

Friends network expansion and reduction: investigating the role of structural and psychological factors

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Abstract. Rich data from social networks sites (SNS) attracts attention of psychologists and sociologists interested in interpersonal dynamics, friendship networks and social capital. The presented study explores the effect of network structural features and psychological characteristics of SNS users on changes in the friendship network. The data from the representative and diverse sample of 375 Russian VKontakte SNS users from Vologda city was used. Two waves of network data collection allow us to estimate changes in the size of friendship networks. Regression analysis reveals similarities in the factors responsible for the change in networks for users who attract or reject friends. We discuss possible explanations of this phenomenon, as well as limitations of the study and further research directions.

Keywords: friendship network, network expansion, propensity to make connections, ego-network, social networking sites

Introduction

Online social networks (OSN) provide people with a wide range of opportunities to manage social ties: to make new friends, recover lost contact, establish contact with friends of the friends, participate in communities of interest. One of the main specific features of OSN is that it make it possible for users to articulate their own social circle, formalizing it as a friend list [1]. The way of collecting social ties online raises a lot of questions. For example, how do people form and manage their personal online ego-networks? What factors influence the network dynamics (expansion or reduction)?

As to the network expansion, one of the strategies of forming social network named by Donath and Boyd [2] at the rise of OSN as “Friendster whores” refers to the indiscriminate friending activity when the goal is to collect as many friends as possible. In the modern era of OSN it seems that such a strategy represents yet not as much as the vanity fair of distinct persons but the instrument of getting monetization of a personal brand, or becoming an informational influencer [3].

In addition, the well-known mechanism responsible for network growth helps to advance the already gained popularity [4]. The “rich get richer” effect (or the Matthew effect) usually observed in real networks, that received formal definition in the model of preferential attachment by Barabashi and Albert, means that the more friends an individual has, the more likely he or she will have more new friends [5].

Stepping out from the specific phenomenon described above, the extant literature on this topic shows that some kind of selection is generally applied by users in shaping their online environment. Typically people accept not all friend requests [6] and primarily use social media for keeping in touch with those who they have an offline connection with [7]. In addition, the communication activity of users aims at addressing those who users know in person [1, 8, 9].

Another factor that might influence the social network expansion is homophily - strong tendency toward forming the relationships selectively with those who possess self-similar demographic parameters, attitudes, personal preferences, appearance, social status or any other attributes [10]. As Aiello and coauthors show, users with similar interests are more likely to be friends [11]. Thus, various online communities might be treated as a source of homophily-based social ties for individuals on OSN. Rykov and colleagues demonstrate a significant contribution of being a member of online groups to accruing social capital [12]. In addition, the user’s personal profile may play a role of “social lubricant”, which assists people in finding something in common serving as a ground for further relationship development. Lampe et al. found that some specific fields of profile are positively related to the number of online friends [13].

Despite the aforementioned mechanisms that guide users’ online friending behavior, some studies evidence that personal networks of Facebook users comprise only 25% of those who are claimed by them as an actual friend [11]. Such granular metric also lets gaining a more accurate estimation of users’ bridging social capital. Ellison et al. suggest that the benefits of having large network are limited and start to decrease after exceeding of the 400-500 threshold of friends in network [14].

Moreover, the so-called “complexity index” [15] found its confirmation in online computer-mediation communication as well [16, 17] suggests that individuals are able to actively communicate and maintain relationship with the limited number of recipients.

Thus, if the communication abilities are constrained and the real social capital benefits follow only from a small share of online friends, the natural suggestion would be that people might “clean” their networks and delete irrelevant social contacts. Surprisingly, to the best of our knowledge there are no studies to date directly addressing the process of network reduction.

Thus, the first gap that we aim to cover is to explore not only how people foster their personal networks but also how they abort their social connections on OSN.

Another research avenue is to place the process of expansion and reduction of social contacts in the psychological context. The role of the individual psychological characteristics that may shape personal networks is considered as understudied [18].

There are evidences that such a personality trait as extraversion explain the difference between people in terms of the size of personal networks and should be consid-

ered when predicting network size. At the same time, Kalish and Robins argue that studying the specific behavioral orientation rather than broad personality traits helps to avoid potential diffusion in capturing behavioral outcomes associated with the latter [18].

Following this trend, we adopt the measure proposed by Totterdell et al. for measuring the so-called “propensity to make connections”. It reflects different aspects of networking attitudes and demonstrates higher predictive validity in accounting for the size of a user’s friendship network than extraversion [19].

It should be noted that prior studies devoted to the process of getting friends online mostly focused on the static number of friends in networks rather than on factors driving the dynamic changes of networks such as growth of social network. In the current study we measure the propensity to make connection for predicting the dynamic changes in size of OSN users.

