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Analyzing heterogeneity in the effects of physical activity in children on social network structure and peer selection dynamics

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Abstract

Background—Social networks influence children and adolescents' physical activity. The focus of this paper is to examine the differences in the effects of physical activity on friendship selection, with eye to the implications on physical activity interventions for young children. Network interventions to increase physical activity are warranted but have not been conducted. Prior to implementing a network intervention in the field, it is important to understand potential heterogeneities in the effects that activity level have on network structure. In this study, the associations between activity level and cross sectional network structure, and activity level and change in network structure are assessed.

Methods—We studied a real-world friendship network among 81 children (average age 7.96 years) who lived in low SES neighborhoods, attended public schools, and attended one of two structured aftercare programs, of which one has existed and the other was new. We used the exponential random graph model (ERGMs) and its longitudinal extension to evaluate the association between activity level and various demographic factors in having, forming, and dissolving friendship. Due to heterogeneity between the friendship networks within the aftercare programs, separate analyses were conducted for each network.

Results—There was heterogeneity in the effect of physical activity on both cross sectional network structure and the formation and dissolution processes, both across time and between networks.

Conclusions—Network analysis could be used to assess the unique structure and dynamics of a social network before an intervention is implemented, so as to optimize the effects of the network intervention for increasing childhood physical activity. Additionally, if peer selection processes are changing within a network, a static network intervention strategy for childhood physical activity could become inefficient as the network evolves.

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CONFLICT OF INTEREST

The authors declare that they have no competing interests.

Keywords

ERGM; STERGM; new network; established program; physical activity; afterschool care program; childhood physical activity; social support; social network; children

INTRODUCTION

Increasingly, there is growing recognition that the multifactorial, interdependent, non-linear, and often time-delayed forces that sustain the obesity epidemic are too complex to reverse by focusing attention on an individual's behavior change, without concurrently addressing change in the larger systems within which that individual is embedded (Hammond, 2009; Levy et al., 2011; Nader et al., 2012; Glickman, 2012). System science approaches have been proposed to inform obesity prevention, treatment, and more generally policy (Gortmaker et al. 2011; Hammond, 2009). As an important method in the toolbox of system science methods, social network analysis can be used to study interacting forces between individuals in influencing health behavior. Specifically, social network analytic models such as exponential random graph models (ERGMs) (Wasserman & Pattison, 1996; Robins et al. 2007a) and its various extensions can be used to analyze and understand the complexity of social networks. Results from such analyses can reveal how an individual's position within a social network influences his or her own health behavior. However, while the study of peer influence is of vital importance, of import as well is the study of peer selection on health behaviour, or how an individual's health behaviour influences their position within a social network. In this paper, we focus on understanding the effects of children's physical activity, an important factor in childhood obesity, on their positions in friendship networks, as well as the effect of physical activity on friendship formation and dissolution processes. We assess differences in these peer selection effects both between networks and across time with particular eye to the consequences of these differences on the design of network interventions.

Social networks have been shown to influence obesity in children, adolescents and adults (Bahr et al., 2009; Valente, 2010; de la Haye et al., 2011a; de la Haye, et al., 2010), with most of the literature regarding social networks focused on adolescent obesity determinants. Previous research has indicated that children tend to model healthy eating habits seen in peers (Birch, 1980), and a systematic review of correlates of physical activity suggest that peers play a role in physical activity (Sallis, Prochaska & Taylor, 2000). A more recent review suggests that the perceived support and friendship with active children tends to increase activity in inactive youth (Salvy et al., 2012). A recent study using social networks suggests that peer influence plays a role in increasing physical activity above and beyond a peer selection effect (Gesell, Tesdahl & Ruchman, 2012). While peer influence effects on children's activity level appear to be consistent across the literature, research has also demonstrated that there is a negative social impact to inactivity and obesity (Pearce et al., 2002). This social impact can take the form of differential peer selection and assortment effects.

Given the role that physical activity plays in preventing or reducing childhood obesity, along with the recent findings that suggest that peer physical activity has an effect on a children's and adolescents' level of physical activity (Gesell, Tesdahl & Ruchman, 2012; de la Haye et al., 2011;), it is also important to understand the effect that physical activity can have on the selection of peers, particularly in light of the potential for interventions to take advantage of peer behavior to increase physical activity. There have been several studies on the effects of children's activity level on peer selection and peer assortment effects. De la Haye et al. (2010) found that for the majority of the networks analyzed, friendships were more likely to exist between adolescents with similar levels of organized physical activity. De la Haye et al. (2011b) found that friendships were more likely to form between adolescents with similar levels of moderate to vigorous physical activity, and Macdonald-Wallis et al. (2011) found using spatial analysis that children with similar levels of moderate to vigorous physical activity tended to cluster in friendship groups. For systematic reviews of studies that use social network analysis to examine childhood physical activity, see Macdonald-Wallis et al. (2012), and Sawka et al., (2013). Of the studies cited in those reviews, only de la Haye et al. (2010), de la Haye et al. (2011b) and Gesell, Tesdahl and Ruchman (2012) use network analysis methods that model either the formation of friendships or the presence of friendships directly to get at the question of peer selection or assortment effects of children's physical activity. Furthermore, de la Haye et al. (2010) allows for heterogeneity in the effect of physical activity between studied networks while de la Haye et al. (2011b) assess heterogeneity between networks and transition points however ultimately fit a homogeneous model across networks and transition points. Finally, Gesell, Tesdahl and Ruchman (2012) assume homogeneity in the effect of physical activity across sample as well as across time. Both the presence of peer selection effects, and potential heterogeneity in those effects have consequences for the design of network interventions for increasing physical activity in children.

A "network intervention" uses social network data to identify pivot points within a network for intervening on for inducing or accelerating behavior change (Valente, 2012). Several studies now suggest that network interventions to increase physical activity are indeed warranted (Bahr, et al., 2009; de la Haye et al., 2011a; de la Haye et al., 2010; Shoham et al., 2012; de la Haye et al., 2011b; Valente et al., 2009; Christakis & Fowler, 2007). While social network data has been shown to be effective in informing intervention strategies in other public health areas such as HIV prevention (for review: Luke & Harris, 2007) and, to a lesser extent, adolescent drug use (Valente et al., 2007), there has been less research on applying network interventions to mitigate childhood obesity. Bahr et al. (2009) used a simulation approach to demonstrate that anti-obesity network interventions might require complex strategies, such as considering friendship clusters and transitivity effects. More recently, Zhang et al. (2015) used a simulation approach to demonstrate that increasing the routine physical activity of highly central nodes (the most popular individuals) could potentially increase physical activity across the whole network more than increasing the routine physical activity of a random selection of individuals. While these simulation studies suggest that a network intervention could be effective in preventing or reducing childhood obesity, they rely on an assumption of homogeneity in the peer selection process. If the peer

selection process changes over the course of the network's lifetime, then an intervention started at the beginning of a network might become inefficient as the network evolves.

