Integration in emerging social networks explains academic failure and success

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Edited by H. Russell Bernard, University of Florida, Gainesville, FL, and approved November 16, 2018 (received for review July 2, 2018)

Academic success of students has been explained with a variety of individual and socioeconomic factors. Social networks that informally emerge within student communities can have an additional effect on their achievement. However, this effect of social ties is difficult to measure and quantify, because social networks are multidimensional and dynamically evolving within the educational context. We repeatedly surveyed a cohort of 226 engineering undergraduates between their first day at university and a crucial examination at the end of the academic year. We investigate how social networks emerge between previously unacquainted students and how integration in these networks explains academic success. Our study measures multiple important dimensions of social ties between students: their positive interactions, friendships, and studying relations. By using statistical models for dynamic network data, we are able to investigate the processes of social network formation in the cohort. We find that friendship ties informally evolve into studying relationships over the academic year. This process is crucial, as studying together with others, in turn, has a strong impact on students’ success at the examination. The results are robust to individual differences in socioeconomic background factors and to various indirect measures of cognitive abilities, such as prior academic achievement and being perceived as smart by other students. The findings underline the importance of understanding social network dynamics in educational settings. They call for the creation of university environments promoting the development of positive relationships in pursuit of academic success.

Social networks are dynamic and complex systems; therefore, their impact on academic achievement is difficult to study. We argue that it is not sufficient to assess students’ integration in social networks in critical periods (e.g., when they prepare for a crucial examination), but it is equally important to understand how those networks evolved in the months and years before. The social networks between students in this study were basically nonexistent before their first university day, as 81% of them had just moved from other cities or countries. By the end of the first year, however, 549 friendship ties emerged, and 61% of the participating students reported that one of their best friends in life was among their fellow students.

To capture the dynamic nature of social networks, we conducted multiple surveys throughout the academic year, measuring three dimensions of student relationships: positive interaction, friendship, and studying together. We further collected self-reported measures of socioeconomic background (sex, age, first language, parental education, and support ties outside the university), abilities and motivation [high-school grade point average (GPA), study motivation, and time spent on studying], psychological well-being (stress, depression, and anxiety), and different types of peer perceptions (being perceived as smart) and behaviors (having a side job and free-time activities). Our study builds upon prior educational research in different scientific fields that looked into the relationship between social integration and academic performance. Prior work, for example, investigated the role of aggregated peer effects (14, 15).

Significance

Understanding the factors that explain academic failure and success of university students is a core interest of educational researchers, teachers, and managers. We demonstrate how the dynamic social networks that informally evolve between students can affect their academic performance. We closely followed the emergence of multiple social networks within a cohort of 226 undergraduate university students. They were strangers to each other on their first day at university, but developed densely knit social networks through time. We show that functional studying relationships tended to evolve from informal friendship relations. In a critical examination period after one year, these networks proved to be crucial: Socially isolated students had significantly lower examination grades and were more likely to drop out of university.

Author contributions: C.S., A.V., T.E., Zs.B., and I.J.R. designed research, performed research, analyzed data, and wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1811388115/-/DCSupplemental.

Published online December 24, 2018.
social influence and selection processes in friendship and advice networks (16–20), and the link between digitally measured interaction networks and academic performance (21).

However, existing studies appear to have at least one of the following limitations: (i) They do not consider multiple dimensions of social relations, especially friendship and collaboration; (ii) they do not explain the emergence of social integration; and (iii) they are not able to identify social integration effects due to confounding individual factors (e.g., being perceived as smart, skills, and motivation). With unique data and methods, we are able to overcome these limitations in a single study.

The dataset we collected combines three social network dimensions collected five times throughout the year (n = 226 students; n = 9,266 observed ties), with a variety of individual and socioeconomic background variables. The empirical setting is exceptional: We were able to follow the emergence of these social networks within a cohort of students who were mostly strangers to each other on day one, but developed meaningful and densely knit social networks during the academic year. We can link these emerging social networks to individual GPA scores in a career-determining examination 11 months after they first met.

Our analysis is performed in two steps. First, stochastic actor-oriented models (22) are applied to investigate the evolution of the social networks of students. Second, the association between students’ social integration and their examination GPA is studied by using linear (network) regression models. We find that studying relations develop informally from prior friendship relations, and these emerging ties have a decisive impact on academic performance—they can mean the difference between success and failure.

The Emergence of Networks

The emergence of the three types of social networks (positive interactions, friendships, and studying together) is illustrated in Fig. 1 and in an animation (SI Appendix, section 2.1.2). The three social networks are structurally overlapping and coevolve. Friendship and studying ties are almost completely embedded in the network of positive interactions, as shown by the Venn diagram (23) in Fig. 1 (96% and 98% overlap). Furthermore, 81% of studying ties exist between friends. This indicates that academic cooperation develops partly within the social context set by the positive interaction and friendship networks.