Apart from the personality traits, the respective online behavior aimed at having and maintaining social connection also plays a part in understanding the friending behavior. Ellison and colleagues proposed the so-called “Relationship maintenance behavior” that implies responding the help-request of online friends and found that it positively affects the social capital [20–22]. It may happen so that users who have already invested a lot of energy in communication with others would be less inclined to get rid of their even irrelevant social contacts.

Finally, while predicting the changes in the network size it seems reasonable to take into account the structural characteristics of users’ ego-networks due to the aforementioned process of preferential attachment [9]. Likewise the size of persons’ network influences its growth which is known as “rich get richer effect”, the network density or number of clusters might follow the same pattern.

To sum up, the aim of the study is to expand understanding the role of psychological and structural factors determining the changes in the size of friendship network of social media users. We explore how the dynamics of growing/reduction of personal networks managed by OSN users themselves are related to their networking attitudes, the respective behavior on investing in the existing social ties and the prior structural ego-network characteristics.

In this paper the terms *networking* and *friending* used as synonyms and connote establishing social network friendship connections. We regard friends as persons who were marked as friend in SNS [23] and focus our study on friending behavior, which we define as behavior to form personal friendship network (expansion or reduction).

Methods

Vologda Project Dataset

In 2017-2018 the Laboratory of Internet studies (LINIS) at National Research University Higher School of Economics conducted an online survey among VKontakte SNS users. The dataset contained psychological, demographics aspects and characteristics of ego-networks from the representative and diverse sample of 375 residents of Rus-

sian Vologda city [24]. It is worth mentioning there were two waves of network data collection allow investigating the dynamic of personal social networks (changes in number of friends) with a year gap between sampling.

The respondents were recruited by means of Vkontakte targeting advertisement service. The ground truth size and the socio-demographic characteristics of the “active”¹ online population of Vologda city was revealed in [12] – it comprises of around 196 000 users. The invitation to take part in the survey was transmitted through the groups of interest until the demographic requirements were saturated. The survey app controls the opportunity of survey retake.

Targeting as a recruiting method could be classified as a “river sampling” [25], which demonstrated the response rate comparable to traditional methods [26].

As a measure of efficiency of the recruiting campaign the Click Through Rate (CTR) and complete rate were used. The CTR comprise 0.022%, the completion rate (11.5% - 375 completed questionnaires per 3266 dropped-out). These scores turned to be comparable to those obtained in previous research of this kind [27–29].

Previously the role of social capital in network expansion was analyzed on the sub-sample of the participants, who increased their friendship network [24]. It was found that only two factors have a significant influence – propensity to make connections and the actual number of friends [24]. In the current study we continue the analysis of dynamics of friendship network considering psychological and structural characteristics.

Variables

Relationship maintenance

Vologda Dataset contains answers to three items adopted from Facebook Relationship Maintenance Behaviors scale (RM) [20]. All items (for example, “When I see a friend or acquaintance sharing important news on Vkontakte, I try to respond”) were measured using a Likert-type response scale ranging from “1=Strongly Disagree” to “5=Strongly Agree”. This scale showed satisfactory reliability (Cronbach’s $\alpha=.71$) and was included in the analysis.

Propensity to make connections (PCO)

Totterdell et al. proposed a concept of “propensity to make connections with others” to study the disposition of individuals to foster social ties [19]. The construct is comprised of three dimensions of individual’s social activity: the propensity to connect with others, the perception of having social ties at the moment and the perception of the person’s own ability to form the social ties with others. Furthermore, the authors consider the “strength” of social tie by proposing to measure the propensity to form three different types of social connections: propensity to make friends, propensity to make acquaintances and propensity to join others [19]. The Vologda dataset contains answers for 6 items of propensity to make connections with others scale introduced by Totterdell [19]. All items (for example, “I like to have many friends”) were measured using a Likert-type response scale ranging from “1=Strongly Disagree” to

¹ By “active” users is meant those 1) with non-deactivated Vkontakte account and 2) who has visited Vkontakte account no later than half-year period counting from the date of data gathering

“5=Strongly Agree”. Propensity to make connections (PCO) scale showed good reliability (Cronbach’s $\alpha=.8$).

Structural network characteristics

The first wave of data collection based on publicly available data from VKontakte network allowed us to calculate structural characteristics of ego-network: the number of friends, density, communities (Girvan-Newman algorithm was applied) and modularity. At the second step we calculated the shift in the number of contacts in friendship networks (delta of friends). To make distribution of number of friends and the shift in friendship network close to normal the log transformation of the variables was made. Running analysis of the whole data set we subtracted minimal value (as there were participants with negative shift) and added 1 to avoid zero values. Running an analysis of subgroups, we include participants who do not change the number of friends into a positive change group and added 1 to avoid zero in logarithm calculations. In the reduction group we used the absolute value of the shift in the number of friends to calculate logarithm.

