The Impact of the Internet on Social Capital

by

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Thesis submitted in partial fulfillment of the requirements for
the Master of Arts Degree in East Asian Studies in the Department of
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ABSTRACT

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Abstract

In this paper I explore the impact of the Internet on social capital. I measure social capital in two ways: embeddedness in social groups and willingness to contribute voluntarily to public projects. To investigate the causal relation between the Internet and social capital, I introduce the natural log of the distance between every individual and the nearest cellular tower as an instrumental variable. I find that (1) owning more types of devices leads to spending more time online; (2) owning more types of devices results in lower likelihood of being organizational members (except private membership) and of contributing voluntarily to public projects; (3) online time is positively related to social capital, but the effect of online time is negative on social capital; and (4) there is a gender gap in the effect of the Internet on social capital.

Contents

List of Tables

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1. Introduction

In Bowling Alone, Putnam attribute the loss of social capital to the use of "television and its electronic cousins" (Putnam, 2000). In an era when the Internet becomes popular, people might be curious whether the Internet has a similar impact on social capital. Like televisions, the Internet allows people to entertain and obtain information privately. Surfing the Internet also takes up time that result in less time for other activities such as meeting people offline. In addition, astonishing news stories online harm social trust because people may tend to assume that others have malicious intentions. Therefore, the Internet has the potential to reduce social capital.

However, some scholars challenge the theory of Putnam (2000) by suggesting that the time spent on social activities is not related to online time. Some are optimistic about the impact of the Internet on social capital because unlike television, the Internet allow people to have conversations online and to develop interpersonal connections online. Moreover, the flow of online information promotes offline gatherings. Recent studies corroborate this positive mechanism by demonstrating that there is positive correlation between overall Internet use and social capital.

However, is the positive correlation driven by the socializing function of the Internet? This assumption is not supported by studies that distinguish between different purposes of Internet use: spending more time online for communication purposes is not related to more social capital. If the Internet is not able to enhance social capital by facilitating interpersonal communications, why would we observe a positive correlation between Internet usage and social capital?

In this paper, I suggest that this unexpected correlation stems from the reverse causality: those with more social capital tend to spend more time online. For example, Party members may be more interested in political news, so they spend more time than non-Party members on reading the news online. Unfortunately, most articles that reveal a positive relation between Internet usage and social capital fail to rule out the possibility that online time might be endogenous to social capital. Therefore, I intend to test if there is a causal relation between the Internet and social capital in this paper. To achieve this goal, I introduce the natural log of the distance between every individual and the nearest cellular tower as an instrumental variable.

Scholars have defined "social capital" in various ways (Neves, 2013). This paper follows the definition proposed by Putnam (2000), which is "social capital refers to connections among individuals – social networks and the norms of reciprocity and trustworthiness that arise from them." In accordance with this definition, I measure social capital in two ways: (1) the embeddedness of an individual in social networks, and (2) the willingness of a person to contribute voluntarily to public projects in her village. I find that Internet use has a negative impact on social capital, in terms of both social networks and social trust.

The rest part of this paper will be organized like this: I first review existing literature and explain why the Internet might have a negative (or the opposite) effect on social capital. Then I introduce the datasets I use to do the empirical test and the way I measure variables. The following empirical design part tests my hypotheses.

2. Literature Review

Does the Internet damage social capital? There does not seem to be a consensus (Neves, 2013). Theoretically, the Internet is a double-edged sword: it privatizes people's leisure time and crowds out social engagement (Putnam, 2000), while simultaneously it provides a platform for people to have online conversations and facilitates the flow of information that enables people to activate latent ties, join social groups, and participate in local activities. Most empirical studies that treat Internet use as a whole suggest that Internet use is positively, or not significantly, related to social capital, which implies that the socializing function of the Internet may be able to create social capital. However, this mechanism is challenged by some studies that distinguish between different purposes for using the Internet, including communicating, entertaining, and information-seeking. These studies reveal that social uses of the Internet, which is expected to boost social capital, is negatively related to social engagement.

The Internet can have a negative impact on social capital through several mechanisms. First, the Internet reduces social capital by replacing face-to-face interactions with personal surfing time. As Putnam (2000) has noticed, the end of the 20th century in the United States is an era when "news and entertainment have become increasingly individualized." This statement is very likely to be true when the Internet becomes more and more popular in developing countries like Vietnam. People do not need to go to village meetings to obtain news, nor do they need to meet friends to play chess or Mahjong to have fun – news websites and online game centers may have displaced a considerable number of offline gatherings. Since offline gatherings are an important source of interpersonal connections, their displacement undoubtably reduces social capital. Although some might argue that those who spend more time reading newspapers or watching news on televisions at the same time are more active in civic engagement, evidence has shown that those who mainly acquire news from online sources are "less likely than their fellow citizens to be civically involved" (Putnam, 2000).

Second, the time spent on using the Internet may crowd out the time used for developing social capital (e.g. social gatherings). According to Putnam (2000), an extra hour spent on television watching is associated with "roughly a 10 percent reduction in most forms of civic activism." We will naturally expect that surfing the Internet can have a similar effect. Since the amount of time in a day is inelastic, Nie (2001) asserts that "Internet use is bound to come at the expense of other previous activities." Nie and Erbring (2000) find that online time replaces the time that previously is used for staying with friends and family and "socializing outside the home."

However, we are not sure if the time being crowded out is exactly the time reserved for creating social capital. For example, if someone prioritizes face-to-face communications with friends, she is not likely to cut down the offline gathering time if she spends some extra time on the Internet. Additionally, if online time is increased at the cost of television-watching time (Nie, 2001), which is expected to reduce interpersonal interactions (Putnam, 2000), we should at least expect Internet use to have no significant effect on social capital, if not a positive effect. This suggestion is supported by empirical evidence. Olken (2009), for example, demonstrates that although access to more television channels increases the time spent on watching televisions, television time is not significantly related with social capital. Anderson and Tracy (2001) explore the pattern of time use of British citizens and conclude that having access to the Internet seems to have "very little immediate and significant impact" on the time used for other activities. Another study on screen time reveals that while watching television has a negative relation with social capital, using the Internet is positively related with social capital indicators (Hooghe & Oser, 2015). In addition, Quan-Haase and Wellman (2004) demonstrate in their study that those who use the Internet heavily are still active in in-person meetings and over-the-phone communications. What's more, Robinson and Martin (2010) find that there is no evidence showing Internet use is replacing the time spent on creating social capital. Although more online time is related to less visits to relatives, it is associated with more visits to friends.

