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A Computational Model of Worker Protest

Journal of Artificial Societies and Social Simulation 14 (3) 1  
http://jasss.soc.surrey.ac.uk/14/3/1.html  
Received: 18-Dec-2009 Accepted: 03-Mar-2011 Published: 30-Jun-2011

Abstract

This paper presents an agent-based model of worker protest. Workers have varying degrees of grievance depending on the difference between their wage and the average of their neighbors. They protest with probabilities proportional to grievance, but are inhibited by the risk of being arrested—which is determined by the ratio of coercive agents to probable rebels in the local area. We explore the effect of similarity perception on the dynamics of collective behavior. If workers are surrounded by more in-group members, they are more risk-taking; if surrounded by more out-group members, more risk-averse. Individual interest and group membership jointly affect patterns of workers protest: rhythm, frequency, strength, and duration of protest outbreaks. Results indicate that when wages are more unequally distributed, the previous outbreak tends to suppress the next one, protests occur more frequently, and they become more intensive and persistent. Group identification does not seriously influence the frequency of local uprisings. Both their strength and duration, however, are negatively affected by the ingroup-outgroup assessment. The overall findings are valid when workers distinguish 'us from them' through simple binary categorization, as well as when they perceive degrees of similarity and difference from their neighbors.

Keywords: Workers Protest, Tags, Group Identity, Trust, Netlogo

Introduction

1.1 Marked increases in wage inequality and major layoffs due to corporate restructuring brought on by a financial crisis triggered a major outbreak of strikes and local protests in South Korea during 1996-97. Although the wave of protest was severe in industrial cities, it never reached its full potential due to lack of solidarity between native Korean and marginalized immigrant workers. Ultimately, coercive efforts by employers and the government were not able to prevent the emergence of a synchronized worker action that spanned both spatial and ethnic diversity in the working class. The story is a familiar one, ethnic and cultural differences among workers are a frequent factor in limiting class solidarity and coordinated protest.

1.2 In this paper, we extend a model of civil violence proposed by Epstein (2002) to examine effects of perceived 'in' and 'out' group membership identity on the shape of protest events. In our model, workers are motivated to protest by grievances based on wage inequality, but it is inhibited by the risk that coercive agents might arrest them. Variations and spatial distribution in grievance and coercion give rise to dynamic patterns of protest activity, but we add a new element. Workers have limited tolerance toward others who they see as different from themselves. They can read "other-ness" from observable 'markers,' to make a distinction between 'us' and 'them' (i.e. native and guest workers). Workers believe that perceived in-group members are more likely to support them, lessening the risk that they will be arrested if they protest. In a series of simulation experiments, we explore the consequences of this similarity-based risk calculus for various features of protest outbreaks over time: rhythms, frequency, intensity, and duration.

Theoretical Background

2.1 Rational choice theory axiomatically states that individuals with (relatively) complete information behave in a rational manner to maximize calculable utility in terms of cost-benefit ratio. This individual-based utilitarian model has been widely implemented to explain collective behavior: an agent will participate in collective behavior if perceived benefits > perceived costs. However, aggregation will not necessarily happen in the real world because individuals see others as distinct from themselves (Richerson and Boyd 2001). This is particularly true in large-sized gatherings with strangers. In this paper, we exclude such aggregates and focus on relatively small groups of agents that can be easily characterized.

2.2 The dynamics of collective behavior among heterogeneous agents is not the same as the dynamics among homogeneous ones (Oliver et al. 1985). There are two approaches to theorizing and modeling it. First, studies on the critical mass (Granovetter 1978; Oliver et al. 1985; Manwell et al. 1988; Briichou and Johnson 2002) highlight roles of a small group of people who are different from the others in terms of interest, resources, and/or commitment. The main argument in Granovetter (1978) is that a small change in the distribution of thresholds in the population makes a dramatic difference in the dynamics of collective action (e.g. the bandwagon effect). As Manwell et al. (1988; 505) summarize it, "when groups are homogeneous, everyone is interchangeable, and the collective action outcome is a simple function of how many people participate. In contrast, in a heterogeneous group, it matters who is organized as well as how many since one person may be willing and able to contribute much more than another." They prove mathematically and computationally that heterogeneity and network centralization increase the overall probability that organizers find a critical mass who trigger and sustain mobilization. Briichou and Johnson (2002) simulate protests by agents who perceive only what happens in their immediate surroundings and estimate the probability of success following a logical curve. They demonstrate that a small number of activists who unconditionally join the on-going protest significantly promote mobilization through positive feedback even under unfavorable conditions for it. Individual differences in participation thresholds, however, is not the only kind of heterogeneity that matters for protest.

2.3 The second approach to the effects of heterogeneity on protest critiques the absence of identities in the classical rational choice model of collective action. Perceived similarity between agents is seen as facilitating cooperation and solidarity in social dilemmas (e.g. Kramer and Brewer 1986; Kollock 1998). Social identity has been highlighted as a central mechanism to understanding other forms of collective action including protest among heterogeneous agents (Reicher 1984; Brewer and Silber 2003; Simon and Wiamersman 2001). Practitioners of the constructivist approach emphasize the role of collective identity in social movements (Cohen 1985; Melucci 1988). This approach is in line with agent-based modeling of collective identity beyond instrumental rationality (e.g. Lusiklo 2005). Collective identity - which is more transient and more emergent rather than nested in socio-cultural categories (Rohlinger and Snow 2003), however, is not our current focus. The present study is instead informed by social psychological research on group identity.