This study proposes to examine heterogeneity in the effect of moderate to vigorous physical activity in peer selection processes and cross sectional characteristics both across time within a network, and between networks. If there is heterogeneity in the peer selection processes within a network across time, this suggests that network interventions on physical activity that rely in peer selection will have to be dynamic, and able to adapt to changing selection processes. If there is heterogeneity between networks on peer selection processes, this would suggest that interventions need to be specifically tailored to the environment that they would be implemented in, and a single intervention strategy would not be efficient.

In this study, we explore potential heterogeneities in the effect of physical activity on network structure and network dynamics two networks of youth. We used ERGMs to examine both the cross-sectional characteristics of the network data, as well as to examine friendship formation and dissolution at each wave transition. We used real-world friendship networks from which multiple waves of data were collected, and to avoid the issues of self-reported behavioral data, we objectively measured physical activity through accelerometry. We also took advantage of network data collected from two different after school programs, one of which was newly formed, and the other which had been established for some time. As a result, we were able to examine the dynamics of the networks over time, the characteristics of the networks at each time point, and assess possible heterogeneity in the effects of physical activity.

We hypothesized that due to the differences between the aftercare programs, and the timescales over which network change was assessed, there would be variability in the effect of physical activity on friendship formation and dissolution. Specifically we tested the effect of physical activity on friendship formation and dissolution based on physical activities effect based on types of effects. We assessed the effect of physical activity on popularity of a child (as measured by indegree), expansiveness of a child (as measured by outdegree) and the effect of the difference in physical activity rates on friendship formation and between children. We hypothesized that we would see heterogeneity in these effects between programs, with the established program demonstrating fewer effects of physical activity on friendship formation and dissolution than the new program. We gave no specific directional hypotheses as to the with-network between-timepoints heterogeneity, other than the hypothesis that the effect of physical activity on friendship formation will not be consistent overtime in either network. This heterogeneity, either between network or across time would have implications for the design of network based interventions that took advantage of peer selection processes.

METHODS

Study Population

The Wake Forest University Health Sciences IRB approved this study. The sample consisted of 81 children, averaging 7.96 years ($SD=1.74$), 56% healthy weight, 23% overweight, 21% obese; 40% African American, 39% White; 19% Latino; and 65.4% female. These children

lived in low SES neighborhoods, attended public schools, and attended one of two afterschool programs. Each afterschool program operated Monday through Friday (3:00–6:00PM), and allotted time for play, homework, and snacks. One program was new and located in a community center with the first wave of collection happening 1 week after the beginning of the program, and the other was established and located in a public school, and had been in progress for several years. Both programs enrolled children from the school in which the school-based program was located, as well as children from other schools in the area. Data collected at baseline, 6 weeks, and 12 weeks were used. This data set is described in detail elsewhere (Gesell, Tesdahl & Ruchman 2012).

Measures

Physical activity—Physical activity levels were captured through ActiGraph GT1M accelerometers (ActiGraph LLC, Pensacola, FL). Details of the physical activity measurements are outlined elsewhere (Gesell, Tesdahl & Ruchman 2012). The ActiGraph is a lightweight activity monitor that is worn on a belt around the waist. It captures the intensity of physical activity from locomotion in continuous 10-second periods, or epochs, to capture the short activity bursts characteristic of children. It does not provide the wearer with any visible feedback. For both waves of measurement, children wore monitors for 5 consecutive days for the duration of the afterschool programs. Empirically validated thresholds were used to code each child's time spent at sedentary, light, moderate, and vigorous activity levels (Pate et al., 2006; Puyau et al., 2002). Raw accelerometer data was analyzed using a procedure analogous to that used with the NHANES data (Tudor-Locke, Johnson, Katzmarzyk, 2009). Activity measuring 420 counts per epoch was categorized as moderate or vigorous physical activity (MVPA), the main outcome for this study.

The total daily minutes of each type of activity over the 5 days of monitoring were averaged to produce the average number of minutes at each activity level per day during that period of assessment. The hours of program-related playtime recorded in each afterschool program were used as cutoff points to accurately capture when children had free choice over their level of activity, versus more sedentary periods (e.g., scheduled snack and homework times). As such only minutes of activity during the free play period were used in calculating level of physical activity.

Each child spent varying amounts of total time in the respective programs, depending on the when parents picked children up after work. To control for individual differences in the amount of playtime that a child has, the main outcome measure in this study was the overall proportion of free playtime recorded in moderate-to-vigorous physical activity (MVPA) over the course of monitoring per wave, as opposed to the raw number of minutes in MVPA.

Demographics and control variables—Age, gender and BMI (body mass index) were all collected. Age and gender, were collected using parent report. Body weight was measured, while wearing light clothing without shoes after voiding, to the nearest 0.1 kg on a calibrated digital scale (Detecto, Webb City, MO, model 758C). Body height without shoes was measured to the nearest 0.1 cm with the attached stadiometer. BMI percentile was

calculated by using the Centers for Disease Control and Prevention calculator, where children with BMI 95th percentile were classified as obese.

Friendship network—Each child's friendship network was documented using an open-ended survey instrument, administered through private interviews. Each student was asked, "Please tell me the names of the friends you hang around with and talk to and do things with the most here in this after-school program." No restrictions were placed on the number of friends each child could name. This name generator is consistent with that employed in other youth social network studies (de la Haye et al., 2010). Children were surveyed at each wave of data collection to capture each child's most salient friendships at each measurement occasion. The total number of friends in each child's network included those friends that each child nominated, and nominations received from others. In order to best model the possible differences between the afterschool settings, the networks ($n = 46$ and $n = 35$) were analyzed separately and results were compared. Model specifics are explained below.

Model Specifications and Estimation

There are several different ways to assess the cross-sectional structure and change in structure of a network over time. More recently, two specific methodologies have come to the fore, exponential random graph models (ERGMs) for assessing cross sectional structure (Robins et al. 2007a) and peer selection effects over time (STERGMs, Krivitsky & Handcock, 2014), and stochastic actor based models (SIENA, Snijders, van de Bunt & Steglich, 2010) which are capable of modeling both peer selection and peer influence effects over time. The peer influence effects of MVPA in this sample have already been assessed in previous work (Gesell, Tesdall, & Ruchman, 2012), and the focus of the current study is on the differences in the peer selection processes operating on the two friendship networks. As such, the analysis will be conducted using ERGMs at each timepoint to assess the cross sectional structure of the networks, and STERGMs to assess the peer selection effects operating during the wave transitions.