Third, the Internet might have a negative effect on reciprocity and generalized trust. The Internet allows people to read a variety of news, some of which report astonishing incidents - these shocking news stories are not often seen on televisions or newspapers - that destroy people's trust in others. Consequently, they would to some extent assume that others have evil intentions. For instance, thanks to the Internet, the Peng Yu case (Peng Yu helped an old woman who fell and later was accused of causing her fall by the old woman) became well-known in China. As a reaction to this case, some Chinese people would hesitate before being "Good Samaritans" (Liu, 2011). The more people are exposed to these pessimistic messages, the more likely the recommendation system will push such information to them. Eventually, people would tend to not trust others and choose not to help others.

That being said, we cannot neglect the role of the Internet in providing a platform for people scattered around the world to communicate synchronously or asynchronously. Internet allows people to maintain Interpersonal ties as well as establish new ties, and facilitate people's participation in groups that fit their interest.

Some scholars believe that the Internet has the potential to enhance social capital, especially virtual networks. For example, according to Wellman, Haase, Witte, and Hampton (2001), since the cost of communication has been lowered by the Internet, people would contact friends and kin more frequently. People can also use the Internet for maintaining interpersonal ties (Rainie & Wellman, 2012; Wellman, 2001). Students can keep in touch with classmates after graduating, and neighbors can contact each other frequently even if they have moved out to another city. The Internet helps people overcome geographical barriers as if they live in the same community. The Internet also allows people to "activate latent ties" (Haythornthwaite, 2005). Facebook's friend suggestion system, for instance, is based on the users' mutual friends, networks, and activities. In that way, people get to establish connections with the friends of their friends, with alumni or colleagues who used to stay in the same school or workplace, with someone who has participated the same activity but did not have the opportunity to have conversations during the activity. Furthermore, thanks to the abundant information online, people are able to find and join groups that fit their interests and build interpersonal ties (Neves & Fonseca, 2015; Wellman, Haase, Witte, & Hampton, 2001). However, while the Internet is able to create virtual connections, online ties might be weaker than offline ties. According to Putnam (2000), since nonverbal expressions are invisible in online conversations, people are less likely to trust each other than in face-to-face chatting.

Some scholars argue that the Internet not only boosts online connections but also enhance offline networks. For example, people can make arrangements online, which is convenient and low-cost, so that they can meet in person later (Wellman, Haase, Witte, & Hampton, 2001). Boase et al. (2006) also find that online communications are positively related to offline gatherings. Furthermore, online information about local activities allows people to meet in person with others who share similar interests with them (Stern & Adams, 2010). Empirically, Stern and Dillman (2006) find that Internet users are more active in social involvement, including "attending local events, being a member of an organization, or taking a leadership role in local undertakings." However, online communications do not always enhance offline interactions due to the fact that emails and social applications can replace unnecessary in-person meetings. Nie (2001) notice that emails in companies have thinned conversations in company hallways or personal offices. Likewise, those who send emails to their family members or relatives report less face-to face interactions with them (Nie, 2000).

Although the social function of the Internet seems promising, unfortunately, studies on the pattern of online time do not support this argument. These studies distinguish between different purposes of Internet use. Shah, Nojin Kwak, R. Lance Holbe (2001) find that social capital is positively correlated with "informational uses" of the internet, but negatively related to "social-recreational uses" of the Internet. A study by Kraut et al. (1998) shows a similar conclusion. Using the Internet for communication purposes, which is expected to enhance interpersonal ties, turns out to reduce participants' communication with family members.

So far, the impact of the Internet on social capital is still vague. If using the Internet for communication purposes is negatively related to social capital, we should expect to see an overall negative relation between Internet use and social capital. However, empirical evidence does not seem to support this expectation. In this paper, I suggest that this inconsistency stems from the possibility that Internet use is endogenous to the indicators of social capital (Bauernschuster, Falck, & Woessmann, 2014). Most of the literature cited above explores the association between Internet use and social capital, rather than the causal relation between them (as I demonstrate in the empirical design section, Internet use is related to social capital positively, but this result changes dramatically after I introduce the instrumental variable). Therefore, in this paper I intend to test the causal relation between the Internet and social capital, taking advantage of an instrumental variable. Specifically, I use the distance between each individual and the nearest cellular tower as an instrumental variable.

3. Hypotheses

Hypothesis 1: Using the distance from the nearest cellular tower as an instrumental variable, those who have more convenient access to the Internet (measured by the number of device types) would spend more time using the Internet.

This hypothesis is consistent with the intuition that the closer people are to the cellular towers, the stronger signals they have, and the more types of devices they would purchase. Consequently, those who own more types of devices would spend more time using them because accessing the Internet is more convenient for them.

As discussed in the literature review part, the Internet can have an isolating effect, and online time has the potential to crowd out the time used for developing social capital as well as to make people hold cynical views of others. Therefore, we can expect that owning more types of devices has a negative effect on social capital.

Hypothesis 2: After addressing endogeneity in selection into internet usage, more Internet use results in lower levels of social capital.

4. Data

Vietnam is the focus of this study. The primary datasets used in this study are the PAPI 2018 data and the CellMapper data. PAPI is the largest public opinion survey in Vietnam assessing the formulation, implementation and monitoring of policy and provision of public services. In 2018, PAPI surveyed 63 provinces, 208 districts, 416 communes/wards, and 14304 individuals. CellMapper provides information on the locations (geographic coordinates) of cellular towers in Vietnam, including the towers established by 5 cellular service providers: Vinaphone, ViettelMobile, MobiFone, Vietnamibile, and Beeline. Descriptions of the key variables used in this paper are presented in Appendix A. Appendix B shows the correlations for any pair of the key variables.

4.1 Internet reception, device ownership, and online time

To get the data on the ability of individuals to receive Internet, I matched the home address of each individual (in PAPI data) with the nearest cellular tower (in CellMapper data) and calculated the distance between them. The distances range from 30 meters to 156,600 meters, with the mean distance being 20,545 meters and the median 7,080 meters.