Demographics and control

As control variables the dataset contains information about age, sex, education and occupation of the respondents. In addition there are two questions about self-esteem (positive and negative), frequency of SNS usage and average time in SNS.

It is worth mentioning that SNS as a new media provides possibility to communicate not only with friends, but also with consumers or for other business purposes. To control this, the dataset contains the question: *“I use Vkontakte for selling goods and services, developing online communities for commercial goals or promoting myself”*. Answers to this question were decoded into binary variable “Prof” – having “0” for response “never” and “1” for all the other answering options. For detailed description, please see [24].

Analysis

To achieve the research goal, we ran a series of nested OLS regressions. The nested OLS regressions were used because they allow us to reveal psychological and structural factors determining the changes in the size of friendship network of social media users and it is a common approach used in many studies in this area (e.g. [12, 14, 19, 20]).

Regression analysis showed that the main factors responsible for changes in social network are the number of communities and modularity (see Appendix, Table 1). Surprisingly, in contrast to the results of previous research, the psychological and behavioral variables and the number of actual friends were insignificant. In addition, the low determinant coefficient was revealed (adj. $R^2 = 0.038$).

For further investigation we decided to divide users into two groups: those who expand their friendship network in the observed period (expansion group) and those with a negative shift in the number of friends in the network (reduction group). The

delta friends variable was calculated as logarithm of absolute value in changes in the number of friends.

This decision was driven by the assumption that these groups may differ in their friending strategy which may lead to the confusing results.

The basic correlation check in expansion and reducing groups showed that density and the number of friends had negative correlation (-0.54 and -0.74 respectively). For expansion group it was below threshold for exclusion, so density was included in regression analysis. For reduction group we decided to remove density from regression analysis.

Regression modeling for the separate groups showed significantly better performance in prediction (for expansion group $\text{adj.R}^2 = 0.388$, for reduction $\text{adj.R}^2 = 0.489$). The Table 2 presents the models' outputs containing only significant variables (full models are presented in Appendix).

In the regression model predicting the shift *for expansion group* the number of friends (log) is a significant factor ($\text{std.beta} = 0.33$, $p < 0.001$) which is in line with the "rich gets richer" effect. Similarly, structural components such as density ($\text{std.beta} = 0.17$, $p < 0.05$), number of communities ($\text{std.beta} = 0.38$, $p < 0.001$) significantly contribute to the model. As for psychological variables, only propensity to make connections reveals its significance ($\text{std.beta} = 0.16$, $p < 0.05$) even in presence of the variable number of friends (log).

Table 1. OLS regression predicting shift (logarithm) in ego-network (expansion group)

<i>Predictors</i>	<i>Delta friends (log)</i>		
	<i>Estimates</i>	<i>std. Beta</i>	<i>P</i>
(Intercept)	-0.57	0.28	0.14
Propensity to make connections (PCO)	0.23	0.16	0.01
Number of friends (log)	0.38	0.30	0.00
Number of communities	0.02	0.38	0.00
Density	3.59	0.17	0.02
Observations	274		
R^2 / R^2 adjusted	0.442 / 0.388		

In regression model for the reduction group we observed almost the same effect of the number of friends variable ($\text{std.beta} = 1.12$, $p < 0.00$) (significant variables are presented in Table 2).

It turns out that the more friends the user has the more friends they remove from their network – so the preferential detachment hypothesis could be formulated regarding the model of network reduction.

We found the opposite effect of the variable the number of communities in comparison with the model of expansion (std.beta = -0.38, $p < 0.00$). The more communities were detected in friendship network the lower shift in friendship network is observed.

The propensity to make connections variable for the reduction group was only borderline significant (std.beta = 0.21, $p = 0.09$). The positive relationship between the intention to have social ties and the removing ones from the network seems paradoxical, but it could be assumed that people may be simultaneously eager to have the social contacts and delete the irrelevant social ties from the network.

Table 2. OLS regression predicting shift (logarithm) in ego-network (reduction group)

<i>Predictors</i>	<i>Delta friends (log)</i>		
	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>
(Intercept)	-1.08	0.54	0.13
Propensity to make connections (PCO)	0.26	0.21	0.09
Number of friends (log)	0.76	0.74	0.00
Number of communities	-0.01	-0.38	0.01
Observations	79		
R ² / R ² adjusted	0.603 / 0.437		

Discussion

The presented work contributes to understanding the role of psychological and structural factors in the processes of growth and decrease of personal ego-networks.