Exponential random graph models and separable temporal exponential random graph models seek to model the observed network (or, in the case of the STERGMs, the change in a network between two observations) as a sample realization from a distribution of networks, specifically a distribution that is in the exponential family of distributions. The parameters in an ERGM represent, in a sense, the probability that certain features of a network occur. These features can be any network characteristic, from the number of edges in a network, to the number of transitive triads, to the absolute difference between individual level covariates. The parameters from an ERGM model are in the log-odds metric, and can be interpreted in a similar fashion to the results from a logistic regression (Wasserman & Pattison, 1996), though they are estimated in a different fashion. Specifically, parameters are estimated using an MCMCMLE approach (Hunter & Handcock, 2006), an iterative MCMC algorithm that approximates the MLE solution for these models. Finally, ERGM and STERGM modeling becomes increasingly difficult with larger networks (500+ individuals), as the number of iterations needed to approximate the MLE for networks increases exponentially as the sample size increases.

ERGM models focus on the cross-sectional characteristics of an observed network. Therefore, care must be taken when interpreting results, as any observed effect for a cross-sectional network model could be the result of either peer selection, or peer influence processes. That being said, cross-sectional ERGM models provide a valuable descriptive tool for describing the structure of the network being studied, and are used in that way here.

STERGM models (Krivitsky & Handcock, 2014) are the longitudinal extension of ERGM models. They seek to model the formation and dissolution of network ties between each observed instance of a network. They are termed separable as the formation process and the dissolution process are modelled as independent of each other, in that edges that form have no relation to edges that dissolve. While this might not be a fully realistic assumption, the estimation of these models is simplified when one assumes that the processes are separable. The parameter estimates from a STERGM can be interpreted in the log-odds metric, and represent an increase or decrease in the probability of edge formation, or edge dissolution during the transition between the observed networks. Furthermore, STERGMs assume that the process of edge formation and dissolution has the Markov property (i.e. is memoryless). This property states that the changes observed in a network are dependent only on the state of the network immediately preceding the changes, and independent of any state of the network before the changes occurred. This assumption is also present in SIENA modelling (Snijders, van de Bunt & Steglich, 2010), and in practice means that the changes in a network occurring during a later transition are independent of any changes happening earlier. STERGMs can be a valuable tool in analyzing peer selection effects, as the models have the capability to parse apart specific effects on edge formation and dissolution. Finally, for both ERGMs and STERGMs, model goodness of fit is assessed by comparing the distribution of network statistics resulting from the estimated parameters to the observed network statistics (Goodreau & Handcock, 2008, for example see Simpson et al. 2011). Goodness of fit plots for each model are presented in Appendix A, with a brief discussion of areas of misfit.

Heterogeneity Between Aftercare Programs and Timepoints

The primary questions of interest are: (1) Is there heterogeneity in the effect of MVPA on cross sectional network structure between the aftercare programs and between the waves of the aftercare program, and (2) Is there heterogeneity in the peer selection processes between each waves. To assess the heterogeneities in the effect of MVPA both within and between programs, two cross sectional ERGMs were fit to all the waves in each program, using a block diagonal constraint to prevent edges from being estimated between waves.

Heterogeneity in the effect of MVPA was assessed using interactions between MVPA and wave, the specifics of which are described below. Additionally, to allow for possible growth in the network size over time, the edge statistic, representing the density of the network at each wave, was allowed to vary between waves. This is equivalent to fitting a categorical by continuous interaction in linear regression, where the main effect of the categorical variable is also included. All other effects were held homogeneous between waves. While there could be heterogeneity in those effects, due to the small sample size of these networks, the effects were held homogeneous to improve model estimation and power, and to reduce the impact of multiple comparisons. While a homogeneous model is too restrictive, a fully

heterogeneous model is far too permissive and would increase the chance that spurious results were recovered, particularly given the lower sample sizes in these networks.

To assess the change in network structure, and to assess differences in the processes of peer selection, separate STERGM models were fit to each wave transition for each network, for a total of 4 STERGM models estimated.

ERGM and STERGM model terms

Structural terms—A number of terms used in the cross-sectional ERGMs could be considered structural, as they are not based on observed individual covariates such as MVPA or gender. In these models, the structural parameters are edges, mutuality and geometrically weighted edgewise shared partners (GWESP).

The edge parameter acts as an intercept for ERGMs, and in practice is included in every ERGM estimation. It can be interpreted as the probability of an edge being present when all other network statistics relating to that edge are zero. The edge parameter was allowed to vary between the waves within a program, and the interaction terms can be interpreted as the difference in the edge parameter from the edge parameter in Wave 1. Mutuality is another common structural parameter, and can be interpreted as the probability that an edge will be reciprocated in the observed network.

GWESP (Hunter, Goodreau & Handcock, 2007) is a term that measures the degree of transitivity in the network. It amounts to a weighted triangle count that tends to discount higher numbers of triangles in a network. This helps to prevent degenerate models, where the parameters suggest a distribution of networks that are either near completely full, or nearly empty. Degenerate models commonly occur when using unweighted triangle counts or triad counts (Handcock, 2003). The degree of weighting in a GWESP term can be considered fixed, and provided by the analyst, or estimated. This estimation is difficult (Hunter and Handcock, 2006), and in the case of every model tried here resulted in degenerate models. As such several weights were tried and considered fixed, and the weights reported in the results were the highest weights in each model that did not result in model degeneracy. The higher the weight, the closer the GWESP term is to an un-weighted triangle term (Goodreau et al. 2008). In the cross sectional models, these parameters were estimated separately for each program, but homogeneously within a program. They were allowed to vary in the STERGM models.

Demographics—Effects for age and gender on probability of sending or receiving a tie were assessed in all models. Specifically, the indegree, outdegree and absolute difference effect of age, and the mixing effect of gender were estimated in each model. Previous literature has consistently demonstrated both gender and age selection effects (Hartl, Laursen & Cillessen, 2015; McPherson, Smith-Lovin & Cook, 2001), and controlling for these effects is vital for obtaining unbiased estimates of the effects of MVPA. The indegree and outdegree effects of age can be interpreted as the association of greater age with more friendship nominations directed towards the individual, and more friendship nominations that the individual makes, while the absolute difference in age can be interpreted as the probability of having friends of different ages. The effect for female-female, male-female

and female-male friendships were estimated, with male-male friendships being considered the reference category. These parameters can be interpreted as the probability of friendships between two individuals with the respective genders. In the cross sectional models, these parameters were estimated separately for each program, but homogeneously within a program. They were allowed to vary in the STERGM models.