I use the number of device types to measure how convenient an individual is to access the Internet. The PAPI data provide information about how many types of devices the respondent has. Devices include computers, mobile phones, public houses, and other kinds. On average, people have 0.73 types of Internet devices. 48.72% of the respondents have no access to the Internet. If these people are excluded, an average respondent will have 1.40 types of Internet devices.

The data on online time also comes from the PAPI data. Respondents were asked to provide information about how many hours on average they spent on using Internet every day. On average, people spend 0.886 hour (53 minutes) on using the Internet. If we exclude those people who have no access to the internet (48.72%), the average time spent on internet would be 1.74 hours (104 minutes).

In this paper, I use Internet reception (the natural log of the distance between the respondent and the nearest cellular tower) as an instrumental variable for device ownership to avoid potential reverse causality problems. For example, party members might be more well-educated and interested in public affairs, so they may feel motivated to buy Internet devices so that they can search for relevant news about government activities. These people might also have higher economic status, so they can afford the Internet as well as Internet devices, resulting in more time using the Internet.

Self-selection is not likely to pose a problem for the exogeneity of my instrumental variable because very few people would consider cellular signal strength as one of the primary determinants when choosing their home addresses. Most people do not work at home. For household entrepreneurs (10.93% of the respondents), most of them (about 90%) are retailors who probably sell things offline. Other household entrepreneurs include restaurant owners, repair workers, photographers, etc. There is only one Internet café owner among all the household entrepreneurs whose Internet café and home might locate in different places.

The Independent variable in this paper, instead of online time, is the number of device types that measure how convenient the respondent is to use the Internet. Online time might not be a good indicator of Internet use because people do not necessarily use the Internet spontaneously. Since the Internet has penetrated everyday life, a considerable number of people are using the Internet to work or study. A middle-aged government employee might use the Internet for eight hours during work time but has very little interest in trying new products and socializing and entertaining online. In this case longer online time does not necessarily mean a more addicted Internet user. At the same time, this government employee is likely to be a Communist Party member as well as a member in labor union or women's union. If we use online time to measure internet use, there will probably turn out to be a positive relation between internet use and organizational affiliation (one of the indicators of social capital).

Therefore, to represent spontaneous Internet use outside of working hours, I count the number of device types each individual owns. More types of devices allow people to use the Internet more conveniently, thereby increasing their willingness to use the Internet, which may give rise to their spontaneous online time. For example, those who can only access the Internet through a public computer might spend less time online than those who own personal computers because going to an Internet Café is far less convenient than staying at home. Those who own not only personal computers but also smart phones would spend more time online than those who only own personal computers because social applications (e.g. Zalo, Instagram, Facebook, etc.) are easier to use on the phone than on the computer. Those who possess smart televisions would also willingly spend more time watching online TV series or online movies than those who do not own smart televisions – the latter either watch TV shows that are pre-arranged by television stations, or use personal computers, whose display sizes are far smaller than televisions, to watch TV series or movies. Some "geeks" might also purchase wearable devices such as smart watches, which allow them to receive and send messages at any time (some people might not bring phones with them when working out) using the applications installed in the watches.

4.2 Dependent Variables

Following Putnam's (2000) definition of social capital, I propose two indicators of social capital: (1) the embeddedness of an individual in organizations (indicator of interpersonal networks), and (2) the willingness of an individual to contribute to public projects (indicator of the norms of reciprocity and trstworthiness). These two indicators are dichotomous variables.

I measure the first indicator based on whether the individual is an active member in any organizations. An average Vietnamese has a probability of 69.72 percentage point to be an organizational member. Organizations can be categorized into three subgroups: the Party, public organizations, and private associations. Public organizations, including labor unions, Women's Union, Youth Union, Veterans Union, and famers unions, are closely monitored by the Party. Private associations are more informal, including religious groups, sports club, recreational clubs, professional associations, alumni associations, etc. 14.23 percent of the respondents are Party members, 54.18 percent of them have affiliation with public organizations, and 36.67 percent of them are members in private associations.

The second indicator is measured by whether the individual has contributed voluntarily to any public projects in her village. Some respondents have contributed money or time to public projects involuntarily (either requested by the village head or the local authorities), and these people do not count towards voluntary contributors. Overall, 20.41 percent of the respondents are voluntary contributors.

4.3 Control Variables

In order to avoid omitted variable bias, I control for several variables that are correlated with device ownership, online time, and social capital.

Rural indicates whether the respondent lives in the rural area. 40.73 percent of the respondents are rural residents. Those who live in the rural areas may own less types of devices because smartphone stores usually locate in urban areas and therefore buying devices are less convenient in rural areas. Living in rural areas may be related to social capital as well in that farmers in rural areas are likely to be members in farmers' unions and that rural residents has a better sense of community because they know each other better than urban residents. When there is a public project, rural residents are more likely to contribute money or time to it because they believe others would do the same and the project would eventually benefit everyone.

Female takes the value 1 if the respondent is a woman. 51.90 percent of the respondents are female. Intuitively, "geeks" are usually males and females are less likely than males to purchase devices. In addition, females usually spend more time than males on taking care of the family and doing household chores, which allow them less free time to be spent online. Females may also be active in organizations such as the Women's Union, whereas they are less likely to be Party members.

Ethnic Vietnamese is 1 if the ethnicity of the respondent is Kinh, the majority ethnic group of Vietnam. 85.27 of the respondents are Kinh people. Kinh people are usually urban residents who can visit electronic device retailers easily and benefit from online shopping. Other ethnic groups may spend less time online because of language barriers. Kinh people are probably more likely to be organizational members due to their large population, which make it easier to find groups that fit their interests.

Age indicates the age of the respondent. The average age of all the respondents is 49.19 years old. Older people are often more reluctant to try new technologies, including new devices, and therefore will purchase less types of devices and spend less time on using them. At the same time, older Vietnamese may be more likely to be organizational members because they have more free time to participate in activities held by organizations.

Income is the equivalized income of the respondent. The unit of this variable is million VND. An average Vietnamese has an equivalized monthly income of 4.88 million VND. In PAPI data, respondents reported their household monthly income in bins. I use the midpoint of the bins to assign each respondent a single value. I then calculate the equivalized income by dividing the household monthly income by the square root of the household size. Those with higher income are likely to buy more types of devices because they are not constrained by budgets and a whole set of devices makes life easier (e.g. Apple products allow users to transfer data easily). Consequently, they spend more time on using the Internet. Wealthier people may also have more hobbies and are more likely to join sports clubs or recreational groups.

