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Examining online social behavior changes after migration: An empirical study based on OSN big data

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ABSTRACT

With fast urbanization and decreasing transportation cost, migration becomes more common. Previous studies have shown the important role of social networks in the process of migration, but little is known about the effect of migration on social networks. To fill the research gap, this study examines the effect of migration on online social behaviors (in terms of network evolution and social interaction), as well as the moderating effect of migrants' characteristics. We collect a four-month big dataset with 2.29 million records from one of the largest online social networks in China. We apply the propensity score matching combined with the difference-in-differences method to compare online social behavior changes after migration. Our results show that, for network evolution behavior, migration positively impacts on the number of tie formation, but non-significantly impacts on the number of tie decay; for social interaction behavior, migration increases the number of contacts but decreases the number of messages. We also find some moderating effects of migrants' characteristics, including gender, age, and degree. This study provides big data empirical evidence and some new insights to our understandings of the impact of migration on online social network behavior.

1. Introduction

With the rapid development of urbanization and transportation, the world has witnessed remarkable growth in migration (Loo, Lam, Mahendran, & Katagiri, 2017). For example, China had approximately 288 million migrant employees in 2018, accounting for more than 20% of its total population (Statista, 2020). In the process of migration, individuals' social networks play an important role. Before migration, individuals need to get information from their friends to help them make migration decisions (Suter, 2012). After migration, individuals have to reorganize their social networks, to avoid loneliness (Oishi, 2013) and get more social support from their friends (Popielarz & Cserpes, 2018).

With the increasing availability of large-scale social network data, the relationship between migration and social behavior has aroused a lot of research interests. Some researchers provided empirical evidence of the effect of migration on social behavior (Chi, 2020; Fudolig, Monsivais, Bhattacharya, Jo, & Kaski, 2021; Phithakkitnukoon, Calabrese, Smoreda, & Ratti, 2011; Yang et al., 2018). However, their research has some limitations. First, these studies were based on Call Detail Records (CDR) data. CDR data reflects merely one of the channels where individuals communicate. As one of the most popular communication ways, online social networks (OSNs) have been ignored. Moreover, compared to OSNs data, the CDR data cannot show the network evolution behavior (i.e. tie formation and tie decay). Second, the existing studies have mixed findings. For example, Chi (2020) found that the number of contacts and calls of migrants increase substantially in the week before migration and go back to normal after migration. However, Yang, et al. (2018) stated that the number of contacts and duration of calls increase after migration. Moreover, Phithakkitnukoon, et al. (2011) documented that the social behavior of migrants would be inactive until four months after migration. The possible reasons for the mixed findings could be the robustness of the findings, caused by small sample size (Phithakkitnukoon et al., 2011), short data period (Yang et al., 2018), and naive methods (such as simple comparison of the social behavior before and after migration).

To fill the research gaps, this study tries to obtain a comprehensive and robust understanding of the effect of migration on social networks. We attempt to answer two key research questions: (1) What and to what extent are the effects of migration on social behavior in OSNs, in terms of network evolution and social interaction? (2) What are the moderating

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effects of users' characteristics on the relationship between migration and social behavior? We collaborate with a leading OSN in China and access a large online social network dataset, which includes 574,129 OSN users' characteristics, location, communication, and relationships information in 4 months, with around 2.29 million records. Among these users, about 5% of them experienced migration in the observation period. To address our research questions, we adopt an econometric model which combines the propensity scores matching technique and difference-in-differences analysis (PSM-DID). We use tie formation (friending) and tie removal (unfriending) to measure network evolution, and use the number of contacts and the number of messages to measure social interaction.

Our results show that migration makes users add 8.65% more ties monthly, whereas it does not significantly influence tie removal. Moreover, migration increases the number of contacts by 1.71%, but decreases the number of messages by 3.25%. Further analyses reveal the moderating effects of gender, age, and degree on the relationship between migration and network evolution. In detail, the positive effect of migration on the number of tie formation and the number of contacts is stronger for females than males, and the positive effect of migration on the number of contacts is strengthened by age. In addition, the degree strengthens the positive effect of migration on the number of tie formation, and weakens the negative effect of migration on the number of tie removal. To check the robustness of our results, we conduct replicate analyses with a different time window, regression model, and subsample, and obtain consistent findings.

To the best of our knowledge, this is the first work to study the effect of migration on online social network behavior using large-scale OSN data. Limited by the CDR dataset used in the literature, the impact of migration on network evolution has not been discussed before. Based on a novel big OSN dataset, this study contributes to the literature on the effect of migration on online social behavior, especially on the effect of migration on network evolution (tie formation and tie removal). Moreover, compared to the mixed findings in the literature caused by the data and method problems, this paper uses the OSN large-scale dataset, the PSM-DID method, and the robustness checks to provide solid and robust results. The findings enrich our understandings of the effect of migration on social behavior, and are meaningful for both research and the OSN industry.

The rest of this paper is organized as follows: Section 2 reviews the related literature and the theoretical background. Section 3 describes the research methodology. Section 4 reports the empirical analyses results, and Section 5 presents the robustness check. Section 6 concludes the paper by discussing the implications of the findings.

2. Related literature and theoretical background

2.1. Related literature

2.1.1. Online social behavior

Social behavior in OSNs has some differences compared to it in offline, telecommunication, and other channels, especially in long-distance relationship. Although telecommunication technology has largely decreased the cost of communication, the OSN is a free tool to connect each other, no matter how far between two users is. At root, migration is a process that the migrant suddenly changes his/her location of residence, which leads to the geographic distance of relationships changes. Numbers of studies showed that geographic distance plays an important role in forming and maintaining social relationships due to communication cost increases with geographic distance (Backstrom & Leskovec, 2011; Liben-nowell, Novak, Kumar, Raghavan, & Tomkins, 2005, pp. 1–6). However, with the development of communication technology, electronic communication tools (such as telephone, email, and social media) sharply reduce the cost of long-distance communication, which leads to the proclamation of 'the death of distance' (Cairncross & Frances, 2001). That is, interpersonal communications cannot be constrained by geographic distance. On the contrary, a considerable amount of studies suggested that the important role of geographic distance in the traditional social networks still exists in OSNs (Onnela, Arbesman, González, Barabási, & Christakis, 2011; Tillema, Dijst, & Schwanen, 2010). Besides the network evolution behavior, our ways of maintaining relationships heavily depend on online social networking (Kwak & Kim, 2017). Individuals communicate with each other to share information and maintain relationships through OSNs. It also makes individuals get social support from their friends.

