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Why are some more peer than others? Evidence from a longitudinal study of social networks and individual academic performance

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ABSTRACT

Studies of peer effects in educational settings confront two main problems. The first is the presence of endogenous sorting which confounds the effects of social influence and social selection on individual attainment. The second is how to account for the local network dependencies through which peer effects influence individual behavior. We empirically address these problems using longitudinal data on academic performance, friendship, and advice seeking relations among students in a full-time graduate academic program. We specify stochastic agent-based models that permit estimation of the interdependent contribution of social selection and social influence to individual performance. We report evidence of peer effects. Students tend to assimilate the average performance of their friends and of their advisors. At the same time, students attaining similar levels of academic performance are more likely to develop friendship and advice ties. Together, these results imply that processes of social influence and social selection are sub-components of a more general a co-evolutionary process linking network structure and individual behavior. We discuss possible points of contact between our findings and current research in the economics and sociology of education.

1. Introduction

Peer influence exists whenever individual behavior is affected by social interactions which are not constrained by pre-assigned roles and social positions (Leifer, 1988). As such the sociological relevance of peer influence is very general. Deviant behavior, opinion formation, generation of research ideas, and the emergence of status hierarchies are all examples of processes for which peer influence is likely to play a central role (Marsden and Friedkin, 1993; Mark et al., 2009; Rawlings and McFarland, 2011; Vásquez, 2010). In this paper we focus on educational settings where the effects of peer influence are viewed as consequences of interactions between students, and where the behavioral outcome of interest is the level of individual academic achievement (Burke and Sass, 2008; Frank et al., 2008; Winston and Zimmerman, 2003).

The existence and possible implications of peer effects in educational settings have been objects of cross-disciplinary debate at least since the influential "Coleman Report" which was among the first studies to suggest that individual academic attainment could depend on the average attainment of school peers (Coleman et al., 1966). Building on this early work, more recent research routinely considers the quality of academic peers at least as important an element of the social context as the

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quality of school resources (Jackson, 2009; Robertson and Symons, 2003). As a consequence of these developments, interest in models of peer influence has been steadily increasing (e.g., Hanushek et al., 2003; Sacerdote, 2001; Wentzel and Caldwell, 1997; Winston and Zimmerman, 2003). Despite extensive research, however, no agreement is yet in sight either about the existence and importance of peer influence, or about the most appropriate way to ascertain its behavioral consequences. Disagreement seems to be organized around two main empirical problems that, while widely acknowledged, remain unresolved.

The first problem is endogenous sorting arising from the fact that: ‘‘When individuals choose their peer groups, high ability students may sort themselves into peer groups with other high ability students. With ability only partially observable, positive estimates of peer effects may result even when no peer effects are present because of a positive correlation between the student's unobserved ability and the observed ability of his peers'' (Arcidiacono et al., 2009, p. 2). If peer group membership and individual attainment are simultaneously determined, then the level of individual attainment may be both an outcome of peer influence, as well as a basis for the formation of network ties between peers (Manski, 1993). Azoulay et al. (2009) consider this situation as an outcome of partially deliberate matching, or individual association decisions based on a limited number of contextually meaningful dimensions. By introducing in the classroom differentiation based on evaluation and ranking, the level of individual academic attainment affects which students are more likely to become ''peers'' (Tuma and Hallinan, 1979). When this happens, a dynamic feedback process links the possible consequences of social networks (social influence) to their antecedents (social selection). Thus it seems that models of peer effects not only have to identify the distinct contributions of social influence and social selection on individual behavior, but also have to account for the emergence of social organization (Coleman, 1988). In this study we develop a longitudinal approach to this problem based on assumptions that are directly testable given appropriate data. While analysis of longitudinal data is not unusual in sociological studies of peer effects in schools and other contexts (Duncan et al., 1968; Kandel, 1978), in this paper we go beyond existing work by emphasizing: (i) the local dependencies that social networks entail; (ii) how such dependencies change over time and across social relational settings, and (iii) the co-evolution of social structure and individual behavior.

The second problem concerns how, exactly, ''peers'' are selected, i.e., the role of agency in *constructing* the social conduits through which peer influence flows. Much of the economic literature on peer effects in education attempts to deal with the problem of endogenous sorting by experimental or quasi-experimental random assignment of students to peer groups (such as, for example, classmates or roommates) while ignoring the self-selection of friends and other peers representing both the *sociologically relevant* referents, as well as *the subjectively meaningful* sources of social influence (Imberman et al., 2009; Sacerdote, 2001; Zimmerman, 2003). Randomization alleviates endogeneity problems by treating peer selection as a research design issue, rather than as a sociological problem that requires modeling. Perhaps not surprisingly, the definition of peer groups by analytic convenience rather than sociological relevance often leads to a failure to find reliable evidence of peer effects (Foster, 2006). This study differs from prior attempts in that we define peers as those considered contextually relevant by the focal student (like, e.g., Lubbers et al., 2006). While this is not the first study of peer effects on academic achievement based on the direct observation of connectedness between students (Babcock, 2008), we are not aware of studies that have (i) analyzed data on complete networks of interaction between students; (ii) specified how patterns of local dependence entailed by these networks affect processes of social selection, and (iii) examined how peer effects may be both the outcome of, and the input to network ties.

We analyze data that we collected on individual academic attainment and interpersonal friendship and advice relations within a cohort of 75 students enrolled in a full-time Master in Business Administration (MBA) program. The cohort represents a complete intake of students and we followed it over the first 12 months of the program dedicated to coursework. Observations were recorded at three distinct occasions according to a panel design. Because educational institutions are both testing grounds for individual attainment as well as agents of socialization (Parsons, 1959), they represent ideal settings for examining how social structure and individual behavior affect one another and co-evolve. The data analysis is based on a family of stochastic models for network dynamics expressing social influence among peers, while at the same time incorporating a wide variety of mechanisms of social selection underlying the endogenous sorting of students into peer groups (Snijders et al., 2010; Steglich et al., 2010).

2. Peer effects under partially deliberate matching

Studies in the sociology and economics of schooling tend to agree that academic attainment is systematically affected by the interaction of school-based, personal, and social resources (Coleman et al., 1982; Hastings et al., 2006; Lazear, 2001; Sørensen, 1970). According to Coleman (1988, p. S104): ''[A]n important form of social capital is the potential for information that inheres in social relations.'' Identification of the effects of social capital on the basis of observed social relations has remained elusive, however, in part because research on peer effects in educational settings spans different levels of analysis ranging from the community (Coleman and Hoffer, 1987; Levine and Painter, 2008), to the school (Angrist and Lang, 2004), the cohort (Carrell et al., 2009), and the classroom (Lavy et al., 2009). In this paper we follow the indications of recent research arguing that peer effects are best examined at the classroom level (Burke and Sass, 2008) and focus on the effects of classroom peers on individual performance, as measured by grades obtained.

Much research on peer effects treats classroom membership as a proxy for actual social relations between students instead of verifying the presence of such relations directly. For example, using the Texas Schools Microdata sample, Hoxby (2000) estimates that an exogenous change of 1 point in peers' (i.e., classroom average) reading scores raises a student's own score between 0.15 and 0.40 points. However, results based on average classroom performance do not tell the whole story about peer effects because evidence suggests that: "All peers, it would seem, are not equal" (Babcock, 2008, p. 2). To address this issue, more recent studies have recognized that social networks play a major role in explaining academic and other kinds of attainment, and have examined how more specific subsets of "peers" affect individual academic performance. For example, using a subsample from the National Longitudinal Survey of Adolescent Health survey, Babcock (2008) selects characteristics of the peer network (but not their individual achievement) to explain possible long-run educational outcomes. Babcock (2008) finds that *indegrees* (number of friendship nominations received, or "popularity") and *outdegrees* (number of friendship nominations given, or "activity") have positive effects on individual attainment, and that being part of a more connected grade cohort is associated with a higher probability of attending college 7 years later. Using the same data, Calvó-Armengol et al. (2009) estimate cross-sectional models in which observed peer effects on individual behavior are produced not only by friends, but by structures of friendship reconstructed in network terms.