2.4 People tend to make distinctions between 'us' and 'them' through 'categorization' (Tajfel 1974), a cognitive process of classifying stimuli on the basis of 'similarities' among them (Turner 1982). This is consistent with the idea of "tagging" (Holland 1996) or a pervasive mechanism in group processes. Human agents rely on heuristic cues such as ethnic and cultural markers (e.g. skin color, speech, manner) to identify themselves from others (Richerson and Boyd 2001). This labeling is facilitated by similarity perception among heterogeneous agents occurring more frequently in large-sized gatherings with strangers (i.e. workers from other workplaces in our model). Our study is interested in the issue of trust driven by categorical membership identity and its impact on individual interest. In our model, workers at risk from coercive agents consider not only the potential benefit of protest (determined by the mechanism between grievance and perceived cost) but also whether they are surrounded by a sufficient number of trustworthy fellows.

2.5 We are concerned with the interplay between class and race. In our model, agents are heterogeneous in "class" in that they receive different incomes. This heterogeneity affects the individual propensity to protest by creating a sense of grievance based on individual relative deprivation. Underpaid workers are more likely to participate in collective behavior in our model. Agents are also heterogeneous in ethnic and cultural markers. As explained above, this heterogeneity affects participation because agents are more likely to trust others of their own kind. In our model, class and race are orthogonal. In real world cases, usually these factors are not, with a marginalized ethnic population systematically being paid less. In the split labor market theory (Bonacioc 1972), for example, more highly paid native workers are forced to compete with guest workers who are more likely to remain as bystanders or strikers (Brown and Bowd 1995). We instead adopt the assumption of the independence of class and race in order to better understand the dynamics of "race" or tag similarity in the absence of confounding factors.

The Model

3.1 The current version of Netlogo (Wilensky 1999) is equipped with Model in Epstein (2002) in the library - the rebellion model (Wilensky 2004). We use it as a starting point, and adopt its basic simulation approach under which agents are randomly selected without any particular schedules. In this way, we can avoid the execution order effect. 'Updating' is synchronous, as in Wilensky (2004), which means that the environment is updated for the next stage only after all agents have finished their actions at the current stage.

3.2 Workers (analogous to Epstein's civilians) without leaders are located on a 20 x 20 torus with some open spaces. They know only what is going on in their immediate surroundings, as is in Epstein (2002) and Briichou and Johnson (2002). In our model, agent observes the behavior of neighboring fellows whose distance from her is less than or equal to six (Epstein used a distance of 7, on a 40x40 grid). The density of workers is fixed at 70%. The grid is also occupied by coercive agents who arrest actively protesting workers. As in Epstein (2002), coercive agents are randomly arranged across the space with a density of 4%.

3.3 In Epstein (2002), both perceived hardship (H) and perceived regime legitimacy (L) determine grievances: \( G = H^2 \cdot (1 - L) \). In our model, we use a different value in his model. Instead of H and L, we define each worker's grievance as a feeling of relative deprivation which motivates to consider joining a protest:

\[
G = 2x \cdot \frac{1}{1 + e^{0.5}} - 0.5
\]
3.4 Whether a worker protests or not is contingent on both grievance and a rational calculation of the net risk. The net risk, in turn, is determined by an exogenously fixed individual-level of risk-aversion and the estimated probability of being arrested. In our model, Net Risk (NR) is equal to Risk Aversion (RA) multiplied by Estimated Arrest Probability (P), as in Epstein's model. But, $R = N(0.5, 0.162^2)$, instead of $R = U(0, 1)$, in his model. That is, we assume that a majority of workers have degrees of risk aversion close to the mean in the population, with a small number of outliers above or below the mean. As with Epstein's model, we calculate $P = 1 - \exp(-k(C/A))$. Here, $C$ is the number of coworkers ($\alpha$) or the number of active workers ($\beta$). That is, the probability that a worker is arrested declines as the ratio of workers protesting to coercive agents increases. Following Wilensky (2004), $k = 2.5$ is a constant set in 'startup' to ensure a reasonable value when there is only one cop and one agent within a certain vision; and we take the floor of $C/\alpha$ - the largest integer less than or equal to $C/\alpha$.

3.5 Each agent has two traits, a tag $t = U(0, 1)$ and a tolerance $T = N(0.5, 0.162^2)$. We assume that tags and tolerance assigned to agents at the initial stage remain constant throughout experiments. Whether the difference between an ego and her alter is labeled as 'othering' is determined by the ego's degree of tolerance. To 'tag difference,' that is, $|t_\text{ego} - t_\text{alter}|$. For instance, if $t_\text{ego} = 0.6$, $t_\text{alter} = 0.2$, and $T = 0.5$, $|0.6 - 0.2| = 0.4$. Hence, the ego categorizes her neighbor as 'out-group.' For another example, if $(t_\text{ego} - t_\text{alter}) > 0.5$, the ego regards her neighbor as 'them.' More generally, agent-perceives/ass in-group only if $|t_\text{ego} - t_\text{alter}| < 0.5$ and otherwise out-group.

