Heterogenous peer effects in body weight, physical activity and dietary choices: does type of peers matter?

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Abstract

This article explores peer effect heterogeneity in adolescent adjusted Body Mass Index (BMI), physical activity and dietary choices. In particular, this paper makes an original contribution by studying peers heterogenous effects based on friendship intensity. Adolescents are assumed to interact through a social network, where they have strong and weak friendships. To identify both types, I use Add-Health's wave II friendship roster questionnaire to calculate a friendship score for every friend listed by each student in the sample: friends with a high score were defined as part of the strong friendship network and the rest were placed in the weak friendship network. It is expected that strong friendships have a greater effect on individuals' observed outcomes. As in Liu and Lee [2010] and Dieye et al. [2017], identification conditions are provided. 2SLS and GMM strategies were used to estimate the econometric model. Preliminary results provide evidence that supports the heterogenous peer effect hypothesis: strong friendships endogenous effects dominate on adjusted body weight, physical activity. Mixed evidence is found for fast food consumption and unhealthy food consumed calories

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Introduction

There are many factors which are often used to explain overweight and obesity among children and youth, such as parental influence, food prices, access to fast food, environment, opportunities for physical activities, school nutrition policies, and advertising. Yet such “root causes” cannot always explain excess variance within regions or racial groups Fletcher [2011]. Complementing these views, a growing body of research has attempted to investigate obesity from the perspective of social interactions (e.g., Christakis and Fowler [2007]; Trogdon et al. [2008]; Kapinos et al. [2014]; Fortin and Yazbeck [2015]; Dieye et al. [2017]). These studies have provided evidence that recognizes the importance of peers in obesity, diet and healthy habits.

The peer effect literature has been developed on the foundations of the linear social interactions model, as proposed by Manski [1993], Bramoullé et al. [2009], and extended by Blume et al. [2015]. The standard approach is to model individual’s outcome as linear function which depends on three arguments: the mean outcome of the group she belongs to; the mean characteristics of her reference group; and, lastly, her own characteristics (e.g. gender, age, parental characteristics, etc...). The first mechanism is known as the endogenous effect while the second one is the contextual effect.

Social interactions have various representations. Friendship may have different intensities, based on the frequency of the interaction and the quality of such interaction. Therefore individuals’ behavior is not equally affected by all their peers. In this sense, the main problem with the traditional linear-in-means framework is that it assumes homogenity and hence it does not allow us to identify the different impacts individuals may exert on each other depending on the many social categories they belong to.

This paper explores hetrogenous peer effects in nutritional outcomes and healthy habits. Considering that weight is determined by the ammount of consumed and burned calories, in this article we focus on the study of body mass index, but we also analyse the peer effect in physical activity, fast food consumption and unhealthy food consumed calories. In particular, this paper makes an original contribution by studying types of peers heterogeneity based on friendship intensity. We expect that closer friends have a stronger effect on individuals’ outcomes.

The article is organized in 6 sections. Section 1 discusses previous research on peer effects on obesity related topics. Section 2 presents the standard theoretical model which allow us to derive the best-reply functions. Section 3 develops the empirical model and discusses the identification strategy to test the heterogenous effects. In section 4 we provide a brief discussion on the used data obtained from Add Health data project. Section 5 presents the main results of the homogenous and heterogenous estimations for adjusted body mass index (zBMI), physical activity and fast food consumption. Finally, section 6 provides concluding remarks.

1 Previous research

In this section we will explore the social network literature on peer effect on obesity, physical activity and dietary choices[1]. We will particularely draw attention on the heterogenous peer effect literature.

The different articles on peer effects and obesity published since Christakis and Fowler [2007] seminal paper are reviewed in Kapinos et al. [2014], Cunningham et al. [2012], and Nie et al. [2014], all of whom provide substantial evidence that peer effects exist among adolescents and adults. It is important to note the different meassures used in the peer effect literature. The most common is the average BMI of friends (e.g., Christakis and Fowler [2007], De La Haye et al. [2011], Kapinos and Yakusheva [2011], Mora and Gil [2013]). Conversely, other studies focus on borader measures, such as the average BMI of a community or school grade (e.g., Trogdon et al.

[1]For an extensive and recent literature review about the peer effects on exercise and dietary choices, consult Chung et al. [2017]

[2008] and Nie et al. [2014]). These two different measures differ on the level of aggregation and on the implications about the social mechanisms operating. For example, Trogdon et al. [2008] argues that the aggregate measures of social networks might work through the establishment of BMI norms and a reference BMI for body image concerns, while more proximal measures of peer effects could operate through influences on diet and physical activity behaviour" (p. 1390).

In the literature that examines th effect on physical activity, exercise was studied either by self-report questionnaires or by accelerometers or pedometers. Adolescents were asked to indicate how frequently they participated in formal sports teams and how many hours they engaged in exercise or in sedentary behaviors during specific time periods (Cheng et al. [2014]; De La Haye et al. [2011], Keresztes et al. [2008]; Salvy et al. [2008]; Shoham et al. [2012],

Most studies found significantly positive associations between adolescents' and peers' exercise. Adolescents were more likely to engage in exercise when their peers spent more time on exercise, when they had more physically active friends (Schofield et al. [2007]); or when they were with their peers, compared to being alone (Salvy et al. [2008]). For instance, in an experiment which simulated ostracism conditions in children, Barkley et al. [2012] concludes that isolation notoriously contributes to children's lack of physical activity.

Regarding dietary choices, food consumption or food frequency was evaluated in two different ways: self-report or observation (Bruening et al. [2012]; Bruening et al. [2014]; De La Haye et al. [2011], Fortin and Yazbeck [2015]); and by asking about their diet and food choices (Rathi et al. [2016]; Watts et al. [2015]; Voorend et al. [2013]). When the intake of different kinds of food such as soft drinks (Bruening et al. [2014]; Wouters et al. [2010]) and snacks (Wouters et al. [2010]) was examined, friends' intake was similar to adolescents. However, Bruening et al. [2012] found that the significance of that association differed, depending on the kind of food. Significant positive associations were found for intake of whole grain and dairy foods between adolescents and their friends; no association was found for fruit intake (Bruening et al. [2012]) . Peers were also influential to adolescents' fast food consumption Fortin and Yazbeck [2015].

There are two studies which concretely explores the effect of friendship intensity in physical activity (Schofield et al. [2007]; Sirard et al. [2013]). These studies found that closer or best friends had a greater influence on physical activity of adolescents than more casual ones. Adolescents interact more closely with their best friends (Miller and Hoicowitz [2004]) and are known to share specific behaviors with them (Collins and Steinberg [2006]). Thus, they could be more susceptible to influences from established friendships than from new friend. Because of this, best friends could have a greater influence on diet and exercise compared to friends with a not so significant relationship intensity.

Due to its contribution from the econometric point of view, there are three relevant articles to be discussed: Hsieh and Lin [2017]; Dieye et al. [2017]; and Patacchini et al. [2017]. citethsieh2017gender apply a high order spatial autoregressive (SAR) model to simultaneously capture heterogeneous peer effects from multiple gender and racial groups, as well as endogenous network formation. In students' GPA and smoking behaviors, the authors find that within-gender endogenous effects are stronger than cross-gender effects. Females and whites are more sensitive to peer influences and more influential than other students. Intra-race spillover effects are stronger than inter-race effects for whites, but not for non-whites.

Dieye et al. [2017] explore heterogenoues peer effects based on gender by using 2SLS and GMM strategies to estimate the model using Add Health data. effects. The results reject the homogeneous model which assumes that effects of all peers on BMI are the same. These results hold even after testing for network endogeneity or including fixed network. The authors conclude that the estimated causal effect of a treatment which influences obesity in a social network is likely to be biased when gender heterogeneity in peer effects is ignored.

Finally, Patacchini et al. [2017] investigate the influence of different types of peers on educational outcomes by using longitudinal Add Health data. The authors find that there are strong and persistent peer effects in education, but peers tend to be influential in the long run only when their friendships last more than a year. The results are consistent with a network model in which convergence of preferences and the emergence of social norms among peers require long-term interactions.

2 Theoretical model

The article considers a model developed by Dieye et al. [2017], who extends Blume et al. [2015] in which n individuals interact through a social network and whose outcome (e.g. dietary choices, physical activity, body weight) is influenced by their behaviour. As shown by Dieye et al. [2017], when isolated individuals are included in the social networks, this model is consistent with a mechanism of strategic complementarity and pure conformity in social interactions. Individuals have two type of bonds: strong and weak. To take into account the heterogeneity, let us define two network adjacency matrices $\mathbf{A}_z$, such that $z = s, w$. Let $a_{i,j}$ be an element of the friendship network adjancecy matrix $\mathbf{A}_s$ (resp. $\mathbf{A}_w$), thus $a_{i,j} = 1$ means that individual i and j have a strong (resp. weak) friendship. The student i's reference group size $n_{i,s}$ (resp. $n_{i,w}$) is the set of strong (resp. weak) friendships by which i is influenced. The social interaction matrix $\mathbf{G}_z$ is a weighted adjacency matrix $\mathbf{A}_z$ such that $g_{zij} = 1/n_{i,z}$ if i is influenced by j, and 0 otherwise. $\mathbf{G}_z$ are assumed to be $non-stochastic$ and known social interaction matrices. Moreover, to simplify the exposition, no isolated individuals are assumed in this sections. [2]

The maximization program of a individual i takes place in a non-cooperative (Nash) model in which every individual maximizes a quadratic utility function subject to a linear production function relating body mass index to effort and individual characteristics.

$$\max_{e_i, y_i} \qquad U_i(e_i, y_i) = -y_i - \frac{e_i^2}{2} + \beta_s \sum_{j=1}^{n} g_{sij} y_i y_j + \beta_w \sum_{j=1}^{n} g_{wij} y_i y_j$$
$$s.t. \qquad y_i = \alpha_0 - \alpha_1 e_i + \alpha_2 x_i + \eta_i$$

where y_i is the outcome variable (BMI) of individual i; e_i stands for the (unobserved) effort of i; g_{zij} is an element of the social interaction matrix $\mathbf{G}_z$; x_i and η_i are vectors of observable and unobservable characteristis, respectively. For notation simplicity, we assume only one observable characteristic.

Utility is separable into two components. The first two terms denote the private component of utility and the rest are the social components. Both the private and social components are strictly concave in individual i 's action. In this model, we do not take into account the situation where very low weight negatively affects health (e.g. anorexia).

Stated in matrix notation, the first order conditions program lead to:

$$\mathbf{Y} = \alpha + \phi_s \mathbf{G}_s \mathbf{Y} + \phi_w \mathbf{G}_w \mathbf{Y} + \alpha_2 \mathbf{X} + \epsilon \tag{1}$$

where $\alpha = \alpha_0 - \mu$, $\phi_s = \mu\beta_s$, $\phi_w = \mu\beta_w$, $\mu = \alpha_1^2$. Note that μ represents the squared marginal productivity of effort on weight level.