2.1.2. Network evolution

A large body of work shows that social networks tend to display instability (Bevan, Ang, & Fearns, 2014; Castellanos-Reyes, 2021; Kossinets & Watts, 2006; Pennington, 2020), due to the temporal activities and variational interests of individuals (Chung, Johnson, Hall-Phillips, & Kim, 2021; Lewis, Kaufman, Gonzalez, Wimmer, & Christakis, 2008). But it is challenging to study the process and mechanism of social network dynamics because of the endogeneity between social network dynamics and individual characteristics (Manski, 1993). Generally, the evolution of social networks is slow and not easy to observe. For another, obtaining the completed time-series social network data is quite challenging. Recently, to overcome these issues, some researchers set up their studies by natural experiments, which take advantage of certain events, such as social events (Chung et al., 2021) and nature disasters (Gao et al., 2015; Phan & Airoldi, 2015). For instance, Gao, et al. (2015) found that the volume spike in communications when individuals are suffering from emergencies. However, Phan and Airoldi (2015) showed that the affected individuals keep a similar frequency of messaging. Moreover, the affected individuals contact fewer individuals, which indicates that individuals pay their attention to a more intimate group (Phan & Airoldi, 2015).

Nature disaster usually leads residents to resettle in other places (Eisenman, Cordasco, Asch, Golden, & Glik, 2007). This process causes their social networks to geographically disperse (Hurlbert, Beggs, & Haines, 2017), and then results in social network dynamics. Similar to it, migration also triggers significant social network dynamics by geographically dispersing. However, there are some differences between natural disasters and migration. Specifically, disaster is associated with increased psychological distress, including anxiety, depression, and post-traumatic stress disorder (Morris & Deterding, 2016). But migration is a milder event, that may have a different effect on social behavior with a natural disaster.

2.1.3. Migration and social network

Migration is defined as "the crossing of the boundary of a predefined spatial unit by persons involved in a change of residence" (Collinson, Kok, & Garenne, 2006). With the increase of urbanization and internationalization, migration has become more popular in recent years, which has attracted more researchers' attention. Meanwhile, the link between migration and social networks also has attracted researchers' attention. It is widely recognized that migrants' social networks play a crucial role in facilitating migration processes (Suter, 2012). However, this effect is not unilateral. Social networks are both shaping and shaped by migration (Ryan, 2011; Schapendonk & Steel, 2014).

Prior research found that migrants tend to expand their social network after migration. For example, Oishi (2013) showed that migrants will expand their social networks because of the anticipated loneliness and sadness. Popielarz and Cserpes (2018) stated that migrants need to reorganize their social network in the new place to get more social support. These findings depended on the traditional methods, like surveys and interviews.

Several studies have shown empirical evidence of social behavior changes of migrants by Call Detail Records (CDR) which is large-scale and high resolution. However, they have mixed findings. Phithakkitnukoon et al. (2011) used 1.3 million users' CDR data with 11 months. They mainly examined the influence of migration on a different level of tie strength, and found that the strongest ties are still persistent while strong and weak ties become weaker. They also found that migrants become significantly socially inactive before and during migration, until the fourth month after migration. To the best of our knowledge, this is the seminal study of network evolution of migration by large-scale CDR data. However, they have contradictory findings with a recent study. The potential problems may be the sparse migrant samples in this dataset which has only 492 migrants of 1.3 million users. Yang et al. (2018) explored 54 million users' CDR data with 1 month. They found that staying migrants have more connections and longer calls than temporary migrants. However, this study did not compare the social behavior before and after migration. It may be because the data period only has 1 month, and the migrant was identified with no call logs in the first 4 days. So, the data before migration is missing. More recently, Chi (2020) and Fudolig et al. (2021) take advantage of more completed and longer period CDR data to further discuss the social behavior changes of migrants. Chi (2020) found that the number of calls and number of contacts of migrants increase in the week before migration but back to normal after migration. However, these findings are different from the results of Fudolig et al. (2021), who found that the social behavior of migrants changes shortly after the move, but the direction of changes depends on the migrants. They also found that only 3.5% of close relationships will be disappeared after four months away from migration.

In summary, the related empirical studies showed mixed findings of the social behavior changes of migrants. It is probably because the methods they used to measure the influence of migration are not very rigorous. They all applied descriptive analysis and visualization to examine the changes in the social behavior of migrants. However, this naïve comparison may ignore selection bias and omit variable bias, which may result in the incorrect coefficient. Furthermore, all of the prior research used CDR data, which only represents the social interaction behavior of migrants. In fact, social interaction is only a part of social behavior. Some social behaviors can not be observed in CDR data, like tie formation and tie removal. Sometimes, individuals construct relationships with new friends, while we do not contact each other. Similarly, when we have no communication with some friends, it does not mean our relationship dissolved. Hence, the patterns of network evolution and social interaction are different (Palla, Barabási, & Vicsek, 2007).

2.2. Theoretical background

2.2.1. Social capital and social support

Social capital refers to "the sum of actual and potential resources embedded within, available through, and derived from the network of relationships possessed by individuals or social unit" (Nahapiet & Ghoshal, 1998). Social capital consists of structural, relational, and cognitive (Nahapiet & Ghoshal, 1998). The structural dimension represents the structural characteristics of social capital which mainly includes the network ties, network morphology, and network configuration. The structure will be changed when migrants add or delete some network ties in online social networks. Due to social capital can bring resources for individuals, it plays an important role in career success (Seibert, Kraimer, & Liden, 2001) and individual health (Poortinga, 2006). However, migrants will lose a part of social capital in the process of migration (Kelly & Lusis, 2006). When the migrant move to other places, some connections between his/her and his/her friends in the original place will be disappeared. On the other hand, migrants need to take advantage of social capital, such as looking for jobs (Aguilera & Massey, 2003). Therefore, migrants are likely to extend their social networks to accumulate more social capital. With the help of online social networks, there is an easier and cheaper way for migrants to build new links, and may remove some redundant links.

Social support is defined as "individuals' perceived available resources from their social interactions", from the perspective of psychosociology (MacGeorge, Feng, & Burleson, 2011). Social support included three dimensions, informational, emotional, and tangible support (Schaefer, Coyne, & Lazarus, 1981). In the process of social interaction in OSNs, individuals can get emotional or informational support. Many studies have shown that social support is beneficial for individuals' well-being (Morelli, Lee, Arnn, & Zaki, 2015; S. Xu, Li, Zhang, & Cho, 2021). In the process of migration, individuals are more likely to be lonely and sad (Oishi, 2013). So, migrants need more social interaction to get emotional support. They will connect more friends, especially their old friends in OSNs to get support. Moreover, individuals need more information to help them live in the new environment.