Unemployment denotes whether the person has a job (job includes student). Unemployment takes the value 0 if the respondent is retired or unemployed. 11.79 percent of the respondents do not have jobs. Unemployed people have more free time so they can spend more time on using the Internet (and buy more products) as well as playing active roles in social groups.

I also control for province fixed effects in case there are unobserved variables that vary across provinces.

5. Empirical Design

I first examine whether having more types of Internet devices has a positive effect on the time spent on using the Internet. Intuitively, people who own more types of devices would spend more time on using them. At the same time, those who spend more time on using the Internet would be more willing to purchase different types of devices. To better examine the causality, therefore, I want to introduce the distance between each individual and the nearest signal tower as an instrumental variable. To that end, I matched every individual in the PAPI 2018 dataset with a signal tower that is geographically closest to her from the CellMapper dataset and calculated the distance between them.

To test the exogeneity of my instrumental variable, here I introduce another variable: village population. In a project studying the locations of cellular towers in Maine, Malmer (2009) suggests that population density is an important factor in deciding the locations of the cellular towers. I assume in Vietnam the cellular towers are also placed near the villages with large population. Since urban areas often have larger population density, service providers might also prioritize cities when deciding the locations of cellular towers. Therefore, we estimate the following OLS regression:

$$\ln(distance) = \beta_0 + \beta_1 village\_population + \beta_2 rural + \alpha + \mu$$

where *distance* is distance between an individual and the nearest cellular tower, *village_population* is the population of the village, *rural* denotes whether the village is in the rural area, α is province fixed effects.

The results are shown in Table 1. The natural log of distance between a village and the nearest cellular tower is significantly correlated with village population and whether the village is in the rural area.

Table 1. Distance to the Nearest Cellular Tower, Village Population, and Rural Areas

VARIABLES	(1) ln(distance)
village_population	-9.28e-05***
	(1.36e-05)
rural	0.976***
	(0.0240)
Province FE	Yes
Constant	6.171***
	(0.0523)
Observations	12,922
R-squared	0.618

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Then I test whether population and area are related with online time. I estimate the following OSL regression:

$$hours\_per\_day = \beta_0 + \beta_1 village\_population + \beta_2 rural + \sum \beta_i X_i + \alpha + \mu$$

where X_i denotes individual controls (female, ethnic Vietnamese, age, equivalized income, unemployment).

The results are presented in Table 2, which suggest that online time is significantly correlated with village population and rural area. Therefore, in the following 2SLS regression I include village population as a control variable to make sure that the natural log of the distance is conditionally exogenous to online time.

Table 2. Online Time, Village Population, and Rural Areas

VARIABLES	(1) hours_per_day
village_population	-4.70e-05***
	(1.59e-05)
rural	-0.409***
	(0.0296)
female	-0.238***
	(0.0257)
ethnic_Vietnamese	0.306***
	(0.0453)
age	-0.0452***
	(0.00125)
income	0.0664***
	(0.00290)
unemployment	0.229***
	(0.0443)
Province FE	Yes
Constant	3.249***
	(0.0964)
Observations	12,602
R-squared	0.200

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I test hypothesis 1 using the following 2SLS regression:

(First stage regression)

$$device\_ownership = \pi_0 + \pi_1 \ln(distance) + \sum \pi_i X_i + \delta + \epsilon$$

(Second stage regression)

$$hours\_per\_day = \beta_0 + \beta_1 \widehat{device\_ownership} + \sum \beta_i X_i + \alpha + \mu$$

Where *device_ownership* is the number of device types the respondent owns, *Xi* represent control variables (rural, female, ethnic Vietnamese, age, equivalized income, unemployment, and village population), and δ and α are province fixed effects.

Table 3 shows the results of the first stage regression. The number of device types is significantly correlated with the natural log of the distance.

Table 4 shows the results of the weak identification test. These results corroborate that my instrumental variable is not weak.

The results of the second stage regression are shown in Table 5. An additional type of device will lead to an increase of 2.153 hours in the time spent on using the Internet, which is consistent with hypothesis 1.

Table 3. Device Ownership and Distance

VARIABLES	(1) number of device types
ln(distance)	-0.0271***
	(0.00485)
rural	-0.295***
	(0.0145)
female	-0.148***
	(0.0121)
ethnic_Vietnamese	0.266***
	(0.0215)
Age	-0.0237***
	(0.000592)
income	0.0440***
	(0.00137)
unemployment	0.127***
	(0.0209)
village_population	-5.45e-06
	(7.49e-06)
Province FE	Yes
Constant	1.868***
	(0.0563)
Observations	12,877
R-squared	0.290

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Weak Identification Test

Weak identification test (Cragg-Donald Wald F statistic):		**29.416**
Stock-Yogo weak ID test critical values:	10% maximal IV size	16.38
	15% maximal IV size	8.96
	20% maximal IV size	6.66
	25% maximal IV size	5.53

Table 5. Online Time and Device Ownership

VARIABLES	(1) online time
device_ownership	2.153***
	(0.426)
rural	0.287**
	(0.142)
female	0.0709
	(0.0675)
ethnic Vietnamese	-0.283**
	(0.127)
age	0.00697
	(0.0104)
income	-0.0311
	(0.0196)
unemployment	-0.0706
	(0.0770)
village_population	-3.88e-05**
	(1.77e-05)
Province FE	Yes
Constant	-0.412
	(0.733)
Observations	12,602
R-squared	0.012

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I then explore the impact of device ownership on social capital. My first measure of social capital is membership in social groups. In additional to treating social groups as a whole, I categorize them into three types: the Party, public organizations, and private associations.

Again, I test whether the natural log of distance is exogenous to organizational membership. The following OLS regression is estimated:

$$membership = \beta_0 + \beta_1 village\_population + \beta_2 rural + \sum \beta_i X_i + \alpha + \mu$$

The results of the OLS regression are displayed in Table 6. In column (1) and column (3), organizational membership is significantly correlated with village population and rural area. I include village population as a control variable in the following 2SLS regression to make sure that the natural log of the distance is conditionally exogenous.

