Informal Social Networking and Community Involvement: Participation in Neighborhood Crime Watches in Japan

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The inclusion of social recreational activities in measures of social capital is often criticized for trivializing civic engagement. This critique, however, ignores a key aspect of social capital theory, the interconnectedness of civil society. I examine the influence of informal social recreation on formal community involvement. I test the impact of social recreation on the likelihood of joining a Japanese neighborhood crime watch, while controlling for other determinants of participation. I use a logistic regression model of 2000 International Crime Victim Survey data. The results verify that social recreation motivates people to join crime watches, suggesting that informal social interaction leads to broader civic engagement.

Does social recreation lead to more formal community involvement? Critics complain that Putnam’s (1993, 2000) inclusion of recreational activities in studies of social capital trivializes civil society. For example, Gannett (2003, 2) posits that using social events such as backyard barbecues as evidence of civic engagement blurs our understanding of participation in more important “political” community involvement. Putnam (2000, 119) suggests that social networks motivate community involvement by facilitating discussion, engendering trust, and instigating norms that lead to participation. For example, a backyard barbecue may enable a discussion of problems in the local school system that leads to involvement in more “political”

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volunteer associations such as the PTA. Critics view this theory as conceptually ambiguous due to a perceived confusion of the social with the political, and dismiss the influence of informal socializing on formal community involvement (see Edwards 2004). Empirical evidence is needed to resolve the debate.

To examine the relationship between civic involvement and social interaction, I test the impact of informal socializing on individuals joining neighborhood crime watches, while controlling for fear of crime, prior crime victimhood, police competence, and socioeconomic determinants of participation. Crime watches are chosen as the dependent variable because joining with neighbors to prevent crime is a clear example of formal communal involvement that these critics say is a better measure of civil society. I test the theory by using a logistic regression model of International Crime Victims Survey (ICVS) data from Japan. I choose Japan because neighborhood solutions to crime are common and used throughout the country (Thornton 1992). Japan is an excellent place to test the relationship between social and civic interaction because crime watches are available for all survey respondents to join. The United States, for example, is a less optimal country to test because crime watch usage is limited and regional (Thornton 1992). Limited usage biases the results from the ICVS national sample since joining is not an option for some respondents. I find that social recreation motivates people to join neighborhood watches, suggesting that Putnam is correct in asserting that informal social interaction leads to broader civic engagement.

Although many recent studies show the benefits of civic engagement on communities and participating individuals, the social mechanisms that cause collective action have not received the attention they deserve (Ostrom 1998). Before we can promote civil society, we first must know what causes people to participate. Social capital scholars study activities that facilitate or
hinder one's opportunities to join. For example, Putnam (2000, 235) shows that television viewing limits joining voluntary associations or even family picnics. He posits that America's recent civic disengagement is caused by the dominance of television, which lowered civic association membership. Involvement in choral societies, soccer clubs, and bowling leagues are not end-goals. Instead, social capital theorists desire the communal benefits created by membership in these associations. Putnam (2000) shows that aggregate participation is higher in regions with dense social networks. He suggests that interaction in face-to-face activities sponsors other community involvement.

Critics complain that there is no relevance to democracy from studying involvement in trifling informal recreational activities (Edwards 2004). Edwards (2004) doubts that informal socializing influences participation in formal community activities. However, the face-to-face interaction that Edwards finds beneficial in formal associations also occurs in informal human relations. Using Edward's logic, backyard barbecues should increase civic engagement as well. Gannett shows that Putnam's chief influence, Tocqueville, differentiated between formal civil and political associations—which are crucial for democracy—and social recreation. Tocqueville thought that recreation may "allow residents to 'taste the enjoyments of private life'" (Gannett 2003, 2), but is not important for politics. Gannett states "we simply cannot equate family picnics with various types of political engagement if we are to make our democracy work" (Gannett 2003, 2). These critics, however, do not test empirically a key concept of Putnam's theory, that social recreation increases participation in formal civil society. If you want to increase community involvement, and social recreation increases involvement, then informal networks are "political" and must be studied.