2.2.2. User differences in OSNs

Individuals show different social behavior patterns in OSNs with various users' characteristics. Gender is the first characteristic that people notice when they meet an individual (Contreras, Banaji, & Mitchell, 2013), and it also has a high impact on others' perceptions of an individual's behavior (Heilman & Chen, 2005). Hence, gender is an essential variable deciding the social behavior in the networks (Aten, DiRenzo, & Shatnawi, 2017). Many studies find the differences between males and females in the network evolution behavior (Kimbrough, Guadagno, Muscanell, & Dill, 2013; Szell & Thurner, 2013; Volkovich, Laniado, Kappler, & Kaltenbrunner, 2014). For example, gender homophily is an important driver of gender differences in men's and women's networks (Cabrera & Thomas-Hunt, 2007). Volkovich et al. (2014) find that the tendency of gender homophily is more marked for women, and females are much more likely to connect with other females as their initial friends. Gender difference is also shown in triadic closure. Tuma and Hallinan (1979) demonstrate that most youths tend to delete a same-sex node than resolve the intransitivity by adding a cross-sex one. These simple, small tendencies toward homophily and sex differences in resolving problems in the structure of relationships mean that boys and girls will move toward very different social circles. Their worlds become gender-segregated, with boys in larger, more heterogeneous cliques and girls in smaller, more homogeneous groups. Similarly, Volkovich, et al. (2014) detect a marked tendency of users to gender segregation, i.e. to form single-gender groups. In addition, social interaction behavior also presents various patterns with different genders. Szell and Thurner (2013) demonstrate that females have more communication partners, but less connection strength than males. Moreover, Smoreda and Licoppe (2000) find that women call more frequently and spend about twice time on communication than men, and a gender homophily effect is found for both genders. In addition, age also matters the social behavior in OSNs. Quinn, Chen, and Mulvenna (2011) found that younger users have substantially higher friends than senior users, while senior users take comments twice the rate of younger users. Smith, Rogers, and Brady (2003) stated that senior users have the smallest social network, which mainly consists of family and very close friends. It indicated that senior users have fewer redundant relations.

Above all, in this study, we examine the effect of migration on network evolution behavior as well as social interaction behavior. In addition, to investigate how the effect of migration various to heterogeneous users, we include characteristics of users as moderators. Here, we summarized the proposed conceptual framework of the effects of migration on social behavior changes in Fig. 1.

3. Research methodology

3.1. Data collection

In this study, we collected a dataset including over 2.2 million monthly-level records over four months from March 2013 to June 2013, collaborating with one of the largest online social networks sites (OSNs) in China. This dataset consists of three parts: a) the characteristics of users, including gender, age, and registration time; b) the login records, including the city codes (masked) where the user login and the number

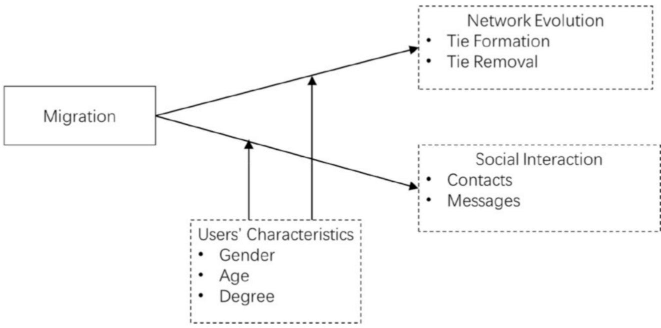

Fig. 1. Conceptual model.

of login days in a month; c) the relationships among users, including social ties and communication records.

To study the migrants' social behavior, above all, we need to identify the migrant. Our dataset includes the users' login location, which depends on the IP address where users logged in. If the user has more than one login location in a month, we only focus on his/her most often login location. The basic method to identify migrants is comparing the location where users logged in most often between two consecutive months, then labeling the users who have different login locations. But this method may misclassify the users who have temporal mobility as migrants, like travel to another city. To avoid misclassification, we divided our four-month dataset into two periods, the first two months and the last two months. First, we selected the users who have the completed login location records in the four months, to make sure we can capture their location changes. Second, we labeled the users who have the same location records in the 4 months as non-migrants. Third, we selected the users who have the same location records in the first two months, but change their location in the third month and keep this changed location in the fourth month. Then labeled them as migrants. This method can help us to identify the migrants who have at least the two-month of mobility. Compared to other migrant identification methods (Phithakkitnukoon et al., 2011; Yang et al., 2018), our method can be regarded as an effective and robust way.

We did the initial data process work in SQL Server, and the detailed data analysis work in R. After that, we get the sample with 574,129 users, including 32,968 migrants (treatment group) and 541,161 non-migrants (control group). Table 1 shows the definition of the main variables. Specifically, the number of tie formation (*NbrTieFormation*) and the number of tie removal (*NbrTieRemoval*) represent the network evolution behavior, and the number of contacts (*NbrContacts*) and the number of messages (*NbrMessages*) represent the social interaction behavior. In addition, a degree means the number of friends that users have. Table 2 shows the summary statistics. To be specific, there are 35% female users in our sample. And most of the users are young people (the median age is 25). The mean number of friends is 17.20 and its S.D. is 26.43, indicating the number of friends is various in different users. As to the network evolution behavior of users, users have a few tie formation and tie removal behaviors in a month (the mean of *NbrTieFormation* and *NbrTieRemoval* are 1.44 and 0.65 respectively). In addition, users send messages to 3.47 friends on average, which is around one-fifth of their total friends (the mean of degree is 17.20). However, they send 98.25 messages on average.

Table 1
The definition of variables.

Variables	Description
$Female_i$	Gender of the user i (1 is female)
Age_i	Age of the user i
$Tenure_i$	Number of weeks since the user i registered
$Treat_i$	Whether the user i is migrant (1 is migrant)
$After_{it}$	Whether the user i is migrated in month t (1 is migrated)
$LoginDays_{it}$	Number of login days user i made in month t
$Degree_{it}$	Number of friends user i had in month t
$NbrTieFormation_{it}$	Number of tie formation user i made in month t
$NbrTieRemoval_{it}$	Number of tie removal user i made in month t
$NbrContacts_{it}$	Number of contacts user i made in month t
$NbrMessages_{it}$	Number of messages user i made in month t

Table 2
Summary statistics.

Variables	median	mean	S.D.	min	max
Demographical Variables (N = 574,129)					
$Female_i$	0.00	0.35	0.48	0.00	1.00
Age_i	25.00	25.49	5.50	11.00	79.00
$Tenure_i$	362.00	364.28	145.88	1.00	695.00
$Treat_i$	0.00	0.06	0.23	0.00	1.00
Time-Variance Variables (N = 2,296,516)					
$LoginDays_{it}$	19.00	16.57	11.72	0.00	30.00
$Degree_{it}$	9.00	17.20	26.43	0.00	936.00
$NbrTieFormation_{it}$	1.00	1.44	2.88	0.00	233.00
$NbrTieRemoval_{it}$	0.00	0.65	2.37	0.00	180.00
$NbrContacts_{it}$	2.00	3.47	3.72	1.00	37.00
$NbrMessages_{it}$	31.00	98.25	176.68	0.00	1479.00

3.2. Research design

The aim of this study is to identify the effect of migration on social behavior. The naïve comparison of social behavior between before and after migration may not accurately estimate the effect of migration, because other time-variant factors may exist that simultaneously influence users' social behavior. So, we applied the difference-in-difference (DID) model to address this issue (Card & Krueger, 2000). The DID model should have treatment and control groups. It first estimates the difference between before and after the treatment in each group. Then it estimates the difference between treatment and control groups. In our context, the migrants serve as a treatment group, and the treatment in the event that users migrate.

