Peer Effects in Bed Time Decisions among Adolescents: a Social Network Model with Sampled Data*

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Abstract

Using unique information on a representative sample of U.S. teenagers, we investigate peer effects in adolescent bed time decisions. We extend the NLS estimator of Wang and Lee (2013a) to estimate network models with network fixed effects and sampled observations on the dependent variable, and show the extent to which neglecting the sampling issue yields misleading inferential results. When accounting for sampling, we find that, besides the individual, family and peer characteristics, the bed time decisions of the peers are important to shape one's own bed time decision.

Key words: missing data, nonlinear least squares, productivity, social interactions, spatial autoregressive model

JEL classification: C13, C21, J22

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"Sleep that knits up the ravelled sleave of care, The death of each day's life, sore labour's bath, Balm of hurt minds, great Nature's second course, Chief nourisher in life's feast."

Shakespeare, Macbeth

1 Introduction

Nearly a third of a person's life is spent in slumber. Yet, sleeping behaviour has received relatively little attention in economics.[1] In particular, there is virtually no study on how the sleeping behaviour is affected by social incentives. While sleep is primarily a function of the body's internal biological clock (circadian rhythm), individual choice also has a big part in determining the timing and duration of sleep. In many circumstances, individual choice in a certain activity cannot be adequately explained by their personal characteristics and the intrinsic utility derived from this activity. Rather, its rationale may be found in how this activity is valued by the peers. There is indeed strong evidence that the peer effect plays an important role in shaping individual choices in many activities.[2] Hence, peer effects might also be important for understanding the sleeping behaviour, which is the residual activity.[3]

In this paper, we exploit the unique information contained in the National Longitudinal Survey of Adolescent Health (Add Health) to study bed time patterns among adolescents in the United States. Sleeping behaviour during teenage years is of particular interest because of its effect on human capital formation. Research outside of economics suggests that lack of sleep reduces attendance, increases tardiness, and lowers grades of adolescent students.[4] Furthermore, lack of sleep in youth is correlated with health and behavioral problems such as moodiness, depression, difficulty controlling behaviour, and increased frustration - all of which make learning in school difficult (National Sleep Foundation, 2006). Sleep also affects productivity on the job, which in some cases represents a public safety concern.

[1] The interest on the topic of sleep has been rapidly growing in the last few years. Most notably, there is an on-going lab-in-the-field experiment in India by Rao et al. (2015) that focuses on how sleep deprivation may have tremendous consequences for the poor.

[2] The integration of social interaction models within economic theory is an active and interesting area of research. See the recent *Handbook of Social Economics* by Benhabib et al. (2011).

[3] Biddle and Hamermesh (1990) study the demand for sleep in this perspective without social incentives.

[4] Wolfson and Carskadon (2003) is an excellent summary of the medical research in this area.

The Add Health data contain unique information on friendship relationships among a nationally representative sample of students in grades 7-12 in the United States together with basic information on individual, family, neighborhood and school characteristics (the in-school survey). The survey design also includes a questionnaire (the in-home survey) administered to a random subsample of the students participating the in-school survey, collecting information on more sensitive topics (health issues, crime, drug, sexual behaviour, etc.) including bed time on week days during the school year. The use of this additional information from the in-home survey, however, comes at a cost. The in-home sampling scheme may result in missing observations on the behaviour of students who were not sampled, and thus induce a measurement error to the endogenous peer effect regressor formulated as the average behaviour of a student's friends. As a result, the existing estimation methods for social network models (see, e.g., Bramoullé et al., 2009; Lee et al., 2010) are not generally valid.[5]

Recently, social network studies have drawn a great deal of attention. Network models are widely used to represent relational information among interacting units and the implications of these relations. Most inference for social network models assumes that all the possible links are observed and that the relevant information of all individuals (nodes) is available. This is clearly not true in practice, as most network data is collected through surveys. In a recent paper, Sojourner (2013) considers a linear-in-means social interaction model with missing observations on covariates. He shows that random assignment of individuals to peer groups can help to overcome this missing data problem. On the other hand, Chandrasekhar and Lewis (2011) consider the estimation of network models with missing observations on network links. They propose a set of analytical corrections for commonly used network statistics and a two-step estimation procedure using graphical reconstruction. In this paper, we focus on the case where all the network links and the covariates can be observed but only the dependent variable of the sampled nodes can be observed.

[5] This issue is typically neglected in most empirical papers using the information on friends together with the in-home survey in the Add Health dataset.

The social network model considered in this paper has the specification of a spatial autoregressive (SAR) process where the average behaviour of the peers is formulated as spatial lags. Kelejian and Prucha (2010) consider the estimation of the SAR model with missing observations on the dependent variable and covariates. They suggest two-stage least squares (2SLS) estimators that are based on a subset of the cross-sectional units for which the dependent variable and covariates are observed, and the spatial lags are either completely observed or partially observed with an asymptotically negligible measurement error. More recently, Wang and Lee consider the estimation of the SAR model with missing observations on the dependent variable for cross-sectional data (Wang and Lee, 2013a) and for random effect panel data (Wang and Lee, 2013b). They propose the generalized method of moments (GMM) estimator, the nonlinear least squares (NLS) estimator, and the 2SLS estimator with imputation. They show that the three estimators are consistent and robust against unknown heteroskedasticity.

In this paper, we extend the NLS estimator in Wang and Lee (2013a) to estimate social network models with network fixed effects and provide the first empirical application of this method. We show that the conventional 2SLS estimator is inconsistent without accounting for sampling. In our empirical study, the 2SLS estimator fails to detect the presence of (endogenous) peer effects. When sampling is taken into account, we instead find that the sleeping behaviour of the friends is important in shaping one's own sleeping behaviour.[6] The main contributions of this paper is summarized as follows.

i) We extend the NLS estimator of Wang and Lee (2013a) to estimate network models with network fixed effects. The proposed NLS estimator is easy to implement in applied works.

ii) We conduct Monte Carlo experiments to investigate the finite sample performance of the proposed NLS estimator and evaluate the bias of the conventional 2SLS estimator when

[6] The validity of the NLS method relies on the exogeneity of the network structure. Based on diagnostic tests, we argue that network structure is exogenous conditioning on individual, family and peer characteristics, together with network-component fixed effects.

estimating a social network model with sampled observations on the dependent variable.

iii) We provide the first empirical application of the method to a unique dataset of friendship networks finding that adolescents respond to the sleeping behaviour of their peer group, holding constant other factors.

The rest of the paper is organized as follows. We start our analysis by describing our data in Section 2. Section 3 presents the network model, together with the identification and estimation strategy. We discuss our estimation results in Section 4, whereas Section 5 provides some robustness checks. Section 6 concludes.

2 Data and Descriptive Evidence

Our data source is the Add Health dataset that has been designed to study the impact of the social environment (i.e. friends, family, neighborhood and school) on adolescents' behaviour in the United States by collecting data on students in grades 7-12 from a nationally representative sample of roughly 130 private and public schools in years 1994-95. Every student attending the sampled schools on the interview day is asked to compile a questionnaire (the in-school survey) containing questions on respondents' demographic and behavioral characteristics, education, family background and friendship. Most notably, students are asked to identify their best friends from a school roster — up to five males and five females. The limit in the number of nominations, however, is not binding (not even by gender),[7] and in the large majority of cases (more than 90 percent) the nominated best friends are in the same school. Hence, it is possible to reconstruct the entire geometry of the friendship networks within each school. In addition, by matching the identification numbers of the friendship nominations to respondents' identification numbers, one can obtain information on the characteristics of nominated friends. This sample contains information on roughly 90,000 students. These features make these data almost unique. It is extremely rare to have information on the universe of network contacts (here school friends), together with their

[7] Less than 1 percent of the students in our sample show a list of ten best friends, less than 3 percent a list of five males and roughly 4 percent a list of five females. On average, they declare to have 4.35 friends with a small dispersion around this mean value (standard deviation equal to 1.41).

detailed characteristics.[8] The survey design also includes a longer questionnaire (the in-home survey) containing questions related to more sensitive individual and household information which is administered to a subset of students. We use the *core sample* of the in-home survey which provides information on a random subset of adolescents, about 12,000 individuals.[9] The in-home questionnaire contains detailed information about the timing and duration of sleep. The questions has been slightly reformulated over time to measure sleeping patterns more precisely. Indeed, the students participating the in-home survey are interviewed again one year later, in 1995–96 (wave II).[10] We derive the information on sleeping patterns by using the wave II question: "During the school year, what time do you usually go to bed on week nights?".[11,12]

Our final sample consists of about 8,000 individuals in 33 networks. The large reduction in sample size with respect to the original sample is mainly due to the network construction procedure — roughly 20 percent of the students do not nominate any friend and another 20 percent cannot be correctly linked.[13] In addition, we focus on networks with sizes between 10 and 400 individuals, since peer effects may be too different in very small and very large networks (see, e.g., Calvó-Armengol et al., 2009).