[2] It is worthy to remind the reader that if the sociomatrix is row-normalized and there are no isolated individuals, as it is the case here, the strategic complementarity model is observationally equivalent to the social conformity one [see Blume et al., 2015, p. 452].

3 Econometric model

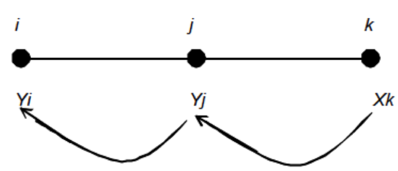
3.1 Reflection, correlated effects and sorting issues

A number of papers have dealt with the identification and estimation of peer effects with network data (e.g. Bramoullé et al. [2009]; Lee et al. [2010]; Calvó-Armengol et al. [2009]; Lin [2010]; Liu et al. [2012]; Lee and Liu [2010]; Dieye et al. [2017]). Below, we review the crucial issues, while explaining how these issues are tackled.

Reflection problem Manski shows that two main identification problems arise in the context of a linear-in-means model. First, it is difficult to distinguish real social effects (endogenous and exogenous) from correlated effects. Second, even in the absence of correlated effects, simultaneity in behavior of interacting agents introduces a perfect collinearity between the expected mean outcome of the group and its mean characteristics. This reflection problem hinders the identification of the endogenous effect from the exogenous effects. [see Bramoullé et al., 2009, p. 41] In short, the reflection problem arises because, in the standard approach, individuals interact in groups, that is individuals are affected by all individuals belonging to their group and by nobody outside the group. In the case of social networks, instead, this is nearly never true since the reference group is individual specific [see Patacchini et al., 2017, p. 195].

Correlated effects While a network approach allows us to distinguish endogenous effects from contextual effects, it does not necessarily estimate the causal effect of peers' influence on individual behavior. The estimation results might be flawed because of the presence of peer-group specific unobservable factors affecting both individual and peer behavior [see Patacchini et al., 2017, p. 196]. For example, a correlation between the individual and the peer-dietary choices may be due to an exposure to common factors (e.g. living in a neighborhood with abundant fastfood restaurants) rather than to social interaction. The way in which this has been addressed in the literature is to exploit the architecture of network contacts to construct valid instrumental variables for the endogenous effect. Consider figure 1: in this particular network, j influences both k and i while k and i are not directed linked. For individual i, the characteristics of peers of peers $\boldsymbol{G}^2\mathbf{X}$ (e.g. $x_{k,r}$) is a valid instrument for peers' behavior $\boldsymbol{G}^2\mathbf{Y}$ (e.g. $y_{j,r}$), since $x_{k,r}$ affects only indirectly through its effect on $y_{j,r}$, at distance 2.

Figure 1: Intransitive triad



Sorting If the variables that drive the choice of peers are not fully observable, potential correlations between (unobserved) peer-group-specific factors and the target regressors are major sources of bias [see Patacchini et al., 2017, p. 196]. This problem is managed by applying the standard technique in the literature that consists in using network fixed effects (e.g. Bramoullé et al. [2009]). Network fixed effects are a remedy for the selection bias that originates from the possible sorting of individualswith similar unobserved characteristics into a network. The underlying assumption is that such unobserved characteristics are common to all the individuals within each network. This might be true in the case of small networks Patacchini et al. [2017]. Given that 75 percent of the networks have less than 100 individuals, this assumption seems reasonable. Furthermore, this assumption implies that such unobserved characteristics are common to both strong and weak ties, which means that there should not be much difference between them.

Network fixed effects can be motivated by a two-step network formation model where agents self-select into different networks in a first step and, then, in a second step, link formation takes place within networks based on observable individual characteristics only. Therefore, the network fixed effect serves as a (partial) remedy for the selection bias that originates from the possible sorting of individuals with similar unobserved characteristics into a network Patacchini et al. [2017]

3.2 The model

Assume R networks, with $r = 1, ..., R$ and allow for isolated students such that $n_{i,z,r} = 0$. The best-response functions for the network r can be written as:

$$\begin{aligned} \mathbf{Y}_r = \boldsymbol{\iota}_{n,r}\boldsymbol{\alpha}_r + \phi_s \mathbf{G}_{s,r}\mathbf{Y}_r + \phi_w \mathbf{G}_{w,r}\mathbf{Y}_r + \delta_s \mathbf{G}_{s,r}\mathbf{X}_r \\ + \delta_w \mathbf{G}_{w,r}\mathbf{X}_r + \gamma \mathbf{X}_r + \boldsymbol{\epsilon_r} \end{aligned} \tag{2}$$

$\boldsymbol{\iota}_{n,r}$ is a n_rx1 vector of ones; $\boldsymbol{\alpha}_r$ indicates a fixed effect specific to network "r". The matrices $\mathbf{G}_{z,r}$ for $z = s, w$ matrices are not row-normalized in the presence of isolated students. In addition, for a sample with R networks, the data is stacked up by defining $\mathbf{Y} = (\mathbf{Y}_1', ..., \mathbf{Y}_R')'$, $\mathbf{X} = (\mathbf{X}_1', ..., \mathbf{X}_R')'$, $\mathbf{G}_s = D(\mathbf{G}_{s,1}', ..., \mathbf{G}_{s,R}')'$, $\mathbf{G}_w = D(\mathbf{G}_{w,1}', ..., \mathbf{G}_{w,R}')'$, $\boldsymbol{\iota}_r = D(\boldsymbol{\iota}_{n1}', ..., \boldsymbol{\iota}_{nR}')'$, $\boldsymbol{\epsilon}_r = (\boldsymbol{\epsilon}_1', ..., \boldsymbol{\epsilon}_R')'$, $\boldsymbol{\alpha}_r = (\boldsymbol{\alpha}_1', ..., \boldsymbol{\alpha}_R')'$, where $D(\mathbf{D}_1...\mathbf{D}_R)$ is a block diagonal matrix. Lastly, let $\bar{\mathbf{G}}(\boldsymbol{\phi}) = \phi_s \mathbf{G}_s + \phi_w \mathbf{G}_w$ and $\bar{\mathbf{G}}(\boldsymbol{\delta}) = \delta_s \mathbf{G}_s + \delta_w \mathbf{G}_w$, where $\boldsymbol{\phi} = (\phi_s, \phi_w)'$, $\boldsymbol{\delta} = (\delta_s, \delta_w)'$. Therefore, the best-response functions for the R networks are:

$$\mathbf{Y} = \iota\boldsymbol{\alpha} + \bar{\mathbf{G}}(\boldsymbol{\phi})\mathbf{Y} + \bar{\mathbf{G}}(\boldsymbol{\delta})\mathbf{X} + \gamma\mathbf{X} + \epsilon \tag{3}$$

This specification allows for network fixed effects. This effect captures the *correlated effect* where agents in the same network may behave similarly as they have similar unobserved characteristics or they have similar uobserved characteristics or they face a similar (e.g. institutional) environment.

3.3 Identification and estimation

In this context, identification is understood as the existence of a consistent estimator of the best-response functions. In this section, we analyze conditions which allow these functions to be identified. The identification of these functions are necessary to recover the fundamentals of the model.

The reduced form representation of the best-response functions in equation (3) requires that the matrix $\boldsymbol{S(\phi)} = (\boldsymbol{I} - \bar{\boldsymbol{G}}(\boldsymbol{\phi}))$ is invertible.

Proposition 1 *Consider equation* (3) *holds* and assume that $|\phi_s| < 1$ and $|\phi_w| < 1$. Then matrix $\boldsymbol{S(\phi)} = (\boldsymbol{I} - \bar{\boldsymbol{G}}(\boldsymbol{\phi}))$ is invertible. [3]

The reduced form model, assuming conditions of proposition (1) are satisfied, is given by:

$$\mathbf{Y} = \boldsymbol{S(\phi)}^{-1}[\gamma\mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta})\mathbf{X} + \boldsymbol{\iota\alpha}] + \boldsymbol{S(\phi)}^{-1}\boldsymbol{\epsilon} \tag{4}$$

Using the reduce form from model (4), $\bar{\boldsymbol{G}}_i\boldsymbol{Y}\ \forall\ \bar{\boldsymbol{G}}_i \in \{w, s\}$ can be expressed as:

$$\bar{\boldsymbol{G}}_i\boldsymbol{Y} = \boldsymbol{W}_i(\boldsymbol{\phi})[\gamma\mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta})\mathbf{X} + \boldsymbol{\iota\alpha}] + \boldsymbol{W}_i(\boldsymbol{\phi})\boldsymbol{\epsilon}$$

where $\boldsymbol{W}_i(\boldsymbol{\phi}) = \bar{\boldsymbol{G}}_i\boldsymbol{S(\phi)}^{-1}$. Therefore for $i \in \{w, s\}$, $\bar{\boldsymbol{G}}_i$ is correlated with ϵ because $\mathbb{E}[(\boldsymbol{W}_i(\boldsymbol{\phi})_i\epsilon)'\epsilon] \neq 0$. It follows that model (3) cannot be consistently estimated by Ordinary Least Squares. Following Dieye et al. [2017], this article uses 2SLS and GMM strategies to estimate our model.

[3] see proof in Dieye et al. [2017] Appendix A

3.3.1 2SLS estimation

This section shows the strategy employed to find the set of instrumental variables, which is based in Liu et al. [2013], Dieye et al. [2017] and Patacchini et al. [2017]. First, let's rewrite the best-response functions using a vector of parameters defined in $\boldsymbol{\theta = (\phi, \gamma, \delta)'}$ and $Z = [\bar{\boldsymbol{G}}_s\boldsymbol{Y}, \bar{\boldsymbol{G}}_w\boldsymbol{Y}, \boldsymbol{X}]$, where $\boldsymbol{X} = [\boldsymbol{X}, \bar{\boldsymbol{G}}_s\boldsymbol{X}, \bar{\boldsymbol{G}}_w\boldsymbol{X}]$. The resulting model is given by the equation below:

$$\boldsymbol{Y} = \boldsymbol{Z\theta} + \boldsymbol{\iota\alpha} + \boldsymbol{\epsilon} \tag{5}$$

Equation (5) allows us to derivate the identification conditions in the case of 2SLS. As in other examples in the peer effects literature, this model accounts for network fixed effects that need to be accounted in the final estimation. To eliminate the network fixed effects, a global transformation was performed. For that purpose, let $\boldsymbol{J} = D(\boldsymbol{J_1, ..., J_R})$ where $\boldsymbol{J_r} = (\boldsymbol{I_r} - \frac{\boldsymbol{\iota_r\iota_r'}}{nr})$ $\forall r \in \{1, ..., R\}$ $\mathbf{J}$ is a global transformation matrix such that $\boldsymbol{J\iota\alpha = 0}$. The result model is:

$$\boldsymbol{JY} = \boldsymbol{JZ\theta} + \boldsymbol{J\epsilon} \tag{6}$$

Note that by applying this transformation, we avoid the *incidental parameters problem* as defined by Neyman and Scott [1948], which in panel models occurs when we have few observation across time and in spatial models.

