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Exponential random graph models of preschool affiliative networks

João R. Daniel[a,*], António J. Santos[a], Inês Peceguina[a], Brian E. Vaughn[b]

[a] UIPCDE, ISPA- Instituto Universitário de Ciências Psicológicas, Sociais e da Vida, Rua Jardim do Tabaco 34, 1149-041, Lisboa, Portugal
[b] Human Development and Family Studies, Auburn University, 203 Spidle Hall, Auburn, AL 36849, USA

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ABSTRACT

Exponential random graph models were used to assess the relevance of reciprocity, popularity, transitivity controlling for effects based upon ego and alter sex, and sex homophily, on the formation of affiliative ties in 19 Portuguese preschool peer groups. The number of times two children were recorded as nearest neighbors in focal samples was used as an indicator of the relationship's strength. Independent parameter estimates of the different models (one for each group) were summarized, separately for the three age groups ("3-year-olds", "4-year-olds" and "5-year-olds") using a multi-level approach to meta-analysis. Results showed that affiliative ties between children were sex segregated, highly reciprocal, more likely to be directed to a restricted number of children and with a tendency to create transitive triads. The structural processes underlying the formation of affiliative ties were quite stable between classrooms.

1. Introduction

Casual observations in preschool settings easily reveal that interactions between children, both affiliative and agonistic, are rarely directed at random to the large number of available partners. Their dyadic behavior reflects individual social discrimination, operationalized in terms of the differential allocation of behavior toward other classroom peers (Strayer, 1980). Evidences of selectivity have been documented for more than 70 years (Challman, 1932; Hagman, 1933), and as early as age two, children develop preferences for specific peers that can last for years (Howes, 1988).

There are several studies describing affiliative structures of preschool peer groups from observational data (Santos and Winegar, 1999; Santos et al., 2000, 2008a, 2008b; Strayer and Santos, 1996), but although procedures like the hierarchical clustering techniques used by Santos, Strayer and co-workers have proven to be a valuable tool for describing preschoolers' cohesive structures, we lack studies that link such structures with the social processes that might have produce them. Without statistical models it is difficult to address this question.

Exponential random graph models (ERGMs; or p^* models) offer a promising framework within which such models can be developed (Robins and Pattison, 2005; Robins et al., 2007a; Snijders et al., 2006; Wasserman and Robins, 2005). ERGMs are probabilistic models that regard observed networks as one realization from a set of possible networks with similar important characteristics (i.e., an observed network is seen as one particular pattern of ties out of a large set of possibilities). The structure of a graph can be interpreted as being generated by the overlap of local configurations that can be seen as outcomes of structural effects in the network. Strength and direction of parameter estimates allow inferences about which configurations are important (e.g., positive and large parameters indicate that the corresponding configuration is more frequent than expected by chance, given other configurations of the model) assisting the judgment about which structural processes could explain how the network emerged.

Entering preschool, generally at three years of age, represents for many children the first opportunity to interact with a great number of peers, and for researchers, an opportunity to study the principles behind network formation on a sample of participants with little prior experience with peers (Schaefer et al., 2010; Snyder et al., 1996). On a recent longitudinal study conducted over a school year on 11 North-American classrooms, from the Head Start program, Schaefer et al. (2010) showed that the importance of the structural effects of reciprocity, popularity and transitivity on relationship formation (and change) cascades over time, from the simple to the most complex. Reciprocity effects remained constant along the year, popularity peaked in importance midway through the school year, while triadic closure increased in importance over time. Their findings agree with earlier ethological studies of preschool affiliative behavior showing that the increased coordination of children's association profiles generated progressively more complex affiliative structures (Strayer and Santos, 1996).

Reciprocity, popularity and transitivity are well-known mechanisms that can help explain the formation of networks (Snijders, 2011). Reciprocity is a basic feature of social life that has been found consistently in preschool peer groups (Snyder et al., 1996; Strayer

* Corresponding author. Tel.: +351 218811700; fax: +351 218860954.
E-mail addresses: jdaniel@ispa.pt (J.R. Daniel), asantos@ispa.pt (A.J. Santos), inespeceguina@gmail.com (I. Peceguina), vaughbe@auburn.edu (B.E. Vaughn).