Figure 1 plots the empirical distribution of the "bed time". The graph shows a notable dispersion around the mean "bed time" value (mean equal to 10:30pm and standard deviation

[8] The information on social network contacts collected in other existing surveys is about "ego-networks", i.e. the respondent is asked to name a few personal contacts and provides (self-reported) information about an extremely limited number of their characteristics.

[9] The *core sample* contains roughly the 60 percent of the individuals interviewed in the in-home survey (which are about 20,000 individuals). The difference is due to the fact that in the in-home sampling design some types of individuals are oversampled.

[10] Those subjects are also interviewed again in 2001-02 (wave III), and again in 2007-08 (wave IV). For the purpose of this paper, we do not use this longitudinal information. The friendship nominations are only collected when the students were at school (i.e. in waves I and II).

[11] The questions on sleep behaviour formulated in wave I do not differentiate between the school period and summer time. The same issue also applies to the other question on sleeping behaviour in Wave II: "How many hours of sleep do you usually get?". Finally, a third question is available: "Do you usually get enough sleep?", which measures a subjective perception, thus increasing measurement errors. In addition, the answers to both questions are not continuous variables, as required by the NLS estimation.

[12] We rescaled each hour in 100 units, so for instance half an hour is transformed to 50 units. We dropped individuals declaring going to sleep before 5pm and after 6am.

[13] This is common when working with Add Health data. The representativeness of the sample is, however, preserved.

equal to 59 minutes). About 50 percent of the students go to bed between 10pm and 11.30pm.

[Insert Figure 1 here]

A detailed description of the explanatory variables (covariates), as well as our sample summary statistics can be found in Table A1. Among the individuals selected in our sample, 53 percent are females, 12 percent are blacks and 9 percent are Asians. The average student is in grade 9, has a good school performance, has parents receiving education higher than high school, and lives in a family with 4 people. The variables on extracurricular activities show that more than 20 percent of the students are in a baseball or softball team, almost 25 percent in a basketball team, roughly 10 percent play soccer, and another 10 percent play volleyball. They are also quite active in terms of activities different from sports.

3 Econometric Analysis

Our aim is to assess the empirical relationship between the individual bed time decisions and the bed time decisions of the peers using the unique information provided by the Add Health data. This exercise requires facing the traditional challenges in identifying social interaction effects, while also overcoming a further (and so far neglected) issue stemming from the sampling design of the Add Health survey. We present the network model in Section 3.1, whereas the estimation of network models with sampling on the dependent variable is discussed in detail in Section 3.2.

3.1 The network model

Consider a population of n individuals partitioned into $\bar{r}$ networks.[14] For the n_r individuals in the r-th network, their connections with each other are represented by an $n_r \times n_r$ adjacency matrix $G_r^* = [g_{ij,r}^*]$ where $g_{ij,r}^* = 1$ if individuals i and j are friends and $g_{ij,r}^* = 0$ otherwise.[15]

[14] In this paper, a network (or a network component) contains a set of individuals (nodes) such that any two individuals in the same network are connected to each other (directly or indirectly) and no individuals from different networks are connected.

[15] For ease of presentation, we focus on the case where the connections are undirected and no agent is isolated so that G_r^* is symmetric and $\sum_{j=1}^{n} g_{ij,r}^* \neq 0$ for all i. The result of the paper holds for a directed network with an asymmetric G_r^*.

Let $G_r = [g_{ij,r}]$ be the row-normalized G_r^* such that $g_{ij,r} = g_{ij,r}^* / \sum_{k=1}^{n_r} g_{ik,r}^*$.

Given the network adjacency matrix G_r, we assume $y_{i,r}$, the "bed time" of individual i in network r, is given by the following network model

$$y_{i,r} = \phi \sum_{j=1}^{n_r} g_{ij,r} y_{j,r} + \sum_{k=1}^{p} x_{ik,r}\beta_k + \sum_{k=1}^{p} (\sum_{j=1}^{n_r} g_{ij,r} x_{jk,r} \gamma_k) + \eta_r + \epsilon_{i,r}. \tag{1}$$

In this model, $\sum_{j=1}^{n_r} g_{ij,r} y_{j,r}$ is the average "bed time" of i's direct friends with its coefficient ϕ representing *the (endogenous) peer effect*. $x_{ik,r}$, for $k = 1, \cdots, p$, are exogenous explanatory variables. For $k = 1, \cdots, p$, $\sum_{j=1}^{n_r} g_{ij,r} x_{jk,r}$ is the average value of the k-th explanatory variable taking over i's direct friends with its coefficient γ_k representing *the (exogenous) contextual effect*. Finally, individuals in the same network tend to behave similarly because they face a common environment. This is usually referred to as *the correlated effect* (Manski, 1993), and is captured by the network-specific parameter η_r. The error term $\epsilon_{i,r}$ is i.i.d. with zero mean and finite variance σ^2.[16] In Appendix B, we provide a microfoundation for this empirical model.

Let $x_{i,r} = (x_{i1,r}, \cdots, x_{ip,r})'$, $\beta = (\beta_1, \cdots, \beta_p)'$ and $\gamma = (\gamma_1, \cdots, \gamma_p)'$. In matrix form, (1) can be rewritten as

$$Y_r = \phi G_r Y_r + X_r\beta + G_r X_r \gamma + \eta_r l_{n_r} + \epsilon_r, \tag{2}$$

where $Y_r = (y_{1,r}, \cdots, y_{n_r,r})'$, $X_r = (x_{1,r}, \cdots, x_{n_r,r})'$, $\epsilon_r = (\epsilon_{1,r}, \cdots, \epsilon_{n_r,r})'$, and l_{n_r} is an $n_r \times 1$ vector of ones.

Let $\text{diag}\{A_j\}_{j=1}^m$ denote a generalized diagonal block matrix with the diagonal blocks being A_j's, where A_j may or may not be a square matrix. Then, for all $\bar{r}$ networks, we can stack the data such that (2) becomes

$$Y = \phi GY + X\beta + GX\gamma + L\eta + \epsilon, \tag{3}$$

[16] For exposition purpose, we assume the error term is homoskedastic. The proposed NLS estimator remains consistent when the error term is heteroskedastic.

where $Y = (Y_1', \cdots, Y_{\bar{r}}')'$, $G = \mathrm{diag}\{G_r\}_{r=1}^{\bar{r}}$, $X = (X_1', \cdots, X_{\bar{r}}')'$, $L = \mathrm{diag}\{l_{n_r}\}_{r=1}^{\bar{r}}$, $\eta = (\eta_1, \cdots, \eta_{\bar{r}})'$, and $\epsilon = (\epsilon_1', \cdots, \epsilon_{\bar{r}}')'$.

The identification and estimation of endogenous peer effects, contextual effects, and correlated effects have been the main interests of social network models. The conventional identification and estimation strategy in the literature (see, e.g., Bramoullé et al., 2009; Lee et al., 2010; Lin, 2010) relies on the assumption that $\mathrm{E}(\epsilon_r | G_r, X_r, \eta_r) = 0$.[17] Based on this assumption, Bramoullé et al. (2009) show that if intransitivities exist in networks so that I_n, G, G^2, G^3, are linearly independent, then model (2) is identified. For estimation, we first eliminate the incidental parameters η using a within-transformation projector $J = \mathrm{diag}\{J_r\}_{r=1}^{\bar{r}}$, where $J_r = I_{n_r} - \frac{1}{n_r} l_{n_r} l_{n_r}'$. As $JL = 0$, premultiplying (3) by J, we have

$$JY = \phi JGY + JX\beta + JGX\gamma + J\epsilon.$$

Let $Z = (GY, X, GX)$ and $\theta = (\phi, \beta', \gamma')'$. For the instrumental variable (IV) matrix $Q = (X, GX, G^2X)$, the 2SLS estimator is given by

$$\widehat{\theta}_{2sls} = (\widehat{Z}' JZ)^{-1} \widehat{Z}' JY, \tag{4}$$

where $J\widehat{Z} = JQ(Q'JQ)^{-1}Q'JZ$ is the predicted JZ from the first-stage regression.

