# Heterogeneous peer effects and gender-based interventions for teenage obesity<sup>\*</sup>

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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 social interaction model which allows for gender-dependent heterogeneity in peer effects. Our empirical approach is consistent with the best response functions of a non-cooperative model where social interactions stem from the channel of pure spillover or pure conformity. 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). This is aligned with the results of the latest cross-country large-scale study showing that since 1990, obesity among children and adolescents has quadrupled worldwide (Phelps et al. 2024). 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 socioeconomic 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; Lim and Cornwell 2023). Most of these studies document the presence of positive and significant peer effects which could increase the prevalence of obesity by shaping body image and/or by boosting the social transmission of unhealthy habits related to diet and physical activity. 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.<sup>1</sup>

Most studies on peer effects assume that social interactions are homogeneous (Manski 1993; Bramoullé, Djebbari, and Fortin 2009; Boucher et al. 2024). 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 accurately reflect reality, particularly when considering adolescent students' weight. This paper proposes an econometric model allowing for heterogeneous peer effects along gender lines and estimates it using detailed network data on teenagers' friendships from the Add Health dataset. Simulations based on our results show that ignoring gender-based 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 detail 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 in this context are rare (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.*,

<sup>&</sup>lt;sup>1</sup>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.

a school). This defines a '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 econometric 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. Differently from them, our paper puts emphasis on the micro-foundation of the econometric model. In particular, we show that our empirical approach is consistent with the best response functions of a noncooperative model where social interactions stem from the channel of pure spillover or pure conformity and that all its parameters are identified under some plausible assumptions.

We illustrate our econometric model using the 1996 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.

When we assume that peer effects are homogeneous within and across gender lines, our findings compare well with the previous literature.<sup>2</sup> When we relax the homogeneity assumption, 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). This result adds to the growing evidence of peer-effect heterogeneity along gender lines. Previous studies on weight-related outcomes suggest that female adolescents are more responsive than males to their peers' behavior.<sup>3</sup> By considering both the within-and between-gender dimensions, we provide evidence that male students are particularly responsive to the weight of their female friends, which is in line with the findings by Kooreman (2007) and Hsieh and Lin (2017) for a number of documented adolescent behaviors other than BMI. This result is compatible with different explanations. For instance, it could be due to the fact that girls are more mature and presumably more influential than

<sup>&</sup>lt;sup>2</sup>Our estimate of the endogenous peer effect in the homogeneous model (0.22 in Table (2)) is in line with the 0.16 coefficient reported by Renna, Grafova, and Thakur (2008) using Add Health data. Corrado, Distante, and Joxhe (2019) report a coefficient of 0.4 for a similar model estimated in logs. Using data on Spanish students, Mora and Gil (2013) report estimates in the 0.17-0.37 range depending on the specification. Using data from rural China, Loh and Li (2013) report peer effects in adolescent bodyweight of around 0.3 with slight variation between two alternative peer definitions. This suggests that peer effects in obesity are robust across countries.

<sup>&</sup>lt;sup>3</sup>This has been documented for purging behavior (Arduini, Iorio, and Patacchini 2019) as well as for BMI (Renna, Grafova, and Thakur 2008; Trogdon, Nonnemaker, and Pais 2008; Yakusheva, Kapinos, and Eisenberg 2014).

boys at the same age during childhood and adolescence. This hypothesis is consistent with recent studies in neurosciences (*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. Also, the stronger influence of girls on boys could be imputed to the dynamics of between-gender relationships and romances (see Hill 2015).<sup>4</sup>

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 also 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 (2023), which provides a natural extension of 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 spillovers of offering meal replacements 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 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 econometric model, and in Section 3 we discuss its microfoundation. Section 4 introduces the data, Section 5 presents our results, and Section 6 describes the simulation exercise. Section 7 concludes. Appendix A provides the mathematical derivation of the theoretical model. Appendix B formalizes the identification conditions and presents the estimation techniques in use.

<sup>&</sup>lt;sup>4</sup>There is an extensive literature in psychology on romantic feelings and experiences of male vs. female adolescents. For instance, Montgomery and Sorell (1998) report that boys fell in love earlier and more often than girls.

# 2 Estimation Strategy

### 2.1 The empirical model

We study a setting where n agents (*i.e.*, students) are distributed across R social networks (*i.e.*, schools), with r = 1, ..., R. In a given network r of size  $n_r$  there are  $n_r^f$  female agents and  $n_r^m$  male agents  $(n_r^f + n_r^m = n_r)$ .<sup>5</sup> These agents interact with both own-gender and other-gender peers and their outcome (*i.e.*, BMI) can be influenced by their behavior.<sup>6</sup>

For each network, we define four fixed and known adjacency matrices:  $\mathbf{A}_{z,r}(z = 1, \dots, 4)$ . The matrix  $\mathbf{A}_{1,r}$  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.<sup>7</sup> The matrix  $\mathbf{A}_{2,r}$  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  $\mathbf{A}_{3,r}$  and  $\mathbf{A}_{4,r}$  are similarly defined for female students, that is,  $\mathbf{A}_{3,r}$  represents the impact of female friends on female students, and  $\mathbf{A}_{4,r}$  the impact of male friends on female students, and  $\mathbf{A}_{4,r}$  the influences j does not necessarily imply that j influences i (e.g., we could have  $a_{1,r,ij} \neq a_{1,r,ji}$ ).<sup>8</sup> We assume that the measurement of  $\mathbf{A}_{z,r}$  is both complete and accurate.<sup>9</sup>

Let us call  $n_{i,r}^m$  and  $n_{i,r}^f$  the number of male and female individuals influencing *i* in the network *r* respectively. The social interaction matrix  $\mathbf{G}_{z,r}$  is the weighted version of matrix  $\mathbf{A}_{z,r}$  such that one has  $g_{1,r,ij} = 1/(n_{i,r}^m + n_{i,r}^f)$  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.*,  $n_{i,r}^m = n_{i,r}^f = 0$ ), the  $\mathbf{G}_{z,r}$ 's matrices are not row-normalized (*i.e.*, not all matrix rows sum up to one). Thus, the social interaction matrix for the whole population in network *r* could be written as  $\mathbf{G}_r = \mathbf{G}_{1,r} + \mathbf{G}_{2,r} + \mathbf{G}_{3,r} + \mathbf{G}_{4,r}$ . The heterogeneous peer effect model for the network *r* writes as

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

where  $\mathbf{y}_r$  is the BMI vector and  $\boldsymbol{\iota}_{n_r}$  is a  $n_r \times 1$  vector of ones.  $\alpha_r$  stands for a fixed effect specific to network r, which takes into account the unobserved factors which commonly

<sup>&</sup>lt;sup>5</sup>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.

<sup>&</sup>lt;sup>6</sup>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.

<sup>&</sup>lt;sup>7</sup>The student i is excluded from his/her own reference group.

<sup>&</sup>lt;sup>8</sup>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.

<sup>&</sup>lt;sup>9</sup>Measurement error in the network topology is an important, yet largely unexplored issue that goes beyond the scope of this paper (De Paula 2017; Bramoullé, Djebbari, and Fortin 2020; Bramoullé and Maes 2024).

influence the BMI of all students within a school. The  $\beta$ s coefficients represent the 'endogenous' peer effects (*i.e.*, the effect of peers' outcomes) which are heterogeneous. For instance,  $\beta_{mm}$  measures the effect of the outcome of male peers on (the BMI of) male students. In the same way,  $\beta_{mf}$  stands for the effect of the outcomes of female peers on male students,  $\beta_{ff}$  of female peers on female students, and  $\beta_{fm}$  of male peers on female students.

We also allow for heterogeneous contextual effects  $\delta s$  that account for the effect of the characteristics of peers on student's outcomes and reads the same way (e.g.,  $\delta_{mm}$  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

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

where  $\mathbf{y} = (\mathbf{y}'_1, ..., \mathbf{y}'_R)'$ ,  $\mathbf{x} = (\mathbf{x}'_1, ..., \mathbf{x}'_R)'$ ,  $\boldsymbol{\iota} = D(\boldsymbol{\iota}_{n_1}, ..., \boldsymbol{\iota}_{n_R})$ ,  $\boldsymbol{\alpha} = (\alpha_1, ..., \alpha_R)'$ ,  $\boldsymbol{\epsilon} = (\boldsymbol{\epsilon}'_1, ..., \boldsymbol{\epsilon}'_R)'$ ,  $\boldsymbol{\beta} = (\beta_{mm}, \beta_{mf}, \beta_{ff}, \beta_{fm})'$ ,  $\boldsymbol{\delta} = (\delta_{mm}, \delta_{mf}, \delta_{ff}, \delta_{fm})'$ ,  $\bar{\mathbf{G}}_z = D(\mathbf{G}_{z,1}, ..., \mathbf{G}_{z,R})$ ,  $\bar{\mathbf{G}}(\boldsymbol{\beta}) = \beta_{mm} \bar{\mathbf{G}}_1 + \beta_{mf} \bar{\mathbf{G}}_2 + \beta_{ff} \bar{\mathbf{G}}_3 + \beta_{fm} \bar{\mathbf{G}}_4$  and  $\bar{\mathbf{G}}(\boldsymbol{\delta}) = \delta_{mm} \bar{\mathbf{G}}_1 + \delta_{mf} \bar{\mathbf{G}}_2 + \delta_{ff} \bar{\mathbf{G}}_3 + \delta_{fm} \bar{\mathbf{G}}_4$ , and D indicates a block diagonal matrix.