3.6 When there is no tag-based group identity, if grievance - perceived risk $>\text{threshold}$, workers become active; and otherwise they remain as bystanders. This default process reflects the classical model of rational choice. It is necessary but not sufficient for considering whether or not to participate in the on-going protest when heterogeneous workers should read signals of trustworthy - a large-sized mobile assembly. Each agent must gauge whether group support is likely. If acting produces greater payoffs than not acting, but probability of support is 0, then the crowd member will not be active (Berk 1974). If tag-based distinction between us and them is manipulated, workers become active only when the first condition (i.e. $G - NR > \text{threshold}$) is satisfied, and when the number of perceived in-group neighbors is more than or equal to the number of out-group members; in this way, agents in our model independently assess the net risk and group support. We introduce the exogenous parameter to determine the degree of tag-based distinction. Whether a random integer number generated from the uniform distribution is bigger than a certain level of tag-based distinction, decision-making is purely rational (i.e. calculating the net risk) without assessing group support; and otherwise it depends on both tag-based risk perception and the net risk assessment.

3.7 Agents can move around within their local neighborhood (Epstein 2002), unlike those in Branchoux and Johnson (2002). This makes our model more realistic and reasonable (See Chapter 4 "Dimension of Space and Time in Protest and Repression" of Francisco (2010)). At the beginning of each round of simulation, we allow workers who are not arrested, and cops, to move to any vacant patch within a distance of 6. Workers then become active if the difference between their grievance and their perceived net risk falls above a fixed threshold (0.1, as in Epstein’s model). If active workers are arrested by cops, companies lay off. They are able to go back to their fellows after a certain period of time. It is a random integer number between 0 and 29, as in Wilensky (2004) where the maximum layoff-term is fixed as 30. This random number approach is justifiable since employment flexibility varies from one workplace to another. Epstein (2002) assumes that jailed agents return to the population with previous levels of net risk aversion and perceived hardship. In the same way, laid-off workers in our model return with the same values of wage, tag, tolerance, and risk aversion.

3.8 Epstein (2002) observes punctuated equilibrium at a relatively high maximum jail term (e.g. 15, 30). He mentions the possibility that increasing the jail term would 'fatten' the distribution of waiting time between protests and release its mean (that is, 7246), but the consequences of decreasing the jail term are not considered. If the maximum jail term is not sufficiently high, say 10, a strong local protest continues (left in Figure 3). In this way, his model is very sensitive to its initial value. Our model does not entail such sensitivity (Right in Figure 3), but it is implied that global patterns of local outbreaks in our model can be still affected by the maximum layoff term.

3.9 Our model uses real number tags (e.g. Rizzo et al. 2001). We argue that cognitive agents may scan the overall similarity to neighboring fellows. However, action can be based on binary distinction between 'us' and 'them,' as in Schelling's original model of residential segregation (Schelling 1971, 1978). To examine the sensitivity of our approach, we construct another model in which each agent has binary tags, 1 or 0 denoting the presence or absence of a single trait (e.g. physical appearance). As above, tolerance levels are normally distributed. A direct comparison of simulation outcomes is not possible since the Schelling-type model is not nested in the proposed model, but it is a critical task to test whether or not protest patterns are seriously contingent on the way of assessing group support. Results and their interpretation are offered in Appendix.
Experimental Design and Measurement

4.1 We present the factorial experimental design in Table 2. We mainly investigate the effects of the degree of inequality and group identification, and their interaction effects on the dynamics of worker protests when holding all other variables constant. For the reason in 3.9, we undertake the same set of experiments in Table 2 at the maximum jail term = 20 and 30.

Table 2: Experimental Design

| Experimental Groups (ID) | Wage Dispersion (WD) | Tag-based Distinction |
|--------------------------|----------------------|-----------------------|
| 1                        | 2                    | 0                     |
| 2                        | 4                    | 0                     |
| 3                        | 2                    | 20                    |
| 4                        | 4                    | 20                    |
| 5                        | 2                    | 40                    |
| 6                        | 2                    | 60                    |
| 7                        | 4                    | 60                    |
| 8                        | 2                    | 80                    |
| 9                        | 4                    | 80                    |
| 10                       | 2                    | 100                   |
| 11                       | 4                    | 100                   |
| 12                       | 2                    | 100                   |

Notes: Controlled parameters are: 1) Population size = 400 (20 x 20); 2) Initial density of cops = 4%; 3) Initial density of workers = 70%; 4) Vision = 6 patches; 5) Threshold = 0.1; and 6) Movement = Yes.

4.2 We explore two levels of wage dispersion. Given that WD = 3 produces the average grievance similar to that in Epstein's model (Table 1), WD = 2 and WD = 4 explore the consequences of narrower and wider wage inequalities, respectively. The range of tag-based labeling is from 0% through 100% in increments of 20. If it is 0%, workers calculate the net risk defined above without 'tagging.' If it is 100%, they always estimate not only the net risk but also the local ratio of trustworthy neighbors to the total number of neighbors. If it is x% (0 < x < 100), x% of workers, on the average for each round, gauge both the net risk and the trustworthiness of neighboring fellows. The rest simply assess the net risk.

4.3 100 replications are performed in each condition. Given two levels of wage dispersion x six levels of tag-based distinction x two levels of the maximum layoff term, the number of independent cases is 2,400 in total. Each simulation is run for 300 iterations.

