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ネットは分断を引き起こすか？

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ネットは分断を引き起こすか？

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【要旨】

・ネットの利用で人々の政治的意見が分極化するか、すなわち左右に分かれる傾向があるかどうかをパネルサーベイで検証した。５万に人に２時点サーベイとするとその間にフェイスブック・ツイッター・ブログなどを始めた人がわずかに現れるので、彼らを追跡することでネット利用開始の効果を推定した。

・その結果、ネットの利用開始で分極化は起こっていなかった。ネット利用を開始した人の意見は左右に分かれるよりむしろ逆に中庸化し、穏健化する傾向が見られた。

・社会の分断の原因としてネットを上げる見解があるが、その実証的論拠は乏しいと思われる。

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Does the Internet cause polarization?
-Panel survey in Japan-

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Summary

There is concern that the Internet causes ideological polarization through selective exposure and the echo chamber effect. This paper examines the effect of social media on polarization by applying a difference-in-difference approach to panel data of 50 thousand respondents in Japan. Japan is good case for this research because other factors affecting polarization like huge wealth gap and massive immigration are not serious issue, thus it offers quasi natural experimental situation to test the effect of the Internet. The results show that people who started using social media during the research period (targets) were no more polarized than people who did not (controls). There was a tendency for younger and politically moderate people to be less polarized. The only case in which the Internet increased polarization was for already radical people who started using Twitter. However, since radical people represent only 20% of the population and there was no effect for Facebook or blogs, the overall effect of the Internet was moderation, not polarization.

Key word: Polarization, Internet, difference-in-difference,Japan,media
JEL code: L82, L86, H80

I. Introduction

Access to more media choices is usually said to benefit society because it promotes competition among media and provides the general public with a variety of information. From the standard economic point of view, the entry of new media is expected to promote social welfare and should be welcomed.

The rise of the Internet as new media, however, has raised doubts concerning the expectation of benefit, with people arguing that the internet may cause ideological polarization by allowing people to choose the information sources they like and listen to like-minded people through partisan blogs and the social media, such as Facebook and Twitter. Such selective exposure creates an "echo chamber" in which people communicate only with others who share their opinions, resulting in their opinions being unilaterally reinforced, such that liberals tend to become more liberal and conservatives tend to become more conservative (Iyengar & Hahn, 2009; Sustein, 2001).

A historical survey conducted by Pew Research Center (2014a) showed that polarization in the US was accelerated during the 2000s, when social media like Twitter and Facebook became common communication tools for the general public. This suggests that the Internet might cause polarization. Polarization also seems to occur in EU countries, as indicated by the rise in leftist and rightist parties in EU parliamentary elections of the last five years. If the internet causes polarization, it represents a serious problem to be analyzed empirically.

Does the Internet really increase ideological polarization? The results of current empirical research are mixed. The Pew Research Center (2014b) reported that social media users were more polarized than non-users, suggesting that the Internet promotes polarization. On the other hand, Gentzkow and Shapiro (2018) reported that polarization was greatest for older generations, who are less likely to use the Internet, indicating that the internet is not the cause of polarization. Empirical analyses of causality based on individual users are very limited.

The aim of this paper is to examine the effects of the internet on ideological polarization using a large panel of Internet users in Japan. For 50 thousand internet users in 2017 and 2018, we applied a difference-in-difference approach in which the targets were people who started to use Facebook, Twitter, and blogs during the research period, with non-users serving as the controls. The results show that people who started using social media during the research period (targets) were no more polarized than the people who did not (controls). There was also a tendency for younger and politically moderate people to be less polarized. There was only one case in which the internet increased polarization: already radical people who started using Twitter. Since already radical people represent only 20% of population, and Facebook and blogs had no effect, the overall effect of the internet was not polarization, but moderation.

II. Literature and approach of this paper

Mass media penetration was expected to reduce polarization by providing people with common information. In theory, people who share information will develop similar, non-polarized opinions. There is some empirical research to support this view. For example, Campante and Hojman (2013) showed that television broadcasting in the US from 1920 to 1970 reduced polarization. Melki and Pickering (2014) examined political parties and media in 22 OECD countries from 1970 to 2003 and reported that the polarization of political parties was reduced by greater penetration of television and radio.

In the case of the Internet, however, there is concern that greater penetration will increase polarization. This concern rests on the ideas of "selective exposure" and the "echo chamber."