Following Liu and Lee [2010] strategy, the best IV matrix for $\boldsymbol{JZ}$ is given by:

$$\boldsymbol{J}\mathbb{E}(\boldsymbol{Z}) = \boldsymbol{J}[\boldsymbol{W}_i(\boldsymbol{\phi})[\gamma\mathbf{x} + \bar{\mathbf{G}}(\boldsymbol{\delta})\mathbf{X} + \boldsymbol{\iota\alpha}]\}_{\{i=s,w\}}, \boldsymbol{X}]$$

and $\boldsymbol{J}Z = \boldsymbol{J}\mathbb{E}(\boldsymbol{Z}) + \boldsymbol{J}[\boldsymbol{W}_s\epsilon]\boldsymbol{e}_1' + \boldsymbol{J}[\boldsymbol{W}_w\epsilon]\boldsymbol{e}_2'$, where $\boldsymbol{e_i}$ is the i'th unit (column) vector of dimension $(\ k+2)$ with $k = dim(\boldsymbol{X})$.

Letting $\boldsymbol{Q}^0_{i,\infty} = [\boldsymbol{W}_i(\boldsymbol{\phi})\boldsymbol{x}, \boldsymbol{W}_i(\boldsymbol{\phi})\bar{\boldsymbol{G}}(\boldsymbol{\delta})\boldsymbol{x}, \boldsymbol{W}_i(\boldsymbol{\phi})\boldsymbol{\iota}]$, $\forall i \in \{s, w\}$. The variables characterized by the multiplication of the interaction matrices and the matrix ι account for the fact that all rows do not sum to one, since there are isolated individuals. As noted by Liu and Lee [2010], this is the Bonacich centrality measure, and its inclusion increases the efficiency of estimates.

If conditions of proposition (1) are satisfied, we can use a series expansion of $\boldsymbol{S(\phi)}^{-1} = \sum_{k=0}^{\infty} \bar{\boldsymbol{G}}(\boldsymbol{\phi})^k$ [4] . Using this expression we can rewrite $\forall i \in \{w, s\}$:

$$\boldsymbol{Q}^0_{i,\infty} = [\boldsymbol{Q}^0_{i,\infty}X, \boldsymbol{Q}^0_{i,\infty}\iota]^5$$

Using a subset of $\boldsymbol{Q}_\infty$ including $\mathbf{X}$, it is possible to show that $\boldsymbol{Q}^i_K$ is a subset of $\boldsymbol{Q}_{i,\infty}$ $\forall$ $i \in \{s, w\}$, where K is the number of instruments. In addition let $\boldsymbol{\epsilon(\theta) = J(Y - Z\theta - \iota\alpha)}$. The moment conditions corresponding to the orthogonality betwen $\boldsymbol{Q}_K$ and $\boldsymbol{J\epsilon}$ is $\boldsymbol{Q}_K^{'}\boldsymbol{\epsilon(\theta)}$.

Proposition 2 *Suppose model (3) holds with correlated effects, Suppose also that* $(\delta_s + \gamma\phi_s) \neq 0$ and $(\delta_w + \gamma\phi_w) \neq 0$. If vector columns of matrix $\boldsymbol{Q}_K$ are linearly independent, then social effects are identified. [6]

Proposition 2 gives the extended conditions of Bramoullé et al. [2009] to the case of two-type (strong and weak) peer effects heterogeneity. There are similarities in the restricition on our set of parameters, except that in this case, the restricitions apply to both categories of individuals and their associated parameters. As stated by Dieye et al. [2017], the condition on linear dependencies

[4] Matrix $\boldsymbol{S(\phi)}^{-1}$ can be rewritten using a series expansion and the newton binomial formula such that $\boldsymbol{S(\phi)}^{-1} = \boldsymbol{I} + \sum_{k=1}^{\infty}\sum_{i=0}^{k\geq 1}\binom{k}{i}([\phi_s\boldsymbol{G}_s]^{k-i}[\phi_w\bar{\boldsymbol{G}_w}]^i)$

[5] where $\boldsymbol{Q}_{s,\infty} = \bar{G}_s(\bar{G}_s\boldsymbol{X}, \bar{G}_w\boldsymbol{X}, \bar{G}_s\bar{G}_w\boldsymbol{X}, ..., \bar{G}_s\boldsymbol{\iota}, \bar{G}_w\boldsymbol{\iota}, \bar{G}_s\bar{G}_w\boldsymbol{\iota}, ...]$ and $\boldsymbol{Q}_{w,\infty} = \bar{G}_w(\bar{G}_s\boldsymbol{X}, \bar{G}_w\boldsymbol{X}, \bar{G}_s\bar{G}_w\boldsymbol{X}, ..., \bar{G}_s\boldsymbol{\iota}, \bar{G}_w\boldsymbol{\iota}, \bar{G}_s\bar{G}_w\boldsymbol{\iota}, ...)$

[6] See proof in Dieye et al. [2017], Appendix C

of vector columns of matrix $\boldsymbol{Q}_K$ can be compared to the condition on linear independency of the interaction matrices stated by Bramoullé et al. [2009]. In concrete, the instruments that are used here are friends of friends for strong and weak ties and, in general, characteristics of friends at distance 2,3,4 *etc.* per categories may be used as instruments to properly estimate the model. The 2SLS estimator of model (3) is given by:

$$\hat{\boldsymbol{\theta}}_{2sls} = (\boldsymbol{Z}'\boldsymbol{P}_K\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{P}_K\boldsymbol{Y}$$

where $\boldsymbol{P}_K = \boldsymbol{Q}_K(\boldsymbol{Q}'_K\boldsymbol{Q}_K)^{-}\boldsymbol{Q}'_K$. The corresponding variave-covariance matrix is given by:

$$\hat{\boldsymbol{V}}_{\hat{\theta}2sls} = (\boldsymbol{Z}'\boldsymbol{P}_K\boldsymbol{Z})^{-1}\boldsymbol{Z}'\boldsymbol{D}\boldsymbol{Z}(\boldsymbol{Z}\boldsymbol{P}_K\boldsymbol{Z}')^{-1}$$

where $\mathbf{D}$ is a nxn diagonal matrix with entries given by the squared residuals from the estimation. According to Liu and Lee [2010], under certain regularity conditions, the 2SLS approach provides a consistent estimator of model (3).

3.3.2 GMM estimation

Liu and Lee [2010] show that the homogeneous version of the best-response functions can be estimated using a GMM estimator. On the other hand, Dieye et al. [2017] adequates this model and propose a GMM estimator of the heterogenous mode. These authors use the 2SLS estimator using additional quadratic moment equations. According to Liu and Lee [2010], the additional quadratic moments exploit the existing correlations between the error term of the reduced for model, thus provide more precision compared to the traditional 2SLS estimators. In addition, Dieye et al. [2017] argue that one of the advantages of using the GMM estimator instead of the 2SLS is that the objective function of the GMM estimator uses the optimal weighting matrix that allows the obtention of more efficient estimators.

To derive the GMM estimator in a heterogenous context, let's first define the IV moments as $g_1(\theta) = \boldsymbol{Q}'_K\epsilon\boldsymbol{\epsilon}(\boldsymbol{\theta})$. The additional quadratic moments are given by:

$$g_2(\theta) = [\boldsymbol{U}'_1\boldsymbol{\epsilon}(\boldsymbol{\theta}), \boldsymbol{U}'_2\boldsymbol{\epsilon}(\boldsymbol{\theta}), ..., \boldsymbol{U}'_q\boldsymbol{\epsilon}(\boldsymbol{\theta})]'\boldsymbol{\epsilon}(\boldsymbol{\theta})$$

where $\boldsymbol{U}_j$ is such that $tr(\boldsymbol{J}\boldsymbol{U}_j) = 0$. [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 the model. Following the stratey of Dieye et al. [2017] for heterogenous peer effects, the optimal weighting matrix associated to the GMM estimation strategy is given by Ω, and it takes the following form:

$$\Omega = Var[g(\boldsymbol{\theta})] = \begin{bmatrix} \tilde{\sigma}^2\boldsymbol{Q}'_K\boldsymbol{Q}_K & \tilde{\mu}_3\boldsymbol{Q}'_K\omega \\ & \\ \tilde{\mu}_3\omega'\boldsymbol{Q}_K & (\tilde{\mu}_4 - 3\tilde{\sigma}^4)\omega'\omega + \tilde{\sigma}^4\Psi \end{bmatrix}$$

where $\omega = [vec_D(\boldsymbol{U}_1, vec_D(\boldsymbol{U}_2, ..., vec_D(\boldsymbol{U}_q)]$, $\Psi = \frac{1}{2}[vec_D(\boldsymbol{U}_1^t), vec_D(\boldsymbol{U}_2^t), ..., vec_D(\boldsymbol{U}_q^t)]$. Also $\forall$ square matrix $\mathbf{E}$ of size n, $\boldsymbol{E}_t = \boldsymbol{E} + \boldsymbol{E}'$ and $vec_D(\boldsymbol{A}) = (a_{11}, a_{22}, ..., a_{nn})$. The feasible optimal GMM estimator is given by:

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

According to Liu et al. [2013], this estimator is consistent under a cretain set of assumptions.

[7] Following Liu and Lee [2010], for any constant matrix $\mathbf{B}$, if we define $\boldsymbol{A} = \boldsymbol{B} - tr(\boldsymbol{J}\boldsymbol{B})\boldsymbol{I}/tr(\boldsymbol{J})$, then $tr(\boldsymbol{J}\boldsymbol{A}) = 0$. In this setting, we use $\boldsymbol{U}_s = \bar{\boldsymbol{G}}_s - tr(\boldsymbol{J}\boldsymbol{G}_s)\boldsymbol{I}/tr(\boldsymbol{J})$ and $\boldsymbol{U}_w = \bar{\boldsymbol{G}}_w - tr(\boldsymbol{J}\boldsymbol{G}_w)\boldsymbol{I}/tr(\boldsymbol{J})$

4 Data

To conduct the empirical analysis, this article uses the National Longitudinal Survey of Adolescent Health (AddHealth), which is a panel study of a nationally representative sample of adolescents in grades 7-12 in the United States.