I estimate hypothesis 2 using the following 2SLS regression:

(First stage regression)

$$device\_ownership = \pi_0 + \pi_1 \ln(distance) + \sum \pi_i X_i + \delta + \epsilon$$

(Second stage regression)

$$membership = \beta_0 + \beta_1 \widehat{device\_ownership} + \sum \beta_i X_i + \alpha + \mu$$

Table 7 presents the results of the first stage regression. The natural log of distance is significantly correlated with the number of device types.

Table 6. Organizational Membership, Village Population, and Rural

	(1)	(2)	(3)	(4)
VARIABLES	Membership	Party	Public	Private
village_population	-1.47e-05***	-4.91e-06	-1.81e-05***	-7.95e-06
	(4.82e-06)	(3.59e-06)	(5.15e-06)	(5.14e-06)
rural	0.00896	-0.0615***	0.0219**	0.00268
	(0.00899)	(0.00669)	(0.00962)	(0.00959)
female	0.0632***	-0.0670***	0.166***	0.00170
	(0.00779)	(0.00580)	(0.00834)	(0.00831)
ethnic_Vietnamese	0.000393	0.00202	0.00172	0.0122
	(0.0138)	(0.0103)	(0.0148)	(0.0147)
age	0.00284***	0.000140	0.00275***	0.00220***
	(0.000381)	(0.000284)	(0.000408)	(0.000406)
income	0.00871***	0.0139***	0.00529***	0.00674***
	(0.000881)	(0.000655)	(0.000942)	(0.000939)
unemployment	0.0511***	0.144***	-0.0300**	0.0892***
	(0.0134)	(0.0100)	(0.0144)	(0.0143)
Province FE	Yes	Yes	Yes	Yes
Constant	0.470***	0.0900***	0.284***	0.176***
	(0.0294)	(0.0219)	(0.0314)	(0.0313)
Observations	12,877	12,877	12,877	12,877
R-squared	0.108	0.121	0.121	0.058

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7. Device Ownership and Distance

	(1)
VARIABLES	Device Ownership
ln(distance)	-0.0271***
	(0.00485)
rural	-0.295***
	(0.0145)
female	-0.148***
	(0.0121)
ethnic_Vietnamese	0.266***
	(0.0215)
age	-0.0237***
	(0.000592)
income	0.0440***
	(0.00137)
unemployment	0.127***
	(0.0209)
village_population	-5.45e-06
	(7.49e-06)
Province FE	Yes
Constant	1.868***
	(0.0563)
Observations	12,877
R-squared	0.290

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the second stage regression are presented in Table 8. The dependent variable in column (1) is the overall membership in social groups. The coefficient for device ownership in column (1) suggests that an increase of one device type is associated with a decrease of 19.4 percentage point in the likelihood of having membership in any social groups. However, this result is not significant. The only significant coefficient is in column (3) where each additional device type leads to a decrease of 51.6 percentage point in the probability of having membership in public organizations. What is worth noting is that membership in private associations increases with the types of devices, though not significant. A potential explanation for this is that members of private associations might communicate and organize activities through the Internet. They might as well recruit new members through the Internet.

Table 8. Organizational Membership and Device Ownership

VARIABLES	(1) Membership	(2) Party	(3) Public	(4) Private
device_ownership	-0.194	-0.0556	-0.516***	0.202
	(0.125)	(0.0886)	(0.160)	(0.124)
rural	-0.0528	-0.0791***	-0.142***	0.0670*
	(0.0408)	(0.0290)	(0.0524)	(0.0406)
female	0.0345*	-0.0752***	0.0904***	0.0315
	(0.0202)	(0.0144)	(0.0260)	(0.0201)
ethnic_Vietnamese	0.0539	0.0173	0.144***	-0.0435
	(0.0374)	(0.0266)	(0.0481)	(0.0372)
age	-0.00176	-0.00118	-0.00946**	0.00699**
	(0.00298)	(0.00212)	(0.00383)	(0.00297)
income	0.0174***	0.0164***	0.0283***	-0.00228
	(0.00563)	(0.00401)	(0.00724)	(0.00561)
unemployment	0.0769***	0.151***	0.0384	0.0624***
	(0.0220)	(0.0156)	(0.0283)	(0.0219)
village_population	-1.53e-05***	-5.10e-06	-1.98e-05***	-7.28e-06
	(5.22e-06)	(3.71e-06)	(6.70e-06)	(5.19e-06)
Province FE	Yes	Yes	Yes	Yes
Constant	0.797***	0.184	1.152***	-0.165
	(0.212)	(0.151)	(0.273)	(0.211)
Observations	12,877	12,877	12,877	12,877
R-squared	-0.045	0.059	-0.486	0.038

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

My second measure of social capital is whether people contribute voluntarily to the public projects in their villages. The following 2SLS regression is used to test hypothesis 2:

(First stage regression)

$$device\_ownership = \pi_0 + \pi_1 \ln(distance) + \sum \pi_i X_i + \delta + \epsilon$$

(Second stage regression)

$$contribute\_voluntarily = \beta_0 + \beta_1 \widehat{device\_ownership} + \sum \beta_i X_i + \alpha + \mu$$

The results of the second stage regression are shown in Table 9. With an increase of one type in device, the likelihood that an individual would contribute voluntarily to public projects decreases by 15.6 percentage point, though not significant. These results confirm my hypothesis that as the number of device types increase, the probability of voluntary contribution drops.

Table 9. Voluntary Contribution and Device Ownership

VARIABLES	(1) Voluntary Contribution
device_ownership	-0.156
	(0.116)
rural	-0.0115
	(0.0374)
female	-0.0607***
	(0.0198)
ethnic_Vietnamese	0.102***
	(0.0358)
age	-0.00589**
	(0.00276)
income	0.0111**
	(0.00538)
unemployment	0.0468**
	(0.0204)
village_population	2.36e-05***
	(4.93e-06)
Province FE	Yes
Constant	0.476**
	(0.199)
Observations	11,367
R-squared	-0.036

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A natural concern is whether the amount of time spent online is associated with social capital. To test their connections, I estimate these OLS regressions:

$$membership = \beta_0 + \beta_1 hpd + \sum \beta_i X_i + \alpha + \mu$$

$$contribute\_voluntarily = \beta_0 + \beta_1 hpd + \sum \beta_i X_i + \alpha + \mu$$

Table 10 and Table 11 show the results. Consistent with the findings in our literature review, more online time seem to increase social capital. In Table 10, an extra online hour corresponds to 1.63 percentage point increase in the likelihood of being a member in social groups. All the coefficients for online time in the 4 columns are positive and significant. These results seem to suggest that the amount of time spent on using the Internet may not be the cause of the decline of social capital. While Table 8 indicates that Party members and public organization members own less types of devices, Table 10 shows that these members spend more time online. A possible explanation for this phenomenon is that Party members spend a great amount of time online for working or learning, under the requirements from the government or the Party. In contrast, non-Party members more often use the Internet for entertaining. In other words, they are more likely to use the Internet spontaneously. Therefore, non-party members purchase more types of devices, but they do not necessarily spend more time online.