In order to eliminate the fixed effects  $\iota \alpha$  avoiding the incidental parameters problem, we perform a global transformation on equation (2).<sup>10</sup> For that purpose we define the global transformation matrix  $\mathbf{J} = D(\mathbf{J}_1, ..., \mathbf{J}_R)$  where  $\mathbf{J}_r = (\mathbf{I}_r - \frac{\iota_r \iota'_r}{n_r}) \forall r \in \{1, ..., R\}$ , such that  $\mathbf{J}\iota \alpha = \mathbf{0}$ , and obtain a transformed model that writes succinctly as

$$\mathbf{J}\mathbf{y} = \mathbf{J}\mathbf{Z}\boldsymbol{\theta} + \mathbf{J}\boldsymbol{\epsilon},\tag{3}$$

where  $\mathbf{Z} = \begin{bmatrix} \bar{\mathbf{G}}_1 \mathbf{y}, \bar{\mathbf{G}}_2 \mathbf{y}, \bar{\mathbf{G}}_3 \mathbf{y}, \bar{\mathbf{G}}_4 \mathbf{y}, \mathbf{X} \end{bmatrix}$ ,  $\mathbf{X} = \begin{bmatrix} \mathbf{x}, \bar{\mathbf{G}}_1 \mathbf{x}, \bar{\mathbf{G}}_2 \mathbf{x}, \bar{\mathbf{G}}_3 \mathbf{x}, \bar{\mathbf{G}}_4 \mathbf{x} \end{bmatrix}$ ,  $\boldsymbol{\theta} = (\boldsymbol{\beta}, \gamma, \boldsymbol{\delta})'$ .

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

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

This corresponds to the specification by Bramoullé, Djebbari, and Fortin (2009) with fixed effects and will be used as a benchmark for our empirical analysis in Section 5.

#### 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.<sup>11</sup> As long as the matrix  $\mathbf{S}(\boldsymbol{\beta}) = (\mathbf{I} - \bar{\mathbf{G}}(\boldsymbol{\beta}))$ , where  $\mathbf{I}$  is the identity matrix, is

<sup>&</sup>lt;sup>10</sup>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.

<sup>&</sup>lt;sup>11</sup>Formally, the conditional exogeneity assumption writes as  $\mathbb{E}(\boldsymbol{\epsilon}|\mathbf{x},\iota\alpha,\mathbf{\bar{G}}_{z=1,\cdots,4})=0.$ 

invertible,<sup>12</sup> we can write the reduced form of equation (2) as

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

which allows us to rewrite

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

where  $\mathbf{W}_z(\boldsymbol{\beta}) = \bar{\mathbf{G}}_z \mathbf{S}(\boldsymbol{\beta})^{-1}$  and  $z = 1, \dots, 4$ . This shows that the right-hand side terms in equation (2) are endogenous ( $\mathbb{E}[(\mathbf{W}_z(\boldsymbol{\beta})\boldsymbol{\epsilon})'\boldsymbol{\epsilon}] \neq 0$ ), 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.<sup>13</sup> 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 the 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  $\mathbf{\bar{G}}_z \mathbf{y}$ . For instance, the instrument set of all matricial products up to the second order (which we use in Section 5) is<sup>14</sup>

$$\mathbf{Q}_{\mathbf{K}} = \mathbf{J} \left[ \bar{\mathbf{G}}_{1}^{2} \mathbf{x}, \bar{\mathbf{G}}_{3}^{2} \mathbf{x}, \bar{\mathbf{G}}_{1} \bar{\mathbf{G}}_{2} \mathbf{x}, \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3} \mathbf{x}, \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{4} \mathbf{x}, \bar{\mathbf{G}}_{3} \bar{\mathbf{G}}_{4} \mathbf{x}, \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1} \mathbf{x}, \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{2} \mathbf{x} \right].$$
(6)

This is an extension of the lagged-friend instrumental strategy which has been widely used in the presence of network data (Calvo-Armengol, Patacchini, and Zenou 2009; Kelejian and Prucha 1998; Patacchini and Zenou 2012). More generally, in the homogeneous social network approach (see Bramoullé, Djebbari, and Fortin 2009), the standard assumptions for identification are that the social network is properly measured and that individual behavior depends on contextual characteristics and behavior of direct peers only. In that case, the characteristics of friends' friends, of friends' friends' friends, *etc.* of the students can be used as excluded instruments for the individual's endogenous peer effect. Our approach is analogous, but it also incorporates heterogeneity within and across gender lines, which allows us to split friends' friends, friends' friends' friends, *etc.* into gender-based

<sup>&</sup>lt;sup>12</sup> 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.

<sup>&</sup>lt;sup>13</sup>This resembles the conditions derived by Arduini, Patacchini, and Rainone (2020).

<sup>&</sup>lt;sup>14</sup>Recall that the matrix ordering leads by construction to the following identities:  $\mathbf{\bar{G}}_1\mathbf{\bar{G}}_4 = 0_{n_r}, \mathbf{\bar{G}}_3\mathbf{\bar{G}}_2 = 0_{n_r}, \mathbf{\bar{G}}_1\mathbf{\bar{G}}_3 = 0_{n_r}, \mathbf{\bar{G}}_2\mathbf{\bar{G}}_1 = 0_{n_r}, \mathbf{\bar{G}}_4\mathbf{\bar{G}}_3 = 0_{n_r}, \mathbf{\bar{G}}_2^2 = 0_{n_r}, \mathbf{\bar{G}}_4^2 = 0_{n_r}.$ 

categories. For instance, we split friends' friends into four categories (*i.e.*, male friends of male friends of students, female friends of their male friends, female friends of their female friends) whose characteristics can be used to build excluded instruments. In summary, characteristics of friends at distance 2,3,4, *etc.* per gender category may be used as instruments to properly estimate the model, as they affect individual behavior only through their effect on peers' behavior.

### 2.3 The endogeneity of social interactions

Endogeneity stemming from network assortativity may arise whenever individual-level unobservables simultaneously determine social interactions and outcomes (*i.e.*, BMI). This type of endogeneity often relates to homophily, that is, the well-documented tendency to create links with individuals with 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.<sup>15</sup> 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) or non-parametrically (*e.g.*, Johnsson and Moon 2021). We tackle the issue by adopting the instrumental-variable method proposed by Jochmans (2023). 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 (2023) 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: (a) that link decisions that involve a given individual are not all independent of one another, but (b) that they are independent of the link decisions made between other pairs of individuals that are located sufficiently far away in the network.<sup>16</sup> For each individual *i* and for  $z = 1, \dots, 4$ , Jochmans (2023) defines the so-called 'leave-own-out network'  $\overline{\mathbb{Q}}_{z,i}$  as the sub-network obtained from  $\overline{\mathbb{G}}_z$  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 since it contains link decisions that do not involve

<sup>&</sup>lt;sup>15</sup>The school-level effects absorb all correlated unobservables common to all students in a given institute, addressing the issue of school-based assortativity.

<sup>&</sup>lt;sup>16</sup>For a discussion how these restrictions accommodate most (cooperative and non-cooperative) peer selection patterns and nest several control-function methods, see Jochmans (2023).

*i* (from restriction (b)). However, it contains predictive information about the latter since link decisions between any triple of individuals are informative about each other (from restriction (a)). Therefore, linear combinations of these leave-own-out networks can serve as instruments for  $\bar{\mathbf{G}}_z \mathbf{y}$  and  $\bar{\mathbf{G}}_z \mathbf{x}$  in equation (2) in analogy with the standard laggedfriend strategy.<sup>17</sup> For the purpose of our study, it boils down to replacing the instrumental variable set in equation (6) with

$$\mathbf{Q}_{\mathbf{K}} = \mathbf{J} \begin{bmatrix} \bar{\mathbf{Q}}_{1} \mathbf{x}, \bar{\mathbf{Q}}_{2} \mathbf{x}, \bar{\mathbf{Q}}_{3} \mathbf{x}, \bar{\mathbf{Q}}_{4} \mathbf{x}, \bar{\mathbf{Q}}_{1}^{2} \mathbf{x}, \bar{\mathbf{Q}}_{3}^{2} \mathbf{x}, \bar{\mathbf{Q}}_{1} \bar{\mathbf{Q}}_{2} \mathbf{x}, \bar{\mathbf{Q}}_{2} \bar{\mathbf{Q}}_{3} \mathbf{x}, \bar{\mathbf{Q}}_{2} \bar{\mathbf{Q}}_{4} \mathbf{x}, \bar{\mathbf{Q}}_{3} \bar{\mathbf{Q}}_{4} \mathbf{x}, \bar{\mathbf{Q}}_{4} \bar{\mathbf{Q}}_{1} \mathbf{x}, \bar{\mathbf{Q}}_{4} \bar{\mathbf{Q}}_{2} \mathbf{x} \end{bmatrix},$$
(7)

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

# 3 Microfoundation

This section discusses the theoretical model underpinning our econometric framework. The mathematical foundation of this model is provided in Appendix A.