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and Santos, 1996). Popularity effects in social network analysis literature refers to the existence of degree differentials, differing from the sociometric definition of popularity, which relates to the verbal assessments of peer likeability or status, and from perceived popularity from student reports. Unequal in-degree distribution can be an emergent phenomenon of underlying variations in individual characteristics that makes some children more attractive as interaction patterns, or a result of children choosing to be friends with others whom many other have also chosen (Barabási and Albert, 1999; Gould, 2002). Transitivity measures the tendency toward triadic closure in networks – "friends of my friends are also my friends". Transitivity in peer groups may arise due to the increased propinquity of individuals who share mutual friends, or from a psychological need for balance – convergence of third parties' evaluation (Schaefer et al., 2010).

The purpose of this study was, thus, to describe the relevance of different local social processes – reciprocity, popularity, transitivity controlling for effects based upon ego and alter sex, and sex homophily- on the creation of affiliative networks of 19 Portuguese preschool groups, using ERGMs. These processes have been shown to sufficiently capture the network structure of affiliative ties (Huitsing et al., in press; Schaefer et al., 2010).

Although both, this and Schaefer et al. (2010) study, tackle the network processes underlying children's peer relationships there are some different elements, described below, that will help strengthen the case for the importance of the fundamental processes presented on relationship formation in preschool peer groups.

To circumvent the difficulty of obtaining reliable parameter estimates due to relatively small networks, Schaefer et al. (2010) analyzed all networks simultaneously by arranging their data as one large matrix with structural zeros between children in different classrooms (Snijders et al., 2008). This implies that parameter values (and consequent structural effects) were considered equal across all classrooms. We followed a different approach. An ERGM was fit to each of the observed networks and then a multi-level approach to meta-analysis (Lubbers, 2003; Lubbers and Snijders, 2007) was used to summarize the independent estimates of the different models. This meta-analytical procedure allows assessment of the extent to which the processes studied vary between classrooms.

Preschool classrooms composition of both studies also differs to some degree. While the Head Start classes observed by Schaefer et al. (2010) ranged in size from 15 to 21 and included mixed age children (range: 37–60 months), Portuguese classrooms were slightly larger (20–27) and included only "same" age children with a wider age-span ("3-year-olds", "4-year-olds" and "5-year-olds"; descriptions provided in Section 2.1).

Also, none of the models presented by Schaefer and co-workers analyzed the effects of popularity and transitivity simultaneously. Given that both processes lead to similar network structures (e.g., cores in networks can arise either by closure-type processes or from popularity, or even a combination of the two), it is important to include both effects simultaneously in the model to distinguish the individual contributions of each process (Robins et al., 2007a), controlling for the effect of the other.

2. Method

2.1. Data

Observational data were collected of all children in nine different preschool classrooms in two centers serving middle class families in the Lisbon area, Portugal, as part of a larger study on preschool children social development. Classrooms were observed once (two classrooms), twice (four classrooms) or in three consecutive years (three classrooms), for a total of 19 preschool peer groups observed: six "three-year-old" groups (i.e., children <48 months of age at the start of the academic year), six "four-year-old" groups (i.e., children between 48 and 60 months of age at the start of the academic year) and seven "five-year-old" groups (i.e., children between 60 and 72 months of age at the start of the academic year). In the classrooms followed in consecutive years, 83% of the children, on average, transited together from one year to the next. The overall sample consisted of 242 different children (122 girls and 120 boys). Classrooms ranged in size from 20 to 27 children, with the proportion of boys ranging between .40 and .68.