4.4 Protest patterns are of great interest in political sociology and the study of social movements (Oliver and Myers 2002; Francisco 2010). The distributions of protest rhythms may be exponential or scale-free. They may display regular cycles, varying degrees of autocorrelation, or various chaotic patterns. Tilly (1978) proposes to measure the magnitude of collective action by size (how many people participate in individual events), duration (how long they last), and frequency (how often they occur). In our paper, a protest event is defined when at least one worker is active without being arrested. An event ceases when the number of active workers falls to zero immediately after all rebels are laid off. Modifying Tilly (1978), we measure the following four outcome variables. First, event frequency is defined by how often there are uprisings (periods of protest activity separated by periods of the absence of protest). In Figure 4, for example, we see four protest events between the beginning of the simulation and the thirty-sixth iteration. Next, the protest strength is measured in two distinctive ways: maximum peak is the largest number of workers protesting at any point during the run. In Figure 4, it is 81, which comes from the number of active workers in the first peak, and average protest strength is the number of active workers per time step, that is, the total number of active workers divided by the total time steps. In Figure 4, average strength is 21.69 (i.e. the sum of 414, 1, 362, and 4 divided by 36 time steps). Lastly, average duration of protest is the sum of peak widths over the total time steps (e.g. 0.611 (= 22/36) in Figure 4).
Results

5.1 The patterns of protest observed across the 2,400 runs of the model have a number of common features. The timing and levels of protest are ragged and chaotic. Patterns are not obviously characterized by regular trends or cycles in either the magnitude or timing of events. While the term used in the literature - "protest cycles" - may seem to suggest regularity, our model does not produce simple patterns. The protest waves in Figure 5 are rather very similar to historical protest sequences (e.g. Figure 1 and 2 in Oliver and Myers (2002)). In almost all runs, the largest uprisings almost always occur at the beginning. The size of the initial protest event is generally larger when wage inequality is greater. The initial protest magnitude is less where workers are more discriminating against 'others.' Also, the overall number of active protesters tends to increase as workers are more likely to discount the benefit of group support.

5.2 If protest events are independent of one another, the distribution of the counts of protests across replications with random starts should follow a Poisson distribution. If the occurrence of one event increases or decreases the likelihood of another, then the distribution of event counts across multiple trials will display over-dispersion (if one event makes another more likely) or under-dispersion (if the occurrence of one protest makes another less likely). We perform the Chi-square test of the event frequency ($\alpha = .05$). Notice that the equi-dispersion that the conditional mean of the outcome should be equal to its conditional variance is a necessary condition but not sufficient condition for the Poisson distribution. In our experiments, the occurrence of protests (Table 3) follows a Poisson distribution at Experimental ID = 1, 3, 5, and 9. The rest at WD = 2 are over-dispersed. The results never satisfy a Poisson distribution at WD = 4, regardless of the degree of tag-based perception of similarity. All distributions at WD = 4 are under-dispersed. Generally, events are not independent as the degree of wage inequality becomes high; the negative auto-correlation increases. This negative time dependence implies that the chance of protest diminishes with time. In other words, the previous outbreak suppresses the next one.

5.3 We present the summary of descriptive statistics of four outcome variables under investigation in Table 4. Across all of the experimental conditions (i.e. 2 x 6 x 2), there are an average of 37 protest events during 300 time steps. The largest protest, on the average, activates 50 workers; the average protest, however, is quite small (4 workers). On the average, protests are not long-lasting. The distribution of the average peak height is highly positively skewed. The distributions of the peak frequency and its average width particularly are less centered with thick tails.

Table 4: Descriptive Statistics of Outcome Variables

| Outcome Variable | N   | Min | Max | Mean | Std.Dev | Skewness | Kurtosis |
|------------------|-----|-----|-----|------|---------|----------|----------|
| Event frequency  | 2400| 10  | 71  | 36.84| 12.90   | 0.021    | -1.28    |
| Maximum peak     | 2400| 5   | 95  | 50.18| 19.02   | -0.93    |          |
| Average protest strength | 2400 | 0.13 | 14.80 | 4.08 | 3.22 | 0.82 | -0.26 |
| Average duration | 2400 | 0.05 | 0.66 | 0.31 | 0.15 | 0.29 | -1.32 |

5.4 We present the histograms of the number of protest events across experimental conditions in Figure 6. Protest is more likely to occur as the degree of wage dispersion becomes large, but we cannot tell at this stage of analysis whether or not it is less likely as workers increasingly make distinctions between in-group and out-group. Figure 6 also seems to suggest the possibility of the interaction effects between wage dispersion and tag-based perception of similarity on the protest frequency. To test all these effects, we use the negative binomial regression model instead of the Poisson regression or the zero-inflated regression model because the average peak frequency is much less than its variance, and also the number of 0s is small in the total number of cases (N = 2,400).
5.5 First, the average peak frequency becomes approximately 90% higher when the degree of wage dispersion doubles. In contrast, it does not increase either sensitively or proportionally to an increase in tag-based discrimination. Higher inequality leads to lower maximum peak and lower support assessment. The incidence density ratio (IDR) of a regression coefficient b because it corresponds to the odds ratio. Also, (e^b - 1) reflects the percent change of the expected peak frequency with a one-unit increase in an explanatory variable.