Other correlates of participation must be controlled to determine the relationship between social and civic orientation. For
example, people may join because they derive direct benefits from group membership (Olson 1990), i.e. instrumental reasons. They may also have a belief or emotional attachment to an issue that does not profit them directly, but still motivates them to join, i.e. personal reasons. Although these reasons are not mutually exclusive, measuring which is the most powerful motivating force can help focus programs that facilitate civil society.

THE POLICY AND THEORETICAL IMPLICATIONS

The results of my research have important policy and theoretical implications. For policymakers, the research is important because many reformers suggest the need for programs to encourage civil society. Determining the causes of participation will provide reformers empirical evidence to improve their programs. If human interaction mobilizes participation, then these programs should focus on deepening their participants’ social networks. If, however, people join because of incentives or personal reasons, then these programs can attenuate these aspects. At this time, experiments to promote Japanese civil society are being conducted with incentive programs such as community currencies, and programs that focus on the specific interests of townspeople. In studying neighborhood watch involvement, my research provides a model to enhance programs.

Theorists frequently debate the importance of institutions to civil society (e.g. Edwards and Foley 2001, and Edwards 2004). The research presented here provides a test of the debate. Jackman and Miller (1998) describe an internal inconsistency within scholarship as to whether civic engagement is endogenous or exogenous of institutions. They prefer James Coleman’s (1990) endogenous research approach. Putnam’s work has grown from an early (1993, 18) thesis that posited an exogenous-only “bottom-up” relationship from civic culture to institutions, to a later stance (2000, 413) in which institutions can promote civil soci-
My research tests these assumptions. If informal social networks promote joining watches, then civic engagement is created by recreational activity, and institutional participation is not the only determinant of civil society.

I find that informal social networks in Japan promote volunteering for crime watches, showing that civic engagement can be developed exogenously of institutions. Jackman and Miller's (1998) endogenous-only approach misses the important interconnectedness of communal life. Of course, participation in institutions may also increase one's civic engagement. Thus, influences of participation in civil society are possibly both endogenous and exogenous of institutions. The research proceeds as follows: after reviewing the hypotheses and data, I determine the influence of everyday casual interaction—defined as "informal social networks"—on civic organizational involvement—defined as "formal social networks."

JAPANESE NEIGHBORHOOD WATCH PARTICIPATION AND CRIME PREVENTION

Japan has low levels of social disorganization (Roberts and Lafree 2004). Social disorganization and social capital are similar concepts, in that both maintain that deep social networks bring collective good. A large body of literature suggests that the high level of social capital—or low level of social disorganization—is responsible for Japan’s low crime rates (Clifford 1976, Vogel 1979, Braithwaite 1989, Bayley 1991, Westermann and Burfeind 1991, Komiya 1999, Roberts and Lafree 2004). Japan is thought to have a communal culture, and these societal ties are linked to crime prevention (Becker 1988, Fujimoto 1994, MacFarlane 1995, Komiya 1999, Roberts and Lafree 2004). Shame and a desire not to hurt one’s group are suggested as limiting levels of deviant behavior (Thornton 1992, Roberts and Lafree 2004). Others scholars disagree with these cultural expla-
nations of Japan's lower relative crime rates. For example, Roberts and Lafree (2004) use time series analysis of aggregate data to show that Japan's high employment and relatively low levels of young males in the population (who commit most crime) account for its lower comparative crime rates. These socio-cultural theories of Japan's low crime rates, however, do not explain why only some people join neighborhood watches, even after controlling for fear of crime, urbanity, prior victimization, police incompetence, and other socioeconomic determinants of participation.