Since mass media provides people with a wide variety of information, including various kinds of opinions, people have access to information that contradicts their own views. People watching television news are forced to listen to opposing opinions as long as they sit in front of their television sets. Newspapers report pros and cons on the same page, resulting in people unintentionally reading opposing views. However, on the Internet, people can choose the information they like by following friends or visiting partisan news sites. Since people tend to choose friends and sites with similar opinions due to homophily (Elanor et al., 2014), the information they obtain through the Internet tends to be one-sided. This "selective exposure" creates an "echo chamber" in which people listen only to the voices of like-minded people, thus unilaterally reinforcing their opinions: Liberals become more liberal, and conservatives become more conservative, polarizing people's political ideologies (Iyengar & Hahn, 2009; Nie et al., 2010; Sustein, 2001). Azzimonti and Fernandes (2018) presented a theoretical model that Internet "bots" play an important role in generating echo chambers and facilitating a polarized equilibrium.

Some empirical research supports this concern by showing a correlation between Internet usage and the degree of polarization. For instance, a survey conducted by Pew Research center showed that Internet users were more polarized than non-users

(Morris, 2007). Nie et al. (2010) found that people who use Internet news sources hold more extreme views than those who rely solely on television news. In other words, people who both watch Fox News and use the Internet are more conservative than people who only watch Fox News.

However, correlation does not imply causation: that is, the Internet does not necessarily cause polarization. Rather, an inverse causality is probable. Polarized people are likely to want to express their opinions or obtain information on the Internet; thus, they will use social media more than non-polarized people (Prior, 2013). The best way to clarify the direction of causality is to find exogenous variables that generate experimental situations. In the case of television, the new entry of TV channels like Fox News have often been used as such exogenous variables (Martin & Yurukoglu, 2017; Vigna & Kaplan, 2007). Unfortunately, the Internet is free-entry media; thus, it is not easy to find large-scale entries.[1]

This paper conducts a large panel survey that queries each person twice and applies a difference-in-difference analysis. With a large enough sample size, some respondents will start using social media between the first survey and the second. If these individuals are more polarized after using social media than non-users, we can say that social media causes polarization. The research details are as follows.

From an econometric point of view, the problem of causal direction is a problem of endogeneity, which is caused by the correlation between an individual's political attribute e_j and usage of social media SM_j, as shown in the following regression:

$$P_j = bSM_j + e_j$$

P_j is the index of polarization of individual j, which depends on usage of social media SM_j and his unobservable political attribute e_j. If the individual is politically active—that is, if e_j is large—it will increase the polarization index P_j and usage of social media SM_j simultaneously. Since SM_j is correlated with e_j, the coefficient b is overestimated.

One way to cope with this endogeneity bias is to conduct the survey twice with each person and calculate the differences between the two surveys. Let P_{j1} and P_{j2} be the polarization indexes of individual j at the first and second survey, respectively. Then,

[1] Broadband penetration could be a candidate for an exogenous variable, although it is very rough measure of penetration of social media. Liang and Nordin (2012) examined the correlation between the penetration of broadband internet and polarization in Sweden and found no correlation.

we have:

$$\mathrm{P}_{j1} = bSM_{j1} + e_j + e_{j1}$$
$$\mathrm{P}_{j2} = bSM_{j2} + e_j + e_{j2}$$
$$\mathrm{P}_{j2} - \mathrm{P}_{j1} = b(SM_{j2} - SM_{j1}) + e_{j2} - e_{j1}$$

In the first and second equation, e_j is a political attribute of individual j that does not change during the research period. E_j is based on the individual's basic characteristics or beliefs generated over his whole life; thus, it does not easily change. E_{j1} and e_{j2} are temporary effects caused by personal political events during the research period.

The political attribute e_j is deleted by taking the difference in the third equation; thus, the endogeneity caused by e_j disappears when we estimate the third equation. If social media usage, SM_j, is a dummy variable equal to one when the individual uses social media, then the difference between term $SM_{j2} - SM_{j1}$ is equal to one when the individual j starts to use social media. This is the difference-in-difference approach we adopt in this paper. The target is individuals who started using social media during the research period, and the control is individuals who did not use social media in either the first or the second survey.

The remaining problem is the endogeneity caused by the term e_{j2}-e_{j1}, the effect of temporary political events, in the third equation. This temporary effect is a result of politics-related personal events, such as joining a non-governmental organization, getting to know an activist friend who triggers an interest in politics, or encountering social issues in the community. If these temporary effects motivate respondents to start using social media, this, again, creates an endogeneity problem. To control this effect, we asked the respondents in survey 1 whether they had a political motivation to start using social media.

This survey was conducted in Japan. The advantage of doing this research in Japan is that other potential factors affecting polarization are controlled. Reportedly, there are two other factors that may cause ideological polarization: an expanding gap between the rich and the poor and an overly rapid increase in immigration. Since neither of these is a serious problem in Japan, Japan is a natural experimental situation to test the effects of the Internet on polarization.