Add Health combines longitudinal survey data on respondents' social, economic, psychological and physical well-being with contextual data on the family, neighborhood, community, school, friendships, peer groups, and romantic relationships, providing unique opportunities to study how social environments and behaviors in adolescence are linked to health and achievement outcomes in young adulthood. During wave I, a subset of adolescents selected from the rosters of the sampled schools, about 20,000 individuals, were asked to compile a longer questionnaire containing more sensitive individual and household information (in-home and parental data). Those subjects were interviewed again in 1995–1996 (Wave II).

From a network perspective, the most interesting aspect of the AddHealth data is the friendship information, which is based upon actual friends' nominations. Indeed, pupils were asked to identify their best friends from a school roster (up to five males and five females).

4.1 Descriptive statistics

The dependent variables considered in this study are adjusted body mass index ($zBMI$), physical activity, fast food consumption and 'unhealthy food' consumed calories. The first variable, adjusted body mass index, is calculated considering age and sex[8]. The z-score BMI is a measure of relative weight adjusted for age according to a (national or international) reference standard and its mean value is equal to .45 with a standard deviation of 1.08. [9]

The second variable, physical activity was measured as the sum of the answers of three different question taken from the in-home questionnaire. The questions are the next ones: '*during the last week, how many times did you: 1. Go roller-blading, roller-skating, skate-boarding, or biclycin; 2) Play an active sport, such as baseball, softball, basketball, soccer, swimming, or footbal ?; and 3. Exercise, such as joging, walking, doing karate, jumping rope, doing gymnastics or dancing?* The mean value is 3.53 and the standard deviation is 2.04.

The third dependent variable, fast food consumption, measures how many times during the last week a given student went to a fast food restaurant. The mean value is 2.36 times per week with a standard deviation of 1.76.

And lastly, 'unhealthy food' consumed calories is equal to the ammount of calories from foods and drinks high in fat, sugar and salt that adolescents in the sample ate during the day before (e.g. fries, chocolate, doughnuts, pizza, etc...).[10] These foods should be avoided as they are high in fat, including saturated fat, sugar and salt. They may promote obesity, which can lead to heart disease, type 2 diabetes and some cancers Amine et al. [2002]. The mean value is equal to 557.60 calories with a standard deviation of 340.12. If we consider the total consumed calories reported in table 1, at the individual characteristics section, we observe that the mean ammount of calories consumed the day before is equal to 1753.59. This implies that individuals in our sample consume around 32% of calories from foods and drinks high in fat, sugar and salt.

As we can observe in the individual characteristics, female students comprise half of the sample and male ones the other half. The average age is around 17 years old, which explains why most

[8]For children and adloscents, BMI is age-and sex-specific and is often referred to as BMI-for-age. A child's weight status is determined using an age- and sex-specific percentile for BMI rather than the BMI categories used for adults, since children's body composition varies as they age and varies between boys and girls. Therefore, BMI levels among children and teens need to be expressed relative to other children of the same age and sex

[9]The package *Zanthro*, available for *Stata*, was used to perform the required computations to obtain the adjusted body mass index

[10]This variable was constructed by using add health's nutritional section data in wave 2. Appendix 1 details the methodology which was followed to contruct such variable.

of the students are enrolled in 11 and 12 grade. Reports from summary statistics also tell us that around 13% of students in our sample suffers from obesity, which is below the national average reported by Ogden et al. [2016], around 20%. This difference might be explained due to the fact that the sample is biassed towards white population and do not contain enough information about other ethnic groups, such as the hispanic population.

In contrast to other peer effects studies in obesity (e.g. Fortin and Yazbeck [2015] and Dieye et al. [2017]), our analysis also includes variables such as eating habits and parents' weight status. The reason to included these variable is because parental weight status is considered to a main risk factor to develop overweight during childhood in the literature (e.g. Agras et al. [2004], Reilly et al. [2005]).

Table 1: Summary statistics

	Mean	Std. Dev.	Min	Max
Dependent variables				
BMI	23.53	5.13	13.75	56.3
zBMI	0.45	1.08	-4.84	3.14
Physical activity	3.53	2.04	0	9
Fastfood	2.36	1.76	0	8
Unhealthy food calories	557.60	340.12	0	1924
Individual characteristics				
Female	0.50	0.50	0	1
Age	16.60	1.55	12	20
White	0.60	0.49	0	1
Black	0.15	0.36	0	1
Asian	0.15	0.35	0	1
Other race	0.12	0.43	0	1
Grade 7 & 8	0.10	0.30	0	1
Grade 9 & 10	0.23	0.42	0	1
Grade 11 & 12	0.61	0.49	0	1
Own decisions to eat	0.85	0.36	0	1
Parents present when eat	4.38	2.41	0	7
Weekly allowance	7.98	11.46	0	95
Obese individual	0.13	0.34	0	1
Total consumed calories	1753.59	692.82	0	5164
Parental characteristics				
Obese mother	0.15	0.36	0	1
Obese father	0.09	0.29	0	1
Mother education	3.15	1.51	0	5
Father education	2.52	1.90	0	5
Residential building quality	1.67	0.80	1	4
N=2648				

4.2 Strong and weak friendships

To construct the strong and weak friendship networks, this articles uses data from the frienship roster questionnaire to construct a frienship score, which has remain unexploited in the peer effects literature so far. In the survey, every student nominated 5 female and male students.

Additionally, for every friend in this list there are 5 questions which allows us to identify the strenght of that particular friendship.[11] If the interviewed student had a positive answer for a given question, a value of 1 was assigned and 0 otherwise. The friendship score is the sum of her 5 answers.

Table 2 shows the average score value for each question. We observe that question 5, talking over the phone, is one of the most common habits friends usually share, followed by spending time during the weekend, while visiting friends houses being the most unusual.

Table 2: Average score for each question

	Mean	Std. Dev.
Question 1	0.40	0.38
Question 2	0.54	0.41
Question 3	0.47	0.41
Question 4	0.46	0.41
Question 5	0.62	0.38

Table 3 shows the average scores for each friend. We can observe that there is a negative relationship between the place of a nominated friend and the score. This means that students assigned places based on the intensity of the relationship, listing their closest friends at the beginning. Moreover, female friendships tend to have a higher score than their male counterpart.

Table 3: Friendship score

	mean	sd	min	max
Female friend 1	3.12	1.64	0	5
Female friend 2	2.39	1.56	0	5
Female friend 3	2.14	1.58	0	5
Female friend 4	1.70	1.40	0	5
Female friend 5	1.68	1.44	0	5
Male friend 1	2.95	1.56	0	5
Male friend 2	2.33	1.58	0	5
Male friend 3	2.10	1.52	0	5
Male friend 4	1.80	1.51	0	5
Male friend 5	1.78	1.51	0	5

The histogram of the friendship score can be visualized in figure 2[12], which reflects a normal-like type of distribution, where the first half of students assigned has less than 3 points, while the other half obtained strictly more than 2 points.

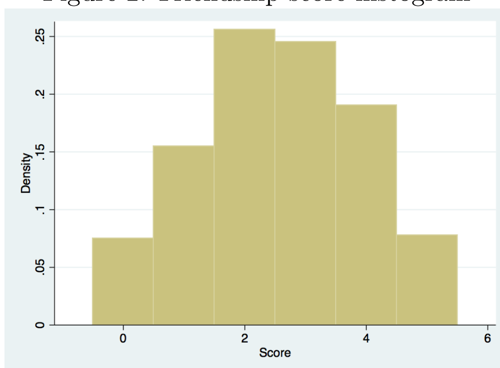
The strong and weak friendships networks were based on this computations by stablishing a certain threshold S_o. Therefore if $score_{i,j} \geq S_o$, then $g_{i,j} \in G_s$, and if $score_{i,j} < S_o$, then $g_{i,j} \in G_w$. In other words, a strong friendship was defined as all the connections greater or equal than S_o points, while a weak friendship was defined as a friend with a score less than S_o. Additionally, considering that i and j could have mutually nominated each other and obtained different scores,

[11] The questions are the following: *1. Did you go to j's house during the past seven days?; 2Did you meet j's after school to hang out or go somewhere during the past seven days?; 3. Did you spend time with j's during the past weekend?; 4. Did you talk to j's about a problem during the past seven days?; and 5. Did you talk to j's on the telephone during the past seven days?*

[12] To produce this graph, I calculated the mean value obtained for all friendships a given student listed and then rounded this number, eliminating decimals and thus having a discrete variable

the following rules was applied: $score_{i,j} = Max\{score_{i,j}, score_{j,i}\}$. This mean, for instance, that if i nominated j and assigned a value of 4 but j nominated i and assigned a value of 2, the final friendship score is equal to 4. Finally, the networks considered in this article are defined as undirected graphs, which means that if i declared j as friend, the friendship becomes bidirectional so the pair of elements $\{g_{i,j}, g_{j,i}\} \in G$ are defined such that $g_{i,j} = g_{j,i} = 1$.

Figure 2: Friendship score histogram



In order to make the network analysis, let's assume a threshold level of $S_0 = 3$[13]. Table 4 presents the descriptive statistics about G_s and G_w, the strong and weak friendship networks. The link density describes a ready index of the degree of dyadic connection in a population. In other words, it is the portion of the potential connections in a network that are actual connections. Clustering is an important property of social networks: People tend to have friends who are also friends with each other, resulting in sets of people among which many edges exist, while a set made from randomly chosen people would have a much smaller number of edges between them. To measure the clustering in a social (or other type of) network, a common measure is the clustering coefficient. The clustering coefficient is a real number between zero and one that is zero when there is no clustering, and one for maximal clustering, which happens when the network consists of disjoint cliques (e.g. everyone is friend with everyone else). According to table 4, the clustering coefficient of the strong friendships network is 36% greater than its counterpart. The number of bilateral links indicate the number of friendships in the network. In the strong friendships network there are 2054 bilateral links and 2393 in the weak one. The average degree refers to the average number of friends. Therefore, the table shows that on average students have more weak friendships than strong ones. Lastly, strong friendship are twice as likely to mutually nominate each other.

Table 4: Network statistics

	G_s	G_w
Link density	0.0006	0.0007
Clustering coefficient	0.098	0.071
Number of bilateral links	2008	2354
Average Degree	1.51	1.78
Mutual nominations	980	584
Mutual nominations (%)	0.49	0.25

[13]Robustness tests were conducted considering different threshold values

5 Results

The aim of this empirical analysis is twofold: (i) to asses the presence of strong friendship peer effect in adjusted body mass index, physical activity and dietary choices and, (ii) to differentiate between the impact of strong and weak friendships. This section is divided in three subsections. For the first two sections, following Liu and Lee [2010] and Liu et al. [2013], two different estimators are considered (2SLS and GMM). The first section discusses the results under a homogenous assumption (e.g. $\phi_s = \phi_w = \phi$). The second section relaxes this assumption and discusses the results of the heterogenous model (e.g. $\phi_s \neq \phi_w$). Finally, the third section provides robustness cheks.