2.2. Social proximity observations

Using a focal individual sampling design, children were observed in a randomly determined order for a 15-s interval. At the end of the sampling interval, the child's nearest peer neighbor was identified. A peer who was within reach (if both children were to reach out, roughly 3–4 feet) and engaged in the same or a similar activity as the target child was considered the nearest neighbor of the target. When two or more children were exactly equally close to the focal child the peer to the child's immediate right was considered as nearest neighbor. For instances in which a child was interacting verbally or physically with a peer at the end of the 15-s interval, the interacting partner was considered as the nearest neighbor, even though another child might be physically closer. If no peer was present in these conditions the child was considered to be alone. Two observers made 200 observation rounds per classroom (100 rounds each; one round corresponds to observing every child present once). Social proximity rounds were interspersed with rounds of other observational data. Children absent from the classroom for 50% or more of the observational rounds were excluded from the analysis. Observational assessments for a given classroom took around three weeks to complete.

Research assistants received training (>80% agreement for the identity of the nearest neighbor) in the observation schedule prior to initiating classroom observations.

2.3. Social network measurement

Children were assigned rows in a dyadic matrix and observed frequencies of proximity with each peer as nearest neighbor were tabulated into columns. This produced an asymmetrical dyadic matrix. At the next step, the matrix was rotated on its major diagonal and added to itself, resulting in a symmetric dyadic co-occurrence matrix. The number of times two children were recorded as nearest neighbors was used as an indicator of the relationship strength. Dyadic co-occurrence data were filtered as follows:

$$Y_{ij} = 1 \text{ if} \frac{o_{ij}}{o_{i+}} > 2\frac{1}{N-1} \tag{1}$$

A tie from child i to child j (Y_{ij}) was treated as having weight 1 if the number of times i and j were nearest neighbors o_{ij} divided by the number of times i was observed with another child o_{i+} exceeded twice the proportion expected by chance (N equals the number of children in the classroom).

Filtering edges always involves some degree of arbitrariness and at the moment there is not a generally accepted approach for doing so. This procedure allows capturing relationships that are important for all children, regardless of their attendance to school. Edges filtered this away allow asymmetric ties, retaining only the stronger connections for each child.

2.4. Model specification

To assess the relevance of the different structural processes we fitted an ERGM, to each observed classroom network, that included the following structural parameters: reciprocity, alternating k-instar, alternating k-outstar, alternating k-triangle transitive and alternating k-two-path, controlling for effects based upon ego and alter sex, and sex homophily.

The alternating k-star parameters are intended to assist modeling the degree distribution (k-instar and k-outstar parameters for in-degree/popularity and out-degree/activity distributions respectively). A positive alternating k-star parameter indicates that the network has a skewed degree distribution, containing some higher degree nodes, whereas a negative parameter suggests that nodes with high degree are improbable (smaller degree variance). The alternating k-triangle transitive parameter measures the tendency to form transitive relations and the extent to which triangles themselves group together in the network. The precondition for triadic closure is the occurrence of two-paths (the sides of a triangle). Alternating k-two-path parameter helps modeling degree distribution. Ego and alter sex, and sex homophily effects, represent the effects of sex on children's propensity to form ties, receive ties, and choose similar others, respectively.

All models were fitted using the pnet software (Wang et al., 2006), conditioned on the number of ties (i.e., the number of ties were fixed during Monte Carlo estimation procedures). Fixing density is designed to diminish the risk of degeneracy problems (non-convergence of the parameters; see below), having minor effects on other parameter estimates (Robins et al., 2007b; Snijders et al., 2006). The weighting parameter λ of the three alternating k network statistics was set to 2. This value has been shown to work well in other investigations (Goodreau, 2007; Hunter, 2007; Hunter and Handcock, 2006; Lubbers and Snijders, 2007; Robins et al., 2007b, 2009; Snijders et al., 2006). The value of λ imposes a constraint on the influence of higher order k configurations. For example, a positive alternating k-triangle transitive parameter indicates an increased tendency for transitive triangle closure to happen alongside with higher number of shared partners. This increase, however, is not linear and, beyond a certain number of additional shared partners the chances of closure are only slightly increased (depending on the value of λ).

2.5. Model selection and goodness of fit

Parameters were estimated using Markov chain Monte Carlo methods (Snijders, 2002; Snijders et al., 2006). Parameters are said to have converged when the mean number of configurations in the sample of simulated graphs is similar to number of configurations in the observed graph:

$$t-\text{ratio} = \frac{(\text{observation} - \text{mean sample})}{\text{standard deviation}} \quad (2)$$

Good convergence is indicated by a t-ratio for all parameter estimates being less than (or close to) .1 in absolute value.