Exploiting the longitudinal nature of our data, we investigate how the two sparser networks—friendship and studying—coevolved in the second half of the year (between December 2016 and May 2017; Fig. 1 B and C) after the initial network growth phase. In particular, we test whether studying relations develop from earlier friendship ties and vice versa.

We apply stochastic actor-oriented network models (SAOMs) to explain changes through time in the friendship and studying networks (22). We test whether the evolution of the two networks is coupled on the level of network ties, while controlling for a large number of dynamic network processes (22, 24). SI Appendix, section 2.2 provides detailed results and robustness checks using exponential random graph models for cross-sectional network data (25). [The two models differ in parameter interpretation (26), but both suggest a strong tie-level association between the networks.]

Results of the SAOM main effects are presented as log-odds ratios in Fig. 2. We find that students are most likely to start studying with someone they already consider a friend. Effect 1 in the figure suggests that friends are 16 times ($e^{2.7}$) more likely than nonfriends to become study partners. Effect 2; the borderline-significant effect is also positive but smaller than the first (studying partners are four times more likely to become friends; $e^{1.4}$). Effects 3 and 4 indicate that students who are already friends and study partners are 27–33 times more likely ($e^{3.3}$ and $e^{3.5}$) to maintain these relations through time than individuals who only have either of those relations.

We thus find strong evidence that studying ties emerge from friendships and that multiplex interpersonal relations are more stable than one-dimensional relationships (i.e., just being friends or study partners). But do the emerging social network ties matter for academic success?

Social Networks Explain Success

After 11 months, 163 students who enrolled in the study program (72%) took the final examination. A total of 108 students (66% of those who tried, 48% in total) reached the minimum passing score of 4.0. The grades ranged from 1.93 to 5.96 (on a scale from

![Fig. 1. The emergence of social networks between students. Data collected in the first study week (September 2016) (A), after 3 months (December 2016) (B), and after 8 months (May 2017) (C) are shown. The final measurement took place two-and-a-half months before the examination period in August 2017. Light blue ties represent positive interactions (the most common relationship), dark blue ties friendships, and red ties studying relationships. Node colors indicate passing (green), failing (yellow), and not attempting the final examination (white). The Venn diagram in C shows the relative number of ties and the overlap between them at the third time point. (n = 183; 43 students were omitted from these plots by criteria described in SI Appendix, section 2.1.)](image-url)
Fig. 2. The coevolution of friendship and studying ties. Estimates and 95% confidence intervals of key parameters in a stochastic actor-oriented model are shown. Additional controls include network processes (e.g., reciprocity, transitivity, and popularity) and mechanisms that relate to individual variables (e.g., perceived cleverness, homophily, and high-school GPA). Full results are provided in SI Appendix, section 2.2.1; in SI Appendix, Table S8, effects 43a, 39a, 43b, and 39b correspond to estimates 1–4, respectively.

1 to 6, with 6 being the best grade) with a mean of 4.26 (SD = 0.96). The level of social integration differs descriptively between those who passed the examination and those who failed. Successful students were on average named by 7.5 others as positive interaction partners (compared with 5.1 for those who failed), by 3.8 others as friends (compared with 2.6), and by 1.5 others as a study partner (compared with 0.6). These differences in social integration are statistically significant (SI Appendix, section 2.1.1) and visually apparent in Fig. 3, where the social networks of the final measurement are shown for successful and unsuccessful students separately. Successful and unsuccessful students are found in all regions of the network: Some are in its center, and some are not connected to anyone. Overall, however, successful students have a higher number of incoming ties in each network and are more likely to be named as a study partner by someone else.

We explore the success factors of the 163 students who took the examination in three linear regression models. (Nonparticipation is not necessarily a sign of academic failure. Some students, for example, decided to enroll in a different study program during the first year.) As controls, we include a number of demographic and socioeconomic background variables (age, gender, first language, high-school GPA, and parental education) and changing variables collected at two or three time points over the year (stress, time spent on studying, and motivation). To capture omitted aspects of cognitive abilities that are not reflected by high-school GPA, we additionally control for being perceived as smart by at least one other student. This variable also serves another important purpose. Being smart (as measured by peer perceptions) can potentially explain both individuals’ academic performance and the probability of being nominated as a friend or a study partner. By controlling for this potential confounder in the regression model, we can be more confident about the direct effect of social integration on academic performance. To assess social network integration, we evaluate which students are mentioned by others at least once in the survey as an interaction partner, a friend, or a study partner. These peer measures constitute one of the strengths of our detailed social network study—classic educational panel studies can only measure self-assessed social integration, but not the perceptions of others within the cohort. We can show (SI Appendix, section 3.3.2) that self-perceived integration measures are correlated with academic success, but are not significant predictors in the linear models and have worse explanatory power.