5.1 Homogenous model estimationsl

5.1.1 Adjusted body mass index

Table 5 shows the estimation results of model (3), assuming homogenous effects $\phi = \phi_s = \phi_w$. In contrast to Dieye et al. [2017], we report the effect body mass index adjusted to age and sex(zBMI), instead of just body mass index, which might be innacurate to understand weight status in children and adolescents. The table reports the 2SLS and GMM estimations. For robustness purposes, we present three different specifications. The third specification takes into consideration parents' weight status (e.g. and whether they suffer from obesity or not) and eating habits, while the second one disregards eating habits, and the first one disregards eating habits and parents' weight status.

As discussed by Liu et al. [2013], estimates obtained through GMM tend to be much precise, as the GMM approach exploits additional (quadratic) moments conditions and the optimal weighting matrix. Therefore, from now on, we will mainly focus in the discussion of the GMM results. Results from table 5 provide robust evidence to support the peer effect on body mass index. The endogenous effect is statistically significant at 5% (model 1 and 3) and at 1% (model 2), and is equal to 0.200 approximately. This may reveal the presence of strategic complementarity between individual and peers weight, which means that peers' BMI positively affect own BMI through channels such as high caloric food intake and physical activity. Under strategic complementarity mechanism, this leads to a social multiplier equal between 1.20 and 1.25 ($= \frac{1}{1-\phi}$ x $0.82 + 1$ x 0.18).[14] This is consistent to the findings in Fortin and Yazbeck [2015] and Dieye et al. [2017], who found a multiplier equal to 1.15 and 1.20, respectively.

Regarding the individual characteristics effects, results from table 5 suggest that having obese parents has a considerable impact on adjusted body mass index. In particular, the effect of having an obese father is the greatest one (0.405). Age and being female affect negatively zBMI. Mother's education level has an impact only in model specification 1, when parental weight status is not considered, as in model 2 and 3.

The first stage F statistic indicates that our instruments have enough explanatory power. Nevertheless, it is important to note that according to the overidentfication test (OIR p-value), we reject the null hypothesis, which means that either one or more of our instruments are invalid or that our structural model is specified incorrectly. This article argues that the explanation to reject the null hypothesis is due to the fact that the model is specified incorrectly, and evidence for this will be presented when we discuss the results in section 4.2, heterogenous zBMI model ($\phi_s \neq \phi_w$).

5.1.2 Physical activity

Table 6 reports the estimation results for the physical activity homogenous model. These results provide robust evidence to support the peer effect on physical activity. The endogenous effect is

[14] Recall that 18% of our sample are isolated students. For them social multiplier is equal to 1

Table 5: Homogenous model zBMI

Dep. var. zBMI						
	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Peer Effects (ϕ)	0.246**	0.281***	0.251***	0.203**	0.256***	0.200**
	(0.101)	(0.098)	(0.091)	(0.101)	(0.091)	(0.087)
Female	-0.106**	-0.104**	-0.105**	-0.105**	-0.102**	-0.098**
	(0.045)	(0.044)	(0.044)	(0.044)	(0.043)	(0.043)
Age	-0.114***	-0.113***	-0.113***	-0.109***	-0.111***	-0.111***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Own decisions to eat	-	-	0.033	-	-	0.030
			(0.044)			(0.048)
Parents present when eat	-	-	-0.003	-	-	-0.002
			(0.003)			(0.003)
Weekly allowance	-	-	0.002	-	-	0.003
			(0.002)			(0.002)
White	0.016	0.007	0.008	0.019	0.015	0.010
	(0.077)	(0.076)	(0.076)	(0.077)	(0.077)	(0.076)
Black	0.041	0.069	0.055	0.020	0.056	0.041
	(0.100)	(0.099)	(0.099)	(0.094)	(0.094)	(0.093)
Asian	-0.007	0.040	0.044	0.007	0.072	0.088
	(0.096)	(0.094)	(0.094)	(0.103)	(0.100)	(0.099)
Grade 9 & 10	0.132	0.149	0.149	0.134	0.142	0.133
	(0.095)	(0.094)	(0.094)	(0.092)	(0.090)	(0.090)
Grade 11 & 12	0.140*	0.154*	0.152*	0.123	0.139*	0.136*
	(0.084)	(0.049)	(0.082)	(0.084)	(0.049)	(0.081)
Obese mother	-	0.297***	0.296***		0.320***	0.334***
		(0.059)	(0.059)		(0.059)	(0.058)
Obese father	-	0.456***	0.460***		0.441***	0.456***
		(0.074)	(0.074)		(0.067)	(0.067)
Mother education	0.025*	0.013	0.012	0.024*	0.011	0.007
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Father education	0.000	0.001	0.000	0.003	0.003	0.003
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
Residential building quality	0.117***	0.100***	0.102***	0.116***	0.104***	0.105***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic	6.42	5.89	5.36	-	-	-
OIR p-value test	0.032	.023	0.021	0.039	0.027	0.025
Observations	2648	2648	2648	2648	2648	2648

Notes: robust standard errors in parentheses
$p* < 0.1; p** < 0.05; p*** < .001$

statistically significant at 1% for every model and is equal to 0.35 approximately. As in the zBMI case, this suggest the presence of strategic complementarity between individual and peers physical activity frequency. Under strategic complementarity mechanism, this leads to a social multiplier around 1.43. The physycal activity multiplier is 22% bigger than the zBMI multiplier.

Results from table 6 indicate that age, gender and weekly allowance appear to be individual factors which have a significant impact on physical activity, while ethnicity, eating habits and parental characteristics are not strong predictors. It should be noted that weekly allowance has a positive relationship. A possible explanation is that weekly allowance subsidies physical activity by lowering the opportunity cost of time.

5.1.3 Fast food consumption

Table 7 shows the estimation results for the fast food consumption homogenous model. These results suggest a positive peer effect on physical activity. The endogenous effect is statistically significant at 5% (2SLS model 1, GMM model 3) and at 1% (2SLS models 2 and 3, and GMM models 1 and 2), and is approximately equal to 0.30. Under strategic complementarity mechanism, this leads to a social multiplier around 1.35. This multiplier is slighty superior to the one found in Fortin and Yazbeck [2015]. The differences might come from different estimations strategies (GMM vs. GSAR) and from the additional instruments used (e.g. Bonacich centrality).

Regarding individual characteristics, table 7 indicates that age, gender, ethnicity and, contrary to zBMI and physical activity, eating habits have a signficant effect on fast food consumption. First, allowing students to make their own decisions seems to produce a positive effect (0.274 in the 2SLS and 0.271 in the GMM); second, teenagers who eat while their parents are present have a lower consumption of fast food (-0.014 in both 2SLS and GMM); and third, the higher ammount of resources an adolescent gets, the more visits to fast food restaurants (0.007 in both 2SLS and GMM). We must note that the effect of making their own dietary choices is the most considerable one if we compare to parents present when eat and weekly allowance. Moreover, the contextual peers characteristics are also significant factor [15]. Estimations show that peers freedom in dietary choices has an effect of 0.292 (statistically signficant at 5%), and a negative effect of -0.019 when peers' parents are present while having dinner (statistically signficant at 5%).

Lastly, similar to the zBMI estimations, the OIR p-value test rejects the hypothesis that the model is well specified in 2SLS and GMM model 3. Therefore we suspect that the heterogenous model specification might be a way to solve this.

5.1.4 Unhealthy food consumed calories

Table 8 reports the estimation results for the physical activity homogenous model. The endogenous effect is statistically significant at 5% (GMM model 1) and at 10% (GMM model 3), and is equal to 0.237 (model 1) and 0.205 (model 3). Under strategic complementarity mechanism, this leads to a social multiplier around 1.25 and 1.21 resectively.

Regarding individual characteristics, table 7 indicates that age, gender, ethnicity and, similarly to the fast food consumption estimations, eating habits have a signficant effect on unhealthy food consumed calories, but this time the effect is statistically significant only for weekly allowance.

Similar to the zBMI and fast food estimations, the OIR p-value test rejects the hypothesis that the model is well specified in 2SL and GMM models 2 and 3. As argued before, the heterogenous specification might help to solve this problem.

[15] Contextual peer effects results are not included in the table. There results are provided under request

Table 6: Homogenous model physical activity

Dep. var. Physical activity	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Peer Effects (ϕ)	0.342***	0.322***	0.329***	0.378***	0.358***	0.359***
	(0.092)	(0.089)	(0.087)	(0.088)	(0.086)	(0.083)
Female	-0.863***	-0.868***	-0.858***	-0.858***	-0.865***	-0.854***
	(0.084)	(0.084)	(0.084)	(0.083)	(0.083)	(0.082)
Age	-0.213***	-0.216***	-0.199***	-0.206***	-0.209***	-0.192***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Own decisions to eat	-	-	-0.094	-	-	-0.079
			(0.082)			(0.080)
Parents present when eat	-	-	0.005	-	-	0.004
			(0.005)			(0.005)
Weekly allowance	-	-	0.013***	-	-	0.014***
			(0.004)			(0.004)
White	0.154	0.153	0.196	0.202	0.192	0.245*
	(0.145)	(0.145)	(0.145)	(0.141)	(0.141)	(0.140)
Black	-0.144	-0.151	-0.180	-0.180	-0.191	-0.225
	(0.174)	(0.175)	(0.176)	(0.171)	(0.171)	(0.172)
Asian	0.120	0.110	0.079	0.085	0.065	0.049
	(0.177)	(0.177)	(0.177)	(0.174)	(0.173)	(0.173)
Grade 9 & 10	0.537***	0.530***	0.529***	0.567***	0.571***	0.554***
	(0.177)	(0.176)	(0.176)	(0.172)	(0.171)	(0.171)
Grade 11 & 12	0.027	0.030	0.017	0.006	0.016	0.005
	(0.151)	(0.049)	(0.151)	(0.147)	(0.049)	(0.146)
Obese mother	-	-0.012	0.007		-0.035	-0.010
		(0.109)	(0.109)		(0.107)	(0.107)
Obese father	-	-0.033	-0.013		-0.017	0.002
		(0.135)	(0.135)		(0.133)	(0.132)
Mother education	0.028	0.029	0.028	0.030	0.032	0.032
	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)	(0.027)
Father education	-0.000	-0.001	-0.003	-0.003	-0.003	-0.005
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Residential building quality	-0.020	-0.019	-0.011	-0.021	-0.020	-0.009
	(0.049)	(0.049)	(0.049)	(0.048)	(0.048)	(0.048)
Observations	2648	2648	2648	2648	2648	2648
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic	5.167	4.892	4.354	-	-	-
OIR p-value test	0.541	0.721	0.940	0.584	0.755	0.951