In the following section, we focus on the sampling issue of the network model that has been largely ignored by the literature.

3.2 Estimation of peer effects with sampling

In our and many other studies, the analysis of the network model (1) has been made possible by the use of a unique database on friendship networks from the Add Health data.[18] As we explain in Section 2, every student attending the sampled schools on the interview day is asked to complete the in-school survey containing questions on respondents' demographic

[17] We will investigate the validity of this assumption for this empirical study in Section 5.

[18] See, e.g. Patacchini and Zenou (2008), Lin (2010) and the references herein.

and behavioral characteristics, education, family background and friendship. Thus, we can observe the covariates of almost all students together with their friendship links in the network. However, as some more sensitive individual information (including information on sleeping behaviour) is in the in-home survey, we only observe the dependent variable for a subsample of the students.[19,20]

Without loss of generality, suppose the first m_r ($m_r > 1$) individuals in network r are sampled. Suppose we can observe network connections $G_r = [g_{ij,r}]$ and covariates $x_{i,r}$ for all individuals in network r, but we can only observe $y_{i,r}$'s of sampled individuals. For the sampled individuals, $i = 1, \cdots, m_r$, (1) becomes

$$y_{i,r} = \phi \sum_{j=1}^{m_r} g_{ij,r} y_{j,r} + x'_{i,r}\beta + \sum_{j=1}^{n_r} g_{ij,r} x'_{j,r}\gamma + \eta_r + \epsilon^*_{i,r}. \quad (5)$$

By comparing (1) and (5), we have $\epsilon^*_{i,r} = \phi \sum_{j=m_r+1}^{n_r} g_{ij,r} y_{j,r} + \epsilon_{i,r}$. Therefore, the error term of model (5) contains two types of errors — the error due to unobserved individual heterogeneity $\epsilon_{i,r}$ and the measurement error due to the sampling design $\phi \sum_{j=m_r+1}^{n_r} g_{ij,r} y_{j,r}$. The measurement error could be correlated with the covariates and, as a result, the 2SLS estimator given by (4) may not be consistent.

To further illustrate this point, we rewrite (5) in matrix form. Let

$$G_r = \begin{bmatrix} G_r^S \\ G_r^N \end{bmatrix} = \begin{bmatrix} G_r^{SS} & G_r^{SN} \\ G_r^{NS} & G_r^{NN} \end{bmatrix},$$

where G_r^S is an $m_r \times n_r$ matrix of the first m_r rows of G_r and G_r^{SS} is an $m_r \times m_r$ matrix of

[19] In this paper, we focus on the missing values of the dependent variable for two reasons. First, in our empirical application, the missing values of the dependent variable are due to the sampling design. Thus, the missing rate of the dependent variable is much higher than those of the covariates (see the last column of Table A1). Second, the missing values of the covariates can be imputed using some conventional methods (see, e.g., Little and Rubin, 2002). As explained later in this section, the consistency of the proposed NLS estimator relies on the condition that $\mathrm{E}(\epsilon_r | G_r, X_r, \eta_r) = 0$. As long as this condition holds when the missing values of the covariates are imputed, the NLS estimator remains consistent.

[20] The use of the *core sample* of the in-home survey is crucial because otherwise the sampled students in the in-home survey are not random.

the first m_r columns of G_r^S. Then, for the sampled individuals, we have

$$Y_r^S = \phi G_r^{SS} Y_r^S + X_r^S \beta + G_r^S X_r \gamma + \eta_r l_{m_r} + \epsilon_r^*, \tag{6}$$

where $Y_r^S = (y_{1,r}, \cdots, y_{m_r,r})'$ denotes the $m_r \times 1$ vector of observations on the dependent variable of the sampled individuals, $X_r^S = (x_{1,r}, \cdots, x_{m_r,r})'$ denotes the $m_r \times p$ matrix of observations on the covariates of the sampled individuals, and $\epsilon_r^* = \epsilon_r^S + \phi G_r^{SN} Y_r^N$ with $\epsilon_r^S = (\epsilon_{1,r}, \cdots, \epsilon_{m_r,r})'$ and $Y_r^N = (y_{m_r+1,r}, \cdots, y_{n_r,r})'$. As $\mathrm{E}(\epsilon_r | G_r, X_r, \eta_r) = 0$, we have

$$\mathrm{E}(\epsilon_r^* | G_r, X_r, \eta_r) = \mathrm{E}(\epsilon_r^S + \phi G_r^{SN} Y_r^N | G_r, X_r, \eta_r) = \phi G_r^{SN} \mathrm{E}(Y_r^N | G_r, X_r, \eta_r).$$

To obtain $\mathrm{E}(Y_r^N | G_r, X_r, \eta_r)$, we need to inspect the reduced form equation of the model. If $(I_{n_r} - \phi G_r)$ is nonsingular, the reduced form equation of (2) is given by

$$Y_r = (I_{n_r} - \phi G_r)^{-1}(X_r \beta + G_r X_r \gamma) + \frac{\eta_r}{1-\phi} l_{n_r} + (I_{n_r} - \phi G_r)^{-1} \epsilon_r. \tag{7}$$

Let $D_r^N = [0_{(n_r - m_r) \times m_r}, I_{n_r - m_r}]$ denote an $(n_r - m_r) \times n_r$ matrix of the last $(n_r - m_r)$ rows of an $n_r \times n_r$ identity matrix. Then, it follows from (7) that

$$\mathrm{E}(Y_r^N | G_r, X_r, \eta_r) = D_r^N \mathrm{E}(Y_r | G_r, X_r, \eta_r) = D_r^N (I_{n_r} - \phi G_r)^{-1}(X_r \beta + G_r X_r \gamma) + \frac{\eta_r}{1-\phi} l_{n_r - m_r}.$$

Therefore,

$$\mathrm{E}(\epsilon_r^* | G_r, X_r, \eta_r) = \phi G_r^{SN} \mathrm{E}(Y_r^N | G_r, X_r, \eta_r) = \phi G_r^{SN} D_r^N (I_{n_r} - \phi G_r)^{-1}(X_r \beta + G_r X_r \gamma) + \frac{\phi \eta_r}{1-\phi} G_r^{SN} l_{n_r - m_r}. \tag{8}$$

If $\phi \neq 0$, then, in general, $\mathrm{E}(\epsilon_r^* | G_r, X_r, \eta_r) \neq 0$. Furthermore, if $m_r / n_r \to c_r$ where $0 \leq c_r < 1$, then the entries of $\mathrm{E}(\epsilon_r^* | G_r, X_r, \eta_r)$ may not converge to zero either. Hence, the 2SLS estimator given by (4) may not be consistent when the dependent variable has missing values.[21]

To overcome this missing data problem due to sampling, we consider the NLS approach suggested by Wang and Lee (2013a) based on the reduced form equation (7). Let $D_r^S = [I_{m_r}, 0_{m_r \times (n_r - m_r)}]$ be an $m_r \times n_r$ matrix of the first m_r rows of an $n_r \times n_r$ identity matrix. Then,

$$Y_r^S = D_r^S Y_r = D_r^S (I_{n_r} - \phi G_r)^{-1} (X_r \beta + G_r X_r \gamma) + \frac{\eta_r}{1 - \phi} l_{m_r} + u_r, \tag{9}$$

where $u_r = D_r^S (I_{n_r} - \phi G_r)^{-1} \epsilon_r$. To eliminate the incidental parameters η_r, we apply a within transformation using the projector $J_r^S = I_{m_r} - \frac{1}{m_r} l_{m_r} l'_{m_r}$ so that (9) becomes

$$J_r^S Y_r^S = J_r^S D_r^S (I_{n_r} - \phi G_r)^{-1} (X_r \beta + G_r X_r \gamma) + J_r^S u_r.$$

The NLS estimator of $\theta = (\phi, \beta', \gamma')'$ is given by

$$\widehat{\theta}_{nls} = \arg\min_{\theta} \textstyle\sum_{r=1}^{\bar{r}} [Y_r^S - h_r(\theta)]' J_r^S [Y_r^S - h_r(\theta)], \tag{10}$$

where $h_r(\theta) = D_r^S (I_{n_r} - \phi G_r)^{-1} (X_r \beta + G_r X_r \gamma)$. As

$$\mathrm{E}(J_r^S u_r | G_r, X_r, \eta_r) = J_r^S D_r^S (I_{n_r} - \phi G_r)^{-1} \mathrm{E}(\epsilon_r | G_r, X_r, \eta_r),$$

the NLS estimator is consistent as long as $\mathrm{E}(\epsilon_r | G_r, X_r, \eta_r) = 0$, which is a common assumption in the social network literature (e.g., Bramoullé et al., 2009; Lin, 2010).