Attempts to relate academic performance to structures of social interaction between students and network ties between specific individuals are useful because they recognize that: (i) the status of "peer" is actually the outcome of individual partner selection decisions (rather than a purely "structural" socio-demographic condition), and that (ii) social selection decisions are affected by complex local dependencies related to known tendencies of social relations to self-organize according to general principles such as, for example, reciprocity and transitivity (Davis and Leinhardt, 1972; Gouldner, 1960). The analytical difficulties with this view are inherent in the instrumental, partially deliberate character of network ties, i.e., in the fact that actors frequently form relations also in anticipation of specific future benefits (Jackson, 2008; Azoulay et al., 2009). This is particularly important in institutional settings structured by episodes of individual performance evaluation such as internal labor markets and education. In studies of educational attainment this view builds directly on Coleman (1990) according to whom students establish network ties, *inter alia*, to access relevant knowledge, resources, and information controlled by peers. Students who establish social ties with competent and helpful others are more likely to achieve higher levels of academic performance and extract additional benefits from their academic experience – thereby profiting from the "utility of friendship" (Frank et al., 2008, p. 1659).

If peer effects come from students learning from other students, then it stands to reason that it should matter greatly who these others might be, and how they are selected. But if network peers are selected partially on the basis of their instrumental value, then identity and quality of peers is endogenous to students' own academic achievement. As a consequence the formation and decay of network ties between students will be affected by status differentials based on social ranking induced by performance evaluation (Coleman, 1959; Tuma and Hallinan, 1979). Failure to account for partially deliberate matching of this sort will result in unreliable estimates of peer effects (Azoulay et al., 2009). To illustrate this point, note that the consequence of peer effects is that connected students tend to attain similar levels of academic performance. Suppose now that social selection on the basis of academic performance makes it more likely to observe connections between students who perform similarly. This might happen, for example, because students interpret grades as observable signals of otherwise hard to observe qualities such as ability, competence, and trustworthiness. To the extent that association is preferred with others possessing these qualities (Lynn et al., 2009), direct network ties will be more likely to be established between students with comparable levels of academic performance (Lazarsfeld and Merton, 1954; McPherson et al., 2001). But then mechanisms of social selection and social influence will produce observationally equivalent outcomes in cross-sectional samples: other conditions being equal, students connected by network ties attain similar levels of academic performance.

The preceding discussion suggests that an empirically testable model of peer effects has to provide safeguards against three major inferential threats. First, similarity between the performance of connected students may be both a consequence and an antecedent of their connectedness. As a result the model has to be able to distinguish the effects of peer influence on individual academic performance, and the potential effects of peer selection based on performance similarity. Second, to represent processes of social selection accurately, the model has to capture the local dependence structures in which individual network ties are embedded. Third, to avoid spurious results, the model has to control simultaneously for individual student characteristics that may affect their academic performance and their social selection decisions. In the next section we outline a recently developed family of stochastic actor-based models for the dynamics of networks and behavior specifically designed to address these concerns (Snijders et al., 2007, 2010; Steglich et al., 2010).

3. Representing and modeling change

According to Coleman (1988), social capital "[C]omes about through *changes in the relations* among persons that facilitate action [as] social capital exists in the *relations* among persons" (1988: S100–101. First emphasis added). How may this process of change be represented? Our strategy involves the specification of stochastic agent-based models expressing empirically observed changes in social relations and individual performance as time-aggregated outcomes of a series of individual decisions (Steglich et al., 2010).

Suppose that information is available on a binary directed network variable x and a discrete behavioral variable z, representing performance, observed for the same N actors at a sequence of discrete time points. Suppose, further, that change is

Table 1
The co-evolution of networks and behavior: component sub-processes.

	Network change	Behavior change
Actors' waiting times	Network rate function	Behavior rate function
Actors' choices	Network objective function	Behavior objective function

generated by two unobserved, interdependent processes taking place continuously between observation moments. The first is the process of change in network ties – the "selection process," which may be affected by individual performance. The second is the process of change in individual outcomes –"performance" in our case – which may be influenced by the quality of peers. Both processes act in parallel on the joint state space of network-behavior configurations. In this way, the selection process affects the opportunities and constraints under which the influence process operates, and vice versa. The total process of dynamic feedback between network and performance interpolates, in continuous time, the consecutive discrete observation moments. The reason for employing a continuous-time model even if the observations are made only at discrete moments is that this model allows a simple representation of the feedback processes that are inherent in network dynamics and in the mutual influence between network and individual behavior. This approach was pioneered by Coleman (1964) and proposed for modeling network dynamics by Holland and Leinhardt (1977). An additional advantage is that different time spacing between observations is possible.

In the model that we propose decisions are driven by actors' goals and constraints as expressed by *objective functions*, which are specified separately for social relations and for performance. In a utility-based approach, such as that followed by Frank et al. (2010) for modeling teacher behavior, the objective functions are derived directly from the actors' utilities, which would imply that they are the same, or at least closely related, for social relations and individual behavior. We do not make this assumption and associate different objective functions to different kinds of decisions. The theoretical view behind this strategy is based on the idea that decisions about change in social relations and decisions about effort/achievement are based on different frames (Lindenberg, 2001). The observed changes between observations are modelled as consequences of a series of small changes, interpretable as decisions myopically optimizing the objective functions plus a stochastic error term, as we now discuss.

The first observation serves as starting value of the dynamic feedback process. At random instants actors get opportunities to make small changes to either their own network neighborhood or their own performance. We call these small changes *microsteps*. A network microstep consists of the addition or deletion of one outgoing tie, i.e., one actor can select a new or deselect an existing network neighbor. A performance microstep consists of the increase or decrease in the performance score by one unit within the range of integer values for z. Both types of microstep are made with probabilities dependent on underlying *objective functions* denoted by f. The frequency of the opportunity to make changes (microsteps) is determined by stochastic waiting times with expected values determined by *rate functions* denoted by λ Table 1 summarizes the component elements of the general processes of change in network-behavior configurations.[1]

The rate functions represent the expected frequencies per unit of time with which actors get an opportunity to make network or behavioral microsteps. We assume that network and behavior rate functions each are period-wise constant, i.e., all actors have equal expected waiting times $1/\lambda^{\mathrm{beh}}$ until the next opportunity for change in their behavior, and equal expected waiting times $1/\lambda^{\mathrm{net}}$ until the next opportunity for change in their network neighborhood.[2] The objective functions determining the relative probabilities of moving to adjacent values of the network-behavior configuration have the following structure:

$$\text{Behavior objective function of actor } i: f_i^{beh}(x,z) = \sum_k \beta_k^{beh} s_{ik}^{beh}(x,z) \quad , \tag{1}$$

$$\text{Network objective function of actor } i: f_i^{net}(x,z) = \sum_k \beta_k^{net} s_{ik}^{net}(x,z) \quad . \tag{2}$$

The first equation is the behavioral performance equation and the second is the social selection equation. The s-terms, called *effects*, are statistics that may depend on the network x in the neighborhood of actor i as well as the distribution of performance z and other actor characteristics in this neighborhood. Both functions contain baseline parameters ('outdegree' for network evolution, and a linear and a quadratic 'shape' parameter for behavior evolution) to account for network density and basic distributional properties of the performance variable net of the other effects.