5.6 We thereafter employ bootstrapped median regression analysis (Hamilton 2003) - sometimes called quantile regression or least absolute value regression instead of robust regression analysis of the conditional mean for the following three reasons (i): the maximum peak’s height, the average strength, and the average durability violate the assumption of normality, according to the Kolmogorov-Smirnov test; they do not satisfy the equal variance assumption, according to the Levene’s test; and there are no influential outliers in the report of Cook’s d statistics. Data are re-sampled with 100 repetitions. Consistent with the inferential statistical analysis above, we specify two models. Model 1 has only the main effects, while Model 2 includes the interaction effects. In Table 6 through 8, we include both the dummy variable of the maximum layoff term (i.e., the maximum layoff term = 20 is omitted) and the average risk as covariates. The average risk is the sum of rationally calculable Net Risk (NR) across the population of workers. There is no collinearity between the average risk and the level of tag-based perception.

5.7 We use the dummy variables of tag-based perception since the relationship between group identification and event frequency would increase by three. We include five dummy variables such as Tag1 (Tagging = 20%), Tag2 (40%), Tag4 (60%), Tag6 (80%), and Tag8 (100%) in the model. Figure 6 shows the frequency distribution of the levels of tag-based discrimination from the intercept of no discrimination (which is similar to felons in their local areas). We notice that the effect of tag-based perception does not have a significant impact after including the interaction term between tag-based discrimination (WD = 4) and the maximum peak's height, the average strength, and the average durability. The effect size significantly increases when workers feel more deprived (p < .01). However, Model 2 in the right panel shows that the negative effect of tag-based group identification depends on the level of wage inequality. Its effect size significantly increases when workers feel more deprived (p < .01). We note that the interaction effects of tag-based discrimination at the levels of 20%, 40%, and 60% significantly as workers are more likely to gauge not only the net risk but also group support by reading tags. Figure 7 also suggests the possibility of the interaction effects on the maximum peak height between wage dispersion and tag-based group identification.

5.8 The texture of protest is determined not only by the frequency of events, but also by their severity. One index of this severity is the size of the largest event, or what we have called the maximum peak. In Figure 7, we present the distribution of the largest protest events across the experimental conditions. First, the maximum peak, on the average, is higher when the level of grievance due to wage disparity is high. It declines as workers are more likely to gauge not only the net risk but also group support by reading tags. Figure 7 also suggests the possibility of the interaction effects on the maximum peak height between wage dispersion and tag-based group identification.
and 60% with wage dispersion are not statistically significant at α = .05.

### Table 6: Median Regression of Maximum Peak on Inequality and Discrimination

| Variable         | Model 1 |          | Model 2 |          |
|------------------|---------|----------|---------|----------|
|                  | b       | SE       | B       | SE       |
| Tagging = 20%    | -2.463** | .733     | -1.900** | .684     |
| Tagging = 40%    | -5.677** | .579     | -5.193** | 1.128    |
| Tagging = 60%    | -8.149** | .732     | -7.490** | 1.292    |
| Tagging = 80%    | -10.290** | .688    | -12.226** | .978     |
| Tagging = 100%   | -13.388** | .902     | -16.358** | 1.389    |
| WD = 4           | 18.696** | .736     | 16.656** | 1.107    |
| Average Risk     | -202.269** | 12.158 | -216.432** | 8.402    |
| Max-layoff = 30  | 2.352**  | .471     | 3.175**  | .615     |
| 20% x WD = 4     | -.119    | 1.106    |         |         |
| 40% x WD = 4     | .198     | 1.485    |         |         |
| 60% x WD = 4     | -.832**  | .129     |         |         |
| 80% x WD = 4     | -.929**  | .133     |         |         |
| 100% x WD = 4    | -1.216** | .153     |         |         |
| Intercept        | 136.557  | 142.59   |         |         |
| Pseudo-R²        | .625     | .629     |         |         |
| N                | 2,400    | 2,400    |         |         |

Notes: * p < .05 ** p < .01 (two-tailed tests)

### Average Protest Strength

5.10 An alternative approach to indexing the severity of protest is the average number of workers involved per event. The average protest strength (Figure 8) exhibits a similar pattern to that of the size of the largest event (Figure 7). We observe that the more wage inequality, the more the average number of protesters in events; and the more tag-based categorization, the smaller number of protesters on average. Once again, the effect of group identification on the average number of rebels seems to be contingent on the degree of wage inequity.

![Figure 8. Histogram of Average Protest Strength](http://jasss.soc.surrey.ac.uk/14/3/1.html)

Notes: Wage Dispersion = 2 (Left); Wage Dispersion = 4 (Right)

5.11 To examine these effects, we perform bootstrapped median regression of the average strength of protest on the same set of variables in the previous analysis. The results in Table 7, consistent with the maximum peak, show that higher levels of inequality markedly increase the average number of protesters (p < .01). The average strength is negatively influenced not only by the average risk but also by the maximum layoff term (p < .01 for both). Worker’s discrimination in trusting ‘others’ significantly reduces the average number of protest participants (p < .01). Lastly, there is also a significant interaction between wage disparity and group identification: the negative effect of discrimination on protest is magnified by higher levels of inequality. All interaction effects in Model 2 are statistically significant (p < .05).