It was found that both of these factors predict the shift in the number of contacts in network.

In line with our expectations the preferential attachment effect was detected in the group of users who have expanded their networks within the observed period of time. Those who have a greater number of friends are characterized by a larger increase in social ties later. Surprisingly, such effect manifests itself for the group of users who have reduced their ego-networks. The more friends those users have the more friends they tend to delete.

It should be noted that the initial sample of users was divided into two separate ones. It means that we did not consider a situation when a user both expands and reduces a network. Thus, the effects revealed in models of extension and reduction of a network should be considered separately. In this vein, the previous result on “detachment” of social ties by those who possessed them more in the earlier period seems logical. It may reflect the simple “hygiene” performed by the user in order to reduce the irrelevant information noise.

In support to this, users who have reduced their networks do not report the intention to have more friends (the variable propensity to make connection has borderline effect in the reduction model). As to the expansion group – the propensity to make connection has a positive effect on the growth of personal network. Users who aim at having more friends demonstrate an increase in the number of social connections in the ego network in the later period. This result is in line with the earlier work of Totterdell and colleagues [19]. Moreover, it serves as additional support of sufficient predictive power of such psychological construct as “propensity to make connections”.

Along with the psychological disposition toward networking activity the role of the respective behavior was tested. It turns out, that investment in the relationship maintenance affects neither the growth nor the reduction of social ties in the network. Such metric has revealed its effect on the specific social capital outcomes [14] which are rooted not in the quantity of social ties but in its quality. Thus, the investment into maintenance of existing relationships is related to the resources gained by the agency of social ties fostered but it does not affect the dynamics of network growth.

Finally, the assumption that structural characteristic of users’ ego network might have an independent effect on the dynamics of reduction or extension of personal network found partial support. The number of communities detected in the users’ networks is positively related to the number of friends users add to their networks in the later period. And at the opposite – those who have more communities in the network are less inclined to remove friends from the network. In addition, the users with denser network would be more inclined to add new friends later. We could speculate that the communities which might to some extent represent different social context [30] could be the possible source of new social connections for users. This would also be in line with the classical formula of “strength of weak ties” the access to which could be gained from the diversity of different groups an individual belongs to [31]. But the limitations of our method do not allow interpreting the results in the causation manner. In other words, from our analysis it is impossible to conclude which of the ties added in the later period has its origin in the clusters presented before. This question might be considered for further investigation.

Limitations of the study

The presented study is exploratory by design and the obtained result should be treated through the prism of several limitations. In particular, the reliability and validity of river-sampling technique is debatable question in social science [32]. Thus, the results should be generalized with cautious on the online population of Russian

OSN users. In addition, the study considers the users of one particular social networking site VKontakte and users of one Russian city Vologda.

The shift in network was assessed only in the scope of 1 year period. Further research needs a more comprehensive way of assessing the substitution of friends in a social network. The presented procedure did not distinguish between the situations when participants do not establish new social ties or invited and removed the equal number of friends during the observed period.

Conclusion

The study aims at studying the effect of structural and psychological factors on the shift in the number of contacts in the ego-networks of SNS users.

We found that considering such diverse processes as adding and removing friends on a social network separately is more productive than combining people with different outcomes in one model. Albeit such approach revealed that the same variables are significant in both models (a priori number of friends, the number of communities detected in a network and the propensity to make social connection) their influence is not homogeneous.

Acknowledgments. This article is an output of a research project implemented as part of the Basic Research Program at the National Research University Higher School of Economics (HSE University).

References

1. Boyd, D.M., Ellison, N.B.: Social Network Sites: Definition, History, and Scholarship. *Journal of Computer-Mediated Communication*. 13, 210–230 (2007). <https://doi.org/10.1111/j.1083-6101.2007.00393.x>.
2. Donath, J., Boyd, D.: Public displays of connection. *bt technology Journal*. 22, 71–82 (2004).
3. Jin, S.V., Muqaddam, A., Ryu, E.: Instafamous and social media influencer marketing. *MIP*. 37, 567–579 (2019). <https://doi.org/10.1108/MIP-09-2018-0375>.
4. Weiqin, E.L., Campbell, M., Kimpton, M., Wozencroft, K., Orel, A.: Social Capital on Facebook: The Impact of Personality and Online Communication Behaviors. *Journal of Educational Computing Research*. 54, 747–786 (2016). <https://doi.org/10.1177/0735633116631886>.
5. Barabási, A.-L., Albert, R.: Emergence of scaling in random networks. *science*. 286, 509–512 (1999).
6. Hu, H., Wang, X.: How people make friends in social networking sites—A microscopic perspective. *Physica A: Statistical Mechanics and its Applications*. 391, 1877–1886 (2012). <https://doi.org/10.1016/j.physa.2011.10.020>.