[1] Note that we do not assume that the network-behavior process is stationary, only that the transition distribution is stationary. Thus, an increasing or decreasing trend in the density of the network or in the average of the behavioral variable is fully compatible with our model assumptions.

[2] This is an assumption about the timing of the microsteps which are not individually observed. A very parsimonious model is reasonable and works well in this case. Diagnostic tests showed no significant deviations from this assumption in our data.

The model proceeds "as if" for any contemplated microstep the objective functions are evaluated for all possible configurations of network (x) and performance (z), as they could be after any permitted change, given current values of the network and the performance of all actors. The choice is made that maximizes the objective function for the result of this choice plus a stochastic error term having the extreme value (Gumbel) distribution. This is the myopic optimization model that underlies the multinomial logistic regression model (Maddala 1983; McFadden 1973), leading to probabilities (3) and (4) as given below.

The actors' decisions are based on a comparison of these evaluations across choice options. The probability for a performance ("behavior") microstep then is given as:

$$\Pr(z(i \updownarrow \delta)|x,z) = \frac{\exp(\sum_k \beta_k^{\text{beh}} s_{ik}^{\text{beh}}(x, z(i \updownarrow \delta)))}{\sum_{\phi=-1}^{1} \exp(\sum_k \beta_k^{\text{beh}} s_{ik}^{\text{beh}}(x, z(i \updownarrow \phi)))} \tag{3}$$

where $z(i \updownarrow \delta)$ denotes the performance configuration of all actors that would result from actor i changing his performance by adding $\delta \in \{-1, 0, +1\}$ to his performance score, and where the sum in the denominator is restricted to changes that do not take the resulting z_i value outside of the permitted range.

Likewise, if $x(i \rightarrow j)$ denotes the network that would be obtained if i changes his connections to j (creation of a new tie or termination of an existing tie, dependent on whether currently there is a tie) and $x(i \rightarrow i)$ denotes no change, then the probability for a network microstep is given as:

$$\Pr(x(i \rightarrow j)|x,z) = \frac{\exp(\sum_k \beta_k^{\text{net}} s_{ik}^{\text{net}}(x(i \rightarrow j), z))}{\sum_{l=1}^{N} \exp(\sum_k \beta_k^{\text{net}} s_{ik}^{\text{net}}(x(i \rightarrow \ell), z))} \tag{4}$$

The repeated nature of the microsteps expresses the feedback between network structure and individual performance outcomes, decomposing the potentially large differences between consecutive repeated observations as the cumulative result of many small, sequentially dependent, changes.

4. Research design, models and methods

4.1. Setting

We followed a cohort of 75 students enrolled in a full-time residential MBA program offered by an elite Italian university. The program attracts students oriented toward managerial careers in private and public companies, consulting and service firms, and in the financial industry. Students come from a variety of backgrounds and are selected into the program on the basis of past academic success and professional achievement. The program requires full-time attendance and consists of a set of 28 core courses followed by all students, each of 50 class hours. During the last four months of the program participants have to include in their curriculum four elective courses (each of 30 class-hours). Because of the heavy course schedule and workload, business schools provide learning as well as socialization environments in which individual achievement is mediated by a variety of social processes (Kilduff, 1990). Students spend a considerable amount of time together interacting intensively in and out of the classroom, and are encouraged to share knowledge and collaborate intensely on assignments and projects. Yet, students also strive individually for grades that are made publicly known and used by recruiters visiting campus to select candidates for job interviews. Our field experience reveals that students routinely share information on their academic performance, and discuss openly the results of exams. Our field experience also reveals that students are well aware of the contingent value of social relations that professional management education affords. Consistent with classic insight on the role of social networks in the labor market (Granovetter, 1974), MBA students are aware of the opportunity provided by attending business schools to build a portfolio of social connections that may be mobilized in the future as their business careers unfold. As a result, we would expect processes of social influence and social selection to be particularly transparent in this empirical setting.

The cohort is a meaningful social unit because students enrolled in the program were not subdivided into different classes or streams, nor were they assigned to permanent teams. The course grades obtained by students represent meaningful measures of individual achievement because team-based assignments may be required in specific courses, but evaluation of learning is based exclusively on individual performance in course examinations. The data set analyzed is the result of a three-wave network-panel design. The overall observation period covers the entire duration of the MBA program dedicated to coursework. The program starts in November. Observation points are roughly equally spaced (March, July, and November) and correspond to exam periods. After the last examination round the classroom period ends. A 5-month in-company project concludes the program.

4.2. Variables and measures

We collected information on a variety of individual attributes to control for socio-demographic differences. As reported in Table 2, students in the largest subgroup have a background in economics and business (approximately 50%). Other academic backgrounds include engineering (14%), humanities (13%), political sciences (11%), law (8%) and natural sciences

Table 2
Attribute variables: descriptive statistics (standard deviations in parentheses) ($N = 75$ subjects).

Variables	Sample statistic	Observed range	Units of measure
Business administration background	50%	1–6	Category
Percentage of foreign students (non-Italian)	13%	1–2	Indicator
Proportion of males	62%	1–2	Indicator
Average age	29.0533 (3.2085)	24–40	Years
Work experience	19.3 (27.8)	0–168	Months
GPA (ability)	105.507 (4.7116)	93–111	Units
Time elapsed since graduation	21.9 (23.3)	1–105	Months
Behavioral dependent variable = performance (test score)	26.043 (1.5935)	20–30	Units

(4%). The proportion of foreign (non-Italian) students is approximately 13%. Female students account for 38% of the total enrollment. Students in MBA programs are slightly older than students in other master programs (the average age is 29 years), and have typically been exposed to relevant professional experiences (52% in our sample). Information on the college graduation score (GPA) obtained from official transcripts is also used to control for individual differences in academic ability. In Italian universities final college graduation scores range from 60 (minimum passing grade) to 110.[3] We also measured the time since graduation (in months) to control for possible time-dependent changes in academic ability.

While privacy laws prevented access to information on social background, our field experience suggests that *variations* in social background may be somewhat less important in this group for explaining the behavioral outcome of interest. This is due to a combination of three contingent factors. The first is self-selection into professional management degrees which tend to attract students with fairly well defined orientations and objectives. Informal discussion with the students revealed common values and similar career ambitions. The second factor is due to age: students in MBA programs tend to be older and more experienced than students in more conventional academic master programs. Autonomy from their family of origin is correspondingly higher. Third, selection into the program is based exclusively on academic achievement. The fee – which is considerable – is not differentiated on the basis of family or individual income. Together, these three factors make our study group more homogeneous than samples typically used to study peer effects in schools. The advantage of this design is to reduce the potentially very large set of confounding factors related to differences in individual academic history and in social, cultural and economic background. In a fundamental sense this design feature of our study makes the notion of "peers" particularly meaningful to describe the subjects in our sample who are tied by friendship or advice relations. Clearly, this analytical advantage has costs. Perhaps the main cost is that the non-random nature of the sample limits the generalizability of the empirical results we report.