III. Data and Descriptive Statistics

The first questionnaire survey was carried out in August 2017. The survey asked

100 thousands internet users about polarization and usage of social media. In February 2018, six months later, the same questionnaire was sent to the same people, and approximately 50 thousand respondents replied. This paper measures the change in polarization of the people who started to use social media during this six-month period. If their political opinions become more polarized than those of people who did not use social media, we can say that the use of social media increases polarization.

Since the sample was collected from the Internet monitors of a research company, there are two biases: age and degree of Internet usage. The sample ratios of people over 60 and under 30 years are lower than the population ratios for these groups, and the sample is biased toward heavy Internet users. We adjusted these biases using weights based on the population's age distribution and other mail-based surveys on Internet usage. All estimations followed in this paper present adjusted results using these two weights.

For the purpose of estimating the effect on polarization, we need a measure of polarization. There are several measures of polarization. Gentzkow and Shapiro (2018) tried nine measures of polarization; however, most of these are not applicable to Japan because they reflect a two-party system and a presidential election. We apply a simple measure of polarization based on conservative–liberal ideologies.

Following the Pew Research Center, we asked respondents a for-and-against question regarding ten political issues, as shown in the Table 1. These ten issues are contemporary issues in Japan on which liberals and conservatives have opposite opinions. Most of these issues are different from those used in the Pew Research Center survey because contemporary issues differ from country to country. For example, race discrimination and homosexuality are important issues in the US, but not in Japan, whereas the amendment of article nine of the constitution is hot issue in Japan.

Table 1 Questions for measuring polarization

	Do you agree with folowoing proposition?	expected reponse liberal	conservative
1	article 9 of constitution should be amended	against	for
2	government shuold increase expenditure of social welfare	for	against
3	law should allow husband and wife to have different last name	for	against
4	environmental considerenation is more important than economic growth	for	against
5	nuclear power generator should be shut down immediately	for	against
6	individuals' interest is given priority over national interest	for	against
7	government should gurrantee job and income to some extent	for	against
8	patriotic spirit should be taught in the school	against	for
9	military measure could be used to push out China's territorial waters infringement	against	for
10	prime minister Abe wants to leads Japan back to prewar's dark age	for	aganst

Choice

1:strongly agree, 2:agree, 3:rather agree, 4:neutral, 5:rather disagree, 6:disagree, 7:strongly disagree
8:don'y know

Answers were given on seven-point scale ranging from 1 (strongly agree) to strongly disagree (7). Let q_{jk} be the answer, 1 to 7, of question k for respondent j. We calculate the political ideology measure by subtracting 4 from q_{jk}: that is $i_{jk}=q_{jk}-4$ ($i_{jk}=4-q_{jk}$ in the case of questions 1, 8, and 9 due to a reversal of the expected for-against). i_{jk} ranges from -3 (strongly liberal) to 3 (strongly conservative). The ideology measure of individual j, I_j, is defined as the average of the ten questions.[2]

$$I_j = \sum_{k=1}^{10} i_{jk} \Big/ 10$$

I_j also ranges from -3 (strongly liberal) to 3 (strongly conservative).

Figure 1 shows the distribution of the ideology measure I_j for all respondents. There is a spike at zero. This spike is caused by respondents who always chose choice 4 (neutral). If we exclude such respondents, the distribution curve become smooth and natural. This suggests that these respondents who always choose 4 are indifferent to politics just like respondents who always chose choice 8 (don't know) and were excluded