7. Lampe, C., Ellison, N., Steinfield, C.: A Face (book) in the crowd: Social searching vs. social browsing. In: Proceedings of the 2006 20th anniversary conference on Computer supported cooperative work. pp. 167–170 (2006).
8. Mayer, A., Puller, S.L.: The old boy (and girl) network: Social network formation on university campuses. *Journal of Public Economics*. 92, 329–347 (2008). <https://doi.org/10.1016/j.jpubeco.2007.09.001>.
9. Subrahmanyam, K., Reich, S.M., Waechter, N., Espinoza, G.: Online and offline social networks: Use of social networking sites by emerging adults. *Journal of Applied Developmental Psychology*. 29, 420–433 (2008). <https://doi.org/10.1016/j.appdev.2008.07.003>.
10. Rivera, M.T., Soderstrom, S.B., Uzzi, B.: Dynamics of Dyads in Social Networks: Assortative, Relational, and Proximity Mechanisms. *Annual Review of Sociology*. 36, 91–115 (2010). <https://doi.org/10.1146/annurev.soc.34.040507.134743>.
11. Aiello, L.M., Barrat, A., Schifanella, R., Cattuto, C., Markines, B., Menczer, F.: Friendship prediction and homophily in social media. *ACM Trans. Web*. 6, 1–33 (2012). <https://doi.org/10.1145/2180861.2180866>.
12. Rykov, Y., Koltsova, O., Sinyavskaya, Y.: Effects of user behaviors on accumulation of social capital in an online social network. *PLoS ONE*. 15, e0231837 (2020). <https://doi.org/10.1371/journal.pone.0231837>.
13. Lampe, C.A.C., Ellison, N., Steinfield, C.: A familiar face(book): profile elements as signals in an online social network. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '07. pp. 435–444. ACM Press, San Jose, California, USA (2007). <https://doi.org/10.1145/1240624.1240695>.
14. Ellison, N.B., Steinfield, C., Lampe, C.: Connection strategies: Social capital implications of Facebook-enabled communication practices. *New Media & Society*. 13, 873–892 (2011). <https://doi.org/10.1177/1461444810385389>.
15. Dunbar, R.I.M.: The Anatomy of Friendship. *Trends in Cognitive Sciences*. 22, 32–51 (2018). <https://doi.org/10.1016/j.tics.2017.10.004>.
16. Pollet, T.V., Roberts, S.G.B., Dunbar, R.I.M.: Use of Social Network Sites and Instant Messaging Does Not Lead to Increased Offline Social Network Size, or to Emotionally Closer Relationships with Offline Network Members. *Cyberpsychology, Behavior, and Social Networking*. 14, 253–258 (2011). <https://doi.org/10.1089/cyber.2010.0161>.
17. Gonçalves, B., Perra, N., Vespignani, A.: Modeling Users' Activity on Twitter Networks: Validation of Dunbar's Number. *PLoS ONE*. 6, e22656 (2011). <https://doi.org/10.1371/journal.pone.0022656>.
18. Kalish, Y., Robins, G.: Psychological predispositions and network structure: The relationship between individual predispositions, structural holes and network closure. *Social Networks*. 28, 56–84 (2006). <https://doi.org/10.1016/j.socnet.2005.04.004>.
19. Totterdell, P., Holman, D., Hukin, A.: Social networkers: Measuring and examining individual differences in propensity to connect with others. *Social Networks*. 30, 283–296 (2008). <https://doi.org/10.1016/j.socnet.2008.04.003>.
20. Ellison, N.B., Vitak, J., Gray, R., Lampe, C.: Cultivating Social Resources on Social Network Sites: Facebook Relationship Maintenance Behaviors and Their

