Household Heterogeneity and Collective Action on the Commons

Eric A. Coleman
Florida State University
Department of Political Science
P.O. Box 3062230
Bellamy 543
Tallahassee, FL 32306-2180
ecoleman@fsu.edu
Tel: 850-644-4540
Fax: 850-644-1367

Krister P. Andersson
University of Colorado at Boulder
Department of Political Science
Environmental Studies Program
Ketchum Hall 126
Boulder, CO 80309-0333
Krister.Andersson@colorado.edu
Tel: 303-492-7871

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SUMMARY

The study of group heterogeneity and how it affects human efforts to create collective goods for society remains one of the great puzzles in the social sciences. This paper seeks to move this research forward by explaining why existing studies reach inconsistent findings, proposing improved metrics of group heterogeneity, and testing some of the main theoretical predictions. Analyzing data from 1311 households across 23 villages in four countries, we find that the effect of heterogeneity is sensitive to the types of heterogeneity and collective action outcomes considered, but find no empirical support for Olson's hypothesis that heterogeneity positively affects human cooperation.

Key Words – Heterogeneity, Inequality, Collective Action, Forestry,

1. INTRODUCTION

The role of group heterogeneity in human efforts to act collectively remains one of the great puzzles in the social sciences (Ostrom, 1997; Bardhan et al, 2007). The origin of this contemporary debate goes back to Olson (1965). In his seminal study, he argued that economic inequality may favor cooperation because wealthier group members hold a disproportionate stake in the collective outcome and may therefore be motivated to assume the start-up costs associated with organizing the collective action. Under perfect economic equality, on the other hand, group members have similar economic stakes in the outcome and will face strong incentives to free-ride on the efforts of others.

More than forty years later, the debate about how heterogeneity affects the collective efforts of groups is still alive and well. Hundreds of subsequent studies, both empirical and theoretical, have produced a great deal of contradictory findings about the varying effects of heterogeneity on collective action. Most previous research focuses on single type of heterogeneity such as economic, caste, ethnic, religious, or preference (Baland & Platteau, 1999; Bardhan & Dayton-Johnston, 2007; Habyarimana et al., 2007, 2009; Molinas, 1998), even if the authors recognize that there are different types of heterogeneity (Ruttan, 2008) which may be highly correlated (Barhan & Dayton-Johnston, 2007).[1]

Theories of heterogeneity in collective action have largely focused on heterogeneity in terms of the initial wealth distribution (Bardhan & Platteau, 1999; Dayton-Johnston & Bardhan, 2002; Hardin 1982; Olson, 1965). The predictions of these models have been applied to other sources of heterogeneity (Ruttan, 2008). That is, researchers have not been careful to assess the different theoretical expectations of different types of heterogeneity—probably because other sources of heterogeneity are difficult to capture in formal, game-theoretic models. There are not well-developed theoretical models which might explain the role of other types of heterogeneity on collective action.

Empirical studies of the effects of economic heterogeneity may have substantial measurement error due to the limited methods used to measure heterogeneity. For example economic heterogeneity is often a subjective, categorical ranking which measures if most people are poor according to local standards (Ostrom & Poteete, 2004; Varughese & Ostrom, 2001) or is proxied by reference to heterogeneity of a single asset—land holdings (Barhan & Dayton-Johnston, 2007; Molinas, 1998; Naidu, 2009). Methods developed in demography and public health are now available to more accurately measure wealth in a group of people according to a portfolio of asset holdings (Montgomery et al. 2000; Filmer & Pritchett, 2001; Howeling, Kunst, & Mackenbach, 2003). These measures can be applied to provide more accurate depictions of wealth heterogeneity in a given area and inform development policy (McKenzie, 2005).

Perhaps not surprisingly, empirical results examining other types of heterogeneity have not supported the theoretical predictions of the models meant to explain the effects of heterogeneity in wealth endowments (Habyarima et al., 2007, 2009; Andersson & Agrawal, 2009; Neupane 2003; Kant 1998; Seabright 1993; Ostrom and Poteete, 2004; Varughese & Ostrom, 2001). Habyarimana et al. (2007, 2009) have investigated different potential causes of a generally perceived negative relationship between ethnic and religious heterogeneity and collective action. The authors explain that members of homogenous groups are better able to identify others and less likely to engage in non-cooperative behavior for which they might be shamed by other group members.