After parameters have been estimated from an observed network, we investigated how well the model parameters succeeded in replicating other features of the observed graph that were not explicitly modeled. There are a great number of these features on which to examine any model and no general rule for selecting such features. The network statistics compared included: standard deviations and skewness of both in-degree and out-degree distributions; correlation between the in-degree and out-degree distribution; and a set of eight global clustering coefficients (see Robins et al., 2009 for details). A t-ratio for these statistics less than 2 in absolute value is not regarded as bad fit, although preferably t-ratios should lie between −1 and 1 (Robins et al., 2007b, 2009).

Table 1
Descriptive statistics.

	3-year-olds	4-year-olds	5-year-olds
Classrooms	6	6	7
Avg. classroom size	23.67 (1.86)	23.83 (1.94)	24.29 (2.06)
% boys	.42 – .60	.40 – .68	.40 – .56
Avg. in/outdegree	1.72 – 3.67	2.48 – 3.75	2.72 – 4.07
Outdegree *SD*	.55 – 1.24	.89 – 1.24	.75 – 1.27
Indegree *SD*	1.14 – 2.16	1.43 – 1.74	1.12 – 2.27
Reciprocity index	.68 – .84	.63 – .84	.75 – .88
Transitivity index	.11 – .46	.16 – .38	.17 – .47
% same sex ties	.58 – .79	.69 – .86	.76 – .96

Note. Statistics represent between classrooms range. The transitivity index measures the proportion of alternating k-two-paths that have a base present to complete an alternating k-triangle transitive.

2.6. Meta-analysis

The ERGMs yielded a set of parameter estimates and standard errors for each of the 19 models. In order to summarize these independent estimates, we followed the multi-level approach to meta-analysis described in Lubbers (2003) and Lubbers and Snijders (2007), using MLwiN software (Rasbash et al., 2009).

Since a substantial proportion of children were observed in consecutive years, the 19 set of estimates are not independent. As such, average effect sizes are presented separately for the three age groups.

A t-ratio of the average parameter estimate tested whether the average effect size μ_η was zero:

$$t_{\mu_\eta} = \frac{\hat{\mu}_\eta^{WLS}}{SE(\hat{\mu}_\eta^{WLS})} \quad (3)$$

Both $\hat{\mu}_\eta^{WLS}$ and $SE(\hat{\mu}_\eta^{WLS})$ are produced by MLwiN. This statistic has approximately a standard normal distribution. Ratios exceeding 1.96 in absolute magnitude indicate a non-zero average effect size. To test whether between classrooms variance σ_η^2 was zero, we used the Q statistic described in Snijders and Baerveldt (2003).

3. Results

3.1. Descriptive statistics

After filtering co-occurrence matrices individual out-degree and in-degree ranged from 0 to 7 and 0 to 10 respectively. Table 1 presents a set of descriptive statistics for the preschool classrooms studied.

3.2. Summary of exponential random graphs model

ERGMs were estimated with the same network effects for all the 19 preschool networks. Models converged successfully with all t-ratios between −.1 and .1 ($M \pm SD$ = .04 ± .03, absolute values). Table 2 resumes the average effect sizes for each of the parameters.

The estimated average effect sizes indicate statistically significant effects for all parameters, excepting for some sex effects (alter sex for "3-" and "4-year-olds"). By far, the strongest effect observed was reciprocity. A high value for the reciprocity parameters (range: 4.54–4.61) was to be expected because almost 80% of the ties observed were mutual ties.

Significant positive values for alternating k-instar parameters (range: .81–1.10) indicate skewed in-degree distributions with some highly popular nodes, i.e., some children were clearly preferred than others as association partners. On the other end, significant negative values for alternating k-outstar parameters (range: −1.12 to −1.75) indicate less variance in outdegree than would be expected by chance.

Table 2
Meta-analysis of parameter estimates.