The gold standard method to understand causal relationships is through running randomized trials (Aral & Walker, 2011), which has been gaining popularity in the information systems literature (Andrews, Andrews, Luo, Fang, & Ghose, 2016; Bapna, Ramaprasad, Shmueli, & Umyarov, 2016). Nevertheless, the ideal experiment is the practical infeasibility of running in our context, due to the users are not randomly assigned to migrants and non-migrants. In other words, the studied population in our study is the self-selected population of users who expressed the desire to migrate. Therefore, the non-migrants cannot be a reliable control group. For example, migrants are probably more active in social behavior than non-migrants. We relied on propensity score matching (PSM) to select the non-migrants who have a similar propensity to migrate with migrants. Thus, to eliminate the endogenous in this study, we applied a standard empirical strategy for observational data, which is based on a combination of propensity score matching and difference-in-difference analysis. integrating PSM with DID analysis helps account for the influence of unobserved characteristics, enhancing the inference related to DID analysis and improving the consistency of the estimates (Stewart & Swaffield, 2007). For these reasons, this method is becoming increasingly popular among empirical researchers in IS (Goh, Heng, & Lin, 2013; K.; Xu, Chan, Ghose, & Han, 2017).

3.2.1. Propensity score matching

At first, we used PSM to construct a pair of similar users, in which one is migrants (treatment group) and the other is non-migrants (control group). In our main matching procedure, we used one-to-one static PSM matching without replacement. To calculate the propensity scores, we relied both on the characteristics (including *age*, *female,* and *tenure*) as well as the behavioral covariates (including *degree* and *longinDays*). After the application of PSM, unmatched units are dropped from our observation to avoid bias, and the matched two groups are balanced, both groups have 32,968 units. As shown in Table 3, the variables of the two

Table 3
T-test of before and after matching.

Variable	Diff.	Mean (Ctrl)	Mean (Treat)	t-value	p-value
Before Matching (N(Ctrl) = 541,161, N(Treat) = 32,968)					
$Female_i$	0.04	0.35	0.31	13.48	0.00
Age_i	1.54	25.58	24.03	56.02	0.00
$Tenure_i$	28.14	365.84	337.70	36.54	0.00
$LoginDays_{it}$	0.15	26.67	26.53	4.76	0.00
$Degree_{it}$	3.23	17.38	14.15	23.34	0.00
After Matching (N(Ctrl) = 32,968, N(Treat) = 32,968)					
Female	0.00	0.31	0.31	−0.52	0.60
Age	0.02	24.06	24.03	0.64	0.52
Tenure	−1.03	336.67	337.70	−0.96	0.34
LoginDays	0.09	26.62	26.53	2.14	0.03
$Degree_{it}$	−0.05	14.10	14.15	−0.30	0.77

groups before matching are all significantly different by the *t*-test, while they all become insignificant differences after matching. Expect the *loginDays*, although they are very close between two groups after matching.

3.2.2. Difference-in-Difference

Then, we employed the difference-in-difference (DID) technique to the matched sample that results from PSM. Considering the dependent variables are the count variable, and the overdispersion (the variance much larger than the mean), we employed the negative binomial model to estimate (Cameron & Trivedi, 2013). Our main estimation equation using the DID model for user *i* in month *t* is,

$$\log(SocialBehavior_{it}) = \alpha_0 + \alpha_1 \times Treat_i + \alpha_2 \times After_{it} + \alpha_3 \times Treat_i \times After_{it} + \alpha_4 \times D_i + \tau_t \tag{1}$$

where $SocialBehavior_{it}$ is the dependent variable (e.g., *NbrTieFormation*, *NbrTieRemoval*, *NbrContacts*, *NbrMessages*). $Treat_{it}$ is a treatment dummy variable (denoted with "1" if the user is migrant and "0" otherwise). $After_{it}$ is a dummy variable that takes the value "0" for the month before migration and "1" for the month t after migration, for user *i*. We also need to control the characteristics of user *i*, denoted as D_i. The last, we included the month fixed effect τ_t, to control the common time shocks. The focal variable is the interaction of *Treat* and *After*, whose coefficient represents the effect of migration on the dependent variable.

After investigating the main effect of migration, we are also interested in the moderating effect of users' characteristics. In particular, we examined how characteristics of migrants moderate the relationship between migration and social behavior. We then included gender, age, and degree in our model, denoted by *Moderator*. Our second estimation equation is,

$$log(\mathrm{SocialBehavior}_{it}) = \alpha_0 + \alpha_1 \times Treat_i + \alpha_1 \times After_i + \alpha_1 \times Treat_i \times After_i + \alpha_1 \times Treat_i \times After_i \times Moderator_i + \alpha_4 \times D_i + \tau_t \tag{2}$$

4. Empirical analysis and results

4.1. Main results

We conducted the PSM-DID model in Equation (1) for the four dependent variables (i.e. *NbrTieFormation*, *NbrTieRemoval*, *NbrContacts*, *NbrMessages*). We showed our main results in Table 4. The interaction term of *Treat* and *After* is our focal variable, and the coefficients of that represent the effect of migration on social behaviors. In column (1) and (2), the coefficients of our focal variable are 0.083 ($p < 0.01$) and −0.018 ($p > 0.1$) respectively. It shows that users are significantly more active in tie formation behavior affected by the migration, while the tie removal behavior changes insignificantly. In columns (3) and (4), the estimated coefficients are 0.017 ($p < 0.01$) and −0.032 ($p < 0.01$) both significantly, which indicates that individuals contact with more friends but send fewer messages. If we interpret the coefficients in terms of the incidence rate ratio, the results indicate that, on average, affected by migration, a migrant constructs 8.65% more relations than a non-migrant in a month. In addition, on average, a migrant contacts 1.71% more friends but sends 3.25% fewer messages.

In summary, we have two main findings. Firstly, migration makes individuals more active in extending their social networks. This finding could be explained by the social capital theory (Putnam, 1993). As one of the important resources, a part of social relationships will become less beneficial in the process of migration (Ryan, Sales, Tilki, & Siara, 2008). Therefore, migrants desire to build more relationships to rapidly accumulate their social capital. Secondly, migration makes individuals tend to contact more friends but send fewer messages. The finding of the increasing number of contacts is consistent with some previous studies (Yang et al., 2018). It could be partially explained by the social support theory, which states that individuals can get supportive resources, like emotional and informational, from their friends (Cohen & Syme, 1985). On the other hand, migrants are more likely to feel loneliness and unhappiness in the process of migration (Oishi, 2013). Hence, migrants are inclined to contact more friends to get their support.

In addition, the coefficients of other variables about user characteristics also show some interesting findings. First, the coefficients of *female* are significantly negative on network evolution behavior (*NbrTieFormation* and *NbrTieRemoval*), while significantly positive on social interaction behavior (*NbrContacts* and *NbrMessages*). It indicates that females are inclined to contact more friends as well as send more messages than males. Second, the coefficients of *age* are negative on all

Table 4
The effect of migration on social behavior changes.