### Table 7: Median Regression of Protest Strength on Inequality and Discrimination

| Variable         | Model 1 |          | Model 2 |          |
|------------------|---------|----------|---------|----------|
|                  | b       | SE       | B       | SE       |
| Tagging = 20%    | -.111   | .0855    | -.00268 | .125     |
| Tagging = 40%    | -.333** | .0678    | -.0515  | .0826    |
| Tagging = 60%    | -.339** | .0634    | -.0663  | .111     |
| Tagging = 80%    | -.587** | .0730    | -.247** | .0993    |
| Tagging = 100%   | -.687** | .0743    | -.231*  | .118     |
| WD = 4           | 1.318** | .0697    | 2.154** | .0965    |
| Average Risk     | -.65.899** | .812 | .0882   | .550**   | .0396 |
| Max-layoff = 30  | -.338** | .0432    | -.349*  | .151     |
| 20% x WD = 4     | -.692** | .169     | -.832** | .129     |
| 40% x WD = 4     | .349**  | .136     | -.929** | .133     |
| 60% x WD = 4     | -.929** | .153     |         |         |
| 80% x WD = 4     | -.216** | .153     |         |         |
| 100% x WD = 4    |        |         |         |         |
| Intercept        | 33.240  | 31.660   |         |         |
| Pseudo-R²        | .074    | .0782    |         |         |
| N                | 2,400   | 2,400    |         |         |

Notes: * p < .05 ** p < .01 (two-tailed tests)

### Average Protest Duration

5.12 The distributions of the mean protest durations across the experimental conditions are shown in Figure 9. Under conditions of higher inequality (right panel), protests are longer, on the average, than under lower inequality (left panel). Regardless of the level of inequality, increased group identification among workers is clearly associated with less durable protests, but to a smaller extent than the protest strength. It seems that not only does tag-based discrimination influence protest duration, but that its effect varies according to the degree of wage disparity.
5.13 The bootstrapped median regression analysis in Table 8 reveals that the more wage dispersion, the more durable worker protest. This positive effect is statistically significant (p < .01). Both the average perceived risk and the maximum layoff term decrease the average duration (p < .01). We find that the more tag-based discrimination, the shorter the duration of the typical protest, but its effect size is much smaller than on the protest intensity. Also, its negative effect is statistically significant only when more than 80% of workers gauge the possibility of support from in-group (p < .05). Protest becomes short-lived as workers are more likely to consider how many others protest at the higher level of inequality (p < .05 only at Tagging = 80%). Nonetheless, tag-based distinction significantly reduces the protest duration in terms of the net effect. When all workers assess group support in addition to the net risk, the protest duration is more likely to decrease at the higher level of inequality.

Table 8: Median Regression of Protest Duration on Inequality and Discrimination

| Variable     | Model 1 | Model 2 |
|--------------|---------|---------|
| Tagging = 20%| -.0024  | -.00494 |
| Tagging = 40%| -.00560 | -.00854 |
| Tagging = 60%| -.0103* | -.0182**|
| Tagging = 100%| -.0195**| -.0216**|
| WD = 4   | .183**  | .179**  |
| Average Risk| -.612***| -.600***|
| Max-layoff = 30| -.362** | -.360** |
| 20% x WD = 4 | .00964  | .00830  |
| 40% x WD = 4 | .00715  | .00785  |
| 60% x WD = 4 | .00534  | .00714  |
| 80% x WD = 4 | .00619  | .00846  |
| 100% x WD = 4| -.00001 | -.00096 |
| Intercept   | .967     | .959    |
| Pseudo-R²   | .774     | .776    |
| N           | 2,400    | 2,400   |

Notes: Wage Dispersion = 2 (Left); Wage Dispersion = 4 (Right)

6.2 In the present study, we instead extend Epstein's model (2002) of civil violence in a different context - workers protest. Workers have different degrees of grievance determined by the difference between their wage and the local average. They protest with probabilities in proportion to grievance, but are inhibited by the perceived risk of being arrested, which depends on the ratio of coercive agents to active followers in the local area. Agents in our model estimate expected costs and benefits, but they are boundedly rational since they know only about their immediate surroundings (i.e. local vision rather than global vision). Instead of free-riders, we can observe agents show deceptive behavior, as in Epstein (2002), which is contingent on the ratio of cops to probable rebels. In these aspects, we are rather interested in crowd dynamics (e.g. Ferguson and Johnson 1988; 1990) in a broader series, which is not embedded in the game-theoretic strategic interaction setting.

6.3 Informed by research concerned with the temporal and spatial dimensions of protest events (Tilly 1978; Wolox 1988; Oliver and Myers 2002; Francisco 2010), we carefully investigate patterns of protest waves such as rhythms, frequency, strength, and duration. The current results indicate that the effects of categorical discrimination among aggrieved workers may be very consequential for various dimensions of protest waves. First, protest rhythms are spiked and ragged rather than cyclic with regularity. As in Epstein (2002), long periods of relative stability are punctuated by globalized uprisings. How often the episode of protest emerges fits into a Poisson distribution when feelings of relative deprivation among workers are smaller and all workers fully assess group support. Otherwise, episodes of local uprisings are represented by recurrent events with negative time dependence. Overall, the protest fit in frequency is influenced heavily by wage inequality and slightly by tag-based group identification. However, higher levels of discrimination among categorical populations result in lower volumes of protest, and that the negative effects on the maximum level of protest and its average are accentuated as the degree of grievance due to wage inequality increases. The resilience of protest in terms of duration after it is once synchronized weaker as workers are more likely to consider how many workers in their local area are "others." In general, greater inequality is associated with greater magnitudes of the key dimensions of protest waves such as strength and duration. Increased distinction among potential protesters reduces the magnitudes of those dimensions - and particularly so at a relatively high wage disparity. We confirm that the overall patterns from the proposed model hold true even if workers distinguish "us" from "them" by the simplest categorization, but the negative tagging effect on both the intensity of protest and its duration is significantly stronger due to lower levels of trust. In other words, protest events are significantly stronger and persistent when workers are able to make more fine-grained distinctions.