Let $J^S = \mathrm{diag}\{J_r^S\}_{r=1}^{\bar{r}}$ and $D^S = \mathrm{diag}\{D_r^S\}_{r=1}^{\bar{r}}$. Let $m = \sum_{r=1}^{\bar{r}} m_r$. If $m/n \to c$, where c is a finite positive constant, then it follows a similar argument in Wang and Lee (2013a) that the NLS estimator $\widehat{\theta}_{nls}$ is consistent with an asymptotic distribution

$$\sqrt{n}(\widehat{\theta}_{nls} - \theta) \xrightarrow{d} N(0, \Sigma_{nls}),$$

[21] It is worth noting that, if $m_r/n_r \to 1$, then the entries of $\mathrm{E}(\epsilon_r^* | G_r, X_r, \eta_r)$ may converge to zero as $n_r \to \infty$. In this case, the 2SLS estimator given by (4) can still be consistent. However, this is certainly not the case in our empirical study, where the sampling rate of the in-home survey is about 13%.

where $\Sigma_{nls} = \lim_{n\to\infty} n(C'B'BC)^{-1}C'B'\Omega BC(C'B'BC)^{-1}$, with $B = J^S D^S (I - \phi G)^{-1}$, $C = [G(I - \phi G)^{-1}(X\beta + GX\gamma), X, GX]$ and $\Omega = \sigma^2 BB'$.

3.3 A simulation experiment

We conduct a Monte Carlo simulation in which we compare the finite sample performance of the 2SLS estimator given in (4) and the NLS estimator given in (10). The data generating process follows model (1) with the adjacency matrices G_r and covariates X_r from the Add Health data.[22] We set $\phi = 0.6$ and $\beta_k = \gamma_k = 1$ for $k = 1, \cdots, p$, and generate the network fixed effect η_r and the error term $u_{i,r}$ as i.i.d. standard normal random variables.

We conduct 2000 repetitions in the simulation. For each repetition, we draw random subsamples of the generated data with the sampling rate of 20 percent, 40 percent, 60 percent, and 80 percent respectively, and estimate model (6) where only the dependent variable of the sampled individuals can be observed. As the empirical distribution of the 2SLS estimates has some outliers, we use robust measures of central tendency and dispersion for summary statistics of the 2SLS and NLS estimators, namely, the median bias (Med. Bias), the median of the absolute deviations (Med. AD), the difference between the 0.1 and 0.9 quantile (Dec. Rge) in the empirical distribution, and the coverage rate (Cov. Rate) of a nominal 95 percent confidence interval.

[Insert Table 1 here]

The simulation results are reported in Table 1.[23] When the sampling rate is low, the 2SLS estimator has a substantial bias with high dispersion in its empirical distribution (i.e. large Med. AD and Dec. Rge). The bias of the endogenous peer effect is negative. As the sampling rate increases, the bias and dispersion of the 2SLS estimator reduce. On the other hand, the NLS estimator is essentially unbiased for all sampling rates considered. The dispersion of the NLS estimator is much lower than that of the 2SLS estimator and it reduces

[22] We use the same set of covariates as column (7) of Table 2 in the empirical study and all real networks with size between 10 and 300. We do not consider large networks (i.e. with size between 300 and 400 individuals) for ease of computation.

[23] To save space, we only report the estimates of ϕ, β_1, γ_1 in Table 1.

as the sample size or sampling rate increases. The coverage rate of the NLS estimator is also closer to the nominal level of 95 percent than the 2SLS estimator.

4 Empirical Results

We estimate model (6) using both NLS and 2SLS, with increasing sets of controls. The estimation results are reported in Table 2. The dependent variable is the time a student go to bed on week nights during a school year.[24] Column (1) of Table 2 gives the NLS estimates controlling for individual characteristics (age, gender, race) and family background (household size, parental education and occupation).[25] It appears that the estimated endogenous peer effect $\widehat{\phi}$ is positive and statistically significant. If we ignore, for the moment, the feedback effect, then one hour delay in the average bed time of the peers translates into a roughly 53 minutes (0.877×60) delay of an individual's bed time holding the covariates constant.

[Insert Table 2 here]

However, similar behaviour of an individual and the peers may be due to the similarity in their characteristics (i.e., the contextual effect), rather than to the endogenous peer effect. The uniqueness of our data where both respondents and friends are interviewed allows us to control for peers' characteristics, thus disentangling the endogenous peer effect from the contextual effect. When peers' characteristics are controlled in the model (column (2) of Table 2), the estimated endogenous peer effect decreases, showing that indeed some of the peer effect attributed to peers' behaviour is in fact due to the similarity to peers' characteris-

[24] If all schools were to start at the same time, by looking at the time students go to sleep we could recover their sleeping duration. This is not the case in the U.S. where school districts set school starting time having in mind the minimization of busing costs. Middle/junior high schools (grades 7 and 8) and high schools (grades 9 to 12) typically have different starting time. However, because all the friends's nominations in our data are within a school (typically within a grade), the effect of school starting time is captured by the network fixed effect.

[25] In the Add Health, less than 0.6 percent of the fathers and less than 3 percent of the mothers are unemployed. None of the parents of the individuals in our final sample is unemployed. Value for 13 percent of the observations, however, are missing. We use a missing value dummy that takes value 1 if the value is missing, and 0 otherwise to minimize the loss of information.

tics.[26] Nevertheless, the estimated endogenous peer effect remains positive and statistically different from zero.

A remaining concern relates to the presence of unobserved factors. The observed characteristics of peers may not capture all the nuances of the social environment. There may be two types of unobservables: (i) unobservables that are common to all individuals in a (broadly defined) social circle and/or (ii) unobservables that are instead individual-specific. The bi-dimensional nature of network data (we observe individuals over networks) allows us to control for the presence of unobserved factors of type (i) by including network fixed effects. By doing so, we purge our estimates from the effects of unobserved factors that are common among directly and indirectly related individuals. Column (3) of Table 2 reports the estimation results when network fixed effects are included in the model. The estimated endogenous peer effect decreases further, but it retains its statistical significance. The presence of type (ii) unobservables is probably the most difficult empirical challenge in the identification of peer effects with network data. Unobservable student characteristics may affect friendship formation, thus making the network structure endogenous; they may arise from unobservable characteristics of the family environment or, more broadly, of the social environment. We address this problem in the following way. First, the richness of our data allows us to use indicators of a set of activities that may be related with bed time decisions as additional controls. Second, we perform a set of robustness checks in Section 5.

The results of the first exercise are contained in columns (4)-(7) of Table 2. In column (4) we introduce a school performance indicator and, in column (5), an indicator of risky behaviour.[27] Next, we add participation in several sports (column (6)) and participation to other extracurricular activities (column (7)) as further controls. The estimated endogenous peer effect decreases substantially across columns, but they remain statistically different from

[26] Observe that in our model we include both individual characteristics and average peer characteristics. Hence, we control for the similarity of an agent with her peers on average (i.e. $x_{ik,r} - \sum_{j=1}^{n_r} g_{ij,r} x_{jk,r} = \sum_{j=1}^{n_r} g_{ij,r}(x_{ik,r} - x_{jk,r})$).