Fig. 4 presents the results of the three linear models. Detailed results and various robustness checks are reported in SI Appendix, section 3. The first model on data collected in the first study week explains 45% of the variance in the dependent variable ($R^2$) and has a predictive accuracy of 75% for passing the examination (predicted GPA $\geq 4.0$, 10-fold cross-validation). Prior academic achievement (high-school GPA) is an important explanatory variable. The estimate is close to 1 (0.96), which is remarkable given that both GPA variables are measured on the same scale from 1 to 6. SI Appendix, section 3.3.4, highlights that high-school GPA is associated with a number of socioeconomic status variables. Social integration at this early stage is not associated with examination GPA 11 months later. In the second model on data collected after 3 months, the fit is increased by 13 percentage points ($R^2 = 0.58$); the predictive accuracy is...
### Table 1: Individual and social network factors explaining success

| Factor                                | Expl. Variance | Expl. Var. (1-8) | Expl. Var. (1-5) | Pred. Accuracy |
|---------------------------------------|---------------|-----------------|-----------------|---------------|
| Age (1)                               | 0.45          | 0.64            | 0.44            | 0.75          |
| Female (2)                            | 0.58          | 0.55            | 0.51            | 0.75          |
| German first language (3)             | 0.43          | 0.55            | 0.44            | 0.75          |
| High-school GPA (4)                   | 0.51          | 0.55            | 0.43            | 0.75          |
| Education parents (5)                 | 0.45          | 0.55            | 0.44            | 0.75          |
| Stress (6)                            |               |                 |                 |               |
| Study time (7)                        |               |                 |                 |               |
| Motivation (8)                        |               |                 |                 |               |
| Perceived as clever (9)               |               |                 |                 |               |
| Pleasant interaction (10)             |               |                 |                 |               |
| Friend nomination (11)                |               |                 |                 |               |
| Studying nomination (12)              |               |                 |                 |               |

### Fig. 4. Individual and social network factors explaining success

The increased model fit thus most likely results from explaining test scores in regions that are not just above and below the passing threshold. Students’ stress level and whether they are perceived as clever by their peers now have an additional effect; social integration does not. However, bivariate correlations of social integration with GPA are positive and significant at this time as shown in *SI Appendix, section 1.4.4*. In the third model data collected after 8 months (two and a half months before the examination), the model fit is increased by another 6 percentage points ($R^2 = 0.64$). The predictive accuracy is increased by 6 percentage points to 81%. Above the earlier factors, time spent on studying has a significant effect, as well as social integration. Being named as a study partner is associated with a GPA increase of 0.45 points, which is a pronounced effect relative to the range of the explained GPA variable (from 1 to 6; the passing threshold is 4). The potential importance of this parameter is highlighted by the fact that 10 students who were studying by themselves were <0.45 points below the passing threshold of 4.0, and 15 students who studied with others were <0.45 points above it (in total, this is >15% of the cohort). The additional social integration effects for friendship and positive interaction are not significant. However, studying ties and friendships are tightly linked over time, and many study relations evolve from friendship ties. On a bivariate level, friendship integration is indeed strongly correlated with GPA, as shown in *SI Appendix, section 1.4.4*.

To take into account that observations in the sample are not independent, but could be dependent through processes of homophily (27)—for example, high-achieving individuals choosing each other as study partners—or social influence (28)—individuals becoming more similar to their study partners—we additionally fit network autocorrelation models (29) and autologistic actor attribute models (25) that are specified akin to the third model in Fig. 4. The positive effect of studying with others is found to be robust across these network analyses that control for observational dependence. We further show the robustness of these findings when taking into account a variety of additional individual factors. The robustness checks are detailed in *SI Appendix, section 3.3*. We conclude that social integration within the student cohort is strongly associated with academic success and that this association is not merely explained by the fact that students who are perceived as clever are more likely to be nominated as friends or study partners.

### Falling Through the Network

The findings in this paper provide important insights into how social network processes within educational contexts affect individuals’ academic success. They indicate that integration in social networks is a critical success factor in academic settings and contradict arguments that friendships at school and college are potentially disruptive for academic development (30). While it may appear to be more important for high achievement to have study partners rather than friends, it is in fact friendship that explains the emergence of collaboration ties through time. Some students may fail in their academic career not due to individual abilities and dispositions, but because they do not benefit from the web of positive social relations: They fall through the network.