Notes: robust standard errors in parentheses
$p* < 0.1; p** < 0.05; p*** < .001$

Table 7: Homogenous model fast food

Dep. var. Fast food restaurants visits						
	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Peer Effects (ϕ)	0.342**	0.361***	0.305***	0.297**	0.303**	0.237**
	(0.140)	(0.134)	(0.106)	-0.133	(0.127)	(0.098)
Female	-0.159**	-0.156**	-0.176**	-0.172**	-0.176**	-0.208***
	(0.073)	(0.073)	(0.073)	-0.071	(0.071)	(0.070)
Age	0.088***	0.087***	0.070**	0.097***	0.095***	0.070**
	(0.031)	(0.031)	(0.031)	-0.03	(0.030)	(0.031)
Own decisions to eat	-	-	0.274***	-	-	0.271***
			(0.072)			(0.069)
Parents present when eat	-	-	-0.014***	-	-	-0.014***
			(0.005)			(0.005)
Weekly allowance	-	-	0.007**	-	-	0.007**
			(0.004)			(0.003)
White	0.025	0.024	0.040	0.053	0.086	0.090
	(0.128)	(0.127)	(0.123)	-0.123	(0.122)	(0.119)
Black	-0.031	-0.029	-0.083	0.02	0.030	-0.021
	(0.157)	(0.158)	(0.156)	-0.153	(0.153)	(0.150)
Asian	0.277*	0.284*	0.289*	0.315**	0.338**	0.322**
	(0.161)	(0.163)	(0.159)	-0.157	(0.157)	(0.153)
Grade 9 & 10	0.052	0.056	0.060	0.036	0.039	0.047
	(0.149)	(0.149)	(0.149)	-0.147	(0.147)	(0.145)
Grade 11 & 12	0.185	0.186	0.165	0.155	0.151	0.145
	(0.138)	(0.049)	(0.138)	-0.137	(0.049)	(0.136)
Obese mother	-	0.107	0.118		0.134	0.120
		(0.097)	(0.096)		(0.094)	(0.093)
Obese father	-	-0.132	-0.139		-0.118	-0.144
		(0.103)	(0.103)		(0.100)	(0.100)
Mother education	0.019	0.018	0.018	0.015	0.014	0.018
	(0.025)	(0.025)	(0.025)	-0.024	(0.024)	(0.024)
Father education	0.006	0.007	0.007	0.005	0.009	0.010
	(0.019)	(0.019)	(0.019)	-0.019	(0.018)	(0.018)
Residential building quality	0.025	0.024	0.021	0.029	0.029	0.032
	(0.046)	(0.046)	(0.046)	-0.045	(0.045)	(0.044)
Observations	2648	2648	2648	2648	2648	2648
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic	2.630	2.319	2.77	-	-	-
OIR p-value test	0.187	0.176	0.061	0.199	0.184	0.065

Notes: robust standard errors in parentheses
$p* < 0.1; p** < 0.05; p*** < .001$

Table 8: Homogenous model unthealthy food consumed calories

Dep. var. Unhealthy food consumed calories	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Peer Effects (ϕ)	0.180	0.123	0.164	0.237**	0.156	0.205*
	(0.123)	(0.117)	(0.112)	(0.120)	(0.113)	(0.107)
Female	-128.3***	-129.6***	-128.2***	-127.8***	-132.1***	-132.2***
	(14.467)	(14.364)	(14.411)	(14.242)	(14.043)	(14.054)
Age	-19.59***	-20.50***	-18.98***	-18.64***	-19.80***	-18.06***
	(6.308)	(6.271)	(6.315)	(6.218)	(6.159)	(6.167)
Own decisions to eat	-	-	-5.006	-	-	-7.957
			(14.284)			(13.912)
Parents present when eat	-	-	0.281	-	-	0.355
			(0.956)			(0.929)
Weekly allowance	-	-	0.947	-	-	1.154*
			(0.683)			(0.679)
White	0.607	2.933	3.348	-1.918	2.512	0.976
	(26.663)	(26.533)	(26.628)	(26.193)	(25.920)	(25.927)
Black	41.368	43.461	38.776	51.640*	52.397*	48.012
	(32.076)	(31.975)	(32.003)	(31.327)	(31.054)	(30.960)
Asian	155.1***	154.4***	154.7***	166.2***	162.1***	160.9***
	(34.094)	(33.911)	(33.999)	(33.554)	(33.228)	(33.134)
Grade 9 & 10	3.275	4.283	4.630	4.772	-1.291	-2.037
	(30.424)	(30.357)	(30.536)	(29.772)	(29.508)	(29.662)
Grade 11 & 12	34.206	33.756	33.930	29.488	24.896	24.701
	(26.655)	(0.049)	(26.855)	(25.984)	(0.049)	(25.985)
Obese mother	-	-4.386	-4.764		-10.992	-11.016
		(18.780)	(18.838)		(18.443)	(18.492)
Obese father	-	5.581	6.585		3.699	9.258
		(23.012)	(23.104)		(22.873)	(22.837)
Mother education	0.104	-0.020	-0.240	-0.278	-0.599	-2.019
	(4.946)	(4.962)	(4.990)	(4.920)	(4.914)	(4.912)
Father education	1.873	1.654	1.356	1.556	1.680	1.240
	(3.728)	(3.721)	(3.742)	(3.690)	(3.660)	(3.671)
Residential building quality	-14.907*	-14.813*	-13.562	-16.065*	-15.873*	-15.140*
	(8.482)	(8.486)	(8.507)	(8.428)	(8.404)	(8.398)
Observations	2648	2648	2648	2648	2648	2648
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic	4.314	4.019	3.569	-	-	-
OIR p-value test	0.102	0.025	0.031	0.117	0.028	0.033

Notes: robust standard errors in parentheses
$p* < 0.1; p** < 0.05; p*** < .001$

5.2 Heterogenous model estimations

5.2.1 Adjusted body mass index

Table 9 presents the estimation results of model (3). These results no longer assume peer effects homogeneity $\phi_s \neq \phi_w$. In all specifications, except 2SLS model 1,strong friendships (ϕ_s) have a larger effect on adjusted body mass index. This impact is approximately equal to 0.260, and it is statisticaly significant at 1% (2SLS model 3, and GMM model 1, 2 and 3). This coefficient is larger than the coefficient obtained in the homogenous model. The increase might occur because we allow heterogenous effect and thus it takes into consideration the effect of stronger friendships. On the other hand, we cannot reject the hypothesis that the effect of weak frienships is equal to zero (2SLS model 2 and 3, and GMM model 1, 2 and 3). As discussed before, according to Liu et al. [2013], estimates obtained through GMM tend to be much precise, as the GMM approach exploits additional (quadratic) moments conditions and the optimal weighting matrix.

The individual characteristics effects remain close to the estimations in the homogenous model (table 5). The only difference is found in the asian ethnicity coefficient. Under GMM model especification number 2, the coefficient is statistically significant at 10% and is equal to 0.208. The contextual peer characteristics seem to have a heterogenous impact as well. Strong friendships who have dinner with parents has a negative effect of -0.006 (significant at 10%). Also, an extra dollar of weekly allowance received by strong peers increases the zBMI in 0.001 (significant at 10%). On the contrary, week friendships eating habits seem to not have an impact, but a week friendship who has an obese father has a positive effect in zBMI around 0.203 (significant at 10%)

The first stage F statistic indicates that our instruments have enough explanatory power. In contrast to the homogenous model, the overidentfication test (OIR p-value) in the heterogenous especification provides evidence to accept the null hypothesis, which means that in this case, the instruments we have used are valid and the structural model is specified correctly.

5.2.2 Physical activity

Table 10 reports the estimation results for the physical activity heterogenous model. Consistent with the results in the heterogenous zBMI model, we find that strong friendships have a significant impact on physical activity, and we cannot reject the hypothesis that weak friendships coefficent is equal to zero, except in 2SLS model 3, where the impact is 0.129 (significant at 10%). The endogenous effect of strong friendships on physical activity is around 0.221 This effect is smaller than the effect of strong frienships. After conducting a test comparing both coefficients in 2SLS model 3, we reject with 1% level of signficance the hyptohesis that $\phi_2 = \phi_w$.

Regarding the contextual peer effects, physical activity shows heterogenous effects. Weak ties mother's education impacts positively on physical activity (0.078, significant at 10%). Weak ties eating habits also have a signficant effect: liberty to make their own diet impacts negatively (-0.321, significant at 5%); parents present during dinner has a positive impact (0.026, significant at 1%). On the other hand, strong friendship characteristics comes from the ethnicity channel: having white stong peers has an effect equal to 0.319 (significant at 10%).

5.2.3 Fast food consumption

Results in table 11 indicate that weak friendships endogenous effects dominate over the strong friendships, contrary to our findings on zBMI and physical activity. This evidence suggest that casual friendships are more important than its counterpart to influence individuals fast food consumption. This is true for all model especifications. The effect of weak friendships is around 0.335 and is statistically significant at 1%. A potential explanation is that weak friendship might influence individuals in some unhealthy behaviors, like going to a fast food restaurant.

Table 9: Heterogenous model zBMI

Dep. var. zBMI						
	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Strong friendships (ϕ_s)	0.198*	0.247**	0.276***	0.242**	0.293***	0.300***
	(0.102)	-0.097	(0.089)	(0.097)	(0.092)	(0.083)
Weak friendships (ϕ_w)	0.229*	0.147	0.157	0.178	0.118	0.155
	(0.125)	-0.114	(0.106)	(0.118)	(0.107)	(0.099)
Female	-0.086*	-0.083*	-0.085*	-0.097**	-0.090*	-0.099**
	(0.049)	-0.048	(0.048)	(0.048)	(0.046)	(0.046)
Age	-0.114***	-0.113***	-0.111***	-0.103***	-0.103***	-0.110***
	(0.020)	-0.02	(0.020)	(0.019)	(0.018)	(0.019)
Own decisions to eat	-	-	0.022	-	-	0.035
			(0.049)			(0.045)
Parents present when eat	-	-	-0.002	-	-	-0.003
			(0.003)			(0.003)
Weekly allowance	-	-	0.001	-	-	0.001
			(0.001)			(0.002)
White	0.016	0.004	0.000	0.011	-0.012	0.003
	(0.080)	-0.08	(0.080)	(0.077)	(0.077)	(0.076)
Black	-0.002	0.028	0.036	-0.015	0.025	0.039
	(0.093)	-0.093	(0.094)	(0.090)	(0.090)	(0.09)
Asian	-0.007	0.038	0.045	0.013	0.067	0.101
	(0.106)	-0.104	(0.104)	(0.101)	(0.099)	(0.098)
Grade 9 & 10	0.093	0.098	0.097	0.104	0.117	0.122
	(0.096)	-0.095	(0.095)	(0.094)	(0.092)	(0.09)
Grade 11 & 12	0.147*	0.161*	0.158*	0.153*	0.176**	0.183**
	(0.087)	-0.086	(0.086)	(0.085)	(0.083)	(0.082)
Obese mother	-	0.301***	0.303***		0.303***	0.307***
		-0.06	(0.060)		(0.057)	(0.057)
Obese father	-	0.456***	0.462***		0.482***	0.505***
		-0.068	(0.069)		(0.066)	(0.066)
Mother education	0.021	0.01	0.007	0.015	0.007	0.007
	(0.016)	-0.015	(0.015)	(0.015)	(0.015)	(0.015)
Father education	0.000	0.001	0.001	0.003	0.003	0.003
	(0.012)	-0.011	(0.011)	(0.011)	(0.011)	(0.011)
Residential building quality	0.120***	0.104***	0.102***	0.113***	0.100***	0.100***
	(0.028)	-0.027	(0.027)	(0.027)	(0.026)	(0.026)
Observations	2648	2648	2648	2648	2648	2648
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic (ϕ_s)	2.489	2.096	2.211	-	-	-
First stage F statistic (ϕ_s)	1.640	1.751	1.597	-	-	-
OIR p-value test	0.421	0.361	0.259	0.448	0.497	0.301