[27] The indicator of risky behavior is the score of a factor analysis run on alcohol consumption, cigarette smoking and general health.

zero. In the specification with the more extensive set of controls (column (7)), having peers going bed one hour later on average translates into an approximately 36 minutes (0.602×60) delay in one's own bed time. The effects of the covariates are in line with previous results in medical research. Indeed we find that, on average, females go to bed about 10 minutes earlier than males, blacks go to bed more than 20 minutes after whites, and students in higher grades and having risky behaviour delay bed time (see, e.g., Lauderdale et al., 2008; National Sleep Foundation, 2010; National Sleep Foundation, 2014). Interestingly, we find that children whose fathers have a military carrier or work in the agricultural sectors go to bed about 18 minutes earlier than children with fathers having other occupations. Having highly educated parents is associated with going to bed later. Observe that our evidence on the existence of peer effects in sleeping behaviour suggests that these quantifications would be different. **Indeed, if $\phi \neq 0$ (in model (5), then the marginal effect of the k-th covariate would be $(I_{n_r} - \phi G_r)^{-1}(I_{n_r}\beta_k + G_r\gamma_k)$, which is an $n_r \times n_r$ matrix with its (i, j)-th element representing the effect of a change in $x_{jk,r}$ on $y_{i,r}$.** The marginal effects are heterogeneous across individuals, since they depend on the individual's position in the network. We show in Table 3 panel (b) the mean, standard deviation, minimum and maximum of the main diagonal elements of the matrix. It can be considered as a summary measure of the own-partial derivatives (labeled as direct effects, LeSage and Pace (2009)). Panel (c) reports mean, standard deviation, minimum and maximum of the cumulative sum of off-diagonal elements. It reflects the cross-partial derivatives and provides a summary measure of spillovers (labeled as indirect effects, LeSage and Pace (2009)).[28] Panel (a) of Table 3 reports the estimates of Table 2 (column 7) for comparison. Table 3 reveals that the direct effects of the exogenous variables (column 2) are about 10% higher than those in column 1. The indirect effects are tiny, but highly heterogeneous across individuals.

[Insert Table 3 here]

[28] See LeSage (2014) for further details.

Before moving to further robustness checks, it is interesting to compare our estimates with those that would be obtained if we had neglected the sampling issue. That is, if we estimate model (6) using 2SLS. Columns (8) and (9) of Table 2 collect the estimates which are obtained using the same set of controls as in columns (3) and (7) respectively. In line with the simulation results, without taking into account the sampling issue, the downwards bias leads the 2SLS estimate of the endogenous peer effect to be statistically insignificant.

5 Robustness Checks

5.1 Endogenous network formation

If the variables that drive the process of selection into friendship networks are not fully observable, potential correlations between (unobserved) network-specific factors and the adjacency matrix G_r could lead to biased NLS estimates. The network fixed effect is a remedy for the selection bias that originates from the possible sorting of individuals with similar unobserved characteristics into a network. The underlying assumption is that such unobserved characteristics are common to the individuals within each network. This assumption is reasonable when the networks are relatively small. However, if there are unobservable individual heterogeneity that drives both network formation and behavioral choice, then G_r is likely to be endogenous even after controlling for the network fixed effect. We provide here a robustness check that helps to alleviate this concern.

For this purpose, we use a dyadic friendship formation model that is common in the empirical literature on network formation (e.g. De Weerdt, 2002; Udry and Conley, 2004; Fafchamps and Gubert, 2007; Mayer and Puller, 2008; Mihaly, 2009; Santos and Barrett, 2010; Graham, 2014). It is an homophily model, where the variables that explain $g^*_{ij,r}$ are distances in terms of observed and unobserved characteristics between students i and j:[29]

$$d_{ij,r} = \alpha + \textstyle\sum_{k=1}^{p} \delta_k x_{ij,k,r} + \theta v_{ij,r} + \eta_r + u_{ij,r}. \tag{11}$$

In (11), $d_{ij,r}$ is the latent dependent variable such that $g^*_{ij,r} = \mathbf{1}(d_{ij,r} > 0)$, where $\mathbf{1}(\cdot)$ is an indicator function. $x_{ij,k,r} = \mathbf{1}(x_{ik,r} = x_{jk,r})$ if $x_{ik,r}$ is a discrete variable, while $x_{ij,k,r} = 1/|x_{ik,r} - x_{jk,r}|$ if $x_{ik,r}$ is a continuous variable. $v_{ij,r}$ is equal to $|v_{i,r} - v_{j,r}|$, where $v_{i,r}$ and $v_{j,r}$ are the residuals from the outcome equation (9) for individual i and j respectively. η_r is a network-specific parameter and $u_{ij,r}$ is the error term. θ is the parameter of interest, which captures how differences in unobserved individual characteristics affect the probability to be friends. The intuition behind the test is to evaluate whether homophily in unobserved factors that drive similar behavioral decisions also helps to explain friendship formation decisions. Statistically significant estimate of θ would suggest that the adjacency matrix G_r is endogenous and the NLS estimator is inconsistent.

[Insert Table 4 here]

OLS and Logit estimates of the network formation model (11) are presented in the first and second columns of Table 4. The results show no sign of correlation between differences in unobserved individual characteristics and link formation. It should also be noted that because there are several thousands individual-pair observations in a given regression, the power to detect small departures from zero is quite high.

In order to get more confidence in our exercise, we perform the following experiment. We deliberately leave out one individual characteristic, which will then act as unobserved factor

[29] Homophily, that is the tendency of people to associate with others similar to themselves has been widely recognized as a pervasive feature of social and economic networks (see, e.g. McPherson et al., 2001; Golub and Jackson, 2012b). In particular, there is ample evidence that inbreeding, that is the decision of agents to connect with others of the same type, holds true for the nationally representative sample of U.S. teenagers covered by the Add Health dataset (see, e.g. Currarini et al., 2009; Currarini et al., 2010; Golub and Jackson, 2012a). The specific homophily model adopted in this paper has been used to explain friendship formation among students from the Add Health dataset by Hsieh and Lee (2014) and Goldsmith-Pinkham and Imbens (2013). Our test is informative under the assumption that this homophily model is a reasonable approximation of network formation.

(to the econometrician). We exclude grade, which is relevant both in the link formation process and in determining "bed time". If our exercise detects this problem, then we should obtain a negative and statistically significant $\widehat{\theta}$. The last two columns of Table 4 report the results. One can see that $\widehat{\theta}$ is indeed different from zero, which suggest the proposed test has a reasonable power.

To conclude, after controlling the (unusually) large set of individual characteristics provided by the Add Health, peer characteristics and network fixed effects, we find no evidence of network endogeneity that could bias the NLS estimator, given the homophily network formation model assumed.[30]

5.2 Simulated peers

Along the lines of Bifulco et al. (2011), we run placebo tests in which we replace the actual peers with simulated peers. We consider different types of simulated peers, that is we draw at random peers within the same family size, or parental education, or parental occupation, or cohort of the actual peers. More specifically, for each individual we draw at random a number of friends equal to the nominated one of a given type, i.e. belonging to a given social circle as defined by parental education, occupation etc. If our estimates simply captures unobserved social circle characteristics, then these regressions should continue to show a statistical significant peer effect. If, on the other hand, our strategy is valid, then we should not find any effect of simulated peers' behaviour on one's own behaviour in these placebo regressions. The results are contained in Table 5. No evidence of significant endogenous peer effect is revealed. Thus, this evidence provides further confirmation that our strategy, which is based on a large set of controls about individuals and their peers as well as network fixed effects, is able to cope with sorting issues that could confound our estimates.

[Insert Table 5 here]

[30] Patacchini and Venanzoni (2014) use a similar strategy to demonstrate the importance of network fixed effects in identifying peer effects in the demand for housing quality.

6 Conclusions

Our study brings two contributions to the literature. One, we extend the NLS estimator in Wang and Lee (2013a) to estimate social network models with sampled observations on the dependent variable. Two, we analyze peer effects in bed time using a representative sample of United States teenagers, finding not-negligible endogenous peer effects. That is, besides the impact of individual and friend characteristics, we show that the sleeping behaviour of the friends is important in shaping own sleeping behaviour. Our findings are consistent with a behavioral model of peer effects with conformist preferences where bed time decisions among peers are partly taken following the peer group norm. However, there are a variety of utility functions (or a variety of social processes) that can be consistent with our evidence. To discriminate between the different mechanisms empirically is an extremely difficult exercise which requires (at least) better data. It is worth noting, however, that our methodology applies to any SAR model, irrespective of its microfoundation.