BMI—The effect of BMI on the probability of sending or receiving a friendship tie was assessed using indegree, outdegree and absolute difference terms. Inclusion of BMI into the model as a control is meant to separate the peer selection effects of general physical health and appearance from that of physical activity, as they are likely highly correlated. Failure to control for BMI could potentially bias the estimates of the effect of physical activity. The interpretation of these terms is similar to the interpretation of the age related terms above. The effect of BMI was held homogeneous within program for the cross sectional models, and allowed to vary in the STERGM models.

MVPA—The effect of MVPA was assessed using indegree, outdegree and absolute difference terms. In the cross sectional ERGMs, these terms assess the effect of MVPA on the probability of receiving a friendship tie, sending a friendship tie, and the effect of the difference in MVPA on the probability that there exists a friendship between two individuals at that time point. These terms were allowed to vary between the waves within a network, and the interaction terms can be interpreted as the difference in the effect of MVPA from Wave 1. The effects of MVPA were allowed to vary in all STERGM models. In the STERGM models, these terms can be interpreted as the effect of MVPA on forming or dissolving any incoming friendship tie (indegree), forming or dissolving any outgoing friendship tie (outdegree), and forming or dissolving a friendship tie with a specific individual who has a given level of MVPA (absolute difference). As the STERGM models were fit separately, there is no test of difference in the effects of MVPA between waves.

RESULTS

Descriptive Statistics

The change in friendships over each wave transition for each network is presented in Table 1, along with Jaccard similarity coefficients (Jaccard, 1901) for each transition. Jaccard similarity is commonly used to assess the amount of change that has occurred between observations of a network, with higher similarity values meaning there is more similarity (less change) in the network. Snijders, van de Bunt and Steglich (2010) suggest that the Jaccard similarity be above .3 to measure gradual change in network structure over a series of observations. However, as the interest here is in the differences between the network dynamics in play at each wave transition, more change in network structure provides more information. The only problematic transition is that of the W1->W2 transition for the new network. It exhibits a similarity of .727, and very few friendships are formed (50), or dissolved (23). However, this is reflected in the analysis of that transition. The remaining transitions exhibit a decent amount of change in friendship nominations, and this is reflected in the results for those transitions

Table 2 contains demographic information regarding the gender proportions and age characteristics of this sample. Also included is information about BMI summarized across all time points for each of the two aftercare programs.

Table 3 contains information about the marginal distributions of moderate or vigorous physical activity (MVPA) at each wave, as well as the distribution of the changes in MVPA at each wave.

As evidenced in Table 3, there are small differences between the mean MVPA at each wave for each program. However, there was substantial variability within individual between the waves as evidenced by the standard deviations on the differences between waves. As there is variability in MVPA within individual between waves, care must be taken when interpreting the cross sectional models, as the cross sectional characteristics of the networks could be due to either peer influence or peer selection effects.

Cross-sectional Models

The primary question in the analysis of the cross sectional networks is, How is physical activity associated with an individual's embeddedness in their friendship network. Specifically, we are interested in physical activity's effect on indegree and outdegree, as well as the effect of the difference in physical activity between two individuals on their probability of having a friendship at any time point. Additionally, to investigate the heterogeneity between aftercare programs, we fit separate ERGM models to each of the program's networks. To investigate heterogeneity between the time points, we allow for different effects of physical activity at each wave. Finally, we control for the effects of age, gender, BMI and transitivity. All results are described below. It is important to note that these models make no claims as to the cause of the relationship between variables and network structure, be it peer influence or peer selection. Rather, these models serve to describe the program friendship networks as they evolve over the twelve week time course of the aftercare program. Table 4 and 5 summarizes the results for the new program and established program respectively.

Only the established program exhibited any heterogeneity in the effect of MVPA. Specifically, the effect of the absolute difference in MVPA was trendingly different at Wave 2 vs. Wave 1 (-2.196 SE: 1.177 , $p < .1$), and the effect of the absolute difference in MVPA was significantly different at Wave 3 vs. Wave 1 (-2.3 SE: 0.983 , $p < .05$). Additionally the outdegree effect of MVPA, or how MVPA is associated with an individual's tendency to send out friendship nominations, was trendingly different at Wave 3 vs. Wave 1 (2.004 SE: 1.022 , $p < .1$). These differences, particularly for Wave 3 suggest that the difference between two individual's MVPA is negatively associated with the probability that a friendship nomination exists between them. In other words, individuals with more similar MVPA scores are more likely to be friends at Waves 2 and 3, rather than at Wave 1 for the established network.

Both program's network exhibited significant effects of geometrically weighted edgewise shared partners (New Network: 1.03 , SE: 0.081 , $p < .001$, Established Program: 0.613 SE: 0.066 , $p < .001$) as well as significant effects of mutuality (New Network: 1.214 SE: 0.167 ,

$p < .001$, Established Program: 1.164 SE: 0.161, $p < .001$) suggesting that at all waves the networks were characterized by the presence of reciprocated friendships and triangle structures. This is not unexpected for children's social networks.

Only the new network exhibited heterogeneity in the edge parameter, with Wave 2 being trendingly different from Wave 1, and Wave 3 being significantly different from Wave 1 (0.298 SE: 0.174, $p < .1$, 0.283 SE: 0.135, $p < .05$, respectively). This suggests that in the new networks, the Wave 2 and 3 networks had more friendship nominations in general than the Wave 1 network.

The effect of BMI differed between the networks. In the new network, the absolute difference in BMI was negatively associated with having friends (-0.04 SE: 0.013, $p < .05$) whereas in the established program, absolute difference in BMI was positively associated with having friends (0.036 SE: 0.018, $p < .05$). The association between BMI and outdegree was non-significant for the established program, and positively significant for the new network (0.044 SE: 0.014, $p < .01$), while the association between BMI and indegree was non-significant for the new network and negatively significant for the established program (-0.075 SE: 0.018, $p < .05$).

The effect of being a different gender than the target was significant and negative for both networks, with the effect for a male-female edge being -0.826 (SE: 0.123, $p < .001$) and -1.304 (SE: 0.169, $p < .0001$) for the new and established programs respectively. The effects for a female to male edge were -0.432 (SE: 0.119, $p < .001$) and -1.47 (SE: 0.162, $p < .001$) for the new and established programs respectively. These effects suggest that mixed-gender friendships were less likely than same-gender friendships (specifically here less likely than male-male friendships, as that is the reference category). There was a significant negative effect for female-female edges (-0.66 SE: 0.111, $p < .001$) for the established programs suggesting that there were fewer female to female friendships than male to male friendships in that network.