Notes: robust standard errors in parentheses
$p* < 0.1$; $p** < 0.05$; $p*** < .001$

Table 10: Heterogenous model physical activity

Dep. var. Physical activity	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Strong friendships (ϕ_s)	0.238**	0.207**	0.155**	0.271***	0.238***	0.219***
	(0.095)	(0.089)	(0.077)	(0.092)	(0.085)	(0.073)
Weak friendships (ϕ_s)	0.058	0.069	0.129*	-0.008	0.011	0.076
	(0.094)	(0.088)	(0.078)	(0.090)	(0.083)	(0.074)
Female	-0.867***	-0.867***	-0.853***	-0.898***	-0.897***	-0.889***
	(0.089)	(0.089)	(0.088)	(0.087)	(0.087)	(0.086)
Age	-0.227***	-0.229***	-0.218***	-0.245***	-0.241***	-0.220***
	(0.038)	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)
Own decisions to eat	-	-	-0.106	-	-	-0.129*
			(0.082)			(0.077)
Parents present when eat	-	-	0.005	-	-	0.006
			(0.005)			(0.005)
Weekly allowance	-	-	0.000	-	-	0.000
			(0.001)			(0.001)
White	0.129	0.125	0.142	0.013	0.004	0.070
	(0.147)	(0.147)	(0.146)	(0.143)	(0.142)	(0.140)
Black	-0.078	-0.091	-0.060	-0.171	-0.186	-0.122
	(0.172)	(0.172)	(0.172)	(0.168)	(0.167)	(0.165)
Asian	0.049	0.045	0.052	-0.001	0.000	0.012
	(0.174)	(0.173)	(0.173)	(0.169)	(0.167)	(0.166)
Grade 9 & 10	0.464***	0.455***	0.456***	0.559***	0.566***	0.551***
	(0.170)	(0.170)	(0.169)	(0.166)	(0.165)	(0.163)
Grade 11 & 12	0.020	0.027	0.037	0.059	0.068	0.048
	(0.148)	(0.148)	(0.147)	(0.144)	(0.143)	(0.140)
Obese mother	-	0.007	0.013		-0.006	0.006
		(0.109)	(0.109)		(0.106)	(0.105)
Obese father	-	-0.052	-0.036		-0.054	-0.022
		(0.135)	(0.134)		(0.131)	(0.129)
Mother education	0.035	0.035	0.030	0.038	0.036	0.026
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)	(0.026)
Father education	-0.002	-0.002	0.002	-0.002	-0.001	0.004
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Residential building quality	-0.014	-0.014	-0.012	0.007	0.000	-0.002
	(0.048)	(0.049)	(0.049)	(0.047)	(0.047)	(0.046)
Observations	2648	2648	2648	2648	2648	2648
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic ϕ_s	2.449	2.459	3.116	-	-	-
First stage F statistic ϕ_s	2.757	2.786	2.616	-	-	-
OIR p-value test	0.320	0.539	0.373	0.348	0.567	0.396

Notes: robust standard errors in parentheses
$p* < 0.1$; $p** < 0.05$; $p*** < .001$

Similar to our findings in the homogenous model, we still observe a notorious influence of eating habits (own decisions to eat and parents present when eating) and ethnicity (being asian) on visits to fast food restaurants. The contextual peer characteristics that seems to matter the most in this model are race and fathers education, but this is true only for strong friendships. Having a close friend who is black increases the visits to restaurants in 0.499 (significant at 1%). On the other hand, additional father's education from a strong friendship decreases visits in -0.091 (significant at 1%).

5.2.4 Unhealthy food consumed calories

Table 12 reports the results for the heterogenous model of unhealthy food consumed calories. Given its correlated natured, we should expected that results from unhealthy food consumed calories and fast food restaurants visits to be similar. However, table 11 suggests that, contrary to the results in fast food restaurants visits, strong friendships have a positive and statistically significant effect and dominates over the weak friendship endogenous effect. In 2SLS model specification 3 the impact is equal to 0.175 (significant at 10%) and equal to 0.160 (significant at 10%) in the GMM model specification 3. The differences found between the endogenous effects on fast food consumption and unhealthy food consumed calories can be explained due to the fact that fast food calories is a subset of the total ammount of unhealthy consumed calories, and thus the scope of the later variable is wider. Unhealthy food calories consumption can be exposed among peers not only in fast food restaurants but as well inside school. Therefore, unhealthy food consumed calories might be affected by a higher level of social interaction, providing with a more precise story about the unhealthy habiths of adolescents.

Similarly to our finding in fast food consumption, the contextual peer effects seem to be heterogenous. Strong friendships' father education reduces the ammount of unhealthy consumed calories of individuals (-9.237, significant at 10%). On the other hand, weak friendships affect through mothers education (-13.237, significant at 10%) and due to having dinner while parents are present (-2.766, significant at 10%).

In contrast to the homogenous model, the overidentfication test (OIR p-value) in the heterogenous especification provides evidence to accept the null hypothesis, which means that in this case, the instruments we have used are valid and the structural model is specified correctly.

Table 11: Heterogenous model fast food consumption

Dep. var. Fast food restaurants visits	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Strong friendships ϕ_s	0.156	0.104	0.086	0.175*	0.120	0.118
	(0.109)	(0.101)	(0.088)	(0.104)	(0.094)	(0.081)
Weak friendships ϕ_w	0.329***	0.337***	0.334***	0.328***	0.327***	0.358***
	(0.103)	(0.099)	(0.094)	(0.099)	(0.093)	(0.087)
Female	-0.126	-0.128	-0.154*	-0.101	-0.081	-0.124*
	(0.079)	(0.078)	(0.079)	(0.076)	(0.075)	(0.075)
Age	0.085***	0.082***	0.058*	0.089***	0.085***	0.052*
	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)
Own decisions to eat	-	-	0.272***	-	-	0.280***
			(0.073)			(0.068)
Parents present when eat	-	-	-0.014***	-	-	-0.014***
			(0.005)			(0.005)
Weekly allowance	-	-	0.001	-	-	0.000
			(0.001)			(0.000)
White	0.030	0.047	0.041	-0.010	0.027	0.006
	(0.122)	(0.122)	(0.120)	(0.117)	(0.116)	(0.114)
Black	-0.046	-0.032	-0.072	-0.082	-0.072	-0.127
	(0.152)	(0.151)	(0.150)	(0.146)	(0.144)	(0.143)
Asian	0.214	0.232	0.231	0.225	0.247	0.259*
	(0.159)	(0.159)	(0.158)	(0.154)	(0.153)	(0.150)
Grade 9 & 10	0.100	0.105	0.124	0.060	0.064	0.094
	(0.148)	(0.147)	(0.146)	(0.144)	(0.142)	(0.141)
Grade 11 & 12	0.240*	0.256*	0.255*	0.188	0.187	0.223*
	(0.141)	(0.141)	(0.138)	(0.136)	(0.135)	(0.133)
Obese mother	-	0.127	0.134		0.077	0.062
		(0.096)	(0.096)		(0.092)	(0.091)
Obese father	-	-0.175*	-0.190*		-0.095	-0.122
		(0.103)	(0.103)		(0.099)	(0.099)
Mother education	0.023	0.021	0.025	0.010	0.011	0.016
	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)
Father education	0.004	0.003	0.005	-0.001	-0.002	0.006
	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
Residential building quality	0.021	0.019	0.007	-0.010	-0.008	-0.030
	(0.046)	(0.046)	(0.046)	(0.044)	(0.044)	(0.043)
Observations	2648	2648	2648	2648	2648	2648
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic ϕ_s	2.097	2.143	2.280	-	-	-
First stage F statistic ϕ_w	2.385	2.336	3.116	-	-	-
OIR p-value test	0.398	0.417	0.280	0.397	0.411	0.264

Notes: robust standard errors in parentheses
$p* < 0.1; p** < 0.05; p*** < .001$

Table 12: Heterogenous model unthealthy food consumed calories

Dep. var. Unthealthy food consumed calories						
	2SLS			GMM		
	(1)	(2)	(3)	(1)	(2)	(3)
Strong friendships (ϕ_s)	0.111	0.095	0.175*	0.080	0.142	0.160*
	(0.121)	(0.106)	(0.102)	(0.101)	(0.115)	(0.094)
Weak friendships ϕ_w)	0.046	0.002	-0.088	-0.001	0.025	-0.053
	(0.115)	(0.109)	(0.099)	(0.103)	(0.110)	(0.092)
Female	-142.0***	-143.6***	-144.4***	-142.1***	-140.7***	-143.826***
	(15.424)	(15.334)	(15.411)	(14.741)	(14.889)	(14.697)
Age	-21.0***	-21.6***	-21.3***	-22.0***	-22.1***	-22.7***
	(6.275)	(6.218)	(6.271)	(6.009)	(6.095)	(6.017)
Own decisions to eat	-	-	-6.814	-	-	-9.674
			(14.459)			(13.725)
Parents present when eat	-	-	0.373	-	-	0.521
			(0.972)			(0.922)
Weekly allowance	-	-	-0.041	-	-	-0.042
			(0.116)			(0.107)
White	-0.219	1.192	2.270	-0.175	-2.615	2.449
	(26.742)	(26.651)	(26.616)	(25.450)	(25.499)	(25.218)
Black	50.304	52.44*	53.1*	50.70*	49.618	56.85*
	(31.332)	(31.241)	(31.451)	(30.237)	(30.452)	(30.144)
Asian	147.6***	147.6***	150.4***	155.5***	153.3***	160.935***
	(33.895)	(33.834)	(33.814)	(32.842)	(32.951)	(32.684)
Grade 9 & 10	10.458	10.493	8.436	-4.766	46.514**	4.135
	(30.065)	(29.971)	(29.778)	(18.020)	(23.324)	(28.657)
Grade 11 & 12	34.540	33.645	32.075	8.382	-3.600	33.680
	(26.872)	(26.737)	(26.637)	(21.985)	(5.350)	(25.716)
Obese mother	-	-3.254	-4.789		6.855	-7.544
		(18.704)	(18.754)		(29.084)	(17.955)
Obese father	-	7.683	8.462		29.575	7.368
		(22.637)	(22.850)		(25.980)	(21.959)
Mother education	-0.537	-0.862	-1.350	-1.378	-1.310	-2.644
	(4.914)	(4.933)	(4.979)	(4.797)	(4.822)	(4.812)
Father education	1.606	1.221	1.121	-0.199	0.626	-0.617
	(3.725)	(3.733)	(3.762)	(3.598)	(3.615)	(3.601)
Residential building quality	-12.194	-12.428	-11.706	-12.756	-11.207	-10.834
	(8.460)	(8.442)	(8.485)	(8.139)	(8.222)	(8.119)
Observations	2648	2648	2648	2648	2648	2648
Network fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
First stage F statistic ϕ_s	1.807	2.013	2.054	-	-	-
First stage F statistic ϕ_w	2.186	2.086	2.442	-	-	-
OIR p-value test	0.932	0.892	0.589	0.941	0.901	0.607