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6.5 We seek to identify the core dynamics of workers protest, but empirical validation of our model remains open for future research. We instead draw some considerable theoretical implications here. First, our model provides general features of protest, either civil unrest or workers riot, such as "spiking points" and "punctuated equilibrium," as in Epstein (2002). Second, as in civil violence where going active prematurely may allow the most aggrieved agents to be arrested before they can catalyze the wider rebellion (Epstein 2002: 724), we suggest that it may be the case with workers protest: higher inequality more frequently generates protests leading to higher levels of arrests, but it retards further protests. Third, our experiments also indicate that group identity may be the key factor in collective behavior. Our study highlights the importance of trust-based coordination in local uprisings and their global synchronization (cf. the bandwagon effect).
We have made a simplifying assumption that class inequality and race/ethnic inequality are orthogonal. A logical next step in extending our understanding of the interplay of race and class in the dynamics of protest is to build an alternative and more realistic model. Otherwise, an exogenous or endogenous spatial correlation between wage disparity and race/ethnic inequality would lead to different patterns of protest waves at the micro and macro level. The current model also can be advanced as follows: examining roles of ‘leaders’ who are distinctive from the masses of workers in the threshold level, enabling workers learn ‘diversity’ over time (instead of bringing laid-off workers with the same tolerance back to the population) under varying scenarios; introducing ‘carrot’ or wage flexibilization policies in addition to the ‘stick’ policy of laying off protesters; and allowing workers, instead of random movement, to move more toward tolerably similar fellows or to leave dissimilar ones.

Appendix

7.1 Rhythms of workers protest in the Schelling-type model (Figure 10) are not significantly different from those in the proposed model (Figure 5). We apply the same test to the frequency distribution. First of all, the patterns of its over-dispersion and under-dispersion in the Schelling-type model (Table 9) are very similar to those in the proposed model (Table 3). All distributions at WD = 2 are over-dispersed, while most of distributions at WD = 4 are under-dispersed. As in the original model, the protest likelihood declines over time at WD = 4. Second, according to the Chi-square test at the same significance level (α = .05), the frequency distribution follows a Poisson distribution at Experimental ID = 1, 3, and 7. Protests events tend to be independent as wage inequality becomes low and workers become less subject to tag-based group identification. In contrast, protests events never satisfy a Poisson distribution at WD = 4, which is also consistent with the results from the original model.

7.2 The distributions of four outcome variables from the Schelling-type model (Table 10) and the proposed model are quite similar (Table 4) except the following respects. First, the strength of the highest protest peak and the average protest strength are significantly weaker when workers assess group support through the simplest categorization. Second, the average duration is a bit shorter. Third, the maximum peak distribution is rather positively skewed. Fourth, the average strength distribution is more centered with thin tails.

7.3 Henceforth, we focus only on the effect of tagging including its interaction effect with wage dispersion. Between two models, there are no significant differences in the effects (i.e. direction and strength) of wage inequality, the average risk, and the maximum layoff term on four dimensions of workers protest. Figure 11 suggests that the effect of tagging on the peak frequency and the interaction effect seem slightly stronger in the Schelling-type model than in the proposed model. Table 11 confirms that, first, the average increment in the peak frequency is almost doubled (from 2.7% to 4.8% in the left panel) although it is trivial. Another difference is that the tagging effect at WD = 2 remains significant in Model 2 when a 60% or greater number of workers distinguish in-group from out-group. Lastly, the positive net effect of tagging at WD = 4 is stronger at a moderate level of tagging (i.e. around 60%).
Figure 11. Histogram of Protest Event Frequency

Notes: Wage Dispersion = 2 (Left); Wage Dispersion = 4 (Right). Equivalent to Figure 6.

Table 11: Negative Binomial Regression of Peak Frequency on Inequality and Discrimination