There was a significant and negative effect of the absolute difference in age for both networks (New Network: -0.143 SE: 0.03, $p < .001$, Established Program: -0.252 SE: 0.031, $p < .001$) suggesting that friendships between children of different ages were less likely than friendships between children of the same age. Finally, in the established program there was a significant effect of age on indegree (0.251 SE: 0.032, $p < .001$) and outdegree (-0.119 SE: 0.033, $p < .001$) suggesting that older children were more popular and had less expansive networks than younger individuals. There was a significant negative effect of age on outdegree for the new network as well (0.061 SE: 0.03, $p < .05$).

In summary, the cross sectional analyses of the new network shows no association of MVPA with network structure at any time point, while for the established program, the difference between MVPA was negatively associated with having friends only in Wave 3 and to a lesser extent in Wave 2. This apparent heterogeneity of the association of MVPA with network structure could be explained in part by peer selection processes, and to that end the wave transition models are presented below

In every model fit, the MCMC chains for the network statistics exhibited good convergence. No model presented resulted in degenerate distributions.

Friendship formation and dissolution

The following models are fit using STERGMs. The effect of MVPA on friendship formation and dissolution was assessed with three parameters, an indegree term which assess the effect of MVPA on the formation and dissolution of incoming friendship nominations, an outdegree term, which assess the effect of MVPA on the formation and dissolution of outgoing friendship nominations, and an absolute difference term, which assesses the effect of the difference in MVPA between two individuals on the formation and dissolution of friendships. We hypothesized that the effect of MVPA on both friendship formation and dissolution will be less in the established program than in the new program

For all formation and dissolution models, the MCMC chains exhibited good convergence to stationary distributions. From visual inspection the formation models exhibited a degree of autocorrelation, however, chains produced a smooth distribution of network statistics, and, with thinning which is automatically performed, the degree of autocorrelation is reduced substantially.

Formation—The results of the friendship formation model for the new program are presented in Table 6, and the results for the established program are presented in Table 7.

Only in the Wave 2 to Wave 3 transition for the new program was the effect of the absolute difference in MVPA significant and negative (-5.859 SE: 2.118 , $p < .01$). This suggests that new friendships between individuals with differing MVPAs were very unlikely for that transition point, controlling for other factors in the model such as shared friendship and gender. This effect points to a strong assortative mixing effect for the wave 2 to wave 3 transition in the new program. This effect was not seen in the established program, for either of the wave transitions.

The outdegree effects of MVPA differed between the networks. For the new program, MVPA was negatively associated with outdegree (-2.198 SE: 0.819 , $p < .01$) suggesting that higher levels of MVPA were associated with fewer friendship nominations sent out. There was no significant effect of MVPA on indegree for that transition, which suggests that MVPA was not associated with the number of friendship nominations received. For the established program, during the Wave 2 to Wave 3 transition, the effect of MVPA on outdegree was significant and positive (2.626 SE: 1.166 , $p < .01$). This suggests that for the established program during the Wave 2 to Wave 3 transition period, a greater MVPA was associated with sending out more friendship nominations.

For all transitions on all networks the GWESP effect was significant and positive, suggesting that having mutual friends was predictive of friendship formation. For both transitions in the established program (Wave 1–2: $.922$ SE: $.298$, $p < .01$; Wave 2–3 $.801$ SE: $.267$, $p < .01$), and for the Wave 1 to Wave 2 transition in the new program (0.943 SE: $.278$, $p < .001$), the effect of mutuality was significant and positive. This suggests that individuals were more likely to reciprocate existing one sided friendships. The absolute difference in BMI had

significant but opposite effects on the Wave 2 to Wave 3 transition for both the new program and the established program. In the new program, absolute difference in BMI was negatively associated with friendship formation (-0.136 SE: 0.065 , $p < .05$). In the program, absolute difference in BMI was positively associated with friendship formation (0.078 SE: 0.039 , $p < .01$). In other words, for the new program individuals who were different in their BMI had a reduced probability of friendship formation, while in the established program, there was a slightly increased probability of friendship formation between individuals of different BMI.

Absolute difference in age had a significant and negative effect for both waves of the established program (W1->W2: -0.241 SE: 0.084 , $p < .01$, W2->W3 -0.176 SE: 0.073 , $p < .05$), and no significant effect for the new program. There was a significant and positive effect of age on indegree in the established program for both transitions (W1 -> W2: 0.218 SE: 0.078 , $p < .01$, W2 -> W3 0.144 SE: 0.07 , $p < .05$).

There was a significant negative effect of male to female friendships during the Wave 1 to Wave 2 transition for both the new and the established program (-0.628 SE: 0.282 , $p < .05$; -1.438 SE: 0.66 , $p < .05$), suggesting that in that transition friendship formation from a male to a female was more unlikely than friendship formation between a male and a male. This effect is small, and doesn't appear in the Wave 2 to Wave 3 transition for either network.

Dissolution—The results for the dissolution models are presented in Tables 8 and 9 for the new and established program respectively.

There was a significant negative effect of MVPA on outdegree dissolution during the Wave 1 to Wave 2 transition for the new program (-5.432 SE: 2.272 , $p < .05$), suggesting that individuals high on MVPA were less likely to dissolve their outgoing friendships. In the established program during the Wave 1 to Wave 2 transition, there was a significant and positive effect of MVPA on indegree dissolution (5.163 SE: 2.123 , $p < .05$), which suggests that friendships directed towards high MVPA individuals were more likely to be dissolved during that transition. These were the only significant effects of MVPA on dissolution.

There were substantially fewer dissolved friendships than formed friendships at each transition, and as such the information about the process of dissolving friendships is limited here. In the new program during the Wave 1 to Wave 2 transition, GWESP was significantly and positively related to the dissolution of friendships ($.639$, SE: $.296$, $p < .05$), suggesting that individuals were more likely to dissolve friendships to individuals with whom they had mutual friends. Additionally, mutuality was significantly and positively related to friendship dissolution for the same transition in the new program (1.538 , SE: 0.715 , $p < .05$) suggesting that mutual friendships more often dissolved than non-mutual friendships.

During the Wave 2 to Wave 3 transition for the new network there was a significant effect of absolute difference in BMI on friendship dissolution (0.243 , SE: 0.122 , $p < .05$). This suggests that for this transition, friendships between two individuals with differing BMIs were more likely to dissolve than friendships between two individuals with similar BMIs.

As for the effect of age on dissolution of friendship, absolute difference in age and the outdegree effect of age was significant and negative for the Wave 1 to Wave 2 transition in

the established program (Abs. Diff: -0.324 , SE: 0.149 , $p < .05$; Outdegree: -0.27 SE: 0.132 , $p < .05$), suggesting that friendships between individuals with dissimilar ages were less likely to be dissolved, as were friendships directed from older children. There was a positive indegree effect of age for the Wave 1 to Wave 2 transition in the new program (0.465 SE: 0.194 , $p < .05$), suggesting that friendships directed at older individuals were more likely to be dissolved than friendships directed at younger individuals.