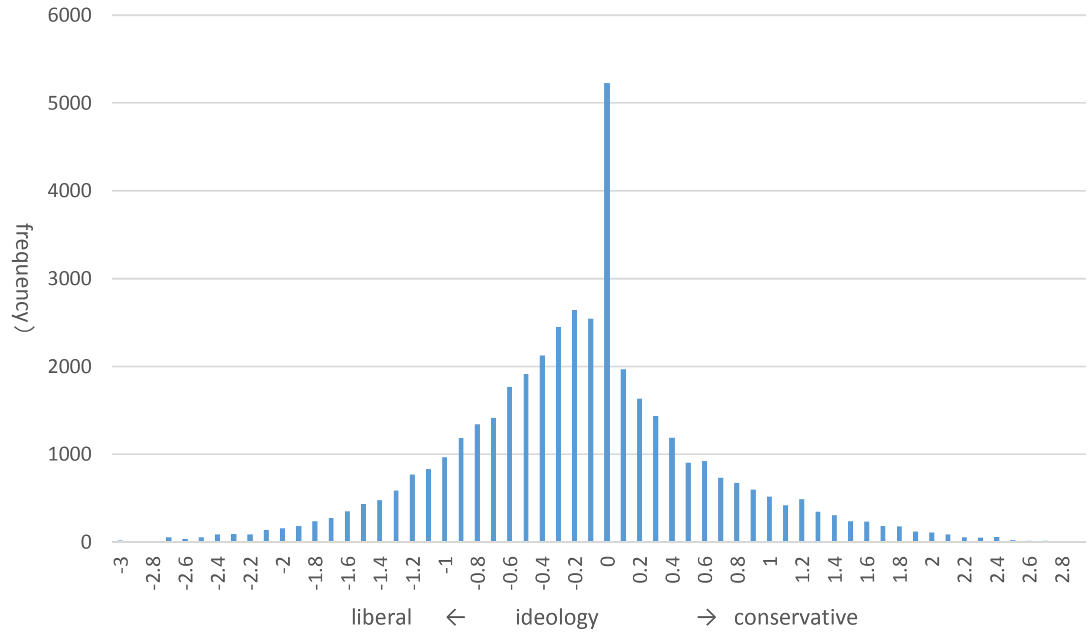
[2] Choice 8 (don't know) was excluded from calculating the average. In other words, strictly speaking, the measure is

$$I_j = \sum_{k \in A_j} i_{jk} / n_j$$

where A_j is the set of question numbers answered by individual j, and n_j is the number of elements of set A_j.

from the measurement. In other words, if a respondent had no interest in political issues, they will always choose choice 8 (don't know) or choice 4 (neutral). Therefore, we exclude the respondents who always chose neutral in the following analysis.

Figure 1 Distribution of ideology at survey1



Since polarization means the radicalization of people's political opinions, whether liberal or conservative, the most simple measure of polarization is to take the absolute value of the ideology measure. The median of the ideology measure is -0.2. Therefore, we define the polarization measure P_j as follows:

$$P_j = |I_j - (-0.2)|$$

where the range of Pj is [0,3], and a large P means that the respondent has a radical political ideology and is, therefore, polarized. This paper explores whether this polarization measure P_j increases when individual j starts to use social media.

Of many social media platforms on the Internet, we focus on Facebook and Twitter because these two media have overwhelmingly dominance in the market of social media and contribute to the formation of public opinions. We also include blogs as a media platform because popular blogs have large numbers of readers and influence public opinion.

In the questionnaire, respondents were asked about their frequency of Facebook, Twitter, and blog usage per week. Usage meant not only writing, but also reading. The results for Facebook, as example, are shown in Table 2. The vertical axis is the usage in the first survey, and the horizontal axis is the usage in the second survey. The usage level was classified into five levels, including "never used," "once or lower in a week," , …, and "almost every day." We defined a Facebook user as a respondent who used the platform at least two times in a week because a usage of once per week or less was considered too low to influence opinion. [3]

The table indicates that 468 respondents did not use Facebook at the time of the first survey, but did use it at the time of the second survey. These 468 respondents started using Facebook during the research period; thus, they are the targets of the difference-in-difference analysis. The controls were the 333,446 non-users of Facebook. If the polarization index for the 468 targets increased more than that for the 33,446 controls, we can say that usage of Facebook increases polarization.

Table 2

non user
33,446

	FaceBook	Survey No2 1 no use	2 once a week or lower	3 2 or 3 days in a week	4 4 or 5 days in a week	5 almost every day
Survey No1	1 no use	33,446	1,366	219	76	173
	2 once a week or lower	1,303	3,847	595	153	154
	3 2 or 3 days in a week	151	815	945	274	223
	4 4 or 5 days in a week	71	219	400	440	343
	5 almost every day	185	270	324	508	3,973

start using
468

keep using
7,430

quit using
407

Similar tables were made for Twitter and blogs, allowing us to identify respondents who started using Twitter and blogs. Let $D^{FB}{}_j$, $D^{TW}{}_j$, and $D^{BL}{}_j$ be equal to one if respondent j start using Facebook, Twitter, or blog-based social media, respectively. The controls are the respondents who did not use Facebook, Twitter, or blogs in either survey 1 or survey 2. The total number of target respondents is 3,260 and the total number of controls is 12,682. .

The difference-in-difference regression is:

[3] If we included persons who use it once per week or less as users, we obtained similar results in the following regression though the coefficients were rather less significant.