The fundamental actor-specific dependent variable is academic performance measured by average grades associated with individual courses. Grades are individual and observed in three distinct examination occasions. The maximum grade is thirty and eighteen is the lowest passing grade. To complete the program students are required to complete a total of 32 exams, each having an oral and a written component. The final grade in an exam is the average of the two components. Each exam period consists of 10–12 exams. Our performance measure is the average grade obtained by students in each exam period, rounded to the closest integer. We received this information directly from the MBA program office. Average overall performance in the first period was 26.1 (s.d. = 1.9, range 22–30), in the second period 26.1 (s.d. = 1.7, range 20–29), and in the third 25.9 (s.d. = 1.7, range 21–30). The distribution of performance is reported in Fig. 1. As one would expect individual grades are correlated over time (the average correlation is 0.72).

Information on social networks was collected through questionnaires administered personally and individually to each student on three distinct occasions. The questionnaires were administered approximately one week before each exam session. We obtained a 100% response rate in each of the three waves, thanks to maintaining a very friendly and productive working relationship with the students throughout the observation period. There was no attrition: no student dropped out from the program, possibly due to a combination of high student quality and the considerable upfront investment that students sustain to join the program.

Building on prior research on social networks in organizations, we consider two distinct relational contents: friendship and program-related advice (Cross et al., 2001; Kilduff, 1992). To collect relational information we relied on the so called "roster method" (Kilduff and Krackhardt, 2008). Each respondent ('ego') was presented with a complete list of names and asked to report the presence of the specified relation with other class members. For friendship we asked respondents to indicate the names of classmates ('alters') with whom they felt they had developed meaningful social ties outside the specific context of the program. The questionnaire specified examples of joint social activities that might be considered as signals of friendship such as going to the movies, having dinner, playing football or going shopping. For advice relations, we asked respondents to indicate the names of other students whom they recurrently consulted for help and support on course-related tasks. The questionnaire included examples of concrete activities which may signal the presence of advice relations such as asking for class notes, borrowing books, calling for help to solve difficult homework problems, and discussing course material. The questions were framed in a non-judgmental manner. Respondents were reassured that there were no right or wrong answers, and that their privacy would be protected. In the first panel we also verified the existence of friendship ties

[3] Table 2 reports a maximum score of 111 (instead of 110) reflecting the "*Summa cum laude*" mention. We registered 16 such cases.

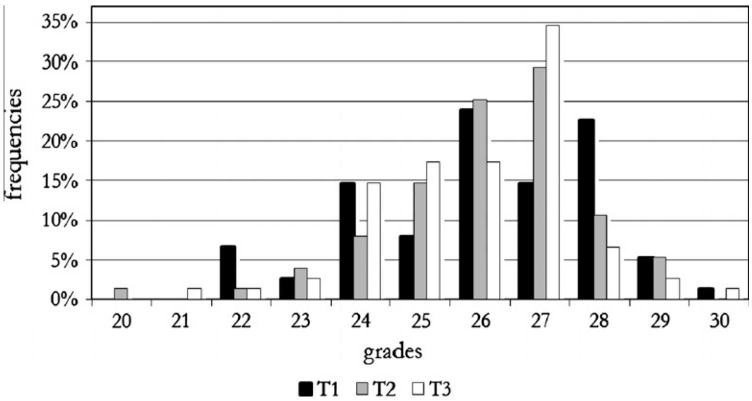


Fig. 1. Distribution of individual performance in three consecutive measurement occasions (30 is maximum possible grade; 18 is the minimum passing grade).

existing before the beginning of the program, but none were reported. The questions about friendship and advice ties were asked identically in each of the three data collection occasions. At each observation point the network questionnaires generated two square adjacency matrices of size 75. In each matrix the generic cell x_{ijkt} is equal to 1 if row actor i indicated the presence of relation k with column actor j at time t, otherwise $x_{ijkt} = 0$. In relational observation schemes the number of observations in each network is typically considered equal to the number of pairs of actors, i.e., $75 \times 74 = 5550$. Hence the analysis of each network is based on 16,650 (5550×3) non-independent observations. Table 3 reports the main descriptive statistics of the two networks. While the average degree does not change much over time, the presence of friendship and advice ties exhibits considerable fluctuation. Stability of networks over time between consecutive observations as measured by Jaccard coefficients ranges between 0.47 and 0.55 for the friendship network and between 0.38 and 0.44 for advice (see Snijders et al., 2010). Friendship and advice ties overlap somewhat: the density of the intersection between advice and friendship ties is approximately 3% (0.028). Because the density of the advice network is approximately 5% (0.055), almost 50% of advisors are also friends.

4.3. Model specification

The results reported in the next section are based on models specified to address directly our questions about the joint effect of social influence and social selection. The inclusion of control covariates is guided by extant empirical research on the effect of peers on academic performance. We adopt the general guidelines to the specification of stochastic agent-based models suggested by Snijders et al. (2010).

Eq. (1) models performance outcomes. We distinguish between endogenous mechanisms, and effects of exogenous covariates on performance change. Endogenous mechanisms are of two kinds, corresponding to the two co-dependent variables 'performance' and 'network.' The baseline for performance dynamics is expressed by the so-called shape parameters which control for the main distributional features of individual performance (Snijders et al., 2010). The linear shape parameter plays the role of an intercept, i.e., it models the average performance to which students tend over time, net of other effects. The quadratic shape parameter models under-dispersion (regression to the mean, when the parameter is negative – converging to unimodal distributions) or over-dispersion (polarization, when the parameter is positive – converging to distributions that are skewed toward either extreme values, or bimodal). Because performance follows a relatively stable, unimodal distribution (see Fig. 1), regression to the mean (a negative quadratic shape parameter) is expected, which would mean that, net of other effects, high performers tend to perform lower and low performers tend to perform higher, over time. Steglich et al. (2010) provide additional discussion about the motivation and interpretation of the linear and quadratic shape parameters.

Next, there are network-based endogenous mechanisms of performance change, which include the tendency towards similarity of an actor's performance to the average performance of his network neighbors (which we call "performance

Table 3
Descriptive network statistics ($N = 5550$ dyads $\times$ $T = 3$ periods).

Network statistics	Definition	Friendship T1	Friendship T2	Friendship T3	Advice T1	Advice T2	Advice T3
Average degree (s.d. in/out)	Average number of edges incident with nodes	9.9 (9.5/6.2)	9.2 (9.3/5.5)	8.3 (6.8/5.3)	4.1 (2.5/5.6)	4.9 (3.1/5.5)	4.5 (3.2/5.7)
Reciprocity	Proportion of reciprocated ties	0.58	0.54	0.57	0.29	0.33	0.33
Clustering	Average density of the open neighborhood around each node	0.44	0.40	0.38	0.24	0.24	0.26

assimilation''), as well as the effects on performance of individual popularity (in-degree) and activity (out-degree). For performance assimilation, we expect a positive effect in both networks, i.e., we expect the average performance of an actor's friends and advisors to attract the actor's own performance. We do not formulate specific expectations regarding effects of ''activity'' and ''popularity'' as it seems unclear *a priori* whether the sheer number of friends and advisors indicates strategic choices, or a lack of focus in the study. Exogenous factors affecting behavioral change include the main effects of gender, ability, age, work experience, nationality and time since graduation. For ability and work experience, we expect positive effects on performance, while for age and time since graduation, we expect negative signs. While we do not model multiplexity, we use each network as an exogenous (dyadic) covariate in models for the other. The upper part of Table 4 illustrates the various types of performance change mechanisms, with qualitative interpretation provided in the context of advice relations. For each effect, the exact definition of the corresponding statistic, and a graphical representation of the change between successive time points are also reported.