DISCUSSION

Our study is among a few studies related to childhood obesity that employed longitudinal social network analysis for an empirically observed network and used an objective measure of physical activity. Additionally, our study is one of the few that evaluate heterogeneity in the longitudinal peer selection process, both in time, and between networks.

Our work suggest that heterogeneity in peer selection effects in children's friendship networks should not be ignored in designing interventions to increase physical activity in the afterschool setting. Our findings suggest that

1. For the *established* program, difference in activity level was predictive of friendship only in the third wave. For friendship formation and dissolution in the established program, however, difference in activity level does not seem to matter. Activity level was associated with an increased number of new friendship nominations in one of the Wave 2 to Wave 3 transition, while activity level was associated with dissolved friendships targeted at the active child for the Wave 1 to Wave 2 transition. Demographics and network structure did play a role in both friendship formation and dissolution.
2. For the *new* program, difference in activity level was related to friendship formation for only the Wave 2 to Wave 3 transition, while activity level itself was associated with a decreased number of friendship nominations for the Wave 1 to Wave 2 transition. These dynamics were not reflected in the cross sectional models. In both wave transitions, demographics and network structure played a role in friendship formation.

These results support our hypotheses that there would be a greater effect of activity level on friendship formation in the new program compared to the established program, as demonstrated by difference in activity level acting as a strong predictor of friendship formation for the Wave 2 to Wave 3 transition only in the new program. However, it is interesting to note that for the established program, there was an association between difference in physical activity and the presence of friendship in Wave 2 and Wave 3. This suggests that while friendships did not form on the basis of physical activity similarity in the established program, individuals that were already friends were similar in their level of physical activity. This in turn suggests an influence effect at work here.

These patterns of results suggests that within our sample of networks there are heterogeneous mechanisms of friendship formation over time that result in a pattern of friendships that show strong matching on activity level. This has implications for

intervention design in the after school setting. The tendency for children to avoid *forming* friendships with children with similar activity levels after the network has become established, suggests that an intervention targeted at grouping sedentary youth with more active peers would not work well as it goes against the network dynamics already present in the networks. On the other hand, the tendency for children to form friendships with peers with similar activity levels sometime after the formation of the network, but before it becomes established, suggests that an intervention that groups sedentary youth into high activity groups might work contrary to the network dynamics at play at that time in the network's history. Additionally, these results suggest that a major issue facing interventions that ignore the existing social structure would be that individuals in some settings have already coalesced into groups with similar levels of activity, which would create a "protective" effect against behavior change in that the sedentary tendencies would be reinforced by sedentary peers, a hypothesis that seemed to be supported by social contagion theory (de la Haye et al., 2011a).

This study highlights the necessity for intervention designers to take into account the characteristics of the sites at which the intervention is targeted. The results here suggest that network structure can be heterogeneous, even between samples that have similar demographics, and that the new and established programs should be distinguished. In this study, the new program, an aftercare program that had been newly formed, showed few effects of activity level on having friendship and new friendship formation. The established program, an aftercare program that had been established for some time, showed no effect of activity level on friendship formation, but rather there was a negative association between difference in physical activity and friendship in the last wave of the study. This suggests one of two things, the first that individuals who were friends with more active individuals became more active (a peer influence effect, consistent with previous findings), or that there was another peer selection effect that caused friendships between youth with similar levels of activity earlier in the history of the stable network, and that in the transition network either that process has not come into play, or that other factors are much more influential on initial formation of friendship, such as shared friendships. The lack of an effect of activity level on *formation* of friendships suggests that while some process, be it selection or influence is happening to cause the established program to show a pattern of association between children based on activity level, the youth are not associating with each other based on activity level above and beyond the association due to shared friends and other demographic information. This suggests that established programs could potentially be able to group sedentary children with active peers without fear that the grouping would fail and that the sedentary children would be rejected simply due to dissimilarities in activity level, while newer programs would have to put measures in place to prevent rejection due to dissimilarities in activity level. Additionally, intervention efforts could take advantage of the consistent finding that shared friends predict friendship formation. However, an intervention could change the network dynamics, so further research is needed as to the effects of an active manipulation of a youth social network.

Limitations

There were several limitations in this study. The first was that the sample size was small. The new program was composed of 46 individuals, which amounts to 2070 possible friendship ties, which are then assessed over 3 waves. The established program comprised 35 individuals, which amounts to 1,190 possible friendship ties. This relatively low sample size is likely to render the estimates of the effect of individual covariates such as activity level underpowered. Further studies should be done over more waves, with more individuals per network.

MVPA was operationalized as a ratio of the time spent in moderate to vigorous physical activity over the total time available for the child to be physically active. This was chosen to control for individual differences in the amount of playtime each child had. However, it could well be the case that time itself spent in physical activity could have a major impact on social structure. In this study, due to individual differences in the amount of playtime available, raw time was not used, as it could confound an individual level effect with the effect of the amount of time spent in physical activity. However, in further research if the design permits, raw time should be used as a measure of MVPA.

Additionally, peer influence processes were not assessed. While this study intentionally focused on peer selection processes due to power constraints, peer influence processes should be assessed for heterogeneity as well. If peer selection processes change over the course of the networks lifetime, then it is not unreasonable to hypothesize that peer influence processes would as well. This study did not assess that, and as such we only have half the picture when it comes to heterogeneity.

Speaking directly to the results on friendship dissolution, there were very few friendships dissolved in this study. As such the results regarding dissolution are somewhat suspect as sampling variability. For future study on friendship dissolution, it is important to have sufficiently volatile friendship networks.

Another limitation in this study was methodological. The use of separate models, while consistent with the hypothesis that there would be heterogeneous effects, is less parsimonious than a model that allows for a change in the temporal dynamics of a network as time progresses, either based on the values of the covariate, or based on some other, distal process. However, further work would be needed to develop such methods.

A further methodological limitation was in the number of statistical tests performed. Because a multiple comparisons correction has not been applied, readers are cautioned to also examine the strengths of the association instead of only relying on statistical significance at the 0.05 level.

Future Research

There are three directions that further research can be conducted. First, the social network analysis in this article could be used as a basis for further simulation for studying the behavior of the system as defined by the environmental, social, and behavioral context described in this paper. Specifically, more work should be done on how network dynamics

change over the lifespan of the network as a function of both time and the covariates in the network. Ideally, a study examining that would consist of several waves across several networks, each at a different point in the lifespan of the network. This would allow for a finer grained picture of the mechanisms of change in network dynamics.