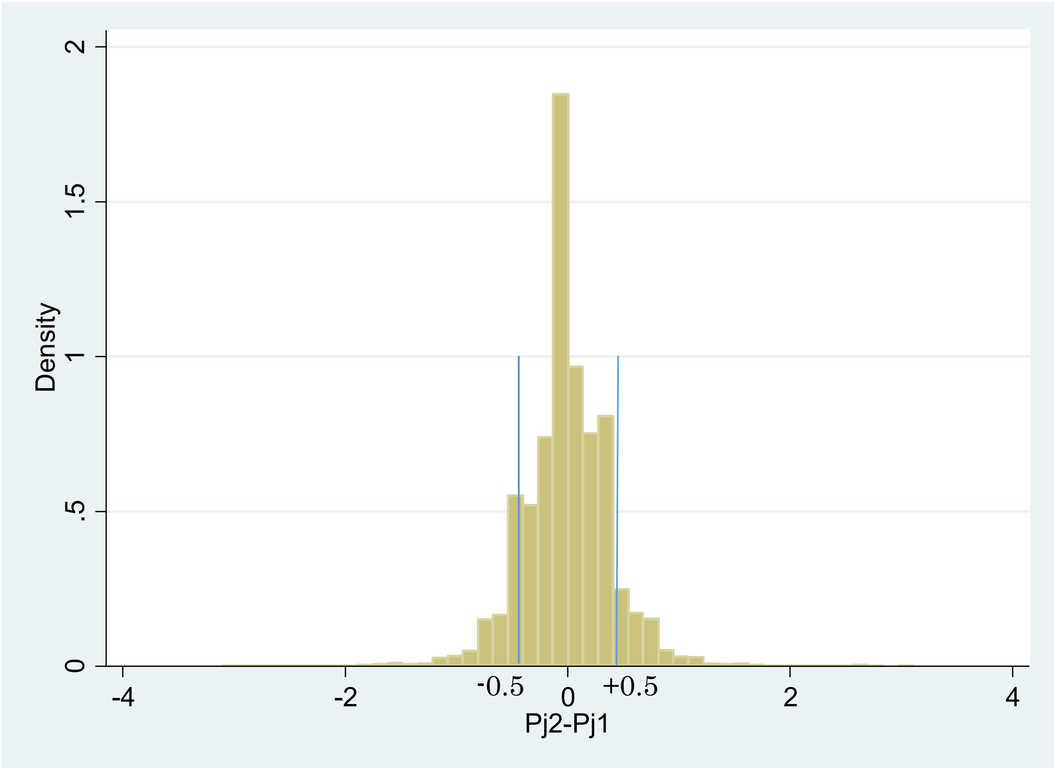
$$P_{j2} - P_{j1} = a + b^{FB} D_j^{FB} + b^{TW} D_j^{FB} + b^{BL} D_j^{BL} + other\ covariates + \epsilon_j \qquad \text{(I)}$$

where P_{jt} is the polarization measure of individual j at time t. The left-side variable, P_{j2}-P_{j1}, is the change in polarization during the research period, and right-side variables $D^{FB}{}_j$, $D^{TW}{}_j$, and $D^{BL}{}_j$ represent respondent j starting to use Facebook, Twitter, or blogs, respectively. If the coefficients b^{FB}, b^{TW}, and b^{BL} are significantly positive, we can say that the social media increases polarization.

Regarding the covariates, we considered two mass media factors and two demographic factors. The two mass media variables were starting to read the newspaper and starting to watch TV talk shows, both of which could have partisan effects on respondents. The demographic variables were sex and age.

Was there enough change to analyze regarding the polarization index? If there was very little change in polarization during the research period, this paper's approach does not make sense. To evaluate this concern, we show in Figure 2 the distribution of the change of the polarization index P_{j2}-P_{j1}: that is, the explained variable in regression (I). A positive number means that the respondent became more polarized, whereas a negative number means that the respondent became more moderate. The polarization indexes of several people—approximately 15%—changed by more than 0.5 during the research period. Since the index is an average of 10 questions, a change of the index by 0.5 means that the respondent changes his/her for-against choice for five questions. In other words, 15% of respondents changed their answers to half of the questions, representing a sufficiently big change to be analyzed by a difference-in-difference approach.

Figure 2 Distribution of Changes in the Polarization Index



IV. Results

Consistency with the former researches

Before showing the result of difference-in-difference regression, we will conduct a simple regression of polarization level on the usage of social media to examine the consistency of this research in Japan with previous research in other countries. The following model is estimated, and the results are shown in Table 2.

$$\mathrm{P}_{j1} = \mathrm{a}' + \mathrm{c}^{FB}FB_j + \mathrm{c}^{FB}TW_j + \mathrm{c}^{FB}BL_j + other\ covariates + e_j \qquad \text{(II)}$$

The left-side variable is the polarization index for respondent j at survey 1[4], and the right-side variables are degrees of usage of social media: FB_j for Facebook, TW_j for Twitter, and Bl_j for blogs. All social media variables measure the degree of usage on a one-to-five index, as shown in Table 1. The covariates are the degree of usage of TV talk shows and newspapers and the two demographic variables of sex and age. The

[4] If we use the polarization index at survey 2, P_{j2}, the result is nearly the same.

third column of Table 2 shows beta coefficients, which are standardized coefficients, to compare the magnitude of effects of the variables.