Dependent variables	NbrTieFormation	NbrTieRemoval	NbrContacts	NbrMessages
	(1)	(2)	(3)	(4)
Treat	0.046*** (0.013)	0.168*** (0.023)	0.012** (0.005)	−0.030*** (0.009)
After	−0.405*** (0.017)	−0.235*** (0.029)	−0.060*** (0.006)	−0.104*** (0.011)
Female	−0.491*** (0.011)	−0.330*** (0.018)	0.126*** (0.004)	0.402*** (0.007)
Age	−0.124*** (0.004)	−0.149*** (0.008)	−0.055*** (0.002)	−0.051*** (0.003)
Age^2	0.002*** (0.0001)	0.002*** (0.0001)	0.001*** (0.00003)	0.001*** (0.0001)
Tenure	−0.080*** (0.002)	−0.061*** (0.004)	−0.008*** (0.001)	0.005*** (0.001)
LoginDays	0.024*** (0.001)	0.052*** (0.002)	0.012*** (0.0003)	0.098*** (0.001)
Degree	0.010*** (0.0001)	0.007*** (0.0002)	0.016*** (0.00004)	0.018*** (0.0001)
Treat * After	0.083*** (0.019)	−0.018 (0.033)	0.017*** (0.007)	−0.032*** (0.012)
Month Fixed	YES	YES	YES	YES
Constant	0.949*** (0.065)	−0.181 (0.121)	1.415*** (0.023)	2.444*** (0.047)
Observations	263,744	263,744	263,744	263,744
Log Likelihood	−222,169	−119,552	−588,014	−1,390,530
AIC.	444,362	239,129	1,176,053	2,781,084

Note: stand error is in the parentheses; ***p < 0.01; **p < 0.05; *p < 0.1.

dependent variables, meanwhile, the coefficients of *age*^{2} are positive on all dependent variables. These coefficients imply the U shape relationship between age and social behaviors. Third, the coefficients of *degree* are all significantly positive on all dependent variables. In general, the users who have a large network size will be more active in social interaction. Moreover, we can find the coefficient of *degree* on *NbrTieFormation* is positive. According to the preferential attachment mechanism, users will more likely to construct the link with the users who have more friends (Newman, 2001). Meanwhile, we observed that users who have more friends also removal more friends.

4.2. Moderating effect

Depended on the findings we observed above, we further examined the moderating effect on the relationship between migration and social behavior. We discussed the moderating effect in terms of users' characteristics, including gender, age, and degree.

4.2.1. The moderating effect of gender

The effect of migration may be different among individuals, in terms of their characteristics. Here, we identify the moderating effect of gender. In Table 5, the results show that: 1) Female is less active in tie formation and removal, however, they contact more friends and send more messages; 2) The effect of migration on tie formation and contacts is stronger for females than males, while it is insignificant on tie removal and messages sent. Furthermore, we plotted figures to better illustrate the moderating effect. Fig. 2 demonstrated the migration effect on *NbrTieformation* and *NbrContact* in different genders. We could find that females are more sensitive to migration. The *NbrTieformation* and *NbrContact* of females would be increased more than males.

4.2.2. The moderating effect of age

We can find that the moderating effect of age is only significant on *NbrContacts*, column (3) of Table 6. In addition, the moderating effect of age shows a U shape (the coefficients of *age* and *age*^{2} are −0.029 and 0.001 respectively). But considering the value range of age (mean = 25.00, S.D. = 5.5), the effect of *age*^{2} is much higher than the effect of *age*. Therefore, the moderating effect of age is positive (not a U shape) in the value range of *age*. Furthermore, Fig. 3 demonstrated the migrating effect on *NbrContact* in different age groups. We could find that the migration effect is strengthened with age increasing. One of the possible reasons is that the relative elder users have stronger connections with their friends (Quinn et al., 2011).

4.2.3. The moderating effect of degree

We can observe that the moderating effect of degree is significant on network evolution behavior (*NbrTieFormation* and *NbrTieRemoval*) in Table 7. Combining with Fig. 4, we can find that the higher existing network size of migrants will strengthen the increase of tie formation. Although the effect is not very high, it is statistically significant. It is reasonable that the migrants with a high degree will become more active

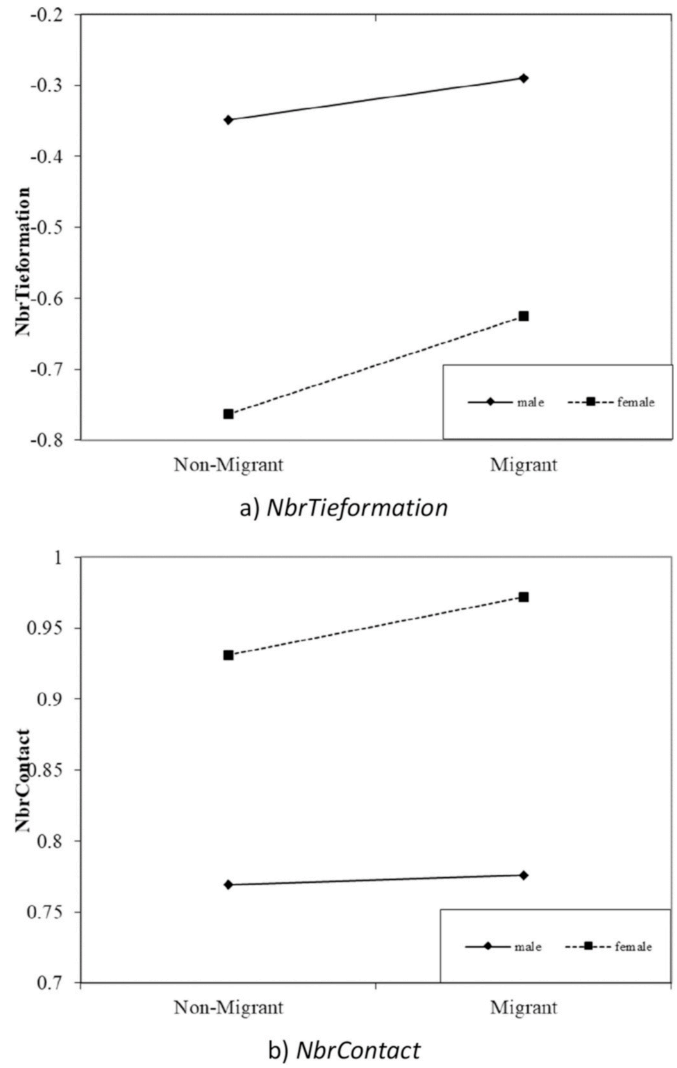

Fig. 2. Moderating effect of gender.

Table 5
The moderating effect of gender.