Taking a dynamic social network perspective is key to understanding the complex evolution of social structures in educational settings and their relation to individual and socioeconomic factors. Our results highlight that even seemingly noninstrumental social relations like positive interaction and friendship can be beneficial, as they naturally evolve into collaboration ties. Those are shown to have a crucial impact on individual academic success.

An important consideration in empirical social science research is the difficulty of establishing causal links. Indeed, it is possible that social integration is explained by being a good student and that causality is thus reversed. Are good students just more popular? We applied a rarely used network measure to control for this possible explanatory link, by asking participants who they believe is particularly clever among their fellow students. We include this variable both in the dynamic network...
model and the regression models and conclude that the findings about dynamic network formation and academic success are not just explained by being perceived as smart. The fact that cleverness perceptions do matter importantly in both analyses indicates the value of this peer measure. Our analyses did not focus on the number of nominations that someone received (their sociometric popularity), but tested whether they are named at least by one other person. Thereby, differences in popularity are disregarded as long as students are not isolated in the networks.

Future research will have to explore the associations between individual characteristics, positive social ties, studying together, and success in different settings to help generalize these findings. State-of-the-art network methods and data-collection techniques as applied here are essential tools in this endeavor (11, 12). Experimental research designs that promote social integration and collaboration can aim for establishing causal links and developing the ground for future intervention strategies. Follow-up studies could further evaluate the interactions between the success factors that we identified in the linear models and explore more complex network effects that relate, for example, to an individuals’ level of embeddedness in groups (31).

While some are able to excel in their academic career on their own, most students perform better when they work together. Educational interventions therefore often focus on enforcing teamwork and social interaction within groups (32). However, we find that studying relations also emerge informally from positive social network ties and, in particular, that friendship is an important precursor of student collaboration. Another type of intervention can thus aim at creating spaces and places for students to get to know each other, to develop positive relationships and group identities. The creation of such environments can enable the emergence of densely knit social networks that could prevent some students from failing in their academic career and help many others to achieve their full potential.

Materials and Methods

Data Collection. The presented analyses are based on a social network panel survey conducted in a first-year cohort (N = 236) of a competitive Swiss university in the academic year of 2016–2017. The survey aimed at understanding the impact of social integration of students on study motivation, mental health, and academic performance. Members of the cohort were admitted to their study program without an entrance examination, which is a characteristic of the Swiss higher education system (there are limited numbers of places for foreign students). However, to proceed to the second year of their program, students had to pass a complex examination at the end of their first year. In the 3 years preceding the study, on average only 54% of students passed this examination on the first try. The rest either had to wait a year and try again or drop out from the program.

The data were collected by various methods. Most of the data were gathered through online surveys using the Qualtrics software. Six detailed questionnaires (1 h each) were distributed over the academic year: the first in the first week of the semester (September), the second 1 month later (October), the third further 2 months later (December), the fourth early in the spring semester (March), the fifth at the end of the second semester (June), and, finally, the sixth right after the first-year examination (August).

Information on sample size and participation rate is provided in SI Appendix.

The six surveys contained questions related to various dimensions of social relations, such as friendship, dislike, romantic ties, perceptions about attributes and behaviors of others, social roles, and joint social activities (e.g., studying together and spending free time together). The networks were measured by using a name generator with limited nominations, maximum 5 or 20 choices depending on the item, validated on a cohort-level roster (SI Appendix). Additionally, we collected data on relationships outside of the cohort (e.g., friends, family, and partners) and their perceived importance to participants.

Survey data were also gathered on individual variables, including socioeconomic background (e.g., country of origin, Swiss region of origin, language, and parents’ education and occupation), behavior (e.g., studying, free-time activities, and substance use), personality traits (e.g., Big Five and self-monitoring), other psychological measures (e.g., affect, depression, anxiety, and motivation scales), and attitudes and opinions (e.g., political opinions and gender role perceptions). A more detailed description of the analyzed network and individual variables can be found in SI Appendix, section 1.4.

Research Ethics. The study was reviewed and approved by the institutional ethics committee of ETH Zürich (approval 2016-N-27). Informed consent was obtained from participants. See SI Appendix, section 1.2 for details on the implemented consent and ethics policies.

Data Availability. The anonymized dataset and materials for replication are available from the authors. Further descriptive information of the data can be found in SI Appendix, section 1.

Social Network Analysis. In each survey wave, participants were asked about (i) their positive interactions, (ii) their friendships, (iii) with whom they study together, and (iv) who they think is clever or smart in the cohort. See SI Appendix, section 1.4.1 for more details about wording, translations, and other measurement aspects.