Table 2 shows that the coefficients for all social media platforms are positive and significant on at least the 10% level. Thus, people using social media tend to be polarized, which is consistent with the results of other researches such as Pew Research Center (2014b) and Nie et al. (2010). The beta coefficients indicate that the effect of social media is largest for Twitter (0.052), second-largest for blogs (0.033), and lowest for Facebook (0.016).

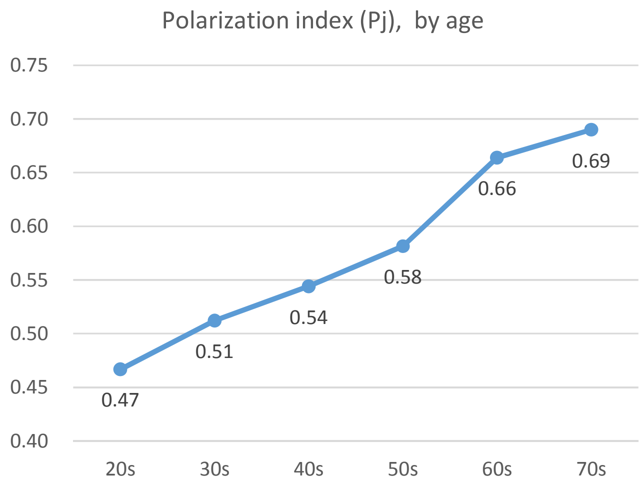
Interestingly, the effect of age is significantly positive (0.00385), meaning that older respondents are more polarized than younger respondents. This result supports Boxell, Gentzkow, and Shapiro (2017), who argued that the Internet does not cause polarization since, if the internet causes polarization, younger respondents, who are heavier Internet users, should be more polarized. The reality, however, is completely opposite. Figure 3 shows the polarization index by age, clearly indicating that the older generation is more polarized.

Table 2

VARIABLES	polarization	
		beta
<social media>		
Facebook	0.00693*	0.016
(Index1-5)	(1.945)	
Twitter	0.0230***	0.052
(Index1-5)	(6.140)	
Blog	0.0131***	0.033
(Index1-5)	(4.184)	
<mass media>		
TV Talk Show	-0.0273***	-0.077
(Index1-5)	(-8.762)	
News Paper	0.00853***	0.028
(Index1-5)	(3.239)	
<demographics>		
Sex	-0.128***	-0.118
(female=1)	(-13.58)	
Age	0.00385***	0.103
	(9.274)	
Constant	0.438***	
	(17.02)	
Observations	41,273	
R-squared	0.038	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 3



Basic result

The basic results of the difference-in-difference regressions (I) are shown in regressions (1) and (2) of Table 3. Regression (1) does not include mass media variables, while regression (2) does. The estimated coefficients for social media are nearly the same between (1) and (2), and none are significant. Therefore, starting to use social media does not increase polarization.

Table 3

VARIABLES	(1) Difference of polarization	(2) Difference of polarization
	All	All
<start of using social media>		
Facebook	0.0105	0.0109
Start using=1	(0.484)	(0.501)
Twitter	-0.00470	-0.00450
Start using=1	(-0.310)	(-0.297)
Blog	-0.0132	-0.0130
Start using=1	(-1.352)	(-1.333)
<start of using mass media>		
TV Talk Show		0.00795
Start using=1		(0.408)
News Paper		-0.0241
Start using=1		(-0.940)
<demographics>		
Sex	0.00528	0.00522
(female=1)	(0.784)	(0.776)
Age	0.000621**	0.000614**
	(2.016)	(1.995)
Constant	-0.0349*	-0.0343*
	(-1.846)	(-1.815)
Observations	15,942	15,942
R-squared	0.001	0.001

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As we discussed in section II, there still exists an endogeneity problem if respondents experience temporary politics-related personal events between survey 1 and survey 2. It is, thus, best to limit the respondents to individuals who did not experience politics-related events or have a political motivation to start using social media. Thus, in survey 1, we asked about the respondents' motivations with respect to using social media. Specifically, respondents were asked to mark the descriptions in Table 4 that applied to them.