The results in Table 11 are consistent with Table 10. More online time is associated with higher probability of voluntary contribution. The coefficient is significant, though small. An additional hour spent online corresponds to 1.51 percentage point increase in the likelihood of voluntary contribution.

Table 10. Organizational Membership and Online Time

VARIABLES	(1) Membership	(2) Party	(3) Public	(4) Private
hours_per_day	0.0163***	0.0152***	0.00550*	0.0226***
	(0.00294)	(0.00221)	(0.00316)	(0.00316)
rural	0.0129	-0.0560***	0.0207**	0.0104
	(0.00936)	(0.00705)	(0.0101)	(0.0101)
female	0.0655***	-0.0648***	0.169***	0.00692
	(0.00813)	(0.00613)	(0.00876)	(0.00874)
ethnic_Vietnamese	-0.000417	0.00296	0.00517	0.00760
	(0.0142)	(0.0107)	(0.0153)	(0.0153)
age	0.00341***	0.000724**	0.00292***	0.00308***
	(0.000417)	(0.000314)	(0.000449)	(0.000448)
income	0.00758***	0.0135***	0.00497***	0.00539***
	(0.000936)	(0.000705)	(0.00101)	(0.00101)
unemployment	0.0473***	0.143***	-0.0359**	0.0905***
	(0.0140)	(0.0105)	(0.0150)	(0.0150)
village_population	-1.26e-05**	-4.64e-06	-1.71e-05***	-5.42e-06
	(5.02e-06)	(3.78e-06)	(5.40e-06)	(5.40e-06)
Province FE	Yes	Yes	Yes	Yes
Constant	0.436***	0.0471*	0.278***	0.107***
	(0.0321)	(0.0242)	(0.0346)	(0.0345)
Observations	11,761	11,761	11,761	11,761
R-squared	0.108	0.131	0.121	0.063

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11. Voluntary Contribution and Online Time

VARIABLES	(1) Voluntary Contribution
hours_per_day	0.0151***
	(0.00275)
rural	0.0410***
	(0.00858)
female	-0.0290***
	(0.00748)
ethnic_Vietnamese	0.0520***
	(0.0131)
age	-0.00159***
	(0.000386)
income	0.00287***
	(0.000883)
unemployment	0.0249*
	(0.0128)
village_population	2.57e-05***
	(4.60e-06)
Province FE	Yes
Constant	0.165***
	(0.0297)
Observations	11,120
R-squared	0.072

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

However, when I introduce the natural log of distance as the instrumental variable for online time, the results point in the other direction. I estimate the following 2SLS regressions:

(First stage regression)

$$hours\_per\_day = \pi_0 + \pi_1 \ln(distance) + \sum \pi_i X_i + \delta + \epsilon$$

(Second stage regression)

$$membership = \beta_0 + \beta_1 hours\widehat{\_per}\_day + \sum \beta_i X_i + \alpha + \mu$$

And,

(First stage regression)

$$hours\_per\_day = \pi_0 + \pi_1 \ln(distance) + \sum \pi_i X_i + \delta + \epsilon$$

(Second stage regression)

$$contribute\_voluntarily = \beta_0 + \beta_1 hours\widehat{\_per}\_day + \sum \beta_i X_i + \alpha + \mu$$

The results of the first stage regression are shown in Table 12. Online time is significantly correlated with the natural log of distance.

Table 12. Online Time and Distance

VARIABLES	(1) Online Time
ln(distance)	-0.0538***
	(0.0102)
rural	-0.342***
	(0.0304)
female	-0.252***
	(0.0255)
ethnic_Vietnamese	0.278***
	(0.0448)
age	-0.0426***
	(0.00125)
income	0.0651***
	(0.00289)
unemployment	0.220***
	(0.0440)
village_population	-4.94e-05***
	(1.58e-05)
Province FE	Yes
Constant	3.448***
	(0.120)
Observations	11,761
R-squared	0.198

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13 shows the results of the weak identification test. These results confirm that my instrumental variable is not weak.

Table 13. Weak Identification Test

membership	**Weak identification test (Cragg-Donald Wald F statistic):**		**27.551**
	Stock-Yogo weak ID test critical values:	10% maximal IV size	16.38
		15% maximal IV size	8.96
		20% maximal IV size	6.66
		25% maximal IV size	5.53
contribute_voluntarily	**Weak identification test (Cragg-Donald Wald F statistic):**		**23.141**
	Stock-Yogo weak ID test critical values:	10% maximal IV size	16.38
		15% maximal IV size	8.96
		20% maximal IV size	6.66
		25% maximal IV size	5.53

The results of the second regressions are displayed in Table 14 and Table 15. Table 14 indicates that more time spent on using the Internet leads to the decline in membership in social groups, except for membership in private associations. This exception is probably due to the fact that private social groups, such as alumni associations and professional associations, more often consists members who reside in different locations and tend to communicate, organize activities, and recruit new members online. The only significant coefficient for online time is in column (3), where an extra hour spent online decreases the likelihood of being a member in a public organization by 25.7 percentage point. Considering the fact that an average Vietnamese has a probability of only 54.2 percentage point to be a member in any public organizations, 25.7 is not a small figure.

Table 7 tells a very similar story: more online time leads to a decline in the willingness to contribute to public projects. Specifically, an additional hour spent on using the Internet reduces the likelihood of voluntary contribution by 9.48 percentage point, though not significant. Table 14 and Table 15 suggest that increasing online time does reduce social capital overall.