Notes: robust standard errors in parentheses
$p* < 0.1$; $p** < 0.05$; $p*** < .001$

5.3 Robustness checks

This section provides with robustness checks for our estimations of the heterogenous model for zBMI, physical activity, fast food consumption and unhealthy food consumed calories. This test analyzes the endogenous effects in both strong and weak friednships considering different friendship intensity levels.

As discussed in section 4.2, the strong and weak friendships networks were defined by establishing a certain threshold S_o for the friendship score: if $score_{i,j} \geq S_o$, then $g_{i,j} \in G_s$, and if $score_{i,j} < S_o$, then $g_{i,j} \in G_w$. S_o have 5 possible different values: $S_o = \{1, 2, 3, 4, 5\}$. Section 5.1 and Section 5.2 present the results considering $S_o = 3$. Complementary, table 13 shows the estimations of the weak and strong friendships endogenous effects for $S_o = \{1, 2, 4, 5\}$.

First, according to these results, the endogenous effects on zBMI seem to hold for all different levels of friendship intensity. The strong friendships endogenous effect always dominate over the endogenous effect of weak friendships. Second, in the case of physical activity, we observe, as long as $SF_0 5$, that the strong friendships endogenous effect also dominate over the endogenous effect of weak friendships. Third, when $SF_0 3$, the strong friendship endogenous effect signficantly dominates over the weak friendships one. This suggest that there might be some other sources of heterogeneity in play. Fourth and finally, the unhealthy food consumed calories show a similar pattern to fast food consumption: for small values of $SF_0 = 1, 2$, the strong friendships endogenous effect dominates over the weak one; for small values of $SF_0 = 4, 5$, the weak frienships endogenous effect domintes ofer the strong one.

Table 13: GMM estimations for endogenous effects at different S_o levels

Dependent variable	Endogenous effect	$S_0 = 1$	$S_0 = 2$	$S_0 = 4$	$S_0 = 5$
BMI	Weak friendships ϕ_w	-0.011	0.146*	0.041	0.040
		(0.086)	(0.085)	(0.083)	(0.081)
	Strong friendships ϕ_s	0.318***	0.222***	0.196**	0.234***
		(0.076)	(0.079)	(0.077)	(0.085)
Physical activity	Weak friendships ϕ_w	0.179**	0.049	0.121*	0.244***
		(0.078)	(0.075)	(0.071)	(0.076)
	Strong friendships ϕ_s	0.213***	0.311***	0.226***	0.088
		(0.079)	(0.074)	(0.072)	(0.073)
Fast food restaurants visits	Weak friendships ϕ_w	0.130	0.141*	-0.015	0.328***
		(0.105)	(0.076)	(0.083)	(0.099)
	Strong friendships ϕ_s	0.203**	0.159*	0.093	0.175*
		(0.091)	(0.086)	(0.086)	(0.104)
Unhealthy food consumed calories	Weak friendships ϕ_w	0.025	0.063	-0.057	0.161*
		(0.103)	(0.097)	(0.086)	(0.095)
	Strong friendships ϕ_w	0.161*	0.104	-0.024	-0.119
		(0.098)	(0.095)	(0.083)	(0.094)
Individual characteristics		yes	yes	yes	yes
Parental characteristics		yes	yes	yes	yes
Eating habits		yes	yes	yes	yes
Contextual effects		yes	yes	yes	yes
Fixed effects		yes	yes	yes	yes
Observations		2648	2648	2648	2648

6 Conclusions

This papers is based on Dieye et al. [2017] non-cooperative model of BMI outcome with effort technology in a network context, which we then use to derive a reduced form of the econometric model.The main contribution of this article is that it allows for friendship intensity heterogeneity in endogenous and contextual peer effects.

We first test the homogenous model, assuming equal friendship intensity among the members in the network. We find evidence that supports the existence of peer effects. Nontheless, the zBMI and unhealthy food consumed calories models fail the overidentification test, suggesting that our instruments are invalid or that the structural model is not specified correctly. Then we estimate the model considering heterogenous effects. The results supports the hypothesis that peers have different impacts depending on the intensity of their relantionship. Closer friends have a stronger impact than more casual ones. In contrast to the homogenous model, the overidentification test suggests that the heterogeneity model is more appropiated to model peer effects in the studied variables. These results are in line with Patacchini et al. [2017], who find that only long term peers have a signficant impact on academic achievement. However, these results are only robust for physical activity and zBMI.

We also find that weak friendships dominate the endogenous peer effects on dietary choices (fast food consumption), while strong friendships dominate on physical activity. This is an interesting fnding for at least two reasons. First, it suggests that individuals tend to choose casual friendships to engage in unhealthy activities. Second, the finding is puzzling since only the strong friendships have a significant effect on zBMI, which indicates that the social mechanisms that influences weight comes mainly from the physical activity channel and less from the nutritional choices one.

There are two way to solve this paradox. The first one could be to find a way to test the different social interaction mechanism behind (e.g. strategic complementarity or conformity). For instance, Liu et al. [2014] find that for sport activities, both social-conformity and social-multiplier effects contribute to the endogenous peer effect and they conclude that *if more than one mechanism is driving social interactions, then neglecting one of them can produce biased inferential results.* [see Liu et al., 2014, p. 50].

A different way to differentiate between these mechanisms is by considering the model developed by Reif [2017], which is based on the dynamic properties of consumption. Intuitively, as the author explains, an increase in conformity causes individuals to place more weight on the average consumption in their group and less weight on their own idiosyncratic preferences. This compresses the distribution of consumption within the group by causing individuals with preferences for a high level of consumption to consume less and individuals with preferences for a low level of consumption to consume more. There is no effect on aggregate consumption because these two opposing effects cancel each other out. Strategic complementarity, by contrast, increases everyone's consumption. [see Reif, 2017, p. 7].

Finally, we should note that ia notorious limitation is that networks are assumed to be exogenous in this work. Evidence of network endoegeneity could be that data shows that students in 11th and 12th grade tend to have more intense links with their peers than students in previous year. Therefore the composition of the strong friendship network could be different, which might be a potential source of bias. Further work should integrate an endogenous network formation framework to the econometric especification.

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Appendices

Appendix 1: Unhealthy food consumed calories

Add health nutritional section details dietary choices. In this section, students were asked about what they have eaten the day before. The answers does not include quantities, therefore we assume a standard measure to calculate the ammount of consumed calories. The measures were taken from the USDA National Nutrient Database. We divided in two different kind of foods: healthy and unhealthy. The maximum ammount of total calories consumed are 6348. The ammount of healthy calories is equal to 4152, and the unhealthy ones is equal to 2125.

Label	Food name	Calories	Quantity	Unit
Unhealthy	Bacon	43	1	Piece
Unhealthy	Chocolate Bars	118	1	Piece
Unhealthy	Cookies	135	1	Serving
Unhealthy	Doughnuts	226	1	Piece
Unhealthy	French Fries	323	100	Grams
Unhealthy	Frozen Yogurt	100	0.5	Cup
Unhealthy	Ground Meat	120	50	Grams
Unhealthy	Hot Dog	127	1	Piece
Unhealthy	Ice Cream	137	0.5	Cup
Unhealthy	Margarine	101	1	Tablespoon
Unhealthy	Mayonnaise	90	1	Tablespoon
Unhealthy	Peanut Butter	188	2	Tablespoon
Unhealthy	Pizza	266	1	Piece
Unhealthy	Potato Chips	151	1	Ouce
Unhealthy	Salad Dressing	71	1	Tablespoon
Healthy	Apple	95	1	Piece
Healthy	Avocadoes	322	1	Each
Healthy	Banana	105	1	Piece
Healthy	Bread	166	1	Slice
Healthy	Breakfast Cereal	150	1	Cup
Healthy	Broccoli	27	0.5	Cup
Healthy	Cabbage	10	0.5	Cup
Healthy	Canned Tuna Fish	158	3	Ounces
Healthy	Carrots	23	0.5	Cup
Healthy	Cereal Bars	90	1	Piece
Healthy	Cheese	126	2	Piece
Healthy	Chick Peas	67	0.25	Cup
Healthy	Chicken	142	1	Piece
Healthy	Dried Beans	130	0.25	Cup
Healthy	Eggs	180	2	Piece
Healthy	Fish	156	3	Ounces
Healthy	Flavored Wated	90	1	Cup
Healthy	Green Beans	180	0.25	Cup
Healthy	Kale	18	0.5	Cup
Healthy	Lettuce	10	1	Cup
Healthy	Mango	50	0.5	Cup
Healthy	Milk	149	1	Cup
Healthy	Mixed Vegetables	20	1	Can
Healthy	Orange Juice	112	1	Cup
Healthy	Oranges	62	1	Piece
Healthy	Other Juices	50	1	Cup
Healthy	Other Potatoes	145	1	Piece
Healthy	Peaches	59	1	Piece
Healthy	Raisins	108	0.25	Cup
Healthy	Rice	100	0.5	Cup
Healthy	Roast Beef	140	0.67	Cup
Healthy	Spaghetti	255	1	Serving
Healthy	Spinach	7	1	Cup
Healthy	Sweet Potatoes	90	0.5	Cup
Healthy	Tofu	78	1	Serving
Healthy	Tomatoes	18	1	Piece
Healthy	Yogurt	154	1	Cup
-	Sum	-	6348	-