Eq. (2) models processes of partner selection as a function of a variety of possible social mechanisms. As before, we distinguish between: (i) endogenous network-based (''structural'') mechanisms; (ii) endogenous performance-based mechanisms (which are the main theoretical interest in our analysis), and (iii) effects related to exogenous individual attributes (as reported in Table 2). The lower part of Table 4 illustrates the various types of network change mechanisms incorporated in our model specifications.

The importance of network-based endogenous mechanisms is recurrently documented in educational as well as other social settings (Burk et al., 2007; Lubbers et al., 2006; Moody, 2001; Robins and Pattison, 2005; van de Bunt et al., 1999). These mechanisms entail statistical dependencies among individuals and among network ties which must be taken into account in any attempt to model processes of social selection. While the exact kind of dependence between network ties that characterizes a social system is ultimately an empirical question, the tendency toward triadic closure (''friends of my friends are my friends:'' $i \rightarrow k$ and $k \rightarrow j$ typically implies $i \rightarrow j$) is generally considered a distinctive feature of social networks (Davis and Leinhardt, 1972). In our models this mechanism is captured by the transitive triplet effects, which is expected to be positive. We included the betweenness effect to control for brokerage tendencies, i.e., the exploitation of non-connectedness of two actors by a go-between ($k \rightarrow i$ and *not* $k \rightarrow j$ implies $i \rightarrow j$) (Burt, 1992). A negative sign of the corresponding parameter would provide additional evidence of network closure because it suggests that non-transitively embedded ties are actually avoided.

The tendency toward mutuality ($j \rightarrow i$ implies $i \rightarrow j$) is another fundamental characteristic of social systems (Gouldner, 1960). It is captured by the ''reciprocity'' parameter, for which a positive sign is expected. The ''outdegree'' parameter is included to capture the latent overall tendency to create network ties. Because both networks are rather sparse a negative sign is expected, which on a logistic scale stands for an empirically realistic density below 50%. Other endogenous mechanisms are tendencies toward global centralization (''preferential attachment'': $k \rightarrow j$ implies $i \rightarrow j$), and local hierarchization in triads ($i \rightarrow k$ and $k \rightarrow j$ jointly imply *not* $j \rightarrow i$). For these mechanisms, the effects of indegree-popularity (expected sign: positive) and 3-cycles (expected sign: negative), respectively, are included. Because advice seeking is a more instrumental relation, it is expected that all students agree more on who advisors are than on who friends are. The global centralization effect therefore is expected to play a stronger role for advice than for friendship. The latter, in turn, is expected to show more hierarchical structuring in small groups, which – unlike for advice seeking – may be incompatible across small groups. Finally, we capture the empirical tendency of friendship and advice ties to co-occur by controlling for advice ties in models for friendship ties and vice versa. We expect the estimates of the corresponding parameters to be positive.

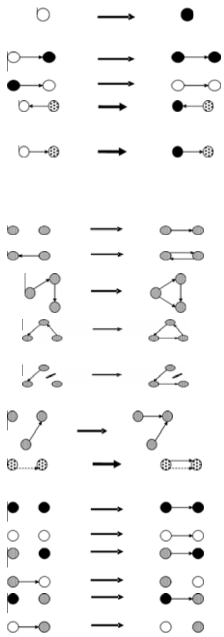
The endogenous performance-based mechanisms of peer selection, as well as the mechanisms based on exogenous variables can be assigned to three basic categories: (i) effects of characteristics of the sender of a relational variable on tie change ('ego' effects), (ii) effects of characteristics of the receiver of the relational variable ('alter' effects), and (iii) effects involving characteristics of both the sender and the receiver ('same' or 'similarity' effects). It is expected that in the instrumental advice network, high performance will attract advice seekers (positive performance alter effect) while reducing own advice seeking (negative performance ego effect). In the more affective friendship network, high performance reduces attractiveness as well as activity (negative ego and alter effects) because high performers focus on work and (e.g., for time budget reasons) may be less engaged in/available to affective relations. For both networks, we expect a positive effect of performance similarity, yet for different reasons. High performers are unlikely to learn much from low performers so they are more likely to select other high performers as advisors. Low performers have more restricted options and are therefore forced to be less selective. As a result we expect a net effect of homophily in advice seeking. For friendship, a high discrepancy in performance introduces status asymmetries that do not correspond to the ideal of friendship, which also implies a performance homophily effect. We consider the effects of gender, ability, age, academic background, work experience, nationality, and time since graduation as mere exogenous control factors.

From the above discussion, it follows that the effects utilizing the *similarity function* are crucial to the modeling of performance-related selection and influence processes. This is formally defined as $sim_{ij} = 1 - |z_i - z_j|/\text{range}(z)$ and standardizes the absolute difference of two actors' performance scores to the unit interval, such that a value of one implies identical performance (because $z_i - z_j = 0$), while a value of zero implies maximally different performance, the actors being at opposite ends of the scale.

To summarize: by including statistics depending on the current network as predictors in the sub-model for behavioral change, and current characteristics of actors' performance as predictors in the sub-model for network change, the interdependence of network structure and individual performance is directly represented and can be tested. The three influence effects estimated below capture the tendency of own performance to become similar to network neighbors' performance

Table 4
Network effects included in the objective functions. Interpretation of the effects is exemplified in the context of advice relations.

Parameter	Network statistics	Interpretation (advice)	Qualitative implications
Social influence mechanisms leading to change in individual performance between consecutive time points (t) → (t + 1)			
Linear and Quadratic Shape	z_i and z_i^2	Representation of shape of the distribution of performance scores in the long run	
Average similarity effect (influence)	$\sum_j x_{ij} sim_{ij} / \sum_j x_{ij}$	Actors tend to assimilate their performance to the average performance of their advisors	
Indegree	$z_i \sum_h x_{hi}$	Actors who receive many advice requests tend to show higher performance.	
Outdegree	$z_i \sum_h x_{ih}$	Actors who send many advice requests tend to show higher performance.	
Social selection mechanisms leading to the formation of network ties between consecutive time points (t) → (t + 1)			
Outdegree effect	$\sum_j x_{ij}$	If negative, actors tend not to seek advice from just anyone	
Reciprocity effect	$\sum_j x_{ij} x_{ji}$	Actors tend to reciprocate advice relations	
Transitive triplets effect	$\sum_{jk} x_{ij} x_{jk} x_{ik}$	Actors tend to seek advice from those others from whom their current advisors also seek advice.	
3-cycles effect	$\sum_{jk} x_{ij} x_{jk} x_{ki}$	If negative, advice is hierarchical: actors do not seek advice in cyclical patterns.	
Betweenness effect	$\sum_{jk} x_{ij} x_{ki} (1 - x_{kj})$	Brokerage: actors seek non-redundant positions between suppliers and seekers of advice.	
Indegree – popularity of alter	$\sum_j x_{ij} \sum_h x_{hj}$	Actors tend to seek advice from those who are often asked for advice by others.	
Effect of exogenous network (e.g., friendship)	$\sum_j x_{ij} w_{ij}$	Actors tend to seek advice from their friends or people they talk to in general	
Attribute similarity effect (homophily) (e.g. Performance)	$\sum_j x_{ij} \text{sim}_{ij}$	Actors tend to seek advice from similar others (e.g., those who have similar performance)	
Attribute alter (e.g. performance)	$\sum_j x_{ij} z_j$	If positive, actors seek advice from others with high performance	
Attribute ego (e.g. performance)	$\sum_j x_{ij} z_i$	If negative, actors with high performance seek less advice from others	



Actor attributes do not matter.
Actor attribute is high.
Actor attribute is low.
Tie in predictor network.
Tie in dependent network.