- Role in Social Capital Processes. *Journal of Computer-Mediated Communication*. 19, 855–870 (2014). <https://doi.org/10.1111/jcc4.12078>.
21. Vanden Abeele, M.M.P., Antheunis, M.L., Pollmann, M.M.H., Schouten, A.P., Liebrecht, C.C., van der Wijst, P.J., van Amelsvoort, M.A.A., Bartels, J., Krahmer, E.J., Maes, F.A.: Does Facebook Use Predict College Students' Social Capital? A Replication of Ellison, Steinfield, and Lampe's (2007) Study Using the Original and More Recent Measures of Facebook Use and Social Capital. *Communication Studies*. 69, 272–282 (2018). <https://doi.org/10.1080/10510974.2018.1464937>.
 22. Ellison, N.B., Vitak, J., Steinfield, C., Gray, R., Lampe, C.: Negotiating Privacy Concerns and Social Capital Needs in a Social Media Environment. In: Trepte, S. and Reinecke, L. (eds.) *Privacy Online*. pp. 19–32. Springer Berlin Heidelberg, Berlin, Heidelberg (2011). https://doi.org/10.1007/978-3-642-21521-6_3.
 23. Thelwall, M.: Social networks, gender, and friending: An analysis of MySpace member profiles. *Journal of the American Society for Information Science and Technology*. 59, 1321–1330 (2008). <https://doi.org/10.1002/asi.20835>.
 24. Sinyavskaya, Y., Porshnev, A.: Propensity to make social connections and structural social capital of SNS users. *Annual Review of Cybertherapy And Telemedicine* 2019. 17, 33–38 (2019).
 25. Lehdonvirta, V., Oksanen, A., Räsänen, P., Blank, G.: Social Media, Web, and Panel Surveys: Using Non-Probability Samples in Social and Policy Research. *Policy & Internet*. n/a., <https://doi.org/10.1002/poi3.238>.
 26. Iannelli, L., Giglietto, F., Rossi, L., Zurovac, E.: Facebook Digital Traces for Survey Research: Assessing the Efficiency and Effectiveness of a Facebook Ad-Based Procedure for Recruiting Online Survey Respondents in Niche and Difficult-to-Reach Populations. *Social Science Computer Review*. 38, 462–476 (2020). <https://doi.org/10.1177/0894439318816638>.
 27. Kapp, J.M., Peters, C., Oliver, D.P.: Research recruitment using Facebook advertising: big potential, big challenges. *J Cancer Educ*. 28, 134–137 (2013). <https://doi.org/10.1007/s13187-012-0443-z>.
 28. King, D.B., O'Rourke, N., DeLongis, A.: Social media recruitment and online data collection: A beginner's guide and best practices for accessing low-prevalence and hard-to-reach populations. *Canadian Psychology/Psychologie canadienne*. 55, 240–249 (2014). <https://doi.org/10.1037/a0038087>.
 29. Pötzschke, S., Braun, M.: Migrant Sampling Using Facebook Advertisements: A Case Study of Polish Migrants in Four European Countries. *Social Science Computer Review*. 35, 633–653 (2017). <https://doi.org/10.1177/0894439316666262>.
 30. McAuley, J., Leskovec, J.: Discovering social circles in ego networks. *ACM Trans. Knowl. Discov. Data*. 8, 1–28 (2014). <https://doi.org/10.1145/2556612>.
 31. Granovetter, M.S.: The Strength of Weak Ties. *American Journal of Sociology*. 78, 1360–1380 (1973).
 32. Devyatko, I.F.: Onlayn issledovaniya i metodologiya sotsial'nykh nauk: novye gorizonty, novye (i ne stol' novye) trudnosti. *Onlayn issledovaniya v Rossii*. 2, 17–30 (2010).

Appendix.

Table 1. Nested regressions for whole sample

<i>Predictors</i>	log.d_friends			log.d_friends			log.d_friends			log.d_friends			log.d_friends		
	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>
(Intercept)	5.62	-0.53	0.01	5.59	-0.55	0.01	5.63	-0.52	0.01	5.64	-0.52	0.01	5.88	-0.54	0.01
age	-0.00	-0.05	0.49	-0.00	-0.05	0.52	-0.00	-0.03	0.73	-0.00	-0.03	0.72	-0.00	-0.05	0.51
sex [male]	0.03	0.08	0.51	0.02	0.06	0.58	0.02	0.05	0.65	0.02	0.05	0.67	0.00	0.01	0.96
edu [1]	0.12	0.32	0.22	0.12	0.34	0.20	0.12	0.32	0.23	0.12	0.32	0.23	0.12	0.33	0.20
edu [2]	0.12	0.33	0.21	0.13	0.34	0.19	0.12	0.31	0.23	0.12	0.31	0.23	0.15	0.41	0.11
edu [3]	0.16	0.44	0.10	0.17	0.47	0.08	0.15	0.41	0.13	0.15	0.42	0.13	0.18	0.49	0.07
edu [4]	0.15	0.39	0.14	0.15	0.41	0.12	0.14	0.39	0.14	0.14	0.39	0.14	0.18	0.49	0.07
edu [5]	0.07	0.18	0.51	0.07	0.19	0.50	0.05	0.14	0.61	0.05	0.14	0.61	0.09	0.23	0.41
occup [1]	0.02	0.06	0.80	0.03	0.08	0.77	0.03	0.08	0.76	0.03	0.09	0.74	0.03	0.08	0.77