Dependent variables	NbrTieFormation	NbrTieRemoval	NbrContacts	NbrMessages
	(1)	(2)	(3)	(4)
Treat	0.083*** (0.015)	0.197*** (0.028)	0.029*** (0.006)	−0.013 (0.011)
After	−0.382*** (0.019)	−0.219*** (0.033)	−0.046*** (0.007)	−0.099*** (0.012)
Female	−0.415*** (0.021)	−0.287*** (0.037)	0.162*** (0.007)	0.444*** (0.013)
Age	−0.021*** (0.001)	−0.041*** (0.002)	−0.004*** (0.0004)	−0.015*** (0.001)
Age^2	0.002*** (0.0002)	0.002*** (0.0003)	0.001*** (0.0001)	0.0004*** (0.0001)
Tenure	−0.091*** (0.002)	−0.073*** (0.004)	−0.013*** (0.001)	0.001 (0.001)
LoginDays	0.024*** (0.001)	0.052*** (0.002)	0.012*** (0.0003)	0.098*** (0.001)
Degree	0.010*** (0.000)	0.007*** (0.000)	0.016*** (0.000)	0.018*** (0.000)
Treat * After	0.058*** (0.022)	−0.050 (0.040)	0.007 (0.008)	−0.021 (0.015)
Treat * After *Female	0.079* (0.042)	0.103 (0.073)	0.034** (0.014)	−0.036 (0.027)
Month fixed	YES	YES	YES	YES
Constant	−0.348*** (0.038)	−1.533*** (0.070)	0.769*** (0.013)	1.980*** (0.025)
Observations	263,744	263,744	263,744	263,744
Log Likelihood	−222,383	−119,629	−588,455	−1,390,575
AIC	444,795	239,286	1,176,938	2,781,178

Note: stand error is in the parentheses; ***p < 0.01; **p < 0.05; *p < 0.1.

Table 6
The moderating effect of age.

Dependent variables	NbrTieFormation	NbrTieRemoval	NbrContacts	NbrMessages
	(1)	(2)	(3)	(4)
Treat	−0.311* (0.161)	−0.156 (0.299)	0.276*** (0.059)	0.117 (0.118)
After	−0.291* (0.164)	−0.737** (0.306)	−0.069 (0.060)	0.063 (0.119)
Female	−0.491*** (0.011)	−0.331*** (0.018)	0.127*** (0.004)	0.402*** (0.007)
Age	−0.136*** (0.008)	−0.169*** (0.016)	−0.038*** (0.003)	−0.039*** (0.006)
Ageˆ2	0.002*** (0.0002)	0.002*** (0.0002)	0.002*** (0.0003)	0.001*** (0.0001)
Tenure	−0.081*** (0.002)	−0.062*** (0.004)	−0.008*** (0.001)	0.005*** (0.001)
LoginDays	0.024*** (0.001)	0.052*** (0.002)	0.012*** (0.0003)	0.098*** (0.001)
Degree	0.010*** (0.0001)	0.007*** (0.0002)	0.016*** (0.00004)	0.018*** (0.0001)
Treat * After	−0.208 (0.229)	0.256 (0.425)	0.414*** (0.083)	−0.028 (0.167)
Treat * After * Age	0.018 (0.016)	−0.017 (0.031)	−0.029*** (0.006)	−0.005 (0.012)
Treat * After * Ageˆ2	−0.0002 (0.0003)	0.0002 (0.001)	0.001*** (0.000)	0.0002 (0.0002)
Month fixed	YES	YES	YES	YES
Constant	1.131*** (0.118)	0.161 (0.221)	1.195*** (0.044)	2.283*** (0.086)
Observations	263,744	263,744	263,744	263,744
Log Likelihood	−222,155	−119,547	−587,940	−1,390,514
AIC	444,347	239,129	1,175,917	2,781,063

Note: stand error is in the parentheses; ***p < 0.01; **p < 0.05; *p < 0.1.

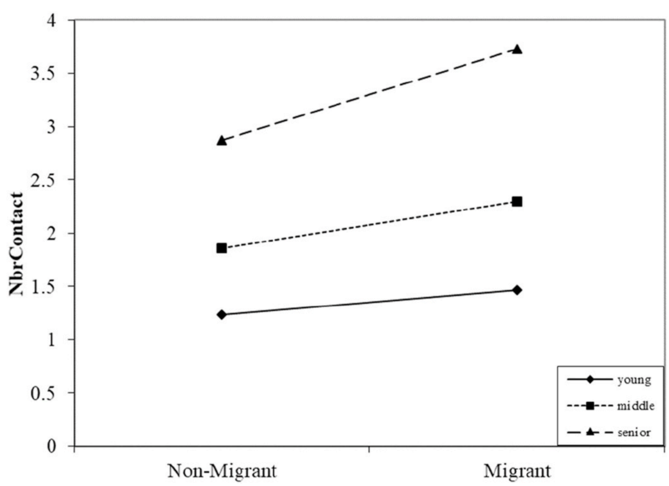

Fig. 3. Moderating effect of age.

in extending their social network because they have a higher demand for social activity. Furthermore, it will weaken the decrease of tie removal. It may be explained by the dumber number (Dunbar, 1992). That is, users have the limited ability to keep their social network. So, the migrants with a high degree will prefer to drop the redundant relationships.

5. Robustness checks

5.1. Alternative time windows

To make the conclusions more convincing, we conduct a robustness check that changed the time window of our study period. In the main results, our research time span is four months (two months before and two months after the migration). Thus, we can narrow the time window into two months (one month before and one month after the migration), to check if the effect of migration still exists. The results are shown in Table 8. It indicates that the results are consistent with our main results (in Table 4), except the coefficient of *NbrMessages* becomes insignificant (the coefficients are close to our main results).

5.2. Alternative regression models

We conduct another robustness check by alternating regression models. Considering that the DV is a count variable in nature, we employ the negative binomial regression to estimate our main model. To further check the robustness, we apply the OLS to estimate. In Table 9, we find that the results are in line with our main results. However, the coefficient of *NbrContacts* turns to be insignificant.

Table 7
The moderating effect of degree.

Dependent variables	NbrTieFormation	NbrTieRemoval	NbrContacts	NbrMessages
	(1)	(2)	(3)	(4)
Treat	0.089*** (0.015)	0.226*** (0.026)	0.012** (0.005)	−0.045*** (0.010)
After	−0.385*** (0.018)	−0.198*** (0.032)	−0.064*** (0.006)	−0.114*** (0.012)
Female	−0.491*** (0.011)	−0.331*** (0.018)	0.126*** (0.004)	0.402*** (0.007)
Age	−0.125*** (0.004)	−0.149*** (0.008)	−0.055*** (0.002)	−0.051*** (0.003)
Ageˆ2	0.002*** (0.0001)	0.002*** (0.0001)	0.001*** (0.00003)	0.001*** (0.0001)
Tenure	−0.080*** (0.002)	−0.061*** (0.004)	−0.008*** (0.001)	0.005*** (0.001)
LoginDays	0.024*** (0.001)	0.052*** (0.002)	0.012*** (0.0003)	0.098*** (0.001)
Degree	0.011*** (0.0002)	0.008*** (0.0005)	0.016*** (0.0001)	0.017*** (0.0002)
Treat * After	0.043** (0.021)	−0.086** (0.038)	0.023*** (0.007)	−0.032** (0.014)
Treat * After * Degree	0.002*** (0.001)	0.004*** (0.001)	−0.0003 (0.0002)	0.00001 (0.0004)
Month fixed	YES	YES	YES	YES
Constant	0.931*** (0.065)	−0.207* (0.121)	1.416*** (0.023)	2.456*** (0.047)
Observations	263,744	263,744	263,744	263,744
Log Likelihood	−222,153	−119,544	−588,013	−1,390,523
AIC	444,337	239,118	1,176,056	2,781,077

Note: stand error is in the parentheses; ***p < 0.01; **p < 0.05; *p < 0.1.