The four network items are used as measures of different social concepts. We use positive interactions and friendships to capture students’ level of integration in the web of informal social relations in the cohort over the academic year. Studying ties represent social relations with a more specific function. They are intuitively closely related to a set of academic variables, including achievement. Finally, clever perceptions are primarily used as indirect measures for cognitive abilities, assuming that being perceived as clever correlates with these abilities.

We apply SAOMs (22, 33, 34) to analyze the joint evolution of the friendship and studying networks in the student cohort. SAOMs are multivariate regression models originally developed for studying the processes that drive the (unobserved) evolution of a network between two or more observed time points. SAOMs can be understood as agent-based simulation models which are calibrated based on observations of real-world networks.

In SAOMs, network change is assumed to be driven by actors and their series of (conscious or subconscious) decisions to create, maintain, or delete ties to other actors. In this approach, changes in an actor’s ties are dependent on a set of exogenous (i.e., covariate-related) and endogenous (i.e., network structure-related) aspects of the “network neighborhood” of the actor (33). The network neighborhood of an actor can be expressed flexibly in the model by specifying various explanatory variables, so-called effects. Examples for simple effects on network change are the number of ties sent, ties received, reciprocated ties, closed triangles, or same-gender ties in which the actor is embedded.

The model estimates an effect parameter vector by simulating hypothetical chains of actor decisions starting from the first observed state of the network and comparing the networks resulting from the accumulated changes to the following observed state (i.e., the next measurement). All periods between two observed network states are modeled jointly when estimating the effect parameters. Each parameter expresses the weight of a given effect statistic on the hypothetical decisions of actors to change their network ties. For example, a positive parameter for the reciprocity effect can be understood as a tendency for actors to create and maintain ties to others from whom they receive a tie. Practically, the estimated parameters can be interpreted as log-odds ratios in standard binary logit models (for additional details, see ref. 22).

Estimation methods for SAOMs were implemented in the R package RSiena (33). In the present analysis, we used an extension of SAOMs that estimates parameters related to the coevolution of multiple networks (22, 35, 36), allowing for processes operating between the networks (e.g., friends becoming study partners or vice versa). The SAOM results presented in this work are based on network data collected in the second half of the year in which we found the networks to be relatively stable in terms of density (the number of ties present). The first network, for example, is a lot more sparse, so we found it unreasonable to assume that initial network growth processes operate similarly to network change processes later. For the SAOMs, we used three waves of network data, presented earlier as waves 3, 4, and 5 (collected in December, March, and May). Further details and supplementary network analyses are presented in SI Appendix, section 2.

GPA Analysis. In the linear regressions presented in Fig. 4, we accounted for network effects on GPA that are related to the incoming ties students have in the measured networks—that is, whether they received any nominations from other students. The predictive accuracy of the linear regression
models was assessed in an out-of-sample prediction in terms of passing the examination (GPA ≥ 4.0), using a 10-fold cross-validation. However, our results may be unreliable if heterogeneity in the error terms arises due to forms of network dependence in GPA observations. For instance, the achievement of friends may be similar due to network mechanisms such as homophilous selection and social influence. To address the validity of our findings regarding network effects, we further estimated network autocorrelation models (29). With these models, it is possible to control for various forms of interdependence between students’ GPA in a linear regression framework. Network autocorrelation models estimate parameters for different weighted aggregates of the outcome variables (autocorrelation structures, such as the average GPA of friends). These models replicate the results of the linear regressions, and so the more widely known method is presented in the main text for simplicity. Results from the network autocorrelation models, as well as from alternative operationalizations of network effects and further robustness checks (e.g., using alternative model specifications or additional individual and socioeconomic background variables) are shown in SI Appendix, section 3. There, we also present results from autologistic actor attribute models (ALAAMs) that predict the binary passing/failing outcome of students while estimating a network autocorrelation term (25).

ACKNOWLEDGMENTS. We thank Tom Snijders, Dirk Helbing, Thomas Grund, James Hollway, Aniko Hannák, Brooks Paige, Per Block, Ulrik Brandes, and the members of the Social Networks Lab at ETH Zurich for helpful comments and suggestions that considerably improved this work; the university management, department officials, Stefan Wehrl, Marion Hoffmann, Kieran Mephem, Julia von Feilgen, Afke Schouten, Charlotte Corrodi, and many others for supporting the data collection; and, most importantly, the anonymous study participants for the invaluable insights into the lives of students that they shared with us. The Swiss StudentLife Study was supported by Swiss National Science Foundation Grant 10001A_169965; and the rectorate of ETH Zürich.

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