Second, building on the results of this study, further research should, from the perspective of intervention design, investigate the reasons why there exists heterogeneity in the tendency for children to assort along different stages in network formation. One theory was proposed here, namely the difference between a new and established program; however there could be other reasons, such as the structure of the aftercare programs, which could considerably change the structure of the friendships and either strengthen the association between individuals of similar physical activity or decrease that association. Further research should expand into classroom settings (such as PE classes), and begin to examine the effects of applied interventions on the friendship network.

Finally, this study assessed heterogeneity in peer selection processes, but did not examine heterogeneity in peer influence processes. Further research should investigate the effects of other covariates on peer influence processes, so as to further optimize intervention strategies.

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TRH analyzed the data, generated the tables and figures, wrote and revised the paper. All authors were involved in study design, interpreting the analyses, writing the paper, and had final approval of the submitted version.

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APPENDIX A

Below are goodness of fit plots for each model fitted. Each plot consists of the distribution of network statistics from a sample of networks generated from the fitted model (the box-plots), plotted against the observed network statistics (the black line). Goodness of fit is evaluated by how well the distributions map onto the observed network statistics.

Model Evaluations for Cross Sectional New Program

From visual inspection of the goodness of fit plots (Figure 1A), the cross sectional model has issues of fit both in outdegree and edgewise shared partners. The model tended to overestimate the proportion of edges with 1 shared partner, and underestimated the tendency

for individuals to have an outdegree of 3–4. The minimum geodesic distance was adequately modelled, while the general trend of the indegree was modelled. The fluctuations of the observed indegree distribution were not captured, but this is likely due to a lower sample size.

Model Evaluation for Cross Sectional Established Programs

Visual inspection of the goodness of fit plots (Figure 2A) indicates that overall the model fit adequately. The mean outdegree was overestimated, while there was slight overestimation in the number of edges with 2 edgewise shared partners. The model did not capture the proportion of nodes with 5 or 6 indegrees, however this is likely due to the small sample size.

Model Evaluation for Wave Transitions in the New Network

A visual inspection of the goodness of fit plots for the STERGMs of the transition network (Figure 3A and Figure 4A) reveal no areas of significant misfit, though the model implied distributions did not map perfectly onto the sample distributions, likely due to small sample size. This suggests that the STERGMs performed adequately at recovering the observed statistics in the transition matrices.

Model Evaluation for Longitudinal Stable Networks

Visual inspection of the goodness of fit plots for the stable network STERGM models (Figure 5A and Figure 6A) shows no particular misfit, though again the fluctuations in the sample distributions were not fully captured in the model implied distribution. There is a slight overestimation of the number of edgewise shared partners in the formation model for the Wave 2 to 3 model. The general form of the model implied distributions tend to follow the observed network structure. On a whole, these goodness of fit plots suggest that the STERGM models do an adequate job of capturing the network statistics.

Figure 1.
Figure 1A. Goodness of Fit for the Cross Sectional ERGM for the New Network

Figure 2.

Figure 2A. Goodness of Fit for the Cross Sectional ERGM for the Established Network

Figure 3.

Figure 3A. Formation and dissolution goodness of fit for the Wave 1 to Wave 2 transition in the new network

Figure 4.

Figure 4A. Formation and dissolution goodness of fit for the Wave 2 to Wave 3 transition in the new network

Figure 5.
Figure 5A. Formation and dissolution goodness of fit for the Wave 1 to Wave 2 transition in the established network

Figure 6.
Figure 6A. Formation and dissolution goodness of fit for the Wave 2 to Wave 3 transition in the established network

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Table 1

Change in Friendship Nominations over Waves

	0->0	0->1	1->0	1->1	Jaccard Similarity
New Network					
W1->W2	1848	151	43	74	.276
W2->W3	1841	50	25	200	.727
Established Program					
W1->W2	940	102	85	98	.343
W2->W3	893	132	70	130	.391

Table 2

Demographics

	New Program	Established Program
N	46	35
Age (SD)	8.4 (1.72)	7.4 (1.63)
% Female	58.6%	74.2%
BMI (SD)	19.36 (3.80)	18.52 (3.34)

Table 3

Moderate or Vigorous Physical Activity Descriptive Statistics

	New Program	Established Program
Wave 1 MVPA	.374 (.14)	.204 (.11)
Wave 2 MVPA	.393 (.13)	.201 (.11)
Wave 3 MVPA	.361 (.18)	.203 (.12)
Differences between Waves		
W1 -> W2 MVPA	.019 (.14)	-.002 (.08)
W2 -> W3 MVPA	.031 (.18)	-.001 (.14)

Table 4

Cross-sectional ERGM for New Network: Log-Odds (SE)

	Main Effects (Wave 1 as Reference)	Wave 2	Wave 3
Edges	-4.029 (0.414) ***	-	-
Edge X Wave	-	0.298 (0.174).	0.283 (0.135) *
GWESP(.6)	1.036 (0.079) ***	-	-
Mutuality	1.214 (0.167) ***	-	-
Abs. Difference in MVPA	-0.492 (0.776)	-	-
Abs Difference in MVPA X Wave	-	0.325 (0.896)	-0.316 (0.901)
Indegree Effect of MVPA	0.86 (0.711)	-	-
Indegree Effect of MVPA X Wave	-	-0.416 (0.919)	-0.553 (0.828)
Outdegree Effect of MVPA	0.525 (0.641)	-	-
Outdegree Effect of MVPA X Wave	-	-0.997 (0.808)	-0.072 (0.072)
Abs. Difference in BMI	-0.04 (0.013) **	-	-
Indegree Effect of BMI	-0.02 (0.014)	-	-
Outdegree Effect of BMI	0.044 (0.014) **	-	-
Female - Female	-0.072 (0.072)	-	-
Male-Female	-0.826 (0.123) ***	-	-
Female - Male	-0.432 (0.119) ***	-	-
Indegree Effect of Age	0.061 (0.03) *	-	-
Outdegree Effect of Age	-0.053 (0.03).	-	-
Abs. Difference in Age	-0.143 (0.03) ***	-	-

Note:

.p < .1,

*
p < .05,**
p < .01,***
p < .001

Table 5

Cross-sectional ERGM for Established program Established program: Log-Odds (SE)