	"3-year-olds"			"4-year-olds"			"5-year-olds"		
	$\hat{\mu}_{WLS}$	*SE*	σ^2	$\hat{\mu}_{WLS}$	*SE*	σ^2	$\hat{\mu}_{WLS}$	*SE*	σ^2
Reciprocity	4.61**	.28	.00	4.59**	.33	.26	4.54**	.24	.00
Alternating k-instar	1.10**	.22	.02	1.12**	.20	.00	.81**	.20	.00
Alternating k-outstar	−1.75**	.09	2.82**	−1.12**	.48	.35	−1.70**	.60	.78*
Alternating k-triangle t	.30**	.08	.02*	.21**	.04	.00	.26**	.06	.01
Alternating k-two-path	−.51**	.10	.03	−.60**	.07	.01	−.34**	.06	.01
Ego sex (♂)	−.63**	.21	.00	−.54**	.21	.00	−.84**	.27	.04
Alter sex (♂)	−.27	.16	.00	−.13	.15	.01	−.59**	.19	.00
Sex similarity	.87**	.15	.00	1.21**	.17	.00	1.57**	.18	.00

Note: $\hat{\mu}_{WLS}$ – estimated average effect size; *SE* – standard error associated to estimated average effect size; σ^2 – estimated variance of the effect size between classes.
* $p < .05$.
** $p < .01$.

Positive alternating *k*-triangle transitive (range: .21–.30) and alternating *k*-two-path parameters (range: −.34–.60) can be interpreted together, suggesting a tendency for triadic closure. The positive *k*-triangle parameter tells us that children tend to spend time with the preferred choices of their partners. The negative alternating *k*-two-path indicates a tendency against non-closed paths (as expected by the significant positive *k*-triangle parameter). Positive values for alternating *k*-instar and alternating *k*-triangle transitive parameters indicate the existence of a core in the preschool networks, created by both popularity and triadic closure effects.

Significant sex similarity effects, reflecting a tendency for sex segregated ties, were found in all age groups (range: .89–1.57 respectively). Additionally, boys of all age groups formed fewer ties than girls (ego sex range: −.54 and −.84 respectively), and "5-year-old" boys, further tended to receive fewer ties than girls (alter sex: −.59).

The variance of network effects observed was small, excepting for the alternating *k*-outstar parameters, indicating some consistency of parameter values across classes within age groups. Due to the small number of classrooms analyzed for each age group it is not possible to make a more substantial analysis, testing for possible effects of group composition variables (e.g., classroom size, sex proportion) on the network structure of preschoolers.

A qualitative comparison of the average effect size of the different parameters between the three age groups seems to indicate an increasing tendency of sex similarity effects. None of the other parameters revealed a consistent trend.

Models had generally a good fit, reproducing well a set of features of the observed networks: standard deviations and skewness of both in-degree and out-degree distributions; correlation between the in-degree and out-degree distribution; and eight global clustering coefficients. Absolute values of *t*-ratios for these configurations were all below 1 in 10 classrooms. One classroom had one *t*-ratio higher than 2 (skew in-degree distribution), and the remaining had either one ($n = 5$) or two ($n = 4$) *t*-ratios ranging between 1 and 2 in magnitude.

4. Discussion

The purpose of this study was to examine the influence of different social processes on the creation of affiliative social structures within Portuguese preschool classrooms.

With affiliative relationships defined using frequency of associations in natural settings, results showed that affiliative ties between preschool children were sex segregated, highly reciprocal, more likely to be directed at popular children and with a tendency to create transitive triads. Structural effects were very similar between classes within age groups, excepting for activity (alternating *k*-outstar parameter).

An apparent increase of sex segregation with age agrees with the ubiquity of sex-segregated patterns of social interaction and its central role in the social organization of preschool peer groups, especially as children grow older (Martin et al., 2005). Appearing around three years of age sex segregation is probably the most noticeable feature of early peer relationships (Bohn-Gettler et al., 2010; Fabes et al., 2003; LaFreniere et al., 1984; Maccoby and Jacklin, 1987; Martin and Fabes, 2001; Martin et al., 2005; Pellegrini et al., 2007). Although the tendency to seek out same-sex partners can both reinforce and shape developmental sex type behavior, preschool children do not choose random playmates from the available same sex partners. Behavioral homophily has been shown to also influence selection – preschoolers tend to be attracted to peers whose behavioral tendencies are similar to their own (Hanish et al., 2005; Martin et al., 2005; Pellegrini et al., 2007). However behavioral homophiles are often sex typed, making it difficult to distinguish both processes (Fabes et al., 2004).