(*average similarity*), and the main effects of *indegree* (popularity) and *outdegree* (activity) on performance. The three selection effects estimated below are associated with selecting others who have similar performance (*performance similarity*), and main effects of sender's and receiver's performance (*performance ego* and *performance alter*). Parameter estimates are obtained *via* Markov chain Monte Carlo methods as explained in (Snijders et al., 2007) and implemented in the *RSiena* software program (Ripley and Snijders, 2010). Overall tests for influence and selection are calculated as score-type tests as explained in Snijders et al. (2007).

5. Results

We start by presenting a qualitative interpretation of the estimates. Then we narrow the focus of the analysis and provide a *post hoc* numerical interpretation of the parameters of major theoretical interest. Table 5a reports the estimates of parameters in Eq. (1) specifying individual performance as a function of individual attributes and academic performance of network associates (or "peers"). Parameters are unstandardized, therefore the estimates for different parameters are not directly comparable. For each network (friendship and advice) we estimated two models for the network-performance co-evolution. The first model (restricted) contains the effects of theoretical interest and controls for structural (i.e., network-based endogenous) network change mechanisms only. The second model (full) is more comprehensive and incorporates a number of exogenous factors that may affect individual performance.

In Table 5a the estimated rate parameters describe the average number of changes (the 'microsteps') in students' performance between measurement points. Estimates reveal that opportunities for change peak in the first period and decline in the second, suggesting a tendency of students' performance to stabilize. Results for average similarity suggest systematic evidence of peer effects: the academic performance of an individual student tends to become similar to (or "assimilate") the performance of his or her peers (or to *remain* similar). Interestingly, the effect is about equally strong for the friendship and the advice network, although the standard errors are somewhat smaller for the former. The effects of activity (*outdegrees*) are positive, but not statistically significant. The effects of popularity (*indegrees*) are positive and, in the advice network, weakly significant, which suggests that being asked for advice might itself act as an incentive to perform well.

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Table 5a
Determinants of individual performance (standard errors in parentheses).

Effects	Friendship (restricted)	Friendship (full)	Advice (restricted)	Advice (full)
Rate period 1	3.976 (0.837)	4.003 (0.871)	4.123 (0.900)	4.127 (1.018)
Rate period 2	2.709 (0.547)	2.764 (0.582)	2.647 (0.632)	2.685 (0.583)
Linear shape	−0.198 (0.162)	−0.224 (0.164)	−0.685* (0.293)	−0.679* (0.307)
Quadratic shape	0.028 (0.048)	0.025 (0.053)	−0.035 (0.039)	−0.037 (0.048)
Average similarity	10.642*** (3.427)	10.876*** (3.802)	10.077* (4.491)	9.841* (4.778)
Indegree (popularity)	0.008 (0.017)	0.015 (0.018)	0.044* (0.022)	0.044* (0.021)
Outdegree (activity)	0.007 (0.011)	0.004 (0.011)	0.015 (0.033)	0.019 (0.034)
Gender	–	0.084 (0.158)	–	0.015 (0.165)
Ability	–	0.024 (0.017)	–	0.009 (0.016)
Age	–	−0.024 (0.035)	–	−0.009 (0.037)
Work experience	–	0.002 (0.005)	–	−0.001 (0.005)
Nationality	–	0.059 (0.264)	–	0.115 (0.288)
Time since graduation	–	0.001 (0.004)	–	0.002 (0.004)

Popularity in the friendship network does not affect performance: being well adjusted to the social setting of the program – in the specific sense of being popular in the friendship network – apparently does not imply higher levels of individual achievement. Control variables (e.g., ability, age, work experience, nationality) do not have significant effects. The difference in the estimated linear shape parameter between the analyses considering friends (no effect) and advisors (negative effect) suggests that advisors tend to systematically pull towards the upward direction (requiring a negative linear shape effect to counterbalance), while friends seem not to have such a systematic directional effect: this result is elaborated in the discussion of Tables 6a and 6b. The non-significant estimates of the quadratic shape parameter suggest that the influence of peers sufficiently explains the observed fluctuation in performance, and that there are no residual tendencies towards regression

Table 5b
Determinants of network ties (Standard errors in parentheses).

Effects	Friendship (restricted)	Friendship (full)	Advice (restricted)	Advice (FULL)
Rate Period 1	13.192 (1.352)	13.388 (1.150)	9.212 (0.888)	9.202 (0.881)
Rate Period 2	8.556 (0.689)	8.667 (0.653)	6.423 (0.537)	6.474 (0.586)
Endogenous network effects				
Outdegree (density)	−1.319*** (0.263)	−1.721*** (0.236)	−2.473*** (0.125)	−3.301*** (0.196)
Reciprocity	1.358*** (0.103)	1.330*** (0.109)	1.065*** (0.127)	0.996*** (0.133)
Transitive triplets	0.213*** (0.016)	0.212*** (0.015)	0.261*** (0.031)	0.249*** (0.030)
3-cycles	−0.114** (0.036)	−0.113** (0.034)	−0.030 (0.066)	−0.018 (0.064)
Betweenness	−0.146** (0.050)	−0.137** (0.041)	−0.035* (0.019)	−0.044** (0.018)
Indegree – Popularity	−0.010* (0.005)	−0.021* (0.009)	0.019*** (0.003)	0.258*** (0.051)
Exogenous network effects				
Friendship	–	–	0.972***(0.091)	0.945*** (0.091)
Advice	0.941*** (0.119)	0.914*** (0.116)	–	–
Control covariates effects				
Gender (M) alter	–	0.111 (0.081)	–	−0.069 (0.096)
Gender (M) ego	–	−0.095 (0.086)	–	−0.239** (0.094)
Same Gender (M)	–	0.187** (0.072)	–	0.094 (0.088)
Ability similarity	–	−0.029 (0.159)	–	0.249 (0.175)
Age alter	–	0.015 (0.016)	–	−0.024 (0.018)
Age ego	–	0.021 (0.019)	–	−0.011 (0.019)
Age similarity	–	0.566* (0.273)	–	0.113 (0.299)
Same academic background	–	0.096 (0.080)	–	0.262** (0.079)
Work experience alter	–	0.001 (0.003)	–	0.002 (0.003)
Work experience ego	–	0.001 (0.003)	–	0.001 (0.003)
Work experience similarity	–	0.647 (0.418)	–	−0.249 (0.468)
Same nationality	–	0.271** (0.098)	–	0.444*** (0.122)
Time since graduation alter	–	−0.005* (0.003)	–	0.002 (0.003)
Time since graduation ego	–	−0.001 (0.003)	–	0.004* (0.002)
Time since graduation similarity	–	−0.128 (0.262)	–	0.303 (0.286)
Performance feedback effects				
Performance alter	–	−0.142*** (0.032)	–	0.156** (0.055)
Performance ego	–	−0.146*** (0.037)	–	−0.090* (0.055)
Performance similarity	–	2.567*** (0.550)	–	1.424* (0.657)

* $p < 0.1$.
** $p < 0.01$.
* $p < 0.05$.
*** $p < 0.001$ (two-sided).

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Table 6a
Influence of friends on log odds of achievement increase compared to achievement decrease, if all friends have the same achievement (achievement low, medium, high = 23, 26, 29; full model).