**DATA**

To test these assumptions, I use ICVS data, which is sponsored by the United Nations Interregional Crime and Justice Research Institute. In Japan, Koichi Hamai of the Ministry of Justice coordinates the survey nationally. The ICVS is performed every four years, and I test data from the latest version conducted in 2000. The survey has a sample of 2,500 and a response rate of 88%. Neighborhood is a dichotomous dependent variable measuring whether someone joined a crime watch, coded "1" if participating and "0" if not. The key causal independent variable is from a question that asks "[h]ow often do you personally go out in the evening for recreational purposes?" Social involvement is coded from no social recreational activity ("0"), once a year ("1"), once a month ("2"), once a week ("3"), and almost every day activity ("4"). Past crime victimization is measured as *Victim* and *Violent*, both are coded "1" if a victim in the last five years, and "0" if not. Fear may motivate someone to join a crime prevention program (Lewis and Salem 1986), and it is coded from

1 *Victim* is combined from various ICVS questions on different types of crime victimization, including assault, robbery, rape, attempted murder, and corruption. See Table I for ICVS variable numbers.
no fear ("1"), little fear ("2"), some fear ("3"), and much fear ("4"). Neighborhood watch participation might also come from a lack of adequate policing. How someone feels about Police competence is coded from very good ("1"), somewhat good ("2"), somewhat poor ("3"), to very poor ("4").

Socioeconomic factors affect the opportunities to join, and unless controlled can bias the results. Along with political knowledge, education may cause a person to become rhetorically skillful and willing to participate (Freitag 2003). Education is measured in years of schooling. The elderly volunteer more often, and have longer ties to their community (Freitag 2003), so I control for Age measured in ascending five-year categories starting from eighteen. Having a job may limit the time to participate, so I include Employment, coded dichotomously with "1" being jobholders and "0" for the unemployed. Women are more communally active (LeBlanc 1999); here Female equals "1" and male is coded "0." Rural areas have a more reciprocal communal life than urban areas (Putnam 2000, 96), so I include Urban, coded ordinally based on town size; ranging from "1" for towns with a population under 10,000 to "6" those with populations over 2,000,000. Singles may have fewer time constraints, and thus participation may be easier for them than for married couples (Freitag 2003); Married is a dichotomous variable with "1" being those married, and "0" those single. Importantly, no control variables are post-treatment, i.e. caused by watch participation.
The data include 1,350 complete cases, out of 2,211. Error occurs when missing data are not missing completely at random (King et al. 2001). Table 1 lists the number of responses for each variable. Many of the cases are missing only one variable’s response, but regression analysis using listwise deletion throws out the entire case. Multiple imputation is a better alternative than listwise deletion (King et al. 2001). Multiple imputation creates data for the missing responses based on information in the case and the other data. Simulated data are more trustworthy than data biased by listwise deletion (King et al. 2001). I use the Amelia (King et al. 2001) program to create five imputed data sets, and each with 2211 cases. I use the Clarify (Tomz, Wittenberg, and King 2003) package from Stata to handle the multiple data sets, run the regressions, calculate the standard errors, and create the

<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>DESCRIPTIVE STATISTICS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Mean</td>
</tr>
<tr>
<td>Neighborhood Watch</td>
<td>0.14</td>
</tr>
<tr>
<td>Social</td>
<td>1.40</td>
</tr>
<tr>
<td>Fear</td>
<td>2.13</td>
</tr>
<tr>
<td>Victim</td>
<td>0.41</td>
</tr>
<tr>
<td>Violent</td>
<td>0.03</td>
</tr>
<tr>
<td>Police</td>
<td>2.35</td>
</tr>
<tr>
<td>Urban</td>
<td>3.37</td>
</tr>
<tr>
<td>Age</td>
<td>7.46</td>
</tr>
<tr>
<td>Education</td>
<td>12.05</td>
</tr>
<tr>
<td>Employment</td>
<td>0.62</td>
</tr>
<tr>
<td>Female</td>
<td>0.51</td>
</tr>
</tbody>
</table>

These are the average descriptive statistics of the multiple imputed data sets. To replicate, use 2000 Japan ICVS variables numbers Social S0060, Fear S0020, Victim C01A000, C02A000, C03A000, C04A000, C05A000, C06A000, C07A000, C08A000, C09A000, C10A000, C11A000, C12A000, C13A000, C14A100, C11A000, C12A000; Violent C11A000, C12A000; Police P00101, Urban D0020, Married D0090, Age D0010, Educ. D0063, Employ. D0050, Gender K040. “N” is the number of cases before multiple imputation.
simulations below. To determine if the imputation is biasing the results, I show the outcomes from two models (see Table 2). One model uses the original complete case data, and one uses the multiple imputation data sets.