Our results are consistent with Schaefer et al.'s (2010) findings that the selective peer preferences are not only determined by individual characteristics, such as sex, but are also contingent on the pattern of existing relationships (i.e., structural effects). Reciprocity is a defining feature of social life (Molm, 2010) and very common phenomena in preschool networks (Schaefer et al., 2010; Snyder et al., 1996). The emergence of reciprocal relations involves minimal information-procession requirements given that individuals only need to return his/her partners' gestures, not needing to be aware of other relationships (Schaefer et al., 2010). Filtering edges from symmetric co-occurrence matrices, as was done in this study, might be boosting the effect of reciprocity. The logic behind the use of a symmetric matrix for this type of data (i.e., nearest neighbor) has to do with the fact that no information is collected of who is the initiator of the interaction that led to proximity, and so we consider *i* and *j* to be associated if either *i* is *j*'s nearest neighbor, or *j* is *i*'s nearest neighbor (although in some cases *i* can be the nearest neighbor of *j* but *j* is not necessarily the nearest neighbor of *i*). That is, although, two individuals might be seen together in a regular basis, it maybe that only one member of the dyad is responsible for all the proximity seeking. Though analyses for weighted networks have been developed in the last years (Barthélemy et al., 2005; Newman, 2004) the great majority of social network analyses require directed or undirected binary networks. This is a drawback, especially for those who infer social relationships from observational data. Filtering edges is always somehow arbitrary and information is lost along the way.

As stated on the initial sections of this paper, existence of higher (in-)degree nodes can be an emergent phenomenon of variation in individual characteristics that influence the probability of a child being selected as a partner, or it can reflect a more complex process of preferential attachment. Despite the differences, both processes make similar predictions for single network observations

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(existence of higher in-degree nodes) that cannot be distinguished using the ERGMs framework used here. In a longitudinal perspective, preferential attachment would continuously bias in-degree distributions, as some children would become more and more popular as time goes by. If what shapes relationships is the assessment of individual characteristics that make a child more or less preferred, then it is expected that the popularity effect maxes out after children had time to assess the "quality" of their peers. Schaefer et al.'s (2010) findings support the later process, with popularity effects peaking in importance in the middle of the school year and remaining constant thereafter. In reality the process might even be more dynamic than this since the "quality" of a child as partner may not be a fixed property, co-evolving alongside the creation of new relational ties.

The positive popularity and triadic closure effects found in our study indicate the presence of core-periphery structure in the networks, created by the conjunction of both effects. Previous applications of ERGMs pointed out that the formation of a core was often the result of, either, popularity or a triadic closure effect, seldom both (Robins et al., 2009). The combination of both effects may turn out to be not as unusual as previously thought (Robins et al., 2009).

Comparing the average effect sizes of popularity and transitivity across age groups did not reveal a consistent upwards trend, indicative of possible developmental processes or long term cascading effects. We suspect that unless Portuguese "three-year-olds" classrooms (where most children are unacquainted with each other) are sampled very early in the school-year, time related variations in structural effects will not be detected. Despite the cascading effects found by Schaefer et al. (2010), a closer look at their models reveals that the change in the popularity and transitivity parameters value, across three time periods in a school year, only slightly changes the odds of a tie being created (parameter estimates: popularity × period = .011, transitivity × period = .010).

In sum, this is the first application of ERGMs in the study of preschool children's social networks and its goal was to reveal the importance of different social processes that shape the emergence of preschool affiliative peer relations. We hope we have contributed to show the benefits of a stochastic modeling approach in order to complement the traditional descriptive analysis of preschool children social networks. Future studies should look for ways in which these processes influence preschool children social development.

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