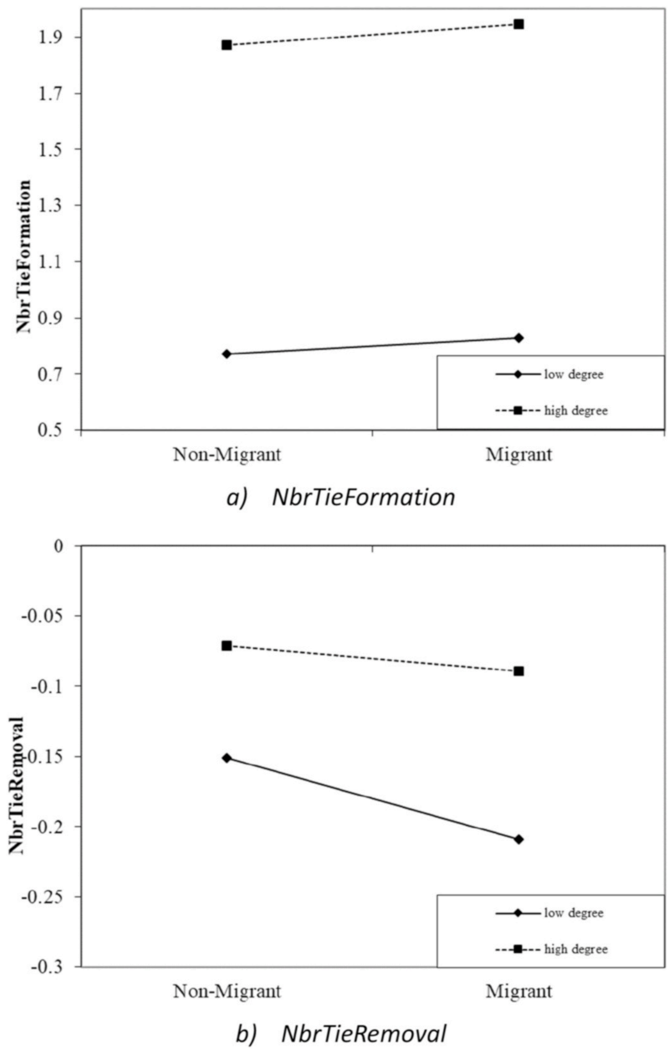

Fig. 4. Moderating effect of degree.

5.3. Subsample analyses

Moreover, we conduct subsample analyses to further understand how migration affects social behaviors. Considering the social network structure tends to be stable after the user joins the OSN for a long time, the effect of migration may show different results for users in terms of their tenure in the OSN. We estimate the effect of migration on the users who are relatively new users in this OSN and on the users who are sophisticated users, respectively. In operationalizing this, we first rank the users based on tenure, which is the number of years between the registration day and the beginning day of our study. We treat users in the bottom 50th percentile and top 50th percentile as those who are relatively new users and sophisticated users, respectively.

The subsample analyses results are presented in Table 10. Firstly, the direction of the migration effect is consistent with our main results, although some of them are insignificant. Secondly, in terms of tie formation behavior, new users are influenced by migration more than sophisticated users. That can be interpreted by that sophisticated users show more stability in their social network structures.

6. Discussion and conclusion

This study analyzed the network evolution and social interaction behavior changes after migration with a large-scale dataset of OSNs. We designed the research by combing propensity score matching (PSM) with the difference-in-difference (DID) approach to eliminate the endogenous issues. We leveraged 2.29 million user-month level data, including the real social behaviors in OSNs, to quantify the migration effect on social behaviors and its moderating effect. Our analyses had two main findings. First, we revealed the changes in network evolution and social interaction behavior after migration. Specifically, migrants become more active (increase 8.65%) in tie formation while insignificantly changes in tie removal. The increase of tie formation indicates that the migrants need to reorganize their social network by using OSNs, although tie removal is decreased, which may be because the users do not need to remove the redundant ties by using OSNs that have unlimited resources. Moreover, they tend to contact more friends but send fewer messages, in terms of the number of contacts (decrease 1.71%) and the number of messages sent (decrease 3.25%). These findings reveal that migration affects individuals to contact more friends, to get more social support from different people, but the communication strength is decreased, which may be limited by their resources of cognitive and time. Second, we address the moderating effect of migrants' characteristics. In depth, females are more sensitive affected by migration. They increase more the number of tie formation and the number of contacts than males. Meanwhile, the elderly users are more sensitively affected by migration, with regards to the increasing the number of contacts. In addition, the high degree migrants have more increase in the number of tie formation and less decrease in the number of tie removal by the effect of migration.

Our study fills the gap of previous research in the following aspects. First, to the best of our knowledge, this study is the first work that reveals the effect of migration on social behavior in OSNs with a large-scale dataset. The previous studies all discussed this effect in the telecommunication network, which can only show the social interaction behavior instead of the network evolution behavior. However, the

Table 8
Alternative time window.

Dependent variables	NbrTieFormation	NbrTieRemoval	NbrContacts	NbrMessages
	(1)	(2)	(3)	(4)
Treat	0.079*** (0.018)	0.201*** (0.033)	0.023*** (0.007)	−0.045*** (0.012)
After	0.013 (0.018)	−0.048 (0.034)	−0.015** (0.007)	−0.042*** (0.012)
Female	−0.474*** (0.015)	−0.296*** (0.026)	0.126*** (0.005)	0.414*** (0.010)
Age	−0.022*** (0.001)	−0.039*** (0.003)	−0.006*** (0.001)	−0.013*** (0.001)
Tenure	−0.076*** (0.003)	−0.078*** (0.005)	−0.005*** (0.001)	0.004** (0.002)
LoginDays	0.021*** (0.001)	0.052*** (0.002)	0.009*** (0.0005)	0.099*** (0.001)
Degree	0.009*** (0.000)	0.007*** (0.000)	0.016*** (0.000)	0.018*** (0.000)
Treat * After	0.095*** (0.026)	−0.022 (0.047)	0.029*** (0.009)	0.005 (0.018)
Constant	−0.411*** (0.051)	−1.602*** (0.096)	0.830*** (0.018)	1.899*** (0.034)
Observations	131,872	131,872	131,872	131,872
Log Likelihood	−115,922	−60,398	−297,498	−697,928
AIC	231,863	120,815	595,014	1,395,875

Note: stand error is in the parentheses; ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 9
OLS estimations.