		Alter		
		Low	Medium	High
Ego	Low	−0.41	1.77	1.77
	Medium	−2.28	−0.11	2.07
	High	−1.98	−1.98	0.19

Table 6b
Influence of advisors on log odds of achievement increase compared to achievement decrease, if all advisors have the same achievement (achievement low, medium, high = 23, 26, 29; full model).

		Alter		
		Low	Medium	High
Ego	Low	−0.34	1.63	1.63
	Medium	−2.75	−0.78	1.18
	High	−3.20	−3.20	−1.23

to the mean. We also tested whether influence operates with different strength in the upward direction ("relations with high performing peers improve individual exam scores") and in the downward direction ("relations with low performing peers depress individual exam scores"). This difference was not significant ($p = .39$ for friends; $p = .19$ for advisors).

Table 5b reports the estimates of parameters in Eq. (2) specifying processes of social selection driving change in network ties over time. In both networks the estimated rate parameters are larger in the first period than in the second, suggesting that networks of friendship and advice tend to become more stable over time. In both networks there is evidence of performance homophily: students attaining similar levels of academic performance are significantly more likely to select similar others as friends and advisors. We find interesting differences across networks in the social selection implications of attainment. High performing students are generally less connected in the friendship network, i.e., initiate fewer friendship ties and are less popular as friends. High performers are sought after as advisors, but they tend not to ask for advice to low performing peers – a result that may be interpreted as an outcome of deference and status ordering. We elaborate on this issue further in our discussion of Tables 6c and 6d.

The estimated effects of the control factors and structural network effects reported in Table 5b are generally consistent with intuition and prior research. The negative outdegree effect suggests that students avoid creating network ties that are not embedded in more complex local configurations. Especially in the friendship network there is a tendency against brokerage, as indicated by the negative estimate of the betweenness parameter. The friendship network is characterized by tendencies toward local hierarchical ordering as suggested by the positive transitivity and negative 3-cycles parameters. In the advice network, the positive effects of performance alter and indegree-popularity suggest a hierarchically organized choice process based partly on academic performance and partly a self-reinforcing tendency. The opposite process holds in the friendship network: the indegree-popularity effect is negative, reflecting that friendship indegrees have a self-stabilizing tendency, i.e., they tend to

Table 6c
Total performance effects on log odds of friendship selection (achievement low, medium, high = 23, 26, 29; full model).

		Alter		
		Low	Medium	High
Ego	Low	1.39	0.19	−1.01
	Medium	0.18	0.52	−0.67
	High	−1.03	−0.69	−0.34

Table 6d
Total performance effects on log odds of advisor selection (achievement low, medium, high = 23, 26, 29; full model).

		Alter		
		Low	Medium	High
Ego	Low	0.08	0.12	0.16
	Medium	−0.62	0.28	0.32
	High	−1.31	−0.42	0.48

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regress toward the mean. We discuss the estimates of control variables reported in Table 5b only briefly and through illustrative examples. The main pattern is homophily, but differentiated with respect to the relation under consideration. The formation of friendship ties is facilitated by similarity in age. The formation of advice ties is facilitated by similarity in academic background. Friendship and advice relations are more likely to be established between students of similar nationality. Males have a lower tendency to ask for advice, and work experience makes students more likely to be chosen as advisors. Friendship and advice affect one another positively: friends tend to become and/or remain advisors, and vice versa.

Tables 6a and 6b present the log-odds of increasing performance compared to decreasing performance in a micro-step for performance, as a function of the median performance of friends (Table 6a) and advisors (Table 6b). Using the notation in (1), this is given by $f^{beh}(x, z+1) - f^{beh}(x, z-1)$, as dependent on the median behavior of the alters. For the other variables the mean values are used. In Appendix A we report the detailed calculations behind the tables.

Table 6a shows that having friends with a median performance identical to one's own leads to a small downward drift at lower performance levels and a very small upward drift for high levels. Friends with performance higher than oneself provide an upward pull, friends with lower performance a downward pull. The pull is slightly stronger for individuals whose performance is in the middle range. For advisors (Table 6b) the picture is similar, except that in the case of advisors with a median performance identical to one's own there is a downward pull, becoming stronger at high levels of performance. This should be seen in the light of the fact that students prefer having high-performing advisors. This is particularly the case for high achievers.

The three effects of performance (performance ego, alter, and similarity) reported in Table 5b are combined in Tables 6c and 6d which provide summary information on the overall contribution of performance (i.e., the sum of the performance alter, performance ego, and performance similarity effects) to the objective function determining the formation of network ties. Again, values of 23, 26, and 29 are used to represent low, medium, and high performance, respectively.

The numbers in the cells represent the contribution of the performance of two individuals (*ego* and *alter*) to the log-probabilities with which, *ceteris paribus*, a student (*ego*) would select a specific other (*alter*) as a network partner. In the friendship network, there is a tendency towards homophily. Furthermore, low performing students tend to make more choices, and are chosen more as friends, than high performing students. Homophily is stronger for low performing students than for high performing students. A different picture emerges in the advice network. Here, high achievers have a strong preference for choosing high over low performing advisors. The performance of students' friends, averaged over all students, is 26.1 – hardly different from the overall performance average of 26.0 – whereas the corresponding estimate for advisors is 27.1. Low performers hardly discriminate between high- and low-performing advisors. It is possible, therefore, that the inability of low performing students to discriminate between high and low quality advisors contributes to their own low performance. The matching process leading to advice relations should also be taken into account. We cannot rule out the possibility that low performing students do have strong preferences for high performing advisors, but the latter are not willing to advise them. Anticipating the expected rejection, low performers effectively choose to get advice from anybody who is willing to provide it. This is in line with the interpretation of the objective function not as preferences but as short-term joint results of preferences and constraints.

The existence of feedback linking social selection and social influence processes is at the heart of our analyses. While the estimates reported in Tables 5a and 5b already show significant evidence for effects in both causal directions, Table 7 provides more complete evidence for the co-existence of both feedback already revealed by the more conservative score test procedure (Snijders et al., 2007, 2010). This procedure tests whether a baseline model shows a significant lack of fit when compared to a tested alternative model that includes more effects.

With respect to selection we tested whether there was such an additional effect of performance (similarity, ego, and/or alter) on partner selection compared to a baseline model controlling for effects of partner selection on performance. If significant, the score test would indicate the presence of feedback from performance on network formation not included in the baseline model. With respect to influence we tested whether there was an additional effect of network position (in-degree and out-degree) and/or assimilation to network neighbors (average similarity) compared to a second baseline model controlling for effects of performance on partner selection. Here, a significant test result would indicate a feedback from the network on performance not included in the baseline model. Tests reported are a joint test for the three selection effects and another joint test for the three influence effects. The significant results reported in Table 7 provide evidence of feedback in both directions. Individual academic performance shapes social selection processes by affecting the formation of network ties. At the same time, individual academic performance is shaped by social influence flowing through the network ties that it contributed to create.

Table 7
Summary tables of score tests for feedback between influence and selection.

	Influence		Selection	
	Chi-squared (*d.f.* = 3)	*p*	Chi-squared (*d.f.* = 3)	*P*
Test I friendship and performance	13.24	<0.01	67.38	<0.001
Test II advice and performance	8.75	<0.033	12.63	<0.006

6. Discussion and conclusions

A major line of contemporary sociological research builds on a theoretical framework which "[A]ccepts the principle of [...] purposive action and attempts to show how that principle, in conjunction with particular social contexts, can account not only for the action of individuals [...] but also for the development of social organization" (Coleman, 1988, p. S96). In this paper we have contributed to the refinement of this framework by providing a model linking the "action of individuals" to specific aspects of their "social organization." We have tested the model in the specific empirical context of academic achievement where individual action takes the form of simultaneous attempts at modifying individual behavior and changing the network structure of the social organization that students build.