METHODS

To determine the impact of social networks on a dependent variable, many researchers perform a multiple regression analysis of survey data with social networks as the causal variable, while controlling for other determinants, such as socioeconomic. I take the same approach with this research. Neighborhood is a dichotomous dependent variable, so I create a logistic model, which is appropriate for binary outcomes (Long 1997). The model is estimated as

\[ Y_{\text{Neighborhood}} = \alpha + \beta_1 \times X_{\text{Social}} + \beta_2 \times X_{\text{Fear}} + \beta_3 \times X_{\text{Victim}} + \beta_4 \times X_{\text{Police}} + \beta_5 \times X_{\text{Urban}} + \beta_6 \times X_{\text{Married}} + \beta_7 \times X_{\text{Age}} + \beta_8 \times X_{\text{Educ}} + \beta_9 \times X_{\text{Employ}} + \beta_{10} \times X_{\text{Gender}} + \epsilon \]

Also, I present below the results from Clarify (Tomz, Wittenberg, and King 2003), which creates simulations drawn from the data to show a quantity of interest. Clarify's authors King, Tomz, and Wittenberg (2000) describe its process thusly: "[t]he program draws simulations of the main and ancillary parameters from their asymptotic sampling distribution, in most cases a multivariate normal with mean equal to the vector of parameter estimates and variance equal to the variance-covariance matrix of estimates." Here, all the other control variables are held at their mean, and the expected probability of participating in a watch is shown for each level of socializing.

Violent crime victims may have different levels of personal satisfaction from stopping crime than less serious crime victims, and both are included in the Victim variable. To determine if
there is a difference, I create a separate Violent variable to measure only those who have suffered violent crime. I create a Receiver Operator Characteristic (ROC) plot of the two models—all crime victims and just violent crime victims—to compare these specifications (see King and Zeng 2002 for more on ROC plots).

In addition, I check against endogeneity between the dependent and causal variables because through joining a crime watch people may meet friends that they socialize with afterwards. Thus, the level of informal socialization may come from civic engagement. I examine the potential bi-casual relationship using an Amemiya Generalized Least Squares (AGLS) model. If the dependent variable is continuous, I can use the familiar two-stage least squares estimator to determine the impact of endogeneity. Here, I use “ivprob” command for Stata to control for endogeneity in a model with a dichotomous dependent variable.²

RESULTS

Goodness of Fit

The ROC plot displayed in Figure 1 shows that there is no significant difference between modeling all and violent crime victims on participation in neighborhood watches. Simply put, the results show that violent crime victimization does not influence joining rates anymore than other types of crime. In addition, the test shows that the model is successfully predicting a high percentage of the binary outcomes, as the lines are significantly above the forty-five degree line of random chance.

² For details of AGLS estimation see Maddalla (1983, 247-252), and Newey (1987, eq. 5.6).
FIGURE 1

Lines represent how well the logistic model does in predicting neighborhood watch participation. The closer the lines are to the upper right corner, the better the model (King and Zeng 2002). The model with violent crime victims is in dashes, the model with all crime victims in solid.