| Variable          | Model 1        | Model 2        |
|-------------------|----------------|----------------|
|                   | b       | SE       | IDR   | b       | SE       | IDR   |
| Tagging = 20%     | 0.0273**| 0.0136   | 1.028 | 0.0208  | 0.0128   | 1.012 |
| Tagging = 40%     | 0.0490**| 0.0136   | 1.050 | -0.0264 | 0.0209   | 0.974 |
| Tagging = 60%     | 0.0554**| 0.0135   | 1.057 | -0.0815**| 0.0122   | 0.922 |
| Tagging = 80%     | 0.0547**| 0.0136   | 1.056 | -0.143**| 0.0215   | 0.866 |
| Tagging = 100%    | -1.111**| 0.0140   | 0.895 | -0.353**| 0.0227   | 0.702 |
| WD = 4            | -0.746**| 0.00817  | 2.115 | 1.012   | 0.249    | 1.025 |
| 20% x WD = 4      | -0.123**| 0.0263   | 1.131 | 1.025   | 0.249    | 1.025 |
| 40% x WD = 4      | -0.219**| 0.0264   | 1.244 | 1.025   | 0.249    | 1.025 |
| 60% x WD = 4      | -0.312**| 0.0286   | 1.386 | 1.025   | 0.249    | 1.025 |
| 100% x WD = 4     | -0.375**| 0.0279   | 1.455 | 1.025   | 0.249    | 1.025 |
| Intercept         | 3.147   |          | 3.253 | 1.025   | 0.249    | 1.025 |
| Pseudo-R²         | 0.183   |          | 0.198 | 1.025   | 0.249    | 1.025 |
| N                 | 2,400   |          | 2,400 | 1.025   | 0.249    | 1.025 |

Notes: *p < .05 **p < .01 (two-tailed tests). Equivalent to Table 5. Shaded areas indicate differences in the statistical significance between two models.

Table 12: Median Regression of Maximum Peak on Inequality and Discrimination

| Variable          | Model 1        | Model 2        |
|-------------------|----------------|----------------|
|                   | b       | SE       | B     | SE       |
| Tagging = 20%     | -6.079**| 637      | -7.448**| 1,201   |
| Tagging = 40%     | -13.192**| 666      | -17.121**| 895     |
| Tagging = 60%     | -19.919**| 728      | -25.810**| 883     |
| Tagging = 80%     | -27.443**| 574      | -29.703**| 818     |
| Tagging = 100%    | -32.746**| 623      | -31.527**| 901     |
| WD = 4            | 13.519**| 458      | 20.328**| 1,340   |
| Average Risk      | -267.130**| 8,184    | -168.060**| 11,306  |
| Max-layoff = 30   | 1.423**| 316      | .669*   | .337    |

Notes: Wage Dispersion = 2 (Left); Wage Dispersion = 4 (Right). Equivalent to Figure 7.

7.4 Figure 12 indicates that the tagging effect on the maximum protest strength may be stronger in the Schelling-type model and also that it depends on the degree of wage inequality. Table 12 reveals that the maximum strength significantly decreases as more workers assess support from in-group by reading observable binary markers. Especially when more than 60% of workers do so (cf. 80% in the original model), the negative effect of tagging increases at a relatively high wage disparity (p < .01).
Consistent with the result from the original model, the average strength of protest is significantly affected by tag-based group identification (Figure 13). The results in Table 13 firstly show that it declines as more workers are subject to the ingroup-outgroup bias based on the simplest categorization. Tagging by relatively small numbers of workers is sufficiently enough to reduce the average number of protesters, which is not the case in the original model. We also find a significant interaction between the main two variables, that is, the negative effect of tagging strengthens when workers on the average feel more deprived.

A negative association between tag-based distinction and the average duration of protest is easily noticeable in Figure 14. Besides, its effect seems to be contingent on the value of wage dispersion. The median regression results in Table 14 show that the more tag-based discrimination, the shorter the duration of the typical protest. Also consistent with patterns from the original model, its effect size is significantly smaller than the protest strength, either its maximum or its average. The negative effect of tag-based distinction at WD = 4 somewhat dwindles at a broader range of tagging (from 40% to 80%), whereas it slightly increases when all workers are subject to tagging.
the KW test and the post-hoc Mann-Whitney test are almost the same with those from bootstrapped median regression of Model 1 without either the average risk or the interaction terms such as Tagging = 20% x WD = 4 and the occurrence of an event affects the rate of subsequent occurrences, quasi-likelihood estimation can be an alternative approach to solve both autocorrelation and over-dispersion (Hannan and Carroll 1992).

One reviewer points out that agents may pursue fairness to resist inequitable outcomes as with the model by Fehr and Schmidt (1999): "Inequity aversion is self-centered if people do not care per se about inequity that exists among other people but are only interested in the fairness of their own material payoff relative to the payoff of others (ibid: 819)." The avoidance of relative deprivation is associated with disadvantageous inequity aversion. We note that agents in our model do not tend to protest if they are in advantageous positions.

Our approach is different from incorporating group identity into models of the critical mass. For example, Granovetter (1978: 1429-30) addresses that most collective-behavior literature proceeds as if the groups discussed contained only people who are strangers to one another. He considers that an individual would be activated by estimating the proportion of participants with more (and less) weights given to friends (and strangers) when it is otherwise impossible. "Take a simple case, where the influence of friends is twice that of strangers, and assume that thresholds are given in terms of reaction to strangers. Consider an individual with threshold 50% in a crowd of 100, where 48 individuals have voted and 52 have not. In the absence of social structure, such an individual would not be activated. But if he knows 20 people in his small group of whom 15 have already joined the riot, then each friend is to be counted twice. Instead of "seeing" 48 rioters and 52 non-rioters, our subject "sees" [(15 x 2) + (33 x 1)] rioters and [(5 x 2) + (47 x 1)] non-rioters, leading him to form a ratio not of 48/100 but of 63/120 = .525. We may then call the 'perceived proportion of rioters' in the previous time period now exceeds this threshold, and the will join (Granovetter 1978: 1429)."

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