To summarize, most of the theoretical work on the role of heterogeneity in collective action makes specific predictions about heterogeneity in initial wealth endowments. Many studies examining the effects of this type of heterogeneity, however, have not found the anticipated effects anticipated by the theoretical models. This may be because wealth inequality is not adequately measured or because another type of heterogeneity is highly correlated with wealth inequality. Finally, the analysis of other types of heterogeneity has also failed to confirm the anticipated effects from these theoretical models.

This paper seeks to contribute to this debate in three ways. First, we aim to explain the existing contradictions in the literature. Second, we propose ways through which future empirical studies might generate less inconsistent findings, and finally we set out to test this approach empirically.

2. THEORY

Empirical and theoretical ambiguities abound in the literature on collective action and the role of heterogeneities. While some agreement seems to exist with regards to the effects of ethnic and religious heterogeneity on collective action—most studies find a monotonically negative correlation (i.e. Habyarimana et al, 2007; Henrich, 2009)—more contradictory findings are associated with the effects of heterogeneity in terms of economic inequalities and environmental preferences. Findings from empirical studies that focus on heterogeneity in heterogeneity of wealth have found a variety of significant relationships with the emergence and effectiveness of collective action, including negative (Andersson & Agrawal, 2009), positive (Wade, 1998), U-shaped (Dayton-Johnson & Bardhan, 2002), inverted U-shaped (Molinas, 1998; Naidu, 2009), or no consistent effect at all (Varughese & Ostrom, 2001). Less research has examined the effects of preferences, although there are similar ambiguities in these effects (see Hardin 1982; Kurien & Dietz 2004; Naidu, 2009).

Among studies on economic inequality and collective action, Hardin (1982) finds that privileged individuals in groups with high levels of economic inequality face stronger positive incentives to make collective action work than individuals in more homogenous groups. Baland and Platteau (1999) recognize this possibility and find that sometimes elites are willing to bear the lion-share of the organizational burden of the collective endeavor in exchange for a proportionately higher share of the benefits flowing from the good or service provided through the collective action. Applying these principles, Wade (1988) found supporting evidence for Olson's hypothesis regarding a positive relationship between economic heterogeneity and collective action outcomes—economically advantaged castes were more likely to accrue the costs of organizing collective action in Indian irrigation.

However, a large subset of studies in this area have found a mostly negative relationship between heterogeneity in wealth and collective action (i.e. Andersson & Agrawal, 2009; Neupane 2003; Kant 1998, Seabright 1993). The explanation for the observed negative effects of heterogeneity, as proposed by these authors, may be summarized as the process through which economic and social inequalities have a tendency to produce social resentment and low levels of trust among group members, which ultimately leads to widespread defection from the commitment to act collectively. For example, economic inequality may lead to discrimination in terms of unequal access to decision-making forums and this may be perceived as unfair and inequitable by those group members who do not have access. Such perceptions of unfairness can generate low levels of trust in the group, "leading to a downward spiral of widespread free-riding, over-harvesting, and unsustainable environmental outcomes" (Andersson & Agrawal, 2009: 12).

A third subset of studies have found a curvilinear relationship between economic heterogeneity and collective action. Comparing the conditions under which rural organizations in Paraguay are successful in organizing cooperation, Molinas (1998) finds an inverted U-shaped relationship between inequality in members' land-holdings (as measured by the Gini-coefficient of the individual members' property holdings) and participation in different collective actions organizations. Naidu (2009) similarly finds that a moderate level of landholding inequality leads to the highest possible levels of collective action. This suggests that extremely low and high levels of heterogeneity of group members productive assets are associated with lower probabilities of cooperation and that there is an optimal level of economic inequality that has a higher likelihood of producing cooperative behavior.