LOGISTIC MODEL RESULTS

The results displayed in Table 2 show that a chief reason people join crime watches is social networking. The data suggests that the more informal social interaction you have, the more likely you are to participate in your community. Social recreation
TABLE 2

LOGISTIC MODEL RESULTS FOR
PARTICIPATION IN NEIGHBORHOOD WATCHES

<table>
<thead>
<tr>
<th>Variable</th>
<th>ME</th>
<th>MI SE</th>
<th>CC</th>
<th>CC SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>0.154†</td>
<td>0.062</td>
<td>0.220†</td>
<td>0.076</td>
</tr>
<tr>
<td>Fear</td>
<td>0.161</td>
<td>0.103</td>
<td>0.068</td>
<td>0.125</td>
</tr>
<tr>
<td>Victim</td>
<td>0.154</td>
<td>0.130</td>
<td>0.169</td>
<td>0.157</td>
</tr>
<tr>
<td>Police</td>
<td>-0.094</td>
<td>0.094</td>
<td>-0.044</td>
<td>0.118</td>
</tr>
<tr>
<td>Urban</td>
<td>-0.224‡</td>
<td>0.044</td>
<td>-0.212‡</td>
<td>0.054</td>
</tr>
<tr>
<td>Married</td>
<td>-0.188</td>
<td>0.146</td>
<td>-0.290</td>
<td>0.182</td>
</tr>
<tr>
<td>Age</td>
<td>0.095‡</td>
<td>0.025</td>
<td>0.077†</td>
<td>0.033</td>
</tr>
<tr>
<td>Education</td>
<td>0.038</td>
<td>0.027</td>
<td>0.014</td>
<td>0.032</td>
</tr>
<tr>
<td>Employment</td>
<td>0.053</td>
<td>0.141</td>
<td>-0.019</td>
<td>0.189</td>
</tr>
<tr>
<td>Female</td>
<td>0.397‡</td>
<td>0.135</td>
<td>0.433†</td>
<td>0.167</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.160</td>
<td>0.609</td>
<td>-2.541‡</td>
<td>0.795</td>
</tr>
<tr>
<td>Number of cases</td>
<td>2,211</td>
<td>1,350</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.03</td>
<td>0.03</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$X^2$</td>
<td>55.60‡</td>
<td>36.71‡</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

MI rows represent the average unstandardized coefficients and standard errors of a logistic model for the likelihood of joining a crime watch from each imputed data set calculated with Clarify. CC rows represent the unstandardized coefficients and standard errors of a logistic model for the likelihood of joining a crime watch from the original complete case data set. † p < .01 ‡ p < .001.

Activity levels have a strong positive significant impact (.154) on neighborhood watch participation, when holding all other variables constant. Crime victimization is not significant, suggesting that personal reasons for joining neighborhood watches are not motivating behavior. Fear of crime does not increase participation in these groups, suggesting that desired benefits (i.e. less crime) do not influence behavior even when people believe there is a problem. The police competence measure is also not significant; showing that institutional failure to provide adequate policing does not affect participation. Note that many (35%) in the study think their police are incompetent. The other significant
variables match their theoretical predictions. Age increases participation. Women have more involvement, and so do those in rural areas. Note that the multiple imputation model and the complete cases model show substantively similar results for every variable and the constant.

**PROBABILITIES OF NEIGHBORHOOD WATCH PARTICIPATION**

The results of the *Clarify* simulation displayed in Figure 2 show that when holding all other variables at their mean, those

**FIGURE 2**

Graph boxes represent the results of a logistic simulation created by *Clarify* (Tomz, Wittenberg, and King 2003). These simulations hold all control variables (victimization, fear of crime, police competence, and socioeconomic variables) at their means and display the predicted value and 95% confidence intervals for the dependent variable (neighborhood watch participation) for each level of the causal variable (social activity).
who are most actively involved with social networks are about twice as likely to join their neighbors to fight crime as those who are not socially active. In Japan, about 11% of those with no social activity are predicted to join, while about 19% of those with the densest social networks join after controlling for \textit{Victim}, \textit{Fear}, \textit{Police}, and socioeconomic determinants of participation. Those with almost every day social activities have a 95% confidence interval lowest bound (.14) that is above the highest bound (.13) for those with no social activities. Thus, social recreational activity increases the likelihood of community involvement as measured by neighborhood watch participation. Thus, Putnam’s theory is verified by these results.