Table 14. Membership and Online Time

VARIABLES	(1) Membership	(2) Party	(3) Public	(4) Private
hours_per_day	-0.103	-0.0183	-0.257***	0.0902
	(0.0645)	(0.0459)	(0.0819)	(0.0662)
rural	-0.0333	-0.0689***	-0.0805**	0.0365
	(0.0268)	(0.0191)	(0.0340)	(0.0275)
female	0.0356*	-0.0731***	0.104***	0.0238
	(0.0183)	(0.0130)	(0.0232)	(0.0188)
ethnic_Vietnamese	0.0351	0.0129	0.0829***	-0.0124
	(0.0244)	(0.0174)	(0.0310)	(0.0250)
age	-0.00167	-0.000698	-0.00822**	0.00595**
	(0.00278)	(0.00198)	(0.00352)	(0.00285)
income	0.0155***	0.0157***	0.0223***	0.000916
	(0.00438)	(0.00312)	(0.00556)	(0.00449)
unemployment	0.0751***	0.151***	0.0250	0.0748***
	(0.0211)	(0.0150)	(0.0268)	(0.0217)
village_population	-1.80e-05***	-6.15e-06	-2.89e-05***	-2.38e-06
	(6.09e-06)	(4.33e-06)	(7.73e-06)	(6.24e-06)
Province FE	Yes	Yes	Yes	Yes
Constant	0.804***	0.150	1.085***	-0.101
	(0.201)	(0.143)	(0.256)	(0.206)
Observations	11,761	11,761	11,761	11,761
R-squared	-0.018	0.114	-0.396	0.027

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 15. Voluntary Contribution and Online Time

VARIABLES	(1) Voluntary Contribution
hours_per_day	-0.0948
	(0.0642)
rural	-0.000576
	(0.0259)
female	-0.0559***
	(0.0176)
ethnic_Vietnamese	0.0846***
	(0.0236)
age	-0.00616**
	(0.00270)
income	0.0103**
	(0.00441)
unemployment	0.0506**
	(0.0203)
village_population	2.17e-05***
	(5.43e-06)
Province FE	Yes
Constant	0.489**
	(0.192)
Observations	11,120
R-squared	-0.062

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Since females spend more online time on communication and use social network sites more often (Joiner et al., 2012), it is natural to expect that there is gender gap in the impact of Internet. Therefore, I explore the effect of the number of device types on the social capital of females and males, respectively. Again, I use the following 2SLS regressions:

(First stage regression)

$$device\_ownership = \pi_0 + \pi_1 \ln(distance) + \sum \pi_i X_i + \delta + \epsilon$$

(Second stage regression)

$$membership = \beta_0 + \beta_1 \widehat{device\_ownership} + \sum \beta_i X_i + \alpha + \mu$$

And,

(First stage regression)

$$device\_ownership = \pi_0 + \pi_1 \ln(distance) + \sum \pi_i X_i + \delta + \epsilon$$

(Second stage regression)

$$contribute\_voluntarily = \beta_0 + \beta_1 \widehat{device\_ownership} + \sum \beta_i X_i + \alpha + \mu$$

The results are shown in Table 16, Table 17, and Table 18. Overall, an extra type of device result in 1.07 percentage point increase in women's likelihood of being organizational members, whereas for males, an additional device leads to 51.3 percentage point decrease in the likelihood of being a member in any social groups. The only significant coefficient in Table 16 is in column (4), where an increase of one device type corresponds to an increase of 30.4 percentage point in the female probability of being a member in private organizations. The other two coefficients for the number of device types are negative, though not significant, suggesting that among females, Party membership and public membership may decrease with the number of device types.

While for women, the number of device types has a considerable positive impact on their membership in private associations, for men this impact (significantly negative) is largely on the membership in public organizations. As shown in Table 17, an additional type of device leads to a 105.4 percentage point decrease in men's likelihood of being members in public organizations. These results imply that women may be more likely to use the Internet for Information about activities held by private associations, whereas men may spend a lot of time interacting with their gadgets at the cost of participation in social groups.

The results in Table 18 are consistent with our expectation that more types of devices lead to less willingness to contribute voluntarily to public projects. Both coefficients are negative, though not significant. The coefficient for females is even smaller than males, implying that females are more likely to be horrified by the bad stories online and therefore less likely to believe that others can be "good Samaritans."

Table 16. Organizational Membership and Device Ownership (Female Only)

VARIABLES	(1) Membership	(2) Party Membership	(3) Public Membership	(4) Private Membership
device_ownership	0.0107	-0.0919	-0.177	0.304*
	(0.138)	(0.101)	(0.156)	(0.160)
rural	-0.0156	-0.0950***	-0.0898*	0.113**
	(0.0480)	(0.0353)	(0.0545)	(0.0557)
ethnic_Vietnamese	-0.00544	0.0334	0.0526	-0.0437
	(0.0390)	(0.0287)	(0.0443)	(0.0453)
age	0.00161	-0.00346	-0.00349	0.0103**
	(0.00352)	(0.00259)	(0.00400)	(0.00408)
income	0.00506	0.0187***	0.0143*	-0.0100
	(0.00716)	(0.00526)	(0.00814)	(0.00831)
unemployment	0.0255	0.147***	-0.0134	0.0765***
	(0.0252)	(0.0185)	(0.0286)	(0.0292)
village_population	-1.49e-05**	-3.71e-06	-2.22e-05***	-2.50e-06
	(6.73e-06)	(4.94e-06)	(7.64e-06)	(7.80e-06)
Province FE	Yes	Yes	Yes	Yes
Constant	0.701***	0.249	0.917***	-0.341
	(0.225)	(0.165)	(0.255)	(0.260)
Observations	6,228	6,228	6,228	6,228
R-squared	0.133	-0.017	0.048	-0.010

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17. Organizational Membership and Device Ownership (Male Only)

