multiplied by vector $\mathbf{x}$ of characteristics if both $(\gamma\beta_1+\delta_1)\neq 0$ and matrices $\mathbf{G_1}, \mathbf{G_1}^2, \mathbf{G_1}^3, \mathbf{G_1}^4, etc.$ are linearly independent. Following the same method and using the other expressions above, we can see that minimal conditions for IV variables to work for each of the four endogenous variables are $(\gamma\beta_2+\delta_2)\neq 0$, $(\gamma\beta_3+\delta_3)\neq 0$ and $(\gamma\beta_4+\delta_4)\neq 0$. In addition, γ needs to be different from zero and matrices $\bar{\mathbb{G}}_1$, $\bar{\mathbb{G}}_2$, $\bar{\mathbb{G}}_3$, $\bar{\mathbb{G}}_4$, $\bar{\mathbb{G}}_1^2$, $\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2$, $\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3$, $\bar{\mathbb{G}}_3^2$, $\bar{\mathbb{G}}_1^3$, ..., $\mathbf{I}$ need to be independent, which corresponds to the condition that vector columns of matrix $\mathbf{Q}_K$ of instruments should be linearly independent. Additional conditions appear whenever one is concerned about adding instruments of higher order of interaction matrices multiplication. In this case, the additional conditions on parameters of the model take the form of $\beta_i\neq 0\ \forall i\in\{2,3,4\}$ and $((j-1)\gamma\beta_l+\delta_l)\neq 0$ and linear independence of j^{th} order interaction of social interaction matrices such that $\mathbf{CG}_i\bar{\mathbb{G}}_l$ adds up to the independence conditions stated above, where $\mathbf{C}$ is either a single interaction matrix or a non-zero product of interaction matrices. For example, $\mathbf{JG}_1\bar{\mathbb{G}}_2\bar{\mathbb{G}}_4\mathbf{x}$ may be used as an instrument if $\beta_2\neq 0$, $(2\gamma\beta_4+\delta_4)\neq 0$ and matrices $\bar{\mathbb{G}}_1$, $\bar{\mathbb{G}}_2$, $\bar{\mathbb{G}}_3$, $\bar{\mathbb{G}}_4$, $\bar{\mathbb{G}}_1^2$, $\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2$, $\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3$, $\bar{\mathbb{G}}_3^2$, $\bar{\mathbb{G}}_1^3$, ..., $\mathbf{I}$ and $\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2\bar{\mathbb{G}}_4$ are linearly independent. Also, $\mathbf{JG}_4\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^2\mathbf{x}$ may be used as an additional instrument if $\beta_2\neq 0$, $\beta_3\neq 0$, $(3\gamma\beta_3+\delta_3)\neq 0$ and matrices $\bar{\mathbb{G}}_1$, $\bar{\mathbb{G}}_2$, $\bar{\mathbb{G}}_3$, $\bar{\mathbb{G}}_4$, $\bar{\mathbb{G}}_1^2$, $\bar{\mathbb{G}}_1\bar{\mathbb{G}}_2$, $\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3$, $\bar{\mathbb{G}}_3^2$, $\bar{\mathbb{G}}_1^3$, ..., $\mathbf{I}$ and $\bar{\mathbb{G}}_4\bar{\mathbb{G}}_2\bar{\mathbb{G}}_3^2$ are linearly independent.

GMM with quadratic conditions

Let the IV moments be given by the expression $g_1(\boldsymbol{\theta})=\mathbf{Q}_K'\boldsymbol{\epsilon}(\boldsymbol{\theta})$ where $\boldsymbol{\epsilon}(\boldsymbol{\theta})=\mathbf{J}\left(\mathbf{y}-\mathbf{Z}\boldsymbol{\theta}-\boldsymbol{\iota\alpha}\right)$. The additional quadratic moments are given by the expression $g_2(\boldsymbol{\theta})=\left[\mathbf{U}_1'\boldsymbol{\epsilon}(\boldsymbol{\theta}),\mathbf{U}_2'\boldsymbol{\epsilon}(\boldsymbol{\theta}),...,\mathbf{U}_q'\boldsymbol{\epsilon}(\boldsymbol{\theta})\right]'\boldsymbol{\epsilon}(\boldsymbol{\theta})$, where $\mathbf{U}_j$ is such that $tr(\mathbf{JU}_j)=0$.[42] In addition,

[42]Following Liu and Lee (2010), we use $\mathbf{U}_k=\bar{\mathbb{G}}_k-tr(\mathbf{JG}_k)\mathbf{I}/tr(\mathbf{J})$ for $k=1,...,4$.

let the combined vector of linear and quadratic empirical moments be given in $g(\boldsymbol{\theta}) = [g_1'(\boldsymbol{\theta}), g_2'(\boldsymbol{\theta})]$. Finally, let $\widetilde{\Omega} = \widetilde{\Omega}(\tilde{\sigma}^2, \tilde{\mu}_3, \tilde{\mu}_4)$ where $\tilde{\sigma}^2$, $\tilde{\mu}_3$ and $\tilde{\mu}_4$ are initial estimators of the second, third and fourth moments of the error term of our model. In our heterogeneous model, the optimal weighting matrix associated with our GMM is given by

$$\Omega = Var\left[g(\boldsymbol{\theta})\right] = \begin{bmatrix} \tilde{\sigma}^2 \mathbf{Q}_K' \mathbf{Q}_K & \mu_3 \mathbf{Q}_K' \omega \\ \\ \mu_3 \omega' \mathbf{Q}_K & (\mu_4 - 3\sigma^4)\omega'\omega + \sigma^4 \Upsilon \end{bmatrix},$$

where $\omega = [vec_D(\mathbf{U}_1), vec_D(\mathbf{U}_2), ..., vec_D(\mathbf{U}_q)]$, $\mathbf{E}^s = \mathbf{E} + \mathbf{E}'$, $\forall$ square matrix $\mathbf{E}$ of size n, $vec_D(\mathbf{A}) = (a_{11}, a_{22}, ..., a_{nn})$ and $\Upsilon = \frac{1}{2}\left[vec(\mathbf{U}_1^s), vec_D(\mathbf{U}_2^s), ..., vec_D(\mathbf{U}_q^s)\right]$. The feasible optimal GMM estimator is given by

$$\hat{\boldsymbol{\theta}}_{gmm} = argmin\ _{\boldsymbol{\theta} \in \Theta} g'(\boldsymbol{\theta}) \widetilde{\Omega}^{-1} g(\boldsymbol{\theta})$$

which is implemented in our estimates of Section 4.