occup [2]	0.10	0.28	0.20	0.11	0.29	0.19	0.10	0.28	0.20	0.11	0.29	0.20	0.09	0.24	0.28
occup [3]	-0.04	-0.12	0.70	-0.04	-0.11	0.73	-0.04	-0.10	0.75	-0.04	-0.10	0.76	-0.07	-0.19	0.55
occup [4]	0.09	0.24	0.38	0.09	0.25	0.37	0.10	0.26	0.35	0.10	0.27	0.34	0.08	0.22	0.44
occup [5]	0.18	0.49	0.12	0.18	0.49	0.12	0.18	0.49	0.12	0.18	0.49	0.12	0.15	0.40	0.20
occup [6]	0.08	0.22	0.32	0.08	0.22	0.31	0.09	0.23	0.29	0.09	0.24	0.28	0.07	0.19	0.38
Prof	0.02	0.07	0.23	0.01	0.05	0.34	0.02	0.06	0.29	0.02	0.06	0.29	0.01	0.03	0.55
SE_pos	0.03	0.11	0.08	0.03	0.09	0.16	0.03	0.09	0.14	0.03	0.09	0.15	0.03	0.10	0.12
SE_neg	0.03	0.11	0.07	0.03	0.11	0.07	0.03	0.11	0.08	0.03	0.11	0.08	0.02	0.08	0.16
freq	-0.00	-0.01	0.91	-0.00	-0.01	0.89	-0.01	-0.03	0.68	-0.01	-0.03	0.69	-0.01	-0.03	0.64
online	0.01	0.05	0.39	0.02	0.06	0.33	0.02	0.06	0.32	0.02	0.06	0.33	0.02	0.09	0.18
PCO				0.02	0.06	0.36	0.03	0.08	0.21	0.03	0.08	0.21	0.03	0.08	0.25
RM							-0.03	-0.08	0.22	-0.03	-0.08	0.21	-0.03	-0.08	0.22
log.friends										-0.00	-0.01	0.86	-0.03	-0.08	0.41
communities													0.00	0.14	0.04

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density					0.20	0.04	0.65
modularity					-0.34	-0.14	0.05
Observations	353		353		353		353
R ² / R ² adjusted	0.062 / 0.011		0.064 / 0.011		0.069 / 0.013		0.069 / 0.010
							0.104 / 0.038

Table 2. Nested regressions for expansion group

	log.d_friends			log.d_friends			log.d_friends			log.d_friends		
<i>Predictors</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>
(Intercept)	2.62	0.23	0.31	1.79	0.09	0.69	-0.56	0.29	0.16	-0.57	0.28	0.14
age	-0.01	-0.08	0.34	-0.01	-0.07	0.36	-0.00	-0.04	0.58	-0.01	-0.07	0.30
sex [male]	-0.19	-0.14	0.27	-0.26	-0.20	0.11	-0.10	-0.07	0.52	-0.11	-0.09	0.43
edu [1]	-0.13	-0.10	0.75	-0.09	-0.07	0.83	-0.21	-0.16	0.57	-0.16	-0.12	0.64
edu [2]	-0.56	-0.42	0.15	-0.45	-0.34	0.23	-0.48	-0.37	0.15	-0.37	-0.28	0.25

edu [3]	-0.60	-0.46	0.13	-0.37	-0.28	0.34	-0.49	-0.37	0.16	-0.43	-0.32	0.20
edu [4]	-0.60	-0.45	0.14	-0.42	-0.32	0.28	-0.56	-0.42	0.11	-0.48	-0.36	0.15
edu [5]	-0.48	-0.37	0.26	-0.43	-0.33	0.30	-0.61	-0.46	0.11	-0.46	-0.35	0.19
occup [1]	0.12	0.09	0.76	0.26	0.20	0.50	-0.05	-0.04	0.88	-0.02	-0.01	0.95
occup [2]	0.37	0.28	0.28	0.51	0.39	0.13	0.13	0.10	0.66	0.02	0.01	0.96
occup [3]	0.07	0.05	0.89	0.28	0.21	0.54	0.07	0.05	0.86	-0.24	-0.18	0.55
occup [4]	0.40	0.30	0.35	0.55	0.42	0.18	0.16	0.12	0.67	0.12	0.09	0.72
occup [5]	0.46	0.35	0.31	0.45	0.34	0.31	0.43	0.33	0.28	0.33	0.25	0.39
occup [6]	0.17	0.13	0.62	0.27	0.20	0.43	0.09	0.07	0.76	0.09	0.07	0.77
Prof	0.16	0.19	0.00	0.09	0.10	0.10	0.06	0.07	0.20	0.02	0.03	0.59
SE_pos	0.11	0.11	0.10	0.02	0.02	0.75	0.04	0.03	0.56	0.04	0.04	0.49
SE_neg	0.01	0.01	0.89	0.02	0.02	0.80	0.01	0.01	0.90	-0.02	-0.02	0.76
freq	0.06	0.06	0.36	0.04	0.05	0.50	0.05	0.05	0.45	0.04	0.05	0.43
online	-0.15	-0.17	0.02	-0.11	-0.13	0.06	-0.06	-0.07	0.25	-0.07	-0.08	0.15