Gender-based heterogeneity in peer effects may operate through two channels (Blume et al. 2015; Boucher and Fortin 2016; Boucher et al. 2024). The first one is the *spillover* (*i.e.*, strategic complementarity) channel, which occurs when an individual's actions indirectly influence the outcomes of others through peer effects. For example, in our context, the transmission of information about the importance of maintaining a healthy lifestyle between friends may be more effective within the same gender or across gender lines. Another example involves students who enjoy going to fast-food restaurants or participating in various sports with friends of the same gender.<sup>18</sup> A second channel is *conformity*, which refers to the extent to which students derive utility from aligning their behavior with that of their peers. In the context of fighting obesity, this channel may differ depending on whether the students have peers of the same or the opposite gender.

In Appendix A we demonstrate that equation (1) is microfounded within a hybrid noncooperative model where peer effects may operate through the channels of spillover and conformity in BMI. In our context, the spillover channel implies that a student's marginal utility of having a healthy weight increases as his peers of a given gender achieve a healthy body weight (that is,  $\psi_{mf} > 0$ ;  $\psi_{mm} > 0$ ;  $\psi_{fm} > 0$ ;  $\psi_{ff} > 0$ , in equations (13) and (15)). In that case, heterogeneity in social interactions is reflected by the fact that the  $\psi$ 's can be different. The channel of conformity implies that one's utility is positively affected by the degree to which he conforms with his peers' outcomes or characteristics (that is,  $\lambda_{mf} > 0$ ;  $\lambda_{fm} > 0$ ;  $\lambda_{fm} > 0$ ;  $\lambda_{ff} > 0$ , in equations (13) and (15)).

In Appendix A we show that a structural model combining both spillover and conformity channels is generally unidentified. However, assuming we have some proxy for

<sup>&</sup>lt;sup>17</sup>Note that, if we relax conditional exogeneity of the network, the contextual peer effects  $\bar{\mathbf{G}}_{z}\mathbf{x}$  become endogenous.

<sup>&</sup>lt;sup>18</sup>Rees and Sabia (2010) documents gender-based heterogeneity in sports participation using the same Add Health data we use.

individual effort (*e.g.*, eating habits) or some slight restrictions on conformity preferences, both the models of pure spillover (no conformity) and pure conformity (no spillover) are identified, but observationally equivalent. Moreover, we show that while the pure spillover channel allows for indirect effects in social interactions, the pure conformity channel implies the absence of such effects (Blume et al. 2015; Boucher and Fortin 2016). The basic intuition for the latter result is that an exogenous shock induces the same direct effect (*i.e.*, without social interactions) on a student's BMI and on that of his peers. Therefore, the (euclidean) gap between these variables is not influenced by the shock. As a result, in the pure conformity model, social interactions between individuals will generate no indirect effects.

As the models with pure spillover and pure conformity are observationally equivalent, they both result in the same probability distribution of observable data. Throughout our paper, we privilege the assumption that social interactions stem from the spillover channel for two reasons. First, it allows for the presence of indirect effects. Second, it is in line with the hypothesis suggested in neuroscience literature (*e.g.*, Gong et al. 2009; Lenroot and Giedd 2010; Lim et al. 2015; Goyal et al. 2019) that, at the same age, girls are more mature and influential than boys. This hypothesis suggests that girls are expected to transmit more valuable information to boys on the importance of fighting obesity than the reverse (thus, one should expect  $\psi_{mf} > \psi_{fm}$ ).

### 4 Data

### 4.1 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.

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 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:  $BMI = (weight in kilograms)/(height in meters)^2$ .<sup>19</sup> 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 relies on observing the whole network topology.<sup>20</sup>

### 4.2 Descriptive statistics

Our estimation sample consists of 2307 students.<sup>21</sup> 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.<sup>22</sup> Table (1) provides descriptive statistics of the variable of interest. The 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 the relevant individual characteristics, we can see that the 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 are remarkably comparable among male and female students. Also, this difference suggests upfront that the gender divide could play a role in what concerns peer effects. 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 and 5 females) may not be binding.<sup>23</sup>

 $<sup>^{19}{\</sup>rm We}$  do not use self-declared body mass indices, although declared BMIs are shown to reflect real variables in the context of Add Health.

<sup>&</sup>lt;sup>20</sup>The exclusion restriction for instrumental variables built from lagged-friends characteristics crucially depends on the network being correctly measured (Bramoullé, Djebbari, and Fortin 2020; Bramoullé and Maes 2024).

 $<sup>^{21}</sup>$ Since we use information from both Wave I and II, we focus on the saturated-sample students interviewed in both waves (2,612 students). The estimation sample is 2,307 because of missing values in the variables of interest.

 $<sup>^{22}548</sup>$  students did not nominate any friend, and 309 of them were also nominated by no one.

 $<sup>^{23}</sup>$ 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 (2022) using Add Health data. This is reassuring in our context where peer effect estimates are significantly positive.

# 5 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.

#### 5.1 homogeneous 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 the education level of the mother and father, respectively.<sup>24</sup> We instrument the term  $\mathbf{\bar{G}y}$  with lagged-friends characteristics of the second degree, that is, the (average) attributes of friends of friends  $\mathbf{\bar{G}}^2\mathbf{x}$ . This boils down to assuming that social interactions are exogenous conditionally on observables and school-level effects (see Footnote 11).

Results indicate that the coefficient associated with the endogenous peer effect ( $\mathbf{Gy}$ ) 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  $\mathbf{\bar{G}x}$ . 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 the transmission of information via learning good health habits.

Table (3) re-estimates the homogeneous peer effects model, allowing for endogenous social interactions (Section 2.3). For the homogeneous model, this consists in instrumenting  $\bar{\mathbf{G}}\mathbf{y}$  and  $\bar{\mathbf{G}}\mathbf{x}$  with  $\bar{\mathbf{Q}}\mathbf{x}$  and  $\bar{\mathbf{Q}}^2\mathbf{x}$ . Results from Table (3) show that estimates remain overall stable (the endogenous peer effect is now at 0.23).<sup>25</sup> 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

 $<sup>^{24}</sup>$ 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.

 $<sup>^{25}</sup>$ Using the Durbin-Wu-Hausman test we do not reject the exogeneity of the endogenous peer effect.

a severe assortativity bias in Add Health data (Goldsmith-Pinkham and Imbens 2013; Boucher 2016; Badev 2021).<sup>26</sup>

### 5.2 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 of 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:  $\mathbf{\bar{G}}_1^2 \mathbf{x}$  and  $\mathbf{\bar{G}}_1 \mathbf{\bar{G}}_2 \mathbf{x}$  (the attributes of male/female friends of male friends of male students);  $\mathbf{\bar{G}}_2 \mathbf{\bar{G}}_4 \mathbf{x}$  and  $\mathbf{\bar{G}}_2 \mathbf{\bar{G}}_3 \mathbf{x}$  (the attributes of male/female friends of female friends of male students);  $\mathbf{\bar{G}}_4 \mathbf{\bar{G}}_1 \mathbf{x}$  and  $\mathbf{\bar{G}}_4 \mathbf{\bar{G}}_2 \mathbf{x}$  (the attributes of male/female friends of female friends of female students);  $\mathbf{\bar{G}}_4 \mathbf{\bar{G}}_1 \mathbf{x}$  and  $\mathbf{\bar{G}}_3^2 \mathbf{x}$  (the attributes of male/female friends of male friends of female students),  $\mathbf{\bar{G}}_3 \mathbf{\bar{G}}_4 \mathbf{x}$  and  $\mathbf{\bar{G}}_3^2 \mathbf{x}$  (the attributes of male/female friends of females friends of female students). The upper panel provides the four endogenous peer effect 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 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 0.229 for the m - m and f - f coefficients, respectively) are similar in magnitude to the f - m coefficient (0.197), 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).<sup>27</sup> This suggests that males respond more to the average BMI of their female friends than the reverse, a result which is also obtained by Kooreman (2007) and Hsieh and Lin (2017) for several adolescent behaviors.

We report the estimates and standard errors related to individual characteristics in columns 1-2, and the ones for contextual effects (within- and between- genders) 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)

<sup>&</sup>lt;sup>26</sup>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)).

<sup>&</sup>lt;sup>27</sup>All pairwise Wald test statistics reject the equality of the m - f coefficient with the other three peereffect estimates (with significance at 10% or below).

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.<sup>28</sup>

Table (5) re-estimates the heterogeneous peer effects model allowing for endogenous social interactions (Section 2.3). This consists in instrumenting  $\bar{\mathbf{G}}_z \mathbf{y}$  and  $\bar{\mathbf{G}}_z \mathbf{x}$  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. 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.

Finally, we acknowledge that weak instruments can affect Tables (4) and (5) instrumentation strategy. This concern applies to all peer effect models estimated on network data, but it is particularly difficult to quantify in our setting.<sup>29</sup>

### 5.3 Potential Mechanisms

In this section, we discuss some of the mechanisms that could explain our findings and test for the ones for which our data allow. Our main results of Table (4) and (5) suggest that peer effects are heterogeneous along gender lines, and that male students are particularly responsive to the BMI of their female friends. As mentioned in the introduction, in our context, this result may be partly related to the fact that girls mature earlier than boys in adolescence.<sup>30</sup> We deepen our analysis by studying whether friends with different characteristics trigger peer effects of different kinds (*e.g.*, effects of virtuous or vicious type) on individual BMI, and how this dimension interacts with gender heterogeneity.

In what follows, we explore three dimensions of peer heterogeneity: nutrition habits, sports activities, and socio-economic status.<sup>31</sup> To do so, we divide peers according to high/low (H/L) type as follows: as for nutrition habits, peers are considered H-type if they ate at a fast-food place at most once during the past week (36% of the individual sample),

<sup>&</sup>lt;sup>28</sup>We also perform a robustness analysis of our results when using the zBMI instead of absolute BMI, and the GMM estimation strategies reveal similar patterns.