VARIABLES	(1) Membership	(2) Party	(3) Public	(4) Private
device_ownership	-0.513*	0.0775	-1.054**	-0.00924
	(0.297)	(0.171)	(0.446)	(0.226)
rural	-0.117	-0.0370	-0.231*	-0.0121
	(0.0873)	(0.0503)	(0.131)	(0.0664)
ethnic_Vietnamese	0.176*	-0.0219	0.339**	-0.00532
	(0.0972)	(0.0560)	(0.146)	(0.0740)
age	-0.00705	0.00308	-0.0187*	0.00140
	(0.00656)	(0.00378)	(0.00985)	(0.00499)
income	0.0307**	0.0113	0.0478***	0.00771
	(0.0122)	(0.00700)	(0.0182)	(0.00925)
unemployment	0.153***	0.150***	0.131*	0.0830**
	(0.0529)	(0.0304)	(0.0794)	(0.0402)
village_population	-2.24e-05**	-9.08e-06	-3.03e-05*	-1.00e-05
	(1.06e-05)	(6.13e-06)	(1.60e-05)	(8.10e-06)
Province FE	Yes	Yes	Yes	Yes
Constant	1.130**	-0.112	1.807**	0.238
	(0.485)	(0.279)	(0.729)	(0.369)
Observations	5,798	5,798	5,798	5,798
R-squared	-0.734	0.163	-2.472	0.052

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 18. Voluntary Contribution and Device Ownership

VARIABLES	(1) Voluntary Contribution (Female Only)	(2) Voluntary Contribution (Male Only)
device_ownership	-0.223	-0.0571
	(0.146)	(0.179)
rural	-0.0503	0.0361
	(0.0501)	(0.0525)
ethnic_Vietnamese	0.103**	0.0853
	(0.0415)	(0.0612)
age	-0.00753**	-0.00353
	(0.00367)	(0.00399)
income	0.0164**	0.00628
	(0.00821)	(0.00733)
unemployment	0.0321	0.0475
	(0.0251)	(0.0328)
village_population	2.59e-05***	2.18e-05***
	(6.81e-06)	(7.41e-06)
Province FE	Yes	Yes
Constant	0.528**	0.291
	(0.232)	(0.299)
Observations	5,894	5,473
R-squared	-0.117	0.050

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Discussion

In this paper I explore the impact of the Internet on social capital. I measure social capital in two ways: membership in social groups and willingness to contribute voluntarily in public projects in villages. To reveal the causal relation between the Internet and social capital, I introduce the natural log of the distance between every individual and the nearest cellular tower as an instrumental variable. I find that the more types of devices a person owns, the more time she will spend on surfing the Internet. More types of devices also contribute to less social capital, and online time is one of the causes of the decline of social capital. The only exception is membership in private associations, which is probably because these people use the Internet to organize activities, communicate with other members, and recruit new members. Consistent with previous literature, online time is positively correlated with membership in social groups when instrumental variable is not used, suggesting that the identity of individuals might be the cause of online time. Since females and males use the Internet for different purposes, I explore the impact of the Internet respectively for women and men. I find that owing an extra type of device has a negative effect on males' membership in public organizations whereas an additional device type leads to higher probability of being members in private associations for females.

Future studies might want to investigate the pattern of Internet use. Using the Internet for working, studying, socializing, information-seeking, and entertaining are very likely to have different impact on a person's social behavior. People's affiliation with organizations also needs further investigation. For example, sports clubs that usually gather people offline and alumni networks that are largely dependent on the Internet may be affected differently by the Internet. In addition, future studies can measure social capital in a variety of ways. For example, the amount of time an individual spends on participating in social activities, the number of friends and kin that an individual has conversation with during a certain period, the extent to which an individual trusts strangers, and the willingness of an individual to help strangers.

Appendix A. Description of Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(distance)	12,115	8.550776	2.004038	3.404483	11.96145
device_ownership	12,115	.7208419	.8038564	0	4
hours_per_day	11,848	.8558574	1.527178	0	24
rural	12,115	.4073463	.4913606	0	1
female	12,115	.519026	.4996585	0	1
ethnic_Vietnamese	12,080	.8527318	.3543878	0	1
age	12,108	49.18773	11.29933	18	96
income	12,115	4.883868	4.69361	.2886751	60.62178
uemployment	12,115	.1178704	.3224679	0	1
village_population	12,068	1218.074	1046.73	51	5298
membership	12,115	.6972348	.4594734	0	1
membership_Party	12,115	.1423029	.349375	0	1
membership_public	12,115	.5418077	.4982696	0	1
membership_private	12,115	.3667355	.4819333	0	1
contribute_voluntarily	11,446	.2040888	.4030518	0	1

Appendix B. Pairwise Correlation between Key Variables

	ln(distance)	device_ownership	hours_per_day	rural	female	ethnic_Vietnamese	Age
ln(distance)	1.0000						
device_ownership	-0.1221	1.0000					
hours_per_day	-0.1003	0.5444	1.0000				
rural	0.2341	-0.2406	-0.1626	1.0000			
female	-0.0223	-0.0988	-0.0840	-0.0217	1.0000		
ethnic_Vietnamese	-0.2838	0.1042	0.0539	-0.2042	0.0042	1.0000	
Age	-0.0950	-0.2878	-0.2826	-0.0917	-0.0414	0.1583	1.0000
income	-0.1447	0.3399	0.2714	-0.2249	-0.0817	0.1341	-0.0191
unemplyment	-0.1314	0.0155	-0.0057	-0.1827	-0.0411	0.0797	0.3777
village_population	-0.0347	-0.1004	-0.0853	0.0663	-0.0117	0.2108	0.0735
membership	0.0001	0.1419	0.0586	-0.0179	0.0546	-0.0080	0.0643
membership_Party	-0.0305	0.3119	0.1360	-0.1415	-0.1195	0.0026	0.0456
membership_public	0.0289	0.0807	0.0090	0.0112	0.1625	-0.0212	0.0315
membership_private	-0.0274	0.1185	0.0708	-0.0226	-0.0103	0.0022	0.0623
contrbute_volntarily	-0.0167	0.1114	0.0803	0.0394	-0.0507	0.0422	-0.0499

	income	unemployment	village_population	membership	membership_Party	membership_public	membership_private
income	1.0000						
unemplyment	0.0936	1.0000					
village_population	-0.0118	-0.0465	1.0000				
membership	0.0727	0.0810	-0.1505	1.0000			
membership_Party	0.2223	0.1838	-0.0914	0.2684	1.0000		
membership_public	0.0152	0.0125	-0.1534	0.7166	0.1740	1.0000	
membership_private	0.0650	0.0910	-0.0757	0.5015	0.1009	0.1402	1.0000
contrbute_volntarily	0.0420	0.0025	0.0053	0.1139	0.0917	0.0963	0.0946

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