Table 4

	Mark descrptions that apply(s) to you (multiple choice)
1	I started NGO(non governmental ogatization) activity recently
2	I am becoming intereted in political and social issues
3	Some of my friends started using Facebook
4	Some of my friends started using Twitter
5	I would like to talk about my hobby and daily life on the Internet
6	I would like to talk about political and social issues on the Internet
7	I am becoming to need using Facebook or Twitter because of my business
8	I am invited to use Facebook by my friends
9	I am invited to use Twitter by my friends

Of these nine descriptions, numbers 1, 2, and 6 could be considered political, whereas the others were not political: the influence of friends (3, 4, 8, 9), fun and leisure (5), and business (7). To avoid endogeneity, we excluded respondents who marked any of the three politics-related descriptions (1, 2, and 6). In other words, we limited the respondents to individuals who did not have political motivations for using social media.

The results are shown in regressions (1) in Table 5. The coefficients for starting social media are not significant as in Table 3; thus, there is no change when we limit the respondents to those who did not have political motivations before starting to use social media. For the purpose to confirm it, I applied instrumental variable estimation by using all variables in Table 4 as dummy variables. The result is presented in regression (2) in Table 5. All coefficients of social media are not significant again.

Table 5

VARIABLES	(1) Difference of polarization	(2) Difference of polarization
	Excl. political motivation	Instrumental Variable
<start of using social media>		
Facebook	-0.00833	0.0344
Start using=1	(-0.282)	(0.100)
Twitter	-0.00556	-0.457
Start using=1	(-0.317)	(-1.347)
Blog	-0.0186	0.129
Start using=1	(-1.555)	(0.710)
<start of using mass media>		
TV Talk Show	0.0116	-0.00164
Start using=1	(0.516)	(-0.0690)
News Paper	-0.0128	-0.0256
Start using=1	(-0.434)	(-0.907)
<demographics>		
Sex	0.00113	0.0132
(female=1)	(0.138)	(1.280)
Age	0.000427	0.000231
	(1.131)	(0.453)
Constant	-0.0231	-0.0169
	(-1.018)	(-0.422)
Observations	11,285	15,942
R-squared	0.000	
Instrumental variables		All variables in Table 4

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Effect of age

Boxell Gentzkow, and Shapiro (2017) reported that polarization occurs largely among older generations, not younger generations who are heavy users of social media. We obtained results consistent with their report, as shown in Table 2, where the coefficient of age is significantly positively related to polarization level. The difference-in-difference regressions in Table 3 also indicate that older generations are more polarized than younger generations because the coefficients of age in regressions (1) and (2) are significantly positive. However, if we limit the sample to respondents without political motivations or apply instrumental variable estimation, the age effect disappears, as shown in Table 5. The effect of age should be analyzed more in detail.

To see the effect of age, we added a cross-term for age and social media. The results are in regression (1) of Table 7. The cross-term for blogs and age is significantly positive (0.00161), and this result is maintained even if we limit the sample to respondents without political motivations, as shown in regression (2). The positive coefficient of the cross-term means that the older generation becomes more polarized than the younger generation when they start using blogs. However, we should note that the level effect of starting to use blogs is significantly negative, as shown in the third row (-0.0970). Thus, to see the overall effect, we divided the sample into two groups: respondents over 40 years old and respondents under 40 years old. The results are regressions (3) and (4), which indicate that blogs' coefficient for the younger generation is significantly negative (-0.0619), whereas that for elder generation is not significant. In summary, there is no significant age effect except for that of blogs reducing polarization among the younger generation.

Table 7

VARIABLES	(1) Difference of polarization	(2) Difference of polarization	(3) Difference of polarization	(4) Difference of polarization
	All	Excl. political motivation	Under 40 years old	Over 40 years old
<start of using net media>				
Facebook	0.0358	-0.0137	0.00729	0.0118
Start using=1	(0.323)	(-0.0929)	(0.0900)	(0.545)
Twitter	-0.0190	0.0209	0.00148	-0.00719
Start using=1	(-0.271)	(0.257)	(0.0392)	(-0.441)
Blog	-0.0970**	-0.120**	-0.0619**	-0.00216
Start using=1	(-2.125)	(-2.253)	(-2.100)	(-0.213)
<start of using net media>*<age>				
Facebook*age	-0.000478	0.000102		
	(-0.249)	(0.0394)		
Twitter*age	0.000278	-0.000575		
	(0.204)	(-0.360)		
Blog*age	0.00161**	0.00202**		
	(1.964)	(2.032)		
<start of using mass media>	included	included	included	included
<demographics>	included	included	included	included
Observations	15,942	11,285	1,813	14,129
R-squared	0.001	0.001	0.006	0.000

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Effect on radicals

Thus far, this paper has shown no significant effect of social media on increased polarization. Is there any cluster of respondents who are polarized by the use of social media? We tried estimations by sex, education, and income, each with no significant effects on polarization. Ultimately, we found only one case in which starting to use social media increases polarization: the case of already polarized person, or radicals.