<sup>&</sup>lt;sup>29</sup>The standard critical values for weak-IV testing (Stock and Yogo 2005) are designed for data without correlation among units and are available for up to 3 endogenous variables. On the other hand, our models have 4 (Table 4) or 32 endogenous regressors (Table 5).

<sup>&</sup>lt;sup>30</sup>According to a neuroscience study by Lim et al. (2015), the optimizing of brain connectivity usually 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. The fact that girls develop faster may, in turn, affect the way same-age boys look at girls and shape their body image in the context of romantic relationships.

<sup>&</sup>lt;sup>31</sup>Information on nutrition and sports habits comes from Wave 2, while the proxies for socio-economic status are retrieved from the parental questionnaire in Wave 1.

and L-type otherwise. As for sport, peers are considered H-type if they practiced sport at least once during the past week (72% of the individual sample), and L-type otherwise. As for socio-economic status, peers are considered as H-type if are not living in precarious conditions (73% of the sample), and L-type if they do.<sup>32</sup> Based on the definitions above, for each dimension of interest, we split all four interaction matrices into two, that is,  $\mathbf{G}_{z,r}^{H} + \mathbf{G}_{z,r}^{L} = \mathbf{G}_{z,r}$  for z = 1, ..., 4, and we provide the results from the GMM estimation of equation (2) separately for H/L-type peers, keeping all the rest of the estimation strategy as before.<sup>33</sup>

Table (6) reports the estimates described above, for the endogenous peer effects only. These results are insightful to shed light on the mechanisms driving gender-based heterogeneity of peer effects in our setting. As for eating habits, we can see that everyone seems to be affected significantly (*i.e.*, presumably dragged down) by friends with bad eating habits. However, when we turn to good eating habits we see that only the m - f and f - f coefficients are significant, suggesting that peer effects flowing through virtuous eating habits stem primarily from females. The reverse pattern is observed when we explore the sports dimension: while friends with virtuous sports habits generate peer effects across all four categories, we notice that only female peers with low sports activity generate significant peer effects (*i.e.*, only the m - f and f - f coefficients appear significant). Taken together, these patterns suggest that females are more likely to generate virtuous peer effects through food habits than through sports practice, which is in line with (and motivates) the discussion of Section 6.4. Add Health data does not provide information on the activities friends do together, and thus, we cannot disentangle whether the observed effects stem from doing activities together (e.g. sport or fast-food eating) or from other channels (e.g., shaping body image, spreading information on healthy lifestyle practices). While the results above cannot be conclusive on the matter, we conjecture that females generate larger peer effects on male friends not necessarily because they eat out with them, but also because they are more mature and more influential (as discussed in Section 1) to convey healthy norms about body image and dietary habits. As for socio-economic status, results reconfirm that the impact of female peers on male students is larger in magnitude across both high- and low-status samples. In the low-status sample, we remark that the f - mcoefficients loose significance, suggesting that females are less impacted by the outcome of some of their male friends, in line with the discussion above.

 $<sup>^{32}</sup>$ Households are coded precarious if they declare not having enough money to pay for bills, or receive targeted subsidies (*e.g.*, food stamps, social security or housing subsidies, unemployment compensation).

<sup>&</sup>lt;sup>33</sup>In principle, our estimation strategy would allow us to split each of the four heterogeneous peer-effect terms along the H- versus L-type lines: that is, we could include two separate m-m coefficients for H-type and L-type friends and so on. However, estimating a model with eight peer-effect terms is not viable in our context due to data and sample size limitations.

#### 5.4 Robustness analysis

Finally, we produce a battery of ancillary results to ensure that our findings are robust to variations in the empirical strategy. Table 7 reports the results of the robustness analysis based on the GMM estimation of equation (2). In the interest of space, we only report coefficients and standard errors for the endogenous peer effects.

In the first line of Table 7, we keep the whole student estimation sample (N=2307), but we exclude links to peers with extreme BMI measures.<sup>34</sup> This is to see whether the gender-heterogeneity of peer effect is sensitive to the exclusion of students with very low or very high BMI. In the second line, we drop from the estimation sample students with declared eating disorders, who may be particularly sensitive to the weight of peers (Arduini, Iorio, and Patacchini 2019).<sup>35</sup> In the third line, we exclude from the estimation sample the students who report extreme values for their body image.<sup>36</sup> In the last two lines, we split the estimation sample based on whether the student declared a recent romantic relationship or not.<sup>37</sup>

Overall, results from Table 7 reconfirm the main pattern of results of Table 4, namely that the peer effects of the m - f type are larger than the other estimated effects. This enhances the credibility of our identification strategy and provides further evidence in support of our results.

## 6 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.

 $<sup>^{34}{\</sup>rm We}$  drop declared links to students below the 1st centile or above the 99th centile of the BMI distribution (50 students).

<sup>&</sup>lt;sup>35</sup>Information on eating disorders comes from Wave 2. We drop students who declare purging via vomit, diet pills or laxative methods.

<sup>&</sup>lt;sup>36</sup>Information on self-reported body image comes from Wave 1 (*'How do you think of yourself in terms of weight?'*) and we drop students who replied *'very underweight'* or *'very overweight'*.

<sup>&</sup>lt;sup>37</sup>The information on romantic relationships comes from Wave 2 (In the last 18 months have you had a romantic relationship with anyone?).

#### 6.1 Treatment effect with Gender Heterogeneity

We aim to assess 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 is represented by the intent-to-treat vector 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<sup>38</sup>

$$\mathbf{y} = \boldsymbol{\iota}\boldsymbol{\alpha} + \gamma \boldsymbol{i}\boldsymbol{t}\boldsymbol{t} + \mathbf{G}(\boldsymbol{\beta})\mathbf{y} + \boldsymbol{\epsilon}$$
(8)

and that the coefficients  $\gamma = (\gamma_f, \gamma_m)$  representing the response to the intervention of (male, female) students could be modelled 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 in females' body size for reasons related to complexion, nutrition or 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).<sup>39</sup>

In a linear intent-to-treat model without peer effects ( $\beta = 0$ ), the total treatment effect would be given by the coefficients  $\gamma$ . 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

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

where  $\mathbf{S}(\boldsymbol{\beta}) = [\boldsymbol{I} - \bar{\mathbf{G}}(\boldsymbol{\beta})]$ , and derive the closed-form of the  $N \times N$  matrix of partial derivatives with respect to the intervention, which we call  $\frac{\partial E(\boldsymbol{y}|\boldsymbol{itt})}{\partial \boldsymbol{itt}}$ . The  $k^{th}$  column of  $\frac{\partial E(\boldsymbol{y}|\boldsymbol{itt})}{\partial \boldsymbol{itt}}$  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* 

<sup>&</sup>lt;sup>38</sup>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 their own BMI through the changes in peers' BMI. Imposing positive contextual peer effects would further increase the estimates of spillovers in Table (8).

<sup>&</sup>lt;sup>39</sup>For the sake of simplicity, we are ruling out complications related to non-random attrition.

treatment effect is the average of the elements in  $\frac{\partial E(\mathbf{y}|itt)}{\partial itt}$ . The *indirect* treatment effect, which operates through the change in the treatment status of peers, is the average of the column (or row) sums of the non-diagonal elements of  $\frac{\partial E(\mathbf{y}|itt)}{\partial itt}$ .<sup>40</sup> The *total* treatment effect is then calculated as the sum of the direct and indirect effects.<sup>41</sup> 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  $\mathbf{S}(\boldsymbol{\beta})$ .

### 6.2 Simulation Procedure

For given values of  $\gamma, \beta$  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  $itt^k$  for k = 1, ..., K;
- 2. generate the interaction matrices as follows: first, we draw the binary matrices  $\mathbf{A}_z$  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  $\mathbf{A}_z$  to obtain  $\mathbf{G}_z$ ;
- 3. compute the (direct, indirect, total) treatment effect (TE) using equation (11) for: all students, males, females;<sup>42</sup>
- 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  $\gamma, \beta$  and the population parameters, which we do as follows. As for  $\gamma$ , 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.<sup>43</sup> 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 suggests that if a student eats one fast-food meal less per week, his/her BMI decreases by 0.85

<sup>&</sup>lt;sup>40</sup>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.

<sup>&</sup>lt;sup>41</sup> 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  $\gamma$ , 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  $(\mathbf{G})^k$  that, for  $k \ge 2$ , have non-zero elements on the diagonal.

<sup>&</sup>lt;sup>42</sup>Note that the randomness of the network structure generates variation in these quantities of interest.

<sup>&</sup>lt;sup>43</sup>One famous campaign in this spirit is Meatless Monday, launched in the 2000s in collaboration with the Johns Hopkins Bloomberg School of Public Health.

in the long term in the absence of social interactions.<sup>44,45</sup> Our first set of results assumes 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 size of consumed portion) 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 (5) (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  $\beta_h$  accordingly.<sup>46</sup>

#### 6.3 Simulation Results

#### 6.3.1 Gender-neutral response

Panel A of Table (8) 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  $\gamma$  in the absence of the intervention.<sup>47</sup> The estimate is stable across models (homogeneous and heterogeneous) and across genders (males and females) as it is expected to be.