PCO		0.44	0.32	0.00	0.25	0.18	0.01	0.23	0.16	0.01
RM		0.03	0.03	0.66	0.06	0.05	0.38	0.05	0.04	0.43
log.friends					0.54	0.43	0.00	0.38	0.30	0.00
communities								0.02	0.38	0.00
density								3.59	0.17	0.02
modularity								0.57	0.06	0.32
Observations	274			274				274		
R ² / R ² adjusted	0.124 / 0.063			0.205 / 0.142				0.350 / 0.296		

Table 3. Nested regressions for reduction group

	log.d_friends			log.d_friends			log.d_friends			log.d_friends		
<i>Predictors</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>	<i>Estimates</i>	<i>std. Beta</i>	<i>p</i>
(Intercept)	3.66	-0.04	0.93	3.17	0.07	0.86	0.25	0.48	0.20	-1.08	0.54	0.13
age	-0.03	-0.36	0.06	-0.03	-0.27	0.18	-0.01	-0.08	0.66	0.00	0.04	0.80

sex [male]	-0.36	-0.30	0.25	-0.50	-0.42	0.11	-0.56	-0.46	0.05	-0.40	-0.33	0.14
edu [1]	-0.02	-0.02	0.96	0.02	0.02	0.97	0.03	0.02	0.96	0.06	0.05	0.89
edu [2]	0.61	0.51	0.35	0.54	0.45	0.40	0.43	0.36	0.45	0.46	0.38	0.40
edu [3]	0.15	0.12	0.82	0.31	0.26	0.64	0.43	0.36	0.47	0.16	0.14	0.77
edu [4]	-0.21	-0.17	0.73	-0.15	-0.12	0.81	-0.16	-0.13	0.77	-0.32	-0.26	0.53
edu [5]	-0.09	-0.07	0.90	-0.20	-0.17	0.76	-0.25	-0.21	0.67	-0.14	-0.12	0.80
occup [1]	0.68	0.56	0.26	0.59	0.49	0.32	0.03	0.02	0.96	-0.27	-0.22	0.62
occup [2]	-0.40	-0.33	0.43	-0.42	-0.35	0.40	-0.79	-0.65	0.09	-0.90	-0.74	0.04
occup [3]	1.17	0.97	0.16	0.87	0.72	0.29	0.10	0.09	0.89	-0.24	-0.20	0.74
occup [4]	1.14	0.94	0.11	0.85	0.70	0.23	-0.38	-0.32	0.58	-0.45	-0.37	0.50
occup [5]	-0.31	-0.26	0.74	-0.20	-0.17	0.83	-0.98	-0.81	0.26	-1.39	-1.15	0.10
occup [6]	-0.23	-0.19	0.62	-0.32	-0.26	0.49	-0.88	-0.73	0.04	-0.86	-0.71	0.04
Prof	-0.04	-0.05	0.68	-0.04	-0.05	0.70	-0.05	-0.06	0.60	0.00	0.00	0.96
SE_pos	0.03	0.03	0.80	-0.05	-0.06	0.69	0.06	0.06	0.63	0.02	0.02	0.86

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SE_neg	-0.21	-0.26	0.07	-0.15	-0.18	0.20	0.09	0.11	0.46	0.08	0.10	0.47
freq	0.06	0.06	0.66	0.04	0.04	0.74	0.03	0.03	0.79	-0.01	-0.01	0.95
online	-0.16	-0.18	0.15	-0.13	-0.15	0.22	-0.15	-0.17	0.13	-0.24	-0.27	0.02
PCO				0.40	0.32	0.03	0.25	0.20	0.13	0.26	0.21	0.09
RM				-0.11	-0.10	0.45	-0.09	-0.09	0.47	-0.14	-0.13	0.25
log.friends							0.53	0.51	0.00	0.76	0.74	0.00
communities										-0.01	-0.38	0.01
modularity										0.93	0.13	0.18
Observations	79			79			79			79		
R ² / R ² adjusted	0.354 / 0.160			0.407 / 0.202			0.539 / 0.369			0.603 / 0.437		