Parameter	Main Effects (Wave 1 as Ref)	Wave 2	Wave 3
Edges	-1.329 (0.506) **	-	-
Edge X Wave	-	0.037 (0.098)	0.013 (0.106)
GWESP(.6)	0.613 (0.066) ***	-	-
Mutuality	1.164 (0.161) ***	-	-
Absolute Difference in MVPA	0.084 (0.76)	-	-
Absolute Difference in MVPA X Wave	-	-2.196 (1.177).	-2.3 (0.983) *
Indegree Effect of MVPA	-0.388 (0.804)	-	-
Indegree Effect of MVPA X Wave	-	1.627 (1.083)	-0.154 (1.045)
Outdegree Effect of MVPA	-0.301 (0.763)	-	-
Outdegree Effect of MVPA X Wave	-	-0.779 (1.101)	2.004 (1.022).
Abs. Difference in BMI	0.036 (0.018) *	-	-
Indegree Effect of BMI	-0.075 (0.018) ***	-	-
Outdegree Effect of BMI	-0.007 (0.018)	-	-
Female - Female	-0.66 (0.111) ***	-	-
Male-Female	-1.304 (0.169) ***	-	-
Female - Male	-1.47 (0.162) ***	-	-
Indegree Effect of Age	0.251 (0.032) ***	-	-
Outdegree Effect of Age	-0.119 (0.033) ***	-	-
Abs. Difference in Age	-0.252 (0.031) ***	-	-

Note:

.p < .1,

*
p < .05,**
p < .01,***
p < .001

Table 6

Formation Results for New Program

Parameters	Wave 1 -> 2	Wave 2 -> 3
Edges	-1.767 (0.992).	-6.826 (1.997) ***
GWESP(.6)	0.866 (0.103) ***	0.766 (0.158) ***
Mutuality	0.943 (0.278) ***	0.62 (0.38)
Absolute Difference in MVPA	-1.17 (0.791)	-5.859 (2.118) **
Indegree Effect of MVPA	-0.279 (0.832)	1.089 (1.819)
Outdegree Effect of MVPA	-2.198 (0.819) **	0.877 (1.896)
Abs. Difference in BMI	-0.008 (0.03)	-0.136 (0.065) *
Indegree Effect of BMI	-0.04 (0.031)	0.035 (0.058)
Outdegree Effect of BMI	0.049 (0.028).	0.085 (0.055)
Female - Female	-0.21 (0.224)	-0.431 (0.439)
Male-Female	-0.628 (0.282) *	-0.499 (0.457)
Female - Male	-0.51 (0.271).	-0.336 (0.476)
Indegree Effect of Age	-0.022 (0.059)	0.059 (0.107)
Outdegree Effect of Age	-0.103 (0.054).	0.02 (0.107)
Abs. Difference in Age	-0.055 (0.06)	-0.234 (0.125).

Note:

.p < .1,

*
p < .05,**
p < .01,***
p < .001

Table 7

Formation Results for Established program

Parameters	Wave 1 -> 2	Wave 2 -> 3
Edges	-0.252 (1.597)	-5.07 (1.309) ***
GWESP(.6)	0.788 (0.172) ***	0.883 (0.196) ***
Mutuality	0.922 (0.298) **	0.801 (0.267) **
Absolute Difference in MVPA	0.66 (1.215)	0.553 (1.078)
Indegree Effect of MVPA	-1.33 (1.061)	0.306 (1.207)
Outdegree Effect of MVPA	0.249 (1.061)	2.626 (1.166) *
Abs. Difference in BMI	0.013 (0.056)	0.078 (0.039) *
Indegree Effect of BMI	-0.096 (0.055).	-0.017 (0.039)
Outdegree Effect of BMI	-0.109 (0.058).	-0.014 (0.039)
Female - Female	0.033 (0.503)	0.082 (0.402)
Male-Female	-1.438 (0.66) *	-0.279 (0.427)
Female - Male	-0.283 (0.569)	-0.558 (0.454)
Indegree Effect of Age	0.218 (0.078) **	0.144 (0.07) *
Outdegree Effect of Age	-0.14 (0.077).	-0.006 (0.072)
Abs. Difference in Age	-0.241 (0.084) ***	-0.176 (0.073) *

Note:

.p < .1,

*
p < .05,**
p < .01,***
p < .001

Table 8

Dissolution Results for New Network

Parameters	Wave 1 -> 2	Wave 2 -> 3
Edges	4.848 (3.2)	0.845 (3.276)
GWESP(.6)	0.683 (0.296) *	0.308 (0.209)
Mutuality	1.538 (0.715) *	0.197 (0.56)
Absolute Difference in MVPA	-2.707 (2.325)	4.094 (3.058)
Indegree Effect of MVPA	1.645 (2.405)	-3.374 (3.125)
Outdegree Effect of MVPA	-5.432 (2.272) *	5.206 (3.007).
Abs. Difference in BMI	-0.191 (0.104).	0.243 (0.122) *
Indegree Effect of BMI	-0.1 (0.082)	0.114 (0.102)
Outdegree Effect of BMI	-0.072 (0.082)	-0.096 (0.096)
Female - Female	-1.54 (0.971)	1.218 (0.71).
Male-Female	-1.441 (0.89)	-0.375 (0.75)
Female - Male	-0.771 (0.779)	0.467 (0.692)
Indegree Effect of Age	0.465 (0.194) *	-0.036 (0.172)
Outdegree Effect of Age	-0.313 (0.197)	-0.225 (0.171)
Abs. Difference in Age	0.23 (0.176)	0.204 (0.205)

Note:

.p <.1,

*

p <.05,

**

p <.01,

p < .001

Table 9

Dissolution Results for Established Program

Parameters	Wave 1 -> 2	Wave 2 -> 3
Edges	-0.645 (2.007)	1.032 (2.221)
GWESP(.6)	0.192 (0.195)	0.139 (0.155)
Mutuality	0.73 (0.499)	1.63 (0.461) ***
Absolute Difference in MVPA	-2.618 (2.064)	0.432 (2.281)
Indegree Effect of MVPA	5.163 (2.123) *	1.268 (2.163)
Outdegree Effect of MVPA	0.086 (1.677)	1.977 (2.207)
Abs. Difference in BMI	0 (0.071)	0.046 (0.082)
Indegree Effect of BMI	-0.092 (0.068)	-0.075 (0.077)
Outdegree Effect of BMI	0.08 (0.066)	0.014 (0.077)
Female - Female	0.574 (0.54)	-0.866 (0.817)
Male-Female	-1.27 (0.783)	-1.187 (1.037)
Female - Male	-1.089 (0.853)	-1.109 (0.843)
Indegree Effect of Age	0.27 (0.137).	0.105 (0.129)
Outdegree Effect of Age	-0.27 (0.132) *	-0.054 (0.136)
Abs. Difference in Age	-0.324 (0.149) *	-0.25 (0.135).

Note:

.p < .1,

*
p < .05,**
p < .01,***
p < .001