Dependent variables	NbrTieFormation	NbrTieRemoval	NbrContacts	NbrMessages
	(1)	(2)	(3)	(4)
Treat	0.018 (0.013)	0.031*** (0.008)	0.116* (0.059)	4.514** (2.099)
After	−0.179*** (0.016)	−0.052*** (0.010)	−0.200*** (0.073)	−10.698*** (2.570)
Female	−0.223*** (0.010)	−0.066*** (0.007)	0.201*** (0.046)	47.425*** (1.623)
Age	−0.008*** (0.001)	−0.010*** (0.001)	−0.015*** (0.005)	−2.808*** (0.168)
Tenure	−0.051*** (0.002)	−0.017*** (0.001)	−0.113*** (0.009)	−1.352*** (0.309)
LoginDays	0.010*** (0.001)	0.009*** (0.001)	0.063*** (0.004)	8.525*** (0.141)
Degree	0.009*** (0.000)	0.002*** (0.000)	0.107*** (0.00)	3.411*** (0.024)
Treat * After	0.045** (0.018)	0.001 (0.012)	0.056 (0.084)	−6.065** (2.968)
Month fixed	YES	YES	YES	YES
Constant	0.696*** (0.035)	0.321*** (0.024)	1.344*** (0.165)	−86.600*** (5.838)
Observations	263,744	263,744	263,744	263,744
R^2	0.021	0.005	0.088	0.088
Adjusted R^2	0.021	0.005	0.088	0.088
F Statistic	557.334***	134.315***	2,537.132***	2,549.979***

Note: stand error is in the parentheses; ***p < 0.01; **p < 0.05; *p < 0.1.

Table 10
Subsample analyses (Panel A: New users). Subsample analyses (Panel B: Old users).

Dependent variables	NbrTieFormation	NbrTieRemoval	NbrContacts	NbrMessages
	(1)	(2)	(3)	(4)
Treat	−0.002 (0.018)	0.087*** (0.030)	−0.015** (0.006)	−0.015 (0.012)
After	−0.394*** (0.022)	−0.237*** (0.038)	−0.063*** (0.008)	−0.073*** (0.015)
Female	−0.528*** (0.014)	−0.260*** (0.023)	0.086*** (0.005)	0.404*** (0.009)
Age	−0.027*** (0.001)	−0.036*** (0.002)	−0.004*** (0.0005)	−0.016*** (0.001)
Tenure	−0.209*** (0.004)	−0.137*** (0.008)	−0.086*** (0.002)	−0.074*** (0.003)
LoginDays	0.025*** (0.001)	0.056*** (0.002)	0.020*** (0.0004)	0.102*** (0.001)
Degree	0.010*** (0.0002)	0.007*** (0.0004)	0.017*** (0.0001)	0.020*** (0.0002)
Treat * After	**0.093*** (0.025)**	**−0.010 (0.043)**	**0.007 (0.009)**	**−0.038** (0.017)**
Month fixed	YES	YES	YES	YES
Constant	0.332*** (0.050)	−1.426*** (0.090)	0.900*** (0.018)	2.194*** (0.034)
Observations	132,432	132,432	132,432	132,432
Log Likelihood	−122,956	−68,331	−295,913	−699,330
AIC	245,934	136,685	591,849	1,398,682
Dependent variables	NbrTie Formation	NbrTie Removal	NbrContacts	NbrMessages
	(5)	(6)	(7)	(8)
Treat	0.123*** (0.019)	0.279*** (0.036)	0.052*** (0.007)	−0.027** (0.013)
After	−0.401*** (0.025)	−0.230*** (0.045)	−0.056*** (0.008)	−0.141*** (0.015)
Female	−0.551*** (0.017)	−0.483*** (0.031)	0.105*** (0.005)	0.369*** (0.010)
Age	−0.016*** (0.002)	−0.051*** (0.004)	−0.007*** (0.001)	−0.020*** (0.001)
Tenure	0.016*** (0.004)	−0.011 (0.008)	0.059*** (0.001)	0.044*** (0.003)
LoginDays	0.029*** (0.001)	0.052*** (0.003)	0.008*** (0.0005)	0.098*** (0.001)
Degree	0.009*** (0.0002)	0.006*** (0.0004)	0.014*** (0.0001)	0.016*** (0.0001)
Treat * After	**0.047* (0.028)**	**−0.033 (0.052)**	**0.022** (0.009)**	**−0.022 (0.018)**
Month fixed	YES	YES	YES	YES
Constant	−1.503*** (0.069)	−1.776*** (0.131)	0.319*** (0.023)	1.836*** (0.042)
Observations	131,312	131,312	131,312	131,312
Log Likelihood	−98,535	−51,032	−288,995	−690,596
AIC	197,092	102,087	578,012	1,381,215

Note: stand error is in the parentheses; ***p < 0.01; **p < 0.05; *p < 0.1.

network evolution behavior is also an important part of individuals' social behavior, which indicates the dynamics of social network structure and social capital of individuals. This study examines these two behaviors simultaneously. Second, considering the mixed findings in prior literature, we provide relatively robust findings using the PSM-DID model. It can enrich the empirical evidence of the effect of migration on social behavior. Third, we examine the moderating role of users' characteristics, including gender, age, and degree. It can also help us to understand the mixed findings by revealing the different effects in various individuals. Moreover, Although the characteristics of users have been shown as an important factor in the process of migration (Kratz, 2020), the effect of characteristics has not been fully discussed in the previous literature.

The results also have implications for OSNs managers. Most people experienced a change of the residential location when they enrolled in the college or transfer to another company. Tremendous people migrate from rural area to city, or from a small city to the first-tier city, like Beijing, Shanghai, and so on, to look for better job opportunities, living conditions, and educational resources. Therefore, individuals in a migration state are of common occurrence (5% of users are during migration in our sample). To provide better service, they have the motivation to understand their users deeper. Our findings implicate for OSNs by uncovering the effect of migration on the changes of user social behavior patterns. For example, when users migrated, they will tend to extend their social network and contact more friends in OSNs. Depending on this, platforms can optimize their recommendation systems, such as increasing the intensity of recommendations when the user migrates. It is also implicated for other service providers, like telecommunications, to recommend suitable packages for migrants due to their communication patterns change.

Some avenues for further research are also identified. First, our study only reveals the short-term effect of migration, with the limitation of our four-month dataset. If possible, data with a longer duration can help to describe the long-term effects and make a comparison with the short-term effects. Second, to protect the privacy of users, our dataset anonymizes the specific city names of users' locations. Therefore, we cannot get the exact geographic distance between their origin cities and destination cities, to reveal the moderating effect of geographic distance. Third, the granularity of our data is monthly level, which cannot capture the dynamics of social networks and the migration time as precise as data at the daily level, although the dynamics of social networks is not quite frequent.

Credit author statement

Xiaobin Ran: Conceptualization, Methodology, Formal analysis, Visualization, Writing. **Yuquan Xu**: Conceptualization, Methodology, Software, Investigation. **Yuewen Liu**: Conceptualization, Supervision, Resources, Writing- Reviewing and Editing. **Jinhu Jiang**: Conceptualization, Supervision, Resources.

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