The indirect treatment effect represents the spillovers 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 spillovers. This indirect effect is sizable, as it represents approximately a 37% increase with respect to the direct

<sup>&</sup>lt;sup>44</sup>Controlling for lagged BMI, Fortin and Yazbeck (2015) find that an extra day of fast food restaurant visits 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  $(23.1 * 0.02)/0.55 \approx 0.85$ .

<sup>&</sup>lt;sup>45</sup>Fortin and Yazbeck (2015) do not provide differential estimates based on individual characteristics (*e.g.*, lagged BMI). Were such estimates available, they could be incorporated into our simulation exercise via the  $\gamma_g$  parameter.

 $<sup>{}^{46}\</sup>beta_h$  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  $\alpha$ ).

<sup>&</sup>lt;sup>47</sup>Although these two quantities do not need to coincide precisely (footnote 41), they often do.

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 spillovers 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 heterogeneity is accounted for, the spillovers (in term of BMI decrease among peers) of the intervention on female students are 33% higher than the corresponding 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.  $itt^1$  depicts a scenario where 50% of students were randomly selected for the obesity-curbing intervention, regardless of their gender.  $itt^2$  represents a scenario where only female students were selected for the intervention, while in  $itt^3$ , 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 peer effect ('without PE') does not take into account the spillovers driven by peer effects.<sup>48</sup> Columns 5 and 6 ('with PE') report the aggregate effect on BMI accounting for 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 spillovers is the same across all treatment vectors (-51 BMI points throughout column 4). Once we account for spillovers, results from  $itt^1$  suggest that treating 50% of students at random (*i.e.*, regardless of gender) decreases aggregate BMI by 69.34 points.<sup>49</sup> 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  $itt^2$ . Conversely, the magnitude of the impact is smaller (-66.8 BMI points) when we treat male students only in  $itt^3$ . 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 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.

<sup>&</sup>lt;sup>48</sup>This boils down to summing up the direct effect over treated individuals.

 $<sup>^{49}{\</sup>rm This}$  statistic is by construction the same for the homogeneous peer-effect model under any intent-to-treat vector.

#### 6.3.2 Gender-heterogeneous response

Panel B of Table (8) 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 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 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 genders, females loose more weight and also influence their peers more. 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 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  $itt^1$ , which hinders a large disparity between the aggregate BMI decrease from treating females only (-84.82 under  $itt^2$ ) and the corresponding value from treating males only (-55.03 under  $itt^3$ ). This suggests that, because of social spillovers, 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 translates into a 54% gain in aggregate BMI decrease from reaching out to female students.

### 6.4 Discussion

Results from Table (8) show that interventions are most effective when targeted to the group generating higher 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).<sup>50</sup> 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, spill 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.<sup>51</sup>

Finally, it is worth noting that, throughout the exercise above, we have modelled 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 their 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.

<sup>&</sup>lt;sup>50</sup>In an extensive meta-analysis, Sharkey et al. 2020 find that gender-targeted programs are more effective in tackling youth obesity, but the results are not statistically significant due to the small sample size.

<sup>&</sup>lt;sup>51</sup>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.

## 7 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 interactions among peers in a way that is microfounded 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).

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 than 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 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 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.

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# Tables and Figures

	Mean	s.d.	Min	Max
Weight Ste	atus			
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
Regresso	rs			
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 Sta	tistics			
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

Table 1:	Descriptive	statistics

N=2307

	(1)	(2)	(3)	(4)
	Individual	$E\!f\!fects$	Contextual	$E\!f\!fects$
	coef.	<i>s.e.</i>	coef.	<i>s.e.</i>
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

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

N=2307. School-level fixed effects included.

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

	(1)	(2)	(3)	(4)
	Individual	Effects	Contextual	$E\!f\!fects$
	coef.	<i>s.e.</i>	coef.	<i>s.e.</i>
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.

	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)	(10)
	Individual	Effects				$\sigma ontextual$	l Effects			
			1 - <i>m</i>	u u	- <i>w</i>	f	f - f		f - (	n
	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
Note: School-level fixed effects incl	luded. $N=230$	07. Peer	effects are de	fined as j	follows: m -	- m is th	e effect of ma	ule peers	on male st	udents,
m-f is the effects of female peers	on male stud	ents, $f - i$	n is the effec	ts of mal	e peers on f	emale stud	lents, $f - f$ is	s the effe	cts of fema	le peers
$on\ female\ students.$										

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

	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)	(10)
	Individual	Effects				Context	ual Effects			
			- <i>w</i>	m	- <i>w</i>	f	f - f	e.,	f - 1	n
	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
Note: School-level fixed effects inc	luded. $N=230$	17. Peer	effects are d	lefined as	follows: n	i - m is	the effect of	male pee	ers on male	students,
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m-f is the effects of female peers on male students, f-m is the effects of male peers on female students, f-f is the effects of female peers on female students.

	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
	- <i>m</i>	m	- <i>m</i>	f	f - f	e.,	f - n	u
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
eating: H	0.012	0.037	$0.227^{*}$	0.126	$0.196^{***}$	0.043	-0.055	0.097
eating: L	$0.298^{***}$	0.049	$0.254^{**}$	0.114	$0.230^{***}$	0.035	$0.365^{***}$	0.084
sport: H	$0.216^{***}$	0.037	$0.277^{***}$	0.088	$0.297^{***}$	0.053	$0.340^{***}$	0.078
sport: L	0.016	0.071	$0.264^{**}$	0.117	$0.202^{***}$	0.032	0.117	0.094
SES: H	$0.237^{***}$	0.052	$0.477^{***}$	0.127	$0.261^{***}$	0.032	$0.290^{***}$	0.077
SES: L	$0.163^{***}$	0.046	$0.305^{***}$	0.118	$0.201^{***}$	0.055	0.110	0.082
Note: coeffi	cients and s.	e. report	ed for endoge	enous pee	r effects only	. School	-level fixed ej	fects
included. N	I=2307. Peen	r effects (	are defined a	s follows.	m-m is t	he effect	of male peer	$uo \ s.$
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Table 6: Split peers by characteristics, endogenous peer effects

male students, m - f is the effects of female peers on male students, f - f is the effects of female peers on female students, f - m is the of male peers on female students.

		(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
0	N	m - r	n	- m	f	f - n	L	- J	f
эдпира		coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
no extreme-BMI links	2307	$0.303^{***}$	0.057	$0.523^{***}$	0.142	$0.236^{***}$	0.037	$0.165^{**}$	0.084
no eating disorder	2262	$0.217^{***}$	0.045	$0.537^{***}$	0.129	$0.238^{***}$	0.034	0.129	0.086
no extreme body image	2185	$0.235^{***}$	0.044	$0.409^{***}$	0.119	$0.203^{***}$	0.033	0.099	0.084
in a relationship	1310	$0.192^{**}$	0.08	$0.562^{**}$	0.283	$0.214^{*}$	0.114	$0.347^{*}$	0.198
not in a relationship	200	$0.319^{***}$	0.086	$0.443^{***}$	0.165	$0.215^{***}$	0.039	-0.106	0.125
Note: coefficients and s.e. re	sported fo	pr endogenous	: peer effe	cts only. Sch	ool-level f	ixed effects in	ncluded. 1	Deer effects	are
defined as follows: $m - m$ i	s the effe	set of male pe	sers on n	<i>vale students</i> ,	$m - f_i$	s the effects	of female	peers on m	ale

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students, f - m is the effects of male peers on female students, f - f is the effects of female peers on female students.

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	
$itt^1$ : 50% students at random				-51	-69.34	(6.35)
$itt^2$ : 50% students, females only				-51	-72.10	(1.65)
$itt^3$ : 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	
$itt^1: 50\%$ students at random				-51	-69.74	(6.51)
$itt^2$ : 50% students, females only				-60	-84.82	(1.94)
$itt^3$ : 50% students, males only				-42	-55.03	(0.98)

Table 8: Simulation results

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

# Appendix A

We now develop a non-cooperative model to microfound our estimating equation through the channels of spillover (*i.e.*, strategic complementarity) and conformity in BMI within the social network. We develop the theoretical model for one network (r = 1) of non-isolated students where heterogeneous peer effects only work through the 'endogenous' channels (the  $\delta$ 's are set to zero). This is done to simplify the notation and is aligned with the simulation exercise of Section 6. 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  $i.^{52}$  The friendship network is defined by four fixed and known binary adjacency matrices  $\mathbf{A}_z(z = 1, \dots, 4)$ , and their weighted version  $\mathbf{G}_z(z = 1, \dots, 4)$ , defined as above. Every individual maximizes a gender-dependent quadratic utility function,  $U_{i,m}(\cdot)$ , 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:

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

s.t. 
$$y_{i,m} = \alpha_0 - \alpha_1 e_{i,m} + \alpha_2 x_{i,m} + \eta_{i,m},$$
 (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*<sup>th</sup> row of the social interaction matrix  $\mathbf{G}_z$ , 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.<sup>53</sup> 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 four last terms in the utility function. The first two terms of the social sub-utility (with the  $\psi$ 's > 0) reflect the fact that social interactions influence preferences through the channel of spillover in BMI between a student and his reference group of each type. For instance, it means that a male student's marginal utility of having a healthy weight (lower BMI) increases as his female peers achieve a healthier body weight (lower average BMI).<sup>54</sup>

<sup>54</sup>More formally, one has: e.g., 
$$\frac{\partial (-\frac{\partial (\mathbf{z}_{i,m})}{\partial y_{i,m}})}{\partial (-\mathbf{g}'_{1i}\mathbf{y}_{f})} = \frac{\partial^{2}U_{i,m}}{\partial y_{i,m}\partial \mathbf{g}'_{1i}\mathbf{y}_{f}} = \psi_{mf} > 0$$

<sup>&</sup>lt;sup>52</sup>Note that the empirical illustration relaxes this assumption, allowing for isolated students.