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Appendices

A Data Description

[Insert Table A1 here]

B Microfoundation

Following Patacchini and Zenou (2012), we present a social network model of peer effects with conformity preferences for the demand for sleep.

B.1 The network

Suppose there are n individuals in the economy partitioned in $\bar{r}$ networks. Let n_r be the number of individuals in the r-th network, so that $n = \sum_{r=1}^{\bar{r}} n_r$. The adjacency matrix $G_r^* = [g_{ij,r}^*]$ of the r-th network keeps track of the direct connections in this network. Here, $g_{ij,r}^* = 1$ if two players i and j are directly connected (i.e. best friends), and $g_{ij,r}^* = 0$, otherwise. We also set $g_{ii,r}^* = 0$. The set of individual i's best friends (direct connections) is: $N_{i,r} = \{j \neq i \mid g_{ij,r}^* = 1\}$, which is of size $g_{i,r}^*$ (i.e. $g_{i,r}^* = \sum_{j=1}^{n} g_{ij,r}^*$ is the number of direct links of individual i). This means in particular that, if i and j are best friends, then in general $N_{i,r} \neq N_{j,r}$ unless the network is complete (i.e. each individual is friend with everybody in the network). This also implies that groups of friends may overlap if individuals have common best friends. To summarize, the *reference group* of each individual i is $N_{i,r}$, i.e. the set of her best friends, which does not include herself.

B.2 Preference

We denote by $y_{i,r}$ bed time of individual i in network r and by $Y_r = (y_{1,r}, ..., y_{n,r})'$ the population bed time profile in network r. Denote by $\bar{y}_{i,r}$ the average bed time of individual i's best friends. It is given by:

$$\bar{y}_{i,r} = \sum_{j=1}^{n_r} g_{ij,r} y_{j,r}, \tag{12}$$

where $g_{ij,r} = g^*_{ij,r}/g^*_{i,r}$. Each agent i in network r decides bed time $y_{i,r} \geq 0$, and obtains a payoff $u_{i,r}(Y_r, G_r)$ that depends on the profile Y_r and on the underlying network G_r, in the following way:

$$u_{i,r}(Y_r, G_r) = a_{i,r}y_{i,r} - \frac{1}{2}y^2_{i,r} - \frac{d}{2}(y_{i,r} - \bar{y}_{i,r})^2 \tag{13}$$

where $d > 0$. The benefit part of this utility function is given by $a_{i,r}y_{i,r}$ while the cost is $\frac{1}{2}y^2_{i,r}$; both are increasing in own time $y_{i,r}$. In this part, $a_{i,r}$ denotes the agent's ex-ante *idiosyncratic heterogeneity*, which is assumed to be perfectly *observable* by all individuals in the network. The second part of the utility function $\frac{d}{2}(y_{i,r} - \bar{y}_{i,r})^2$ reflects the influence of friends' behaviour on own action. It is such that each individual wants to minimize the *social distance* between herself and her reference group, where d is the parameter describing the *taste for conformity*. Here, the individual loses utility $\frac{d}{2}(y_{i,r} - \bar{y}_{i,r})^2$ from failing to conform to others.[31] In the context of adolescents' bed time decisions, a taste for conformity captures the idea that adolescents tends to make similar decisions to their friends. For example, if in a given friendship circle it widespread the idea that going early to bed is "not cool" or childish, then all members of that group would tend to go to bed later to conform to the social norm.

Observe that the social norm here captures the differences between individuals due to network effects**.** It means that individuals have different types of friends and thus different reference groups $\bar{y}_{i,r}$. As a result, the social norm each individual i faces is endogenous and depends on her location in the network as well as the structure of the network.

B.3 Nash equilibrium and econometric model

In this game where agents choose $y_{i,r} \geq 0$ simultaneously, there exists a unique Nash equilibrium (Patacchini and Zenou 2009) with the best response function given by:

$$y^*_{i,r} = \phi \sum_{j=1}^{n_r} g_{ij,r}y^*_{j,r} + (1 - \phi)a_{i,r} \tag{14}$$

[31] This is the standard way economists have been modelling conformity (see, e.g., Akerlof, 1980; Akerlof, 1997; Bernheim, 1994; Fershtman and Weiss, 1998; Kandel and Lazear, 1992; Patacchini and Zenou, 2012).

where $\phi = d/(1+d)$. The equilibrium bed time $y^*_{i,r}$ depends on the individual ex ante heterogeneity and on the average bed time of the reference group.

The econometric model considered in this paper follows the equilibrium best response function (14) by assuming

$$(1-\phi)a_{i,r} = \sum_{k=1}^{p} \beta_k x_{ik,r} + \sum_{k=1}^{p} \gamma_k \sum_{j=1}^{n_r} g_{ij,r} x_{jk,r} + \eta_r + \varepsilon_{i,r}. \tag{15}$$

Although we assume $a_{i,r}$ is perfectly observable by all individuals in the network, we allow some components of $a_{i,r}$ to be unobservable to the researcher. In (15), $x_{ik,r}$ corresponds to the observable (to the researcher) characteristics of individual i (e.g. sex, race, age, parental education, etc.). η_r denotes the unobservable (to the researcher) network characteristics and $\varepsilon_{i,r}$ represents the unobservable (to the researcher) characteristics of individual i.

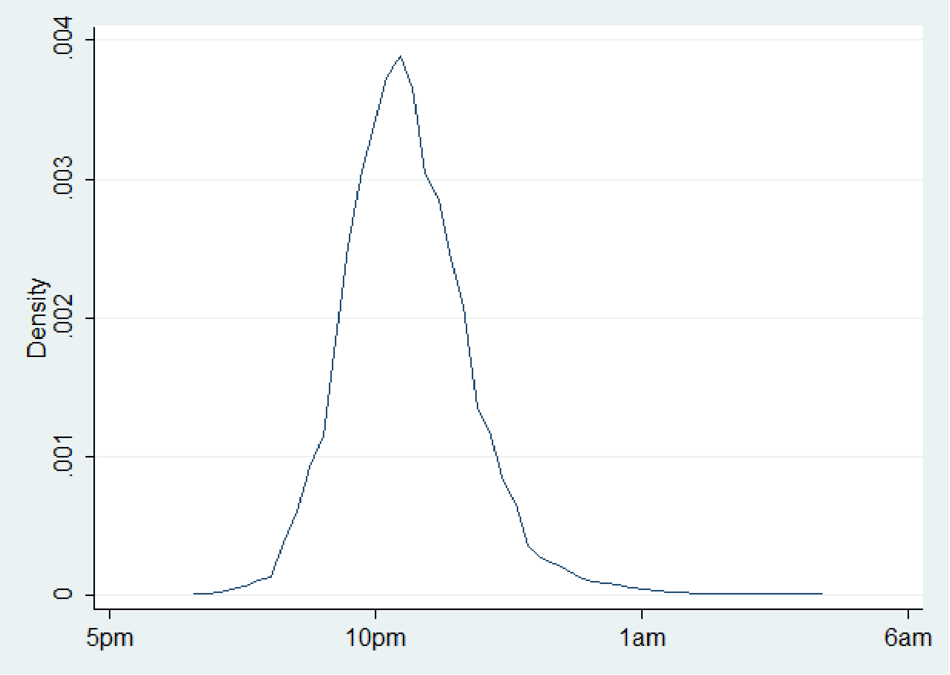
Table A1: Variable Definition and Summary Statistics