\textbf{AGLS Regression Model}

For the AGLS model, I use \textit{Education} as an instrument. Many studies show that education increases social networking (e.g. Huckfeldt and Sprague 1995, Putnam 2001). Surprisingly, however, education does not influence joining crime watches, as shown in Table 2. Thus, this is a counter-intuitive instrument, but it still may control for bi-causality. Indeed, I find that \textit{Education} is significantly correlated with \textit{Social} ($b$ 0.08, s.e. 0.01), but not Neighborhood watch ($b$ 0.038, s.e. 0.027). Sensitivity analysis revealed that taking \textit{Education} out of the model had no discernable effect on \textit{Social}. In the AGLS model, socialization strongly positively influences the likelihood of joining a crime watch ($b$ 0.530, s.e. 0.409). The large standard error for \textit{Social} is probably due to imprecision in the instrument. Thus, we must be cautious in interpreting this model, but the results suggest that there is no bi-causal relationship. The AGLS results show similar effects for all other variables. The robustness of the results suggests that involvement does not influence the amount of socializing.
### TABLE 3
AGLS MODEL RESULTS FOR PARTICIPATION IN NEIGHBORHOOD WATCHES

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>0.530</td>
<td>(0.409)</td>
</tr>
<tr>
<td>Crime</td>
<td>0.042</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Fear</td>
<td>-0.108</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Police</td>
<td>-0.123*</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Female</td>
<td>0.404*</td>
<td>(0.179)</td>
</tr>
<tr>
<td>Age</td>
<td>0.083*</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Urban</td>
<td>-0.104†</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Employment</td>
<td>0.149</td>
<td>(0.193)</td>
</tr>
<tr>
<td>Marital</td>
<td>0.078</td>
<td>(0.172)</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.253*</td>
<td>(1.599)</td>
</tr>
<tr>
<td>Number of cases</td>
<td>2,211</td>
<td></td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>$X^2$</td>
<td>47.20†</td>
<td></td>
</tr>
</tbody>
</table>

Cells represent the average unstandardized coefficients and standard errors of an AGLS model for the likelihood of joining a crime watch from each imputed data set. Education is the instrument variable. *p < .05 † p < .01 ‡ p < .001.

### CONCLUSION

I find that recreational activity encourages people to join crime watches in Japan. The results show that informal social networking leads to participation in other areas. We cannot ignore the benefits to civil society from institution-exogenous informal social recreation. Critics of the inclusion of recreational activities in civil society measures should not dismiss their influence on traditional political participation. The research approach advocated by Gannett (2003), Edwards (2004), Edwards and Foley (2004) and Miller and Jackman (1998) ignores the impact of social interaction on institutional involvement. Both formal and informal interaction must be measured and considered to determine the full scope of civil society. These critics encourage
a focus only on the institution-endogenous determinants of civil society. Ignoring real-world complications in a quest for clarity only further confuses our understanding of the multifaceted relationships we are studying. Additionally, the results reported here suggest that although motivating involvement may be crucial to stopping crime, incentive or specialized interest programs will not motivate joiners. Increasing the density of social connectedness is where reformers should focus their energies. The results show that informal networks increase communal participation to reduce crime, suggesting other types of communal involvement will be influenced in a similar relationship.

Some caution, however, is needed in interpreting these results. The ability to examine this test is limited to the validity of the survey data, question wording, and methodology (Zaller 1992). This is particularly true when only examining one survey as I did here. In addition, there are no questions of social psychology in the ICVS data, so possible determinants such as trust, tolerance, and efficacy cannot be included in the model. Finally, the inability to find a more precise instrument variable leaves open the question of bi-causality. Despite these limitations, the research provides some evidence of the positive impact of social recreation on civic life.

REFERENCES


INFORMAL SOCIAL NETWORKING & COMMUNITY INVOLVEMENT