 $<sup>^{53}</sup>$ We are ignoring here a situation where very low weight negatively affects health (*e.g.*, anorexia).

The last two terms correspond to a channel of conformity in social interactions (with the  $\lambda$ 's > 0). This means that an individual's utility is negatively affected by the (euclidean) distance between his BMI and the mean BMI of each type of peer due, for instance, to the presence of social norms.

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:

$$\max_{y_{i,f},e_{i,f}} U_{i,f}(e_{i,f},\mathbf{y}) = -y_{i,f} - \frac{e_{i,f}^2}{2} + \psi_{ff}y_{i,f}\mathbf{g}'_{3i}\mathbf{y} + \psi_{fm}y_{i,f}\mathbf{g}'_{4i}\mathbf{y} \qquad (14)$$
$$-\frac{\lambda_{ff}}{2}(y_{i,f} - \mathbf{g}'_{3i}\mathbf{y})^2 - \frac{\lambda_{fm}}{2}(y_{i,f} - \mathbf{g}'_{4i}\mathbf{y})^2$$
$$s.t. \quad y_{i,f} = \alpha_0 - \alpha_1 e_{i,f} + \alpha_2 x_{i,f} + \eta_{i,f} \qquad (15)$$

Heterogeneity in social interactions is reflected by the fact that the  $\psi$ 's (or the  $\lambda$ 's) can be different. The first-order conditions of the type-*m* maximization program lead to the following best response function:

$$\mathbf{y}_m = \alpha_m \boldsymbol{\iota}_m + \beta_{mm} \mathbf{G}_1^m \mathbf{y} + \beta_{mf} \mathbf{G}_2^m \mathbf{y} + \tilde{\alpha}_2 \mathbf{x}_m + \boldsymbol{\epsilon}_m \tag{16}$$

where  $\alpha_m = (\alpha_0 - \mu)/(1 + \mu(\lambda_{mm} + \lambda_{mf})), \ \beta_{mm} = \mu(\psi_{mm} + \lambda_{mm})/(1 + \mu(\lambda_{mm} + \lambda_{mf})), \ \beta_{mf} = \mu(\psi_{mf} + \lambda_{mf})/(1 + \mu(\lambda_{mm} + \lambda_{mf})), \ \tilde{\alpha}_2 = \alpha_2/(1 + \mu(\lambda_{mm} + \lambda_{mf})), \ \text{where } \mathbf{G}_z^m$  corresponds to the social interaction matrix z of male agents, and 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 the following best response function:

$$\mathbf{y}_f = \alpha_f \boldsymbol{\iota}_f + \beta_{ff} \mathbf{G}_3^f \mathbf{y} + \beta_{fm} \mathbf{G}_4^f \mathbf{y} + \bar{\alpha}_2 \mathbf{x}_f + \boldsymbol{\epsilon}_f \tag{17}$$

where  $\alpha_f = (\alpha_0 - \mu)/(1 + \mu(\lambda_{ff} + \lambda_{fm})) \ \beta_{ff} = \mu(\psi_{ff} + \lambda_{ff})/(1 + \mu(\lambda_{ff} + \lambda_{fm})), \ \beta_{fm} = \mu(\psi_{fm} + \lambda_{fm})/(1 + \mu(\lambda_{ff} + \lambda_{fm})), \ \bar{\alpha}_2 = \alpha_2/(1 + \mu(\lambda_{ff} + \lambda_{fm})), \ \text{and where } \mathbf{G}_z^f \text{ corresponds to the social interaction matrix z of female agents.}$ 

Assuming that the absolute value of the  $\beta$ 's is less than one, if we concatenate equations (16) and (17), and that  $\lambda_{mm} + \lambda_{mf} = \lambda_{ff} + \lambda_{fm}$ , so that  $\alpha_m = \alpha_f = \alpha$  and  $\tilde{\alpha}_2 = \bar{\alpha}_2 = \gamma$ , we obtain the following best-response functions for the whole population of students, given the others' weight level (Nash equilibrium):

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

It is clear that the parameters of the structural model are not identified from the reduced form equation (18). While the latter equation allows us to estimate six parameters  $(\alpha, \beta_{mm}, \beta_{mf}, \beta_{ff}, \beta_{fm}, \gamma)$ , the structural model includes 10 parameters to be estimated  $(\psi_{mm}, \psi_{mf}, \psi_{ff}, \psi_{fm}, \lambda_{mf}, \lambda_{ff}, \lambda_{fm}, \alpha_0, \alpha_1, \alpha_2)$  with  $\lambda_{mm} = \lambda_{ff} + \lambda_{fm} - \lambda_{mf}$ .

Even when we impose homogeneity, the structural model is still unidentified. In that case, all  $\psi$ 's are equal  $(=\psi)$  and all  $\lambda$ 's  $(=\lambda)$  are equal as well. Therefore,  $\beta_{mm} = \beta_{mf} = \beta_{ff} = \beta_{fm} = \beta_h$ . This corresponds to equation (4), with one network and no contextual peer effects:

$$\mathbf{y} = \alpha \boldsymbol{\iota} + \beta_h \mathbf{G} \mathbf{y} + \gamma \mathbf{x} + \boldsymbol{\epsilon}, \tag{19}$$

where  $\beta_h = \frac{\mu(\psi+\lambda)}{1+\mu\lambda}$ . While equation (19) allows us to estimate three parameters  $(\alpha, \beta_h, \gamma)$ , the structural model includes five coefficients  $(\psi, \lambda, \alpha_0, \alpha_1, \alpha_2)$ . In particular, neither  $\psi$  nor  $\lambda$  are identified. Therefore, the social multiplier (which is equal to  $\frac{1}{1-\mu\psi}$ ) is not identified. However, in the presence of pure conformity  $(\psi = 0)$ , the social multiplier is equal to one (no indirect effects). Besides, the social multiplier is identified in the presence of pure spillover  $(\lambda = 0)$  as it is equal to  $\frac{1}{1-\beta_h}$ . In that case, as long as  $0 < \beta_h < 1$ , the pure spillover channel generates positive indirect effects. Also, assuming that we have a proxy for  $\mu, \psi$  can be recovered as it is equal to  $\beta_h/\mu$ .

Under gender heterogeneity in peer effects, the models under pure spillover and under pure conformity are exactly identified and are observationally equivalent. In particular, under pure spillover, both structural and reduced form models include six coefficients to be estimated when assuming that we have a proxy for  $\mu$ , one exogenous effect and no contextual effects.<sup>55</sup> Indeed, excluding  $\mu$ , six structural coefficients, that is,  $(\psi_{mm}, \psi_{mf}, \psi_{ff}, \psi_{fm}, \alpha_0, \alpha_2)$ , can be recovered from the six reduced form coefficients  $(\alpha, \beta_{mm}, \beta_{mf}, \beta_{ff}, \beta_{fm}, \gamma)$ . Note that tests on the reduced form coefficients  $\beta's$  are equivalent to tests on the structural coefficients  $\psi$ 's, as  $\beta_{qr} = \mu \ \psi_{qr}$ , for all q, r = m, f. In particular, the model allows us to test whether girls have a stronger positive effect on boys' incentive to invest in their health than the reverse, that is,  $\beta_{mf} > \beta_{fm}$  or, equivalently,  $\psi_{mf} > \psi_{fm}$ . The pure spillover assumption allows us to recover the indirect effects when there is an exogenous shock that affects students' weight levels.

The model with heterogeneity is also identified under pure conformity, when one assumes that  $\lambda_{mm} = \lambda_{ff} + \lambda_{fm} - \lambda_{mf}$  (see above). In that case, six structural coefficients  $(\lambda_{mf}, \lambda_{ff}, \lambda_{fm}, \alpha_0, \alpha_1, \alpha_2)$  can be recovered from the six estimated reduced form coefficients  $(\alpha, \beta_{mm}, \beta_{mf}, \beta_{ff}, \beta_{fm}, \gamma)$ . As in the homogeneity case, pure conformity imposes the absence of indirect effects.

<sup>&</sup>lt;sup>55</sup>The two latter assumptions do not influence the identifiability of the structural model.

# Appendix B

### Proof of proposition 1

To prove our proposition, we assume that  $\mathbf{S}(\boldsymbol{\beta})$  is invertible (see footnote 12 for sufficient conditions), and we use the formula of the inverse of the 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:<sup>56</sup>

$$\mathbf{S}_{k}(\boldsymbol{\beta}) = \sum_{i=0}^{k \ge 1} \binom{k}{i} \left[ (\beta_{mm} \bar{\mathbf{G}}_{1})^{k-i} + (k-i)\beta_{mf} (\beta_{mm} \bar{\mathbf{G}}_{1})^{k-i-1} \bar{\mathbf{G}}_{2} \right] \cdot \left[ (\beta_{ff} \bar{\mathbf{G}}_{3})^{i} + i\beta_{fm} (\beta_{ff} \bar{\mathbf{G}}_{3})^{i-1} \bar{\mathbf{G}}_{4} \right]$$

- 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  $\mathbf{W}_i(\boldsymbol{\beta}) = \bar{\mathbf{G}}_i \mathbf{S}(\boldsymbol{\beta})^{-1}$  and  $\mathbf{W}_i(\boldsymbol{\beta}) \bar{\mathbf{G}}(\boldsymbol{\delta})$  $\forall i \in \{1, 2, 3, 4\}.$
- 4. Write  $\{\mathbf{W}_{\mathbf{i}}(\boldsymbol{\beta}) [\gamma \mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta})\mathbf{x} + \iota \boldsymbol{\alpha}]\}_{\{i=1,2,3,4\}}$  as a function of instruments and extract instruments and the associated restrictions on the parameters of the model, premultiplied by matrix **J**.