Variable	Description	mean	std dev	min	max	n. obs.	Missing rate
Sampled variable							
Bed time	Answer to the question "During the school year, what time do you usually go to bed on week nights? An hour is rescaled in 100 units, half an hour is thus 50 units. The mean is thus 10.37 pm and std dev is about an hour.	1060.236	100.254	800	1,800	1,740	93%
Demographic characteristics							
Female	Dummy variable taking value one if the respondent is female.	0.535	0.499	0	1	7,916	1%
Grade	Grade of student in the current year.	9.598	1.610	7	12	7,916	1%
Black	Race dummies. "White" is the reference group.	0.123	0.328	0	1	7,916	0%
Asian	""	0.092	0.289	0	1	7,916	0%
Family characteristics							
Family size	Number of people living in the household, category “6” includes 6 or more people.	4.466	0.993	1	6	7,916	4%
Mother occ. prof. tech	Mother occupation dummies. Closest description of the job of the (biological or nonbiological) mother who is living with the child.	0.271	0.445	0	1	7,916	0%
Mother occ. manager	""	0.062	0.241	0	1	7,916	0%
Mother occ. sales	""	0.244	0.430	0	1	7,916	0%
Mother occ. manual	""	0.114	0.318	0	1	7,916	0%
Mother occ. military	""	0.004	0.064	0	1	7,916	0%
Mother occ. farmer	""	0.037	0.190	0	1	7,916	0%
Father occ. prof. tech	Father occupation dummies. Closest description of the job of the (biological or nonbiological) mother who is living with the child	0.213	0.410	0	1	7,916	0%
Father occ. manager	""	0.148	0.355	0	1	7,916	0%
Father occ. sales	""	0.077	0.267	0	1	7,916	0%
Father occ. manual	""	0.366	0.482	0	1	7,916	0%
Father occ. military	""	0.041	0.198	0	1	7,916	0%
Father occ. farmer	""	0.054	0.225	0	1	7,916	0%
Father occ. other	""	0.023	0.149	0	1	7,916	0%
Parental education	Schooling level of the (biological or nonbiological) parents who are living with the child, distinguishing between "never went to school", "not graduate from high school", "high school graduate", "graduated from college or a university", "professional training beyond a four-year college", coded as 0 to 4. We consider the maximum education across the parents who are present in the household. If the information on one parent is missing, we use the education of the other one.	2.440	0.828	0	4	7,916	9%
Activities							
Drama	Extracurricular activity dummies. Dummy variable taking value one if the respondent participates (or plans to participate in the current school year) to the listed activity.	0.086	0.280	0	1	7,916	0%
Band	""	0.161	0.367	0	1	7,916	0%
Cheer\dance	""	0.103	0.304	0	1	7,916	0%
Chorus	""	0.140	0.347	0	1	7,916	0%
Orchestra	""	0.025	0.156	0	1	7,916	0%
Other club	""	0.244	0.430	0	1	7,916	0%
Baseball\softball	""	0.222	0.416	0	1	7,916	0%
Basket	""	0.244	0.430	0	1	7,916	0%

Field hockey	""	0.016	0.124	0	1	7,916	0%
Football	""	0.138	0.345	0	1	7,916	0%
Hockey	""	0.024	0.152	0	1	7,916	0%
Soccer	""	0.100	0.300	0	1	7,916	0%
Swimming	""	0.063	0.243	0	1	7,916	0%
Tennis	""	0.072	0.258	0	1	7,916	0%
Track	""	0.155	0.362	0	1	7,916	0%
Volley	""	0.104	0.306	0	1	7,916	0%
Wresling	""	0.039	0.195	0	1	7,916	0%
Other sport	""	0.127	0.333	0	1	7,916	0%
School performance	Average across available test scores in Math, English, Science and History/Social Science at the most recent grading period. Test scores are coded as A=4, B=3, C=2, D=1. .	2.798	0.811	1	4	7,916	13%
Risk behaviour	Total score of a factor analysis run on alcohol consumption, cigarette smoking, and health. Alcohol consumption is obtained using the response to the question: “How often did you drink beer, wine or liquor?", coded as 0= never, 1= once or twice, 2= once a month or less, 3= 2 or 3 days a month, 4=once a week, 5=3 to 5 days a week, 6=nearly everyday. Information on cigarette smoking is obtained using the response to the question: “How often did you smoke cigarettes?", coded as 0= never, 1= once or twice, 2= once a month or less, 3= 2 or 3 days a month, 4=once a week, 5=3 to 5 days a week, 6=nearly everyday. Information on respondent’s health status is obtained using the question: “In general, how is your health?", coded as 5= excellent, 4= very good, 3= good, 2=fair, 1=poor.	1.177	1.160	0	6.227	7,916	7%

Notes: 7,916 individuals over 33 networks, with network size between 10 and 400 individuals. The missing rate is the ratio between the number of observations with missing values and the entire sample size in the original sample. Missing value dummies are used for parental occupations.

Figure 1: Kernel density estimate of “Bed time”



Notes. Kernel = Epanechnikov, bandwidth = 40.429. We report the distribution of student by the time they go to sleep.

Table 1: Simulation results

Sampling Rate		2SLS	NLS
20%	ϕ	-0.588 (0.588) [0.191] {0.000}	0.002 (0.019) [0.071] {0.927}
	β_1	0.378 (0.383) [0.631] {0.661}	-0.000 (0.094) [0.357] {0.939}
	γ_1	0.980 (0.985) [1.263] {0.331}	-0.002 (0.163) [0.600] {0.943}
40%	ϕ	-0.567 (0.567) [0.194] {0.000}	0.001 (0.014) [0.052] {0.951}
	β_1	0.378 (0.379) [0.516] {0.486}	-0.003 (0.061) [0.233] {0.950}
	γ_1	0.994 (0.997) [1.123] {0.232}	-0.001 (0.112) [0.448] {0.935}
60%	ϕ	-0.536 (0.536) [0.207] {0.002}	0.001 (0.012) [0.045] {0.950}
	β_1	0.368 (0.370) [0.487] {0.450}	-0.005 (0.048) [0.188] {0.955}
	γ_1	0.973 (0.976) [1.155] {0.223}	-0.001 (0.091) [0.355] {0.943}
80%	ϕ	-0.452 (0.452) [0.228] {0.007}	0.001 (0.011) [0.040] {0.952}
	β_1	0.326 (0.332) [0.573] {0.594}	-0.001 (0.042) [0.161] {0.953}
	γ_1	0.878 (0.889) [1.435] {0.353}	-0.008 (0.080) [0.317] {0.949}

Notes: Med. Bias (Med. AD) [Dec. Rge] {Cov. Rate}. Number of replications =2000. Sample size = 1961. Network size between 10 and 300.

Table 2: Peer effect estimation – increasing set of controls

Dependent variable : bed time	NLS							2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Endogenous peer effect	0.877***	0.825***	0.798***	0.782***	0.737***	0.658***	0.602***	0.025	0.016
	(0.019)	(0.003)	(0.103)	(0.141)	(0.154)	(0.126)	(0.132)	(0.021)	(0.023)
Female	-0.211	-11.373***	-7.616	-6.715	-7.429	-8.629	-12.346**	-12.429***	-15.282***
	(5.162)	(3.162)	(5.228)	(4.842)	(4.679)	(5.550)	(5.831)	(4.509)	(5.622)
Grade	1.856***	22.592***	32.125***	32.182***	30.761***	31.188***	29.932***	27.940***	24.772***
	(0.627)	(1.955)	(6.600)	(5.726)	(5.284)	(5.147)	(4.894)	(2.303)	(2.255)
Black	-1.006	23.618***	30.005*	29.686**	34.593***	35.595***	34.433***	21.280**	29.150***
	(2.861)	(6.436)	(15.748)	(13.591)	(12.659)	(12.075)	(11.703)	(8.668)	(8.794)
Asian	7.413	26.292***	22.680	23.355	25.368*	23.099	22.124	26.193**	26.294**
	(5.792)	(9.020)	(17.390)	(14.776)	(14.190)	(14.197)	(14.248)	(12.889)	(12.863)
Household size	1.797	-0.083	-0.643	-0.665	0.694	0.322	0.170	-1.639	-1.175
	(2.003)	(1.190)	(1.974)	(1.996)	(1.987)	(1.925)	(1.945)	(2.084)	(2.074)
Parental education	5.713*	3.650	6.033*	6.467**	7.853**	7.748**	7.512**	6.460*	7.388**
	(3.361)	(2.722)	(3.080)	(3.223)	(3.210)	(3.171)	(3.171)	(3.380)	(3.369)
Father occ. military	6.253	-19.224**	-25.997**	-25.319**	-20.809*	-22.308*	-22.937*	-21.889	-18.587
	(15.817)	(8.737)	(11.850)	(12.050)	(12.196)	(12.045)	(12.197)	(13.870)	(13.691)
Father occ. farmer	3.508	-17.951**	-18.232	-18.443	-18.707	-20.547*	-21.562*	-23.228**	-23.300**
	(13.212)	(8.826)	(12.279)	(12.295)	(11.935)	(11.770)	(11.593)	(11.601)	(11.473)
School performance				-3.412	2.056	2.255	1.652		2.876
				(3.320)	(3.312)	(3.298)	(3.311)		(3.324)
Risky behavior					14.643***	14.726***	14.752***		14.293***
					(2.141)	(2.116)	(2.0839)		(2.041)
Parental occupation dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extracurricular sport	No	No	No	No	No	Yes	Yes	No	Yes
Extracurricular other	No	No	No	No	No	No	Yes	No	Yes
Contextual effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Network fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1,740 Sampled individuals over 7,916 individuals in 33 networks									