We divide the sample according to the polarization index, P_j, into two groups: radicals and moderates. A P_j above 1.1 indicated a radical, while a P_j under 1.1 indicated a moderate. Radicals represented approximately 20% of total sample. The results of the difference-in-difference regression applied to these two groups are shown in Table 8. The first two columns are the results for radicals: regression (1) for the basic case and regression (2) for respondents without political motivation. In both regressions, coefficients for Twitter were significantly positive. In other word, radicals became more polarized if they started using Twitter. On the other hand, the coefficients for moderates were negative and significant in regression (4), meaning that moderates became less polarized if they started using Twitter. In summary, radicals became more radical and moderates became more moderate after starting to use Twitter.

Table 8

VARIABLES	(1) Difference of polarization	(2) Difference of polarization	(3) Difference of polarization	(4) Difference of polarization
	Radicals (P_j>=1.1)	Radicals (P_j>=1.1)	Moderates (P_j<1.1)	Moderates (P_j<1.1)
		Excl. political motivation		Excl. political motivation
<start of using net media>				
Facebook	-0.000185	-0.160	0.0207	0.0251
Start using=1	(-0.00274)	(-1.568)	(1.018)	(0.981)
Twitter	0.130***	0.130**	-0.0233	-0.0285*
Start using=1	(2.855)	(2.185)	(-1.545)	(-1.672)
Blog	-0.00813	-0.0343	-0.00327	-0.00549
Start using=1	(-0.275)	(-0.846)	(-0.351)	(-0.496)
<start of using mass media>	included	included	included	included
<demographics>	included	included	included	included
Observations	2,591	1,594	13,351	9,691
R-squared	0.032	0.038	0.001	0.001

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As discussed in Section II, several social media researchers have warned that social media causes polarization. The results in Table 6 indicate that their warnings are well-founded, as there is a cluster of people who are polarized by social media. However, the cluster polarized by social media is limited, since radicals account for only 20% of the population, and only Twitter was found to be polarizing. The remaining 80% of people become more moderate upon using Twitter. Furthermore, younger respondents (under 40 years old), representing approximately half of population, become more moderate when they read blogs, as shown in Table 6. The overall effects of social media are not significant, as shown in the basic regression in Table 3. In summary, thus, the effects of social media on polarization are limited and weak, and, rather than increasing polarization, social media tends to increase moderation.

III Conclusion and Discussion

The difference-in-difference analysis in this paper indicates that the effect of social media on polarization is very limited. Although there is a small cluster of people who become more polarized when using Twitter, the overall effect of social media, including Facebook and blogs, is not to increase polarization, but, rather, to decrease it.

Why does social media fail to increase polarization? One of the hypothetical explanations is that the "selective exposure" theory of the internet is not true. For example, Gentzkow and Shapiro (2011) investigated access to news sites on the Internet and found that people who visited extremely conservative sites also visited extremely liberal sites. Conservative people tended to visit conservative news sites 60% of the time and liberal news sites the remaining 40% of the time. This figure of 40% seems too high to indicate an "echo chamber." Barbera (2015) collected Twitter users' follower-followed relation data in the US, Germany, and Spain and estimated the degree of selective exposure. The ratio of followed persons with ideologies opposite those of their followers was approximately 30 to 40% in these three countries, which corresponds with the results of Gentzkow and Shapiro (2011). Garrett (2009) examined the tracking records of partisan websites and found that visitors read not only reinforcing news, but also challenging news, suggesting that the effect of the echo chamber was limited.

Given these findings, we should compare selective exposure of social media with that of mass media. Selective exposure could also occur in mass media, and the ratio might be higher than that in social media, since, to access mass media, people must pay a fee or adjust their time schedule (e.g. to purchase a newspaper or sit down in front of a TV). Therefore, people may be more reluctant to intentionally read or watch ideologically opposing newspapers or TV programs. On the other hand, social media is free media in two senses: we can access it without fees and can read it whenever we like. Because of this low cost of access, users of social media can easily access opposing information sources. Therefore, the ratio of people accessing opposite viewpoints may be higher for social media than mass media. In other words, selective exposure may occur less in social media than in mass media. If it is the case, it is natural that social media does not increase polarization, rather decrease it.

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