For sake of simplicity, let subscripts mm, mf, ff and fm in  $\beta$  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  $\mathbf{S}_k(\beta)$  using the expression below:

$$\mathbf{S}_{1}(\boldsymbol{\beta}) = \left[\beta_{1}\bar{\mathbf{G}}_{1} + \beta_{2}\bar{\mathbf{G}}_{2}\right] \times \left[\beta_{3}\bar{\mathbf{G}}_{3} + \beta_{4}\bar{\mathbf{G}}_{4}\right]$$

$$\mathbf{S}_{2}(\boldsymbol{\beta}) = \left[\beta_{1}^{2}\bar{\mathbf{G}}_{1}^{2} + 2\beta_{1}\beta_{2}\bar{\mathbf{G}}_{1}\bar{\mathbf{G}}_{2}\right] + 2\left[\beta_{1}\bar{\mathbf{G}}_{1} + \beta_{2}\bar{\mathbf{G}}_{2}\right] \times \left[\beta_{3}\bar{\mathbf{G}}_{3} + \beta_{4}\bar{\mathbf{G}}_{4}\right] + \left[\beta_{3}^{2}\bar{\mathbf{G}}_{3}^{2} + 2\beta_{3}\beta_{4}\bar{\mathbf{G}}_{3}\bar{\mathbf{G}}_{4}\right]$$

$$\begin{aligned} \mathbf{S}_{3}(\boldsymbol{\beta}) &= \begin{bmatrix} \beta_{1}^{3}\bar{\mathbf{G}}_{1}^{3} + 3\beta_{1}^{2}\beta_{2}\bar{\mathbf{G}}_{1}^{2}\bar{\mathbf{G}}_{2} \end{bmatrix} + 3\begin{bmatrix} \beta_{1}^{2}\bar{\mathbf{G}}_{1}^{2} + 2\beta_{1}\beta_{2}\bar{\mathbf{G}}_{1}\bar{\mathbf{G}}_{2} \end{bmatrix} \times \begin{bmatrix} \beta_{3}\bar{\mathbf{G}}_{3} + \beta_{4}\bar{\mathbf{G}}_{4} \end{bmatrix} \\ &+ 3\begin{bmatrix} \beta_{1}\bar{\mathbf{G}}_{1} + \beta_{2}\bar{\mathbf{G}}_{2} \end{bmatrix} \times \begin{bmatrix} \beta_{3}^{2}\bar{\mathbf{G}}_{3}^{2} + 2\beta_{3}\beta_{4}\bar{\mathbf{G}}_{3}\bar{\mathbf{G}}_{4} \end{bmatrix} + \begin{bmatrix} \beta_{3}^{3}\bar{\mathbf{G}}_{3}^{3} + 3\beta_{3}^{2}\beta_{4}\bar{\mathbf{G}}_{3}^{2}\bar{\mathbf{G}}_{4} \end{bmatrix} \end{aligned}$$

$$\begin{aligned} \mathbf{S}_{4}(\boldsymbol{\beta}) &= \begin{bmatrix} \beta_{1}^{4} \bar{\mathbf{G}}_{1}^{4} + 4\beta_{1}^{3} \beta_{2} \bar{\mathbf{G}}_{1}^{3} \bar{\mathbf{G}}_{2} \end{bmatrix} + 4 \begin{bmatrix} \beta_{1}^{3} \bar{\mathbf{G}}_{1}^{3} + 3\beta_{1}^{2} \beta_{2} \bar{\mathbf{G}}_{1}^{2} \bar{\mathbf{G}}_{2} \end{bmatrix} \times \begin{bmatrix} \beta_{3} \bar{\mathbf{G}}_{3} + \beta_{4} \bar{\mathbf{G}}_{4} \end{bmatrix} \\ &+ 6 \begin{bmatrix} \beta_{1}^{2} \bar{\mathbf{G}}_{1}^{2} + 2\beta_{1} \beta_{2} \bar{\mathbf{G}}_{1} \bar{\mathbf{G}}_{2} \end{bmatrix} \times \begin{bmatrix} \beta_{3}^{2} \bar{\mathbf{G}}_{3}^{2} + 2\beta_{3} \beta_{4} \bar{\mathbf{G}}_{3} \bar{\mathbf{G}}_{4} \end{bmatrix} + 4 \begin{bmatrix} \beta_{1} \bar{\mathbf{G}}_{1} + \beta_{2} \bar{\mathbf{G}}_{2} \end{bmatrix} \\ &\times \begin{bmatrix} \beta_{3}^{3} \bar{\mathbf{G}}_{3}^{3} + 3\beta_{3}^{2} \beta_{4} \bar{\mathbf{G}}_{3}^{2} \bar{\mathbf{G}}_{4} \end{bmatrix} + \begin{bmatrix} \beta_{4}^{3} \bar{\mathbf{G}}_{3}^{4} + 4\beta_{3}^{3} \beta_{4} \bar{\mathbf{G}}_{3}^{3} \bar{\mathbf{G}}_{4} \end{bmatrix} \end{aligned}$$

<sup>&</sup>lt;sup>56</sup>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:  $\mathbf{G}_{1,r}.\mathbf{G}_{4,r} = 0_{n_r}, \mathbf{G}_{3,r}.\mathbf{G}_{2,r} = 0_{n_r}, \mathbf{G}_{1,r}.\mathbf{G}_{3,r} = 0_{n_r}, \mathbf{G}_{3,r}.\mathbf{G}_{1,r} = 0_{n_r}, \mathbf{G}_{2,r}^{k\geq 2} = 0_{n_r}, \mathbf{G}_{4,r}^{k\geq 2} = 0_{n_r}, \mathbf{G}_{4,r}.\mathbf{G}_{3,r} = 0_{n_r}, \mathbf{G}_{4,r}.\mathbf{G}_{3,r} = 0_{n_r}, \mathbf{G}_{4,r}.\mathbf{G}_{4,r} = 0_{n_r}$ 

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,  $\forall i \in \{1, 2, 3, 4\}$ ,  $\mathbf{W}_i(\boldsymbol{\beta}) [\gamma \mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta})\mathbf{x} + \iota \boldsymbol{\alpha}]$  as:

$$\begin{split} \mathbf{W}_{1}(\boldsymbol{\beta}) \left[ \gamma \mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta}) \mathbf{x} + \boldsymbol{\iota} \boldsymbol{\alpha} \right] &= \gamma \bar{\mathbf{G}}_{1} \mathbf{x} + (\gamma \beta_{1} + \delta_{1}) \left[ \bar{\mathbf{G}}_{1}^{2} + \beta_{1} \bar{\mathbf{G}}_{1}^{3} + \beta_{1}^{2} \bar{\mathbf{G}}_{1}^{4} + \beta_{1}^{5} \bar{\mathbf{G}}_{1}^{2} \right] \mathbf{x} \\ &+ (\gamma \beta_{2} + \delta_{2}) \left[ \bar{\mathbf{G}}_{1} \bar{\mathbf{G}}_{2} \right] \mathbf{x} + \beta_{1} (2\gamma \beta_{2} + \delta_{2}) \left[ \bar{\mathbf{G}}_{1}^{2} \bar{\mathbf{G}}_{2} \right] \mathbf{x} \\ &+ \beta_{2} (2\gamma \beta_{3} + \delta_{3}) \left[ \bar{\mathbf{G}}_{1} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3} \right] \mathbf{x} + \beta_{2} (2\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{1} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{4} \right] \mathbf{x} \\ &+ \left[ \bar{\mathbf{G}}_{1} + \beta_{1} \bar{\mathbf{G}}_{1}^{2} + \beta_{2} \bar{\mathbf{G}}_{1} \bar{\mathbf{G}}_{2} + \beta_{1}^{2} \bar{\mathbf{G}}_{1}^{3} + 2\beta_{1} \beta_{2} \bar{\mathbf{G}}_{1}^{2} \bar{\mathbf{G}}_{2} + \ldots \right] \boldsymbol{\iota} \boldsymbol{\alpha} \\ &+ \bar{\mathbf{G}}_{1} \sum_{k=5}^{\infty} \mathbf{S}_{k}(\boldsymbol{\beta}) \left[ (\gamma + \bar{\mathbf{G}}(\boldsymbol{\delta})) \mathbf{x} + \boldsymbol{\iota} \boldsymbol{\alpha} \right] \end{split}$$