Notes: Robust standard errors in parentheses, *** p<0,01, ** p<0,05, * p<0,1. Parental occupation dummies are described in Table A1. We report the effects of parental occupation that are statistically significant. Extracurricular sport includes dummies for the participation in teams of football, soccer, baseball/softball, basketball, swimming, volley, track, tennis, and other sports. Extracurricular other includes dummies for the participation in bands, teams of cheer dancing, chorus, orchestra, drama, and other activities. See Table A1 for the definition of these variables.

Table 3: Direct and indirect effects of exogenous variables

	Panel (a)	*Panel (b)*				*Panel (c)*			
	β	Direct effects				Indirect effects			
		mean	std	min	max	mean	std	min	max
Female	-12.346	-13.651	1.063	-19.346	-12.580	-0.057	0.321	-11.644	-0.000
(minutes)	*(-7)*	*(-8)*	*(1)*	*(-12)*	*(-8)*	*(0)*	*(0)*	*(-7)*	*(0)*
Grade	29.932	33.148	2.581	30.547	46.977	0.140	0.780	0.000	28.275
(minutes)	*(18)*	*(20)*	*(2)*	*(18)*	*(28)*	*(0)*	*(0)*	*(0)*	*(16)*
Black	34.433	38.105	2.967	35.116	54.003	0.161	0.897	0.000	32.504
(minutes)	*(21)*	*(23)*	*(2)*	*(21)*	*(32)*	*(0)*	*(1)*	*(0)*	*(19)*
Parental education	7.512	8.311	0.647	7.659	11.778	0.035	0.195	0.000	7.089
(minutes)	*(5)*	*(5)*	*(0)*	*(5)*	*(7)*	*(0)*	*(0)*	*(0)*	*(4)*
Father occ. military	-22.937	-25.382	1.976	-35.971	-23.390	-0.107	0.597	-21.650	-0.000
(minutes)	*(-14)*	*(-15)*	*(1)*	*(-22)*	*(-14)*	*(0)*	*(0)*	*(-12)*	*(0)*
Father occ. farmer	-20.547	-23.866	1.858	-33.824	-21.994	-0.101	0.562	-20.358	-0.000
(minutes)	*(-12)*	*(-14)*	*(1)*	*(-20)*	*(-13)*	*(0)*	*(0)*	*(-12)*	*(0)*

Marginal effects are reported (minutes in parenthesis). Direct effects for variable k are computed using the average of the main diagonal elements of the matrix $(I_{n_r} - \varphi G_r)^{-1}(I_{n_r}\beta_k + G_r\gamma_k)$. Indirect effects are the averages of the cumulative sum of off-diagonal elements. Direct and indirect effects are computed within each network. Only statistically significant effects are reported.

Table 4: Robustness check – endogenous network formation

	Full set of controls		Grade omitted	
Dependent variable: probability to form a link (g_{ij})	OLS	LOGIT	OLS	LOGIT
Residuals	-0.117	-0.919	-0.361***	-9.364***
	(0.091)	(2.275)	(0.078)	(1.853)
Female	0.007***	0.187***	0.007***	0.217***
	(0.002)	(0.069)	(0.002)	(0.039)
Grade	0.121***	3.185***		
	(0.012)	(0.097)		
Black	0.025***	0.543***	0.022***	1.029***
	(0.007)	(0.168)	(0.005)	(0.103)
Asian	0.008*	0.385***	0.010***	0.418***
	(0.004)	(0.114)	(0.003)	(0.123)
Household size	-0.003	0.021	-0.003	0.077
	(0.015)	(0.370)	(0.014)	(0.351)
Parental education	0.002	0.203	0.002	0.315
	(0.002)	(0.244)	(0.002)	(0.272)
Father occ. Military	0.002	0.256	0.002	0.283
	(0.004)	(0.265)	(0.003)	(0.312)
Father occ. farmer	0.007***	0.294***	0.006***	0.398***
	(0.003)	(0.103)	(0.003)	(0.153)
School performance	0.007***	0.312***	0.012***	0.260***
	(0.002)	(0.078)	(0.002)	(0.051)
Risky behavior	0.016***	0.491***	0.019***	0.418***
	(0.005)	(0.117)	(0.004)	(0.062)
Parental occupation dummies	Yes	Yes	Yes	Yes
Extracurricular sport	Yes	Yes	Yes	Yes
Extracurricular other	Yes	Yes	Yes	Yes
Network fixed effects	Yes	Yes	Yes	Yes
Observations	123,319	123,319	123,319	123,319
1,740 Sampled individuals over 7,916 individuals in 33 networks				

Notes. See Table 3. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The difference in residuals is divided by one hundred thousand and the difference in household size is divided by 10.

Table 5: Robustness check – simulated peers

Dependent variable : bed time	*Matching Criterion*				
	Parental education	Household size	Father occupation	Mother occupation	Grade
Peer effect	-0.001	-0.004	-0.003	0.003	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Female	-13.054 **	-13.012**	-13.049**	-13.120**	-13.045**
	(5.862)	(5.857)	(5.858)	(5.858)	(5.860)
Grade	27.045***	26.952***	26.954***	27.029***	27.087***
	(4.466)	(4.464)	(4.467)	(4.467)	(4.467)
Black	29.774***	29.755***	29.613***	29.767***	29.821***
	(10.175)	(10.170)	(10.172)	(10.172)	(10.179)
Asian	26.497	26.656	26.498	26.503	26.439
	(15.543)	(15.545)	(15.537)	(15.538)	(15.543)
Household size	-0.753	-0.720	-0.718	-0.687	-0.763
	(2.054)	(2.052)	(2.053)	(2.054)	(2.054)
Parental education	6.452*	6.580*	6.497*	6.498*	6.488*
	(3.390)	(3.391)	(3.389)	(3.389)	(3.396)
Father occ. military	-22.862*	-22.401*	-23.059*	-23.141*	-22.996*
	(13.616)	(13.622)	(13.616)	(13.612)	(13.623)
Father occ. farmer	-26.823**	-26.556**	-26.854**	-26.404**	-26.891**
	(11.427)	(11.427)	(11.421)	(11.430)	(11.426)
School performance	3.553	3.552	3.500	3.667	3.561
	(3.361)	(3.356)	(3.355)	(3.359)	(3.358)
Risky behavior	14.122***	14.087***	14.133***	14.169***	14.136***
	(2.109)	(2.107)	(2.108)	(2.109)	(2.109)
Parental occupation dummies	Yes	Yes	Yes	Yes	Yes
Extracurricular other	Yes	Yes	Yes	Yes	Yes
Extracurricular sport	Yes	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes	Yes
Network fixed effects	Yes	Yes	Yes	Yes	Yes
1,740 Sampled individuals over 7,916 individuals in 33 networks					

Notes. See Table 3. For each individual, we draw at random a number of friends equal to the nominated one of a specific type. As a matching criteria, parental education is recoded as a dummy taking value equal to 1 if the parent has graduated from college and above, and 0 otherwise. Household size is recoded as a dummy taking value equal to 1 if the number of household members is greater than 4, and 0 otherwise. Father and mother occupation is recoded as a dummy taking value equal to 1 if the occupation is “Manager”, “Sales” or “Technical”, and 0 otherwise. Grade is coded as a dummy taking value equal to 1 if the student is in grades 9 to 12 (high school), and 0 otherwise (middle school).