We found clear evidence of peer effects. Students tend to "assimilate" the average performance of their friends and their advisors. At the same time, students attaining similar levels of academic performance are more likely to form friendship and advice ties. Our analysis also sustains more specific conclusions and reveals subtle differences in how social influence and social selection processes operate. For example, we found that processes of social influence operate similarly and with similar strength for friendship and advice networks. Processes of social selection, however, operate differently across networks: high performing students are less prone to initiating friendship and advice relations, are less likely to be chosen as friends by others, but are sought after as advisors.

This result resonates with earlier studies viewing social relations between students as the result, at least in part, of attempts to access contextually relevant information and knowledge resources (Coleman, 1990). We also found that low-performing students have a much higher tendency to choose other low-performing students as friends – a tendency which, over time, may amplify initial performance differences possibly caused by differences in individual ability. The effects of individual attributes on processes of social influence and social selection also vary. None of the individual attributes we measured seems to be significantly associated with individual performance. But specific attributes (like, for example, gender) do affect social selection processes through homophily (Lazarsfeld and Merton, 1954). One possible interpretation of our results, therefore, is that the effects of individual differences and similarities on performance are mobilized by – and act through social networks.

We think that the results reported also have more general theoretical implications as they clearly illustrate the analytical and sociological value of considering explicitly the role played by social networks in determining peer effects. Consider, for example, contemporary research on the economics and sociology of schooling that emphasizes the role of identity in academic attainment and social capital acquisition (Akerlof and Kranton, 2002). This line of research posits an implicit connection between social networks and individual achievement determined by the two main objectives that students are assumed to pursue: to be successful and to "fit in." Building on earlier work (Coleman, 1961) this literature argues that social identity categories (such as "nerd," "jock," and "burnout") are systematically associated to detectable differences in individual attitudes, self-perceptions, and educational achievement (Akerlof and Kranton, 2002). Yet, the system of social interactions that ultimately makes such categories sociologically meaningful, and out of which boundaries around identities emerge, crystallize or change, plays no theoretical or analytical role in this explanation. Studies of social networks, on the other hand, link individual identities directly to social networks because "Each identity has its own field of ties which differ from any other identity's in what tie goes to which others" (White, 1992, p. 116). While in this paper we have barely scratched the surface of this debate, we believe that understanding peers as subjectively relevant contacts has the potential to enrich the exchange between economic and sociological views on educational attainment. Developing explicit models for the endogenous dynamics of social selection along the lines suggested in this paper will help unravel the sources of tension between these two alternative ways of thinking about the role played by identity in individual achievement, and behavior more generally.

To reduce the risk of over-interpretation it is useful to reflect on the causal standing of our results. We have suggested one plausible account for how social influence and social selection processes mutually shape one another in educational settings. By including in our models variables representing alternative explanations for peer selection and academic achievement, we were able to rule out some, but obviously not all, alternative explanations. We cannot rule out that unobservable individual factors are correlated with what we have identified as the effects of social influence – a problem that is rather general and not unique to our models. We think that to make progress along this line, future studies should heed Goldthorpe's (2001) suggestions to move from association to causation by developing generative models for the underlying social processes involving interdependent dynamics of peer selection and individual achievement. Better models for these processes in an educational context are obviously needed. As proposed by Cox (1992) it will be necessary to construct such models for processes that operate at deeper levels such as, for example, motivation and individual attainment strategies.

In closing it is perhaps appropriate to mention four main limitations of our study which also reveal clear possibilities for further research. First, we have not attempted to identify the exact proportion of individual performance that is due to the influence of peer effects, and that is due to social selection of peers of similar ability. Methods for identifying and quantifying effects of influence and selection on individual behavior are complicated exactly because of the feedback processes that we have documented, and are the object of on-going research (Steglich et al., 2010). Second, following recent trends in the study of peer effects in educational contexts, we have provided within-classroom evidence of social influence. However, processes between peers tend to give rise to multilevel problems as network ties may connect distant settings by spanning classrooms, cohorts, schools, and social neighborhoods. As the potential range of social networks increases, the boundaries around relevant social units become fuzzier and more permeable. For this reason, we suspect that future studies carried out in less

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constrained social settings will benefit from considering larger social networks and weaker social ties. Third, we collected information on friendship and advice relations between students. Our field experience and prior work on social networks gave us sufficient confidence about the contextual significance of these relations (Cross et al., 2001; Krackhardt and Porter, 1985). However, other relations between students may also have been relevant to explain variations in individual educational outcomes. Considering additional relations will also allow the study of multiplex influence effects, i.e., non-additive results of being connected by several types of tie. Finally, we acknowledge that the educational setting studied here presents a number of idiosyncrasies which limit the scope of our results. Yet, characterizing the co-evolutionary dynamics of social structures and individual behavior remains a problem of general sociological relevance that transcends the empirical boundaries of our study. We believe that at the current stage of development the subtleties and nuances of social influence and social selection processes are such that carefully documented case studies conducted in specific settings such as the one we presented may stimulate progress toward more general results.

Appendix A. Computing the contributions to objective functions

Based on the full model estimates reported in Table 5a, we computed the figures included in Tables 6a and 6b by including only the terms corresponding to linear and quadratic tendencies, average similarity, and outdegree. We held constant all the remaining terms which depend only on the attributes of the actors. Because the attribute variables are centered on the overall mean, dropping them from the equation is equivalent to filling in the average value. The four remaining terms are defined as follows: β_1–β_4 are the parameters, z is performance minus its mean (26.04), z_{alt} is the median value of centered performance of the network partners. The similarity measure $\text{sim}(z, z_{\text{alt}})$ is defined as $\text{sim}(z, z_{\text{alt}}) = \text{sim}_0(z, z_{\text{alt}}) - b$, where $\text{sim}_0(z, z_{\text{alt}}) = (1 - |z - z_{\text{alt}}|/10)$ is a similarity coefficient ranging from 0 to 1, the division being by 10 because performance has range 10 (from 20 to 30), and b is the mean between all pairs of actors (i, j), of the values $\text{sim}_0(z_i, z_j)$. Using these definitions, the relevant part of the objective function for performance change is:

$$f^{beh}(z) = \beta_1 z + \beta_2 z^2 + \beta_3 \text{sim}(z, z_{\text{alt}}) + \beta_4 x_{i+} z \tag{A1}$$

For the outdegree x_{i+} we use the average value, 9.1 for friendship and 4.5 for advice. Mean performance used for centering is 26.04, mean similarity is $b = 0.80$, and the parameter values β_1–β_4 are as in Table 4.

The log-odds for going up versus going down are computed as

$$f^{beh}(z+1) - f^{beh}(z-1) \tag{A2}$$

Based on the full model estimates reported in Table 5b, we computed the figures reported in Tables 6c and 6d by considering only the terms directly related to performance. Denoting ego by i and alter by j, the sum of the alter, ego, and similarity effects is given by

$$\beta_1 z_j + \beta_2 z_i + \beta_3 \text{sim}(z_i, z_j) \tag{A3}$$

where the similarity coefficient is defined as above, and z_i and z_j are the centered performance values of ego and alter.

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