$$\begin{split} \mathbf{W}_{2}(\boldsymbol{\beta}) \left[ \gamma \mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta}) \mathbf{x} + \boldsymbol{\iota} \boldsymbol{\alpha} \right] &= \gamma \bar{\mathbf{G}}_{2} \mathbf{x} + (\gamma \beta_{3} + \delta_{3}) \left[ \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3} + \beta_{3} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3}^{2} + \beta_{3}^{2} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3}^{3} + \beta_{3}^{3} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3}^{3} \right] \mathbf{x} \\ &+ (\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{4} \right] \mathbf{x} + \beta_{3} (2\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3} \bar{\mathbf{G}}_{4} \right] \mathbf{x} \\ &+ \beta_{3}^{2} (3\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3}^{2} \bar{\mathbf{G}}_{4} \right] \mathbf{x} + \beta_{3}^{3} (4\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3}^{3} \bar{\mathbf{G}}_{4} \right] \mathbf{x} \\ &+ \left[ \bar{\mathbf{G}}_{2} + \beta_{3} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3} + \beta_{3}^{2} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3}^{2} + 2\beta_{3} \beta_{4} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3} \bar{\mathbf{G}}_{4} + \ldots \right] \boldsymbol{\iota} \boldsymbol{\alpha} \\ &+ \bar{\mathbf{G}}_{2} \sum_{k=5}^{\infty} \mathbf{S}_{k}(\boldsymbol{\beta}) \left[ (\gamma + \bar{\mathbf{G}}(\boldsymbol{\delta})) \mathbf{x} + \boldsymbol{\iota} \boldsymbol{\alpha} \right] \end{split}$$

$$\begin{split} \mathbf{W}_{3}(\beta) \left[ \gamma \mathbf{x} + \bar{\mathbf{G}}(\delta) \mathbf{x} + \iota \alpha \right] &= \gamma \bar{\mathbf{G}}_{3} \mathbf{x} + (\gamma \beta_{3} + \delta_{3}) \left[ \bar{\mathbf{G}}_{3}^{2} + \beta_{3} \bar{\mathbf{G}}_{3}^{3} + \beta_{3}^{2} \bar{\mathbf{G}}_{3}^{4} + \beta_{3}^{3} \bar{\mathbf{G}}_{3}^{5} \right] \mathbf{x} \\ &+ (\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{3} \bar{\mathbf{G}}_{4} \right] \mathbf{x} + \beta_{3} (2\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{3}^{2} \bar{\mathbf{G}}_{4} \right] \mathbf{x} \\ &+ \beta_{3}^{2} (3\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{3}^{3} \bar{\mathbf{G}}_{4} \right] \mathbf{x} + \beta_{3}^{3} (4\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{3}^{4} \bar{\mathbf{G}}_{4} \right] \mathbf{x} \\ &+ \left[ \bar{\mathbf{G}}_{3} + \beta_{3} \bar{\mathbf{G}}_{3}^{2} + \beta_{4} \bar{\mathbf{G}}_{3} \bar{\mathbf{G}}_{4} + 2\beta_{3} \beta_{4} \bar{\mathbf{G}}_{3}^{2} \bar{\mathbf{G}}_{4} + \ldots \right] \iota \alpha \\ &+ \left[ \bar{\mathbf{G}}_{3} \sum_{k=5}^{\infty} \mathbf{S}_{k}(\beta) \left[ (\gamma + \bar{\mathbf{G}}(\delta)) \mathbf{x} + \iota \alpha \right] \end{split}$$

$$\begin{split} \mathbf{W}_{4}(\boldsymbol{\beta}) \left[ \gamma \mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta}) \mathbf{x} + \boldsymbol{\iota} \boldsymbol{\alpha} \right] &= \gamma \bar{\mathbf{G}}_{4} \mathbf{x} \quad + \quad (\gamma \beta_{1} + \delta_{1}) \left[ \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1} + \beta_{1} \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1}^{2} + \beta_{1}^{2} \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1}^{3} + \beta_{1}^{3} \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1}^{4} \right] \mathbf{x} \\ &+ \quad (\gamma \beta_{2} + \delta_{2}) \left[ \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{2} \right] \mathbf{x} + \beta_{1} (2\gamma \beta_{2} + \delta_{2}) \left[ \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1} \bar{\mathbf{G}}_{2} \right] \mathbf{x} \\ &+ \quad \beta_{2} (2\gamma \beta_{3} + \delta_{3}) \left[ \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{3} \right] \mathbf{x} + \beta_{2} (2\gamma \beta_{4} + \delta_{4}) \left[ \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{2} \bar{\mathbf{G}}_{4} \right] \mathbf{x} \\ &+ \quad \left[ \bar{\mathbf{G}}_{4} + \beta_{1} \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1} + \beta_{2} \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{2} + \beta_{1}^{2} \bar{\mathbf{G}}_{4} \bar{\mathbf{G}}_{1}^{2} + \ldots \right] \boldsymbol{\iota} \boldsymbol{\alpha} \\ &+ \quad \bar{\mathbf{G}}_{4} \sum_{k=5}^{\infty} \mathbf{S}_{k}(\boldsymbol{\beta}) \left[ (\gamma + \bar{\mathbf{G}}(\boldsymbol{\delta})) \mathbf{x} + \boldsymbol{\iota} \boldsymbol{\alpha} \right] \end{split}$$

The above expressions provide sufficient conditions for the 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 occurring instruments 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  $\mathbf{JG_1x}$ ,  $\mathbf{JG_1}^2\mathbf{x}$ ,  $\mathbf{JG_1}^3\mathbf{x}$  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,  $\gamma$  needs to be different from zero and matrices  $\mathbf{\bar{G}}_1$ ,  $\mathbf{\bar{G}}_2$ ,  $\mathbf{\bar{G}}_3$ ,  $\mathbf{\bar{G}}_4$ ,  $\mathbf{\bar{G}}_1^2$ ,  $\mathbf{\bar{G}}_1\mathbf{\bar{G}}_2$ ,  $\mathbf{\bar{G}}_2\mathbf{\bar{G}}_3$ ,  $\mathbf{\bar{G}}_3^2$ ,  $\mathbf{\bar{G}}_1^3$ , ..., 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 the 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  $\mathbf{CG}_i \bar{\mathbf{G}}_l$ 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,  $\mathbf{JG}_1\mathbf{G}_2\mathbf{G}_4\mathbf{x}$  may be used as an instrument if  $\beta_2 \neq 0$ ,  $(2\gamma\beta_4 + \delta_4) \neq 0$  and matrices  $\bar{\mathbf{G}}_1$ ,  $\bar{\mathbf{G}}_2$ ,  $\bar{\mathbf{G}}_3$ ,  $\bar{\mathbf{G}}_4^2$ ,  $\bar{\mathbf{G}}_1^2$ ,  $\bar{\mathbf{G}}_1\bar{\mathbf{G}}_2$ ,  $\bar{\mathbf{G}}_2\bar{\mathbf{G}}_3$ ,  $\bar{\mathbf{G}}_3^2$ ,  $\bar{\mathbf{G}}_1^3$ , ...,  $\mathbf{I}$  and  $\bar{\mathbf{G}}_1\bar{\mathbf{G}}_2\bar{\mathbf{G}}_4$  are linearly independent. Also,  $\mathbf{J}\mathbf{G}_4\bar{\mathbf{G}}_2\bar{\mathbf{G}}_3^2\mathbf{x}$  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  $\bar{\mathbf{G}}_1$ ,  $\bar{\mathbf{G}}_2$ ,  $\bar{\mathbf{G}}_3$ ,  $\bar{\mathbf{G}}_4$ ,  $\bar{\mathbf{G}}_1^2$ ,  $\bar{\mathbf{G}}_1\bar{\mathbf{G}}_2$ ,  $\bar{\mathbf{G}}_2\bar{\mathbf{G}}_3$ ,  $\bar{\mathbf{G}}_3^2$ ,  $\bar{\mathbf{G}}_3^1$ , ...,  $\mathbf{I}$  and  $\bar{\mathbf{G}}_4\bar{\mathbf{G}}_2\bar{\mathbf{G}}_3^2$  are linearly independent.

### GMM with quadratic conditions

Let the IV moments be given by the expression  $g_1(\theta) = \mathbf{Q}'_K \boldsymbol{\epsilon}(\theta)$  where  $\boldsymbol{\epsilon}(\theta) = \mathbf{J}(\mathbf{y} - \mathbf{Z}\boldsymbol{\theta} - \iota\boldsymbol{\alpha})$ . The additional quadratic moments are given by the expression  $g_2(\theta) = [\mathbf{U}'_1\boldsymbol{\epsilon}(\theta), \mathbf{U}'_2\boldsymbol{\epsilon}(\theta), ..., \mathbf{U}'_q\boldsymbol{\epsilon}(\theta)]' \boldsymbol{\epsilon}(\theta)$ , where  $\mathbf{U}_j$  is such that  $tr(\mathbf{J}\mathbf{U}_j) = 0.5^7$  In addition, let the combined vector of linear and quadratic empirical moments be given in  $g(\theta) = [g'_1(\theta), g'_2(\theta)]$ . Finally, let  $\tilde{\Omega} = \tilde{\Omega}(\tilde{\sigma}^2, \tilde{\mu}_3, \tilde{\mu}_4)$  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

<sup>&</sup>lt;sup>57</sup>Following Liu and Lee (2010), we use  $\mathbf{U}_k = \bar{\mathbf{G}}_k - tr(\mathbf{J}\mathbf{G}_k)\mathbf{I}/tr(\mathbf{J})$  for k = 1, ..., 4.

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 5.