These results stand in sharp contrast to those of Dayton-Johnson and Bardhan (2002) who find a U-shaped relationship. Drawing on an illustration from fishery common pool resource, they interpret this finding in the following way:

> "At perfect wealth equality, conditional conservation is a best response for each fisher to conditional conservation by the other…Mean-preserving spreads of the wealth distribution will reduce one fisher's wealth to the point where his claim on the final-period fish stock provides insufficient incentive to conserve. As the wealth distribution becomes even more unequal, however, conservation becomes a dominant strategy for the wealthier fisher. The poorer fisher's inefficient period one fishing is too small (because his fishing capacity is so small) to dissuade the wealthier fisher from conserving. Beyond a certain threshold, then, the more unequal the wealth distribution, the smaller the amount of inefficient first-period fishing that occurs" (p. 579).

In Table 1 we summarize some of the existing theoretical propositions in the literature. It is important to note that there is not consistent empirical support for the purported theoretical relationships. However, new theoretical models have not been developed to account for the anomalous empirical findings vis-à-vis economic heterogeneity.

[TABLE 1 ABOUT HERE]

Important theory has been developed to explain a consistently observed negative relationship between ethnic and religious heterogeneity and collective action. Habyarimana et al. (2007, 2009) investigate three different potential causal mechanisms that might account for this relationship. They find no evidence to support that co-ethnics are better able to use language or other cultural cues to better coordinate behavior and act collectively. Instead, the authors find that co-ethnics are better able to identify one another and are less likely to engage in non-cooperative behavior when there is a possibility of social shaming.

At least part of the reason for the limited consensus on how heterogeneity affects environmental outcomes, as illustrated by the summary in Table 1, lies in the diverse dimensions along which collective action is measured and upon which equality exists (Rae, 1981; Sen, 1995; Velded, 2000). Inequality can reflect the distribution of social, political, as well as economic factors (Dayton-Johnson, 2000). Furthermore, there are significant difficulties in generating measures of equality that adequately capture the differences in distributions of these variables along many different dimensions (Andersson & Agrawal, 2009; Prasad, et al. 2006). Each source of inequality, and each way that inequality is measured, may induce differences in the measured effects on resource governance and collective action outcomes. These issues are particularly pronounced when measuring preference heterogeneity, which is fundamentally unobservable.

In Table 1 we also divide collective action into different ways in which collective action is conceptualized and measured. This poses another possible reason for the inconsistent results. Ruttan (2007) demonstrates that it is important to distinguish between different types of collective action outcomes. She argues that we might see people acting collectively yet failing to provide a collective good. It is also possible that we might see people providing a collective good without engaging in collective action. Hence, it seems necessary to distinguish between at least two different types of collective outcomes—those that relate to collective action behavior (do group members contribute to the provision of the collective good/service?), as well as outcomes related to the quality of the collective good/service that is being produced (what is the state of the common pool resource?).

After recognizing the possibility that different types of heterogeneity may have vastly different and even opposing effects on different measures of collective action, scholars in this field of research are starting to move away from generalized measures of group heterogeneity and collective action, opting to use more specific measures (Dayton-Johnson & Bardhan, 2002; India, 2009; Bardhan, et al, 2007; Ruttan, 2007). Surprisingly few studies, however, analyze the potential simultaneous effects of these multiple aspects of heterogeneity on the different outcome measures of collective action (although, see Varughese & Ostrom, 2001; Ostrom & Poteete, 2004; Naidu, 2009). Furthermore, most studies rely on aggregated or categorical measures of inequality. In this paper, we seek to explain variation in two distinct types of collective action outcomes by measuring all four types of heterogeneity using household data.

3. ANALYSIS

To measure the effects of heterogeneity on collective action behaviors and outcomes we utilize data gathered in Bolivia, Kenya, Mexico, and Uganda. This data was collected as part of the International Forestry Resources and Institutions (IFRI) program. This IFRI data is comprised of field research conducted in various villages and forests in these four countries. Both forest institutional data (data on the rules used in the forests) and biological data have been collected.

IFRI protocols demand that researchers spend time in each village coding variables that are used in this analysis. This data is largely gathered through ethnographic research methods including semi-structured interviews, rapid rural appraisal, and key informant interviews. Biological data on the forest is collected in the nearby forests. Forest mensuration is performed; a process of randomly selecting forest plots and taking measures related to trees, plants, and soils.

In 2008 this data was augmented with household surveys in each country. Interviewers contacted households and filled out surveys of approximately 100 questions taking about 1 hour. Household were asked to provide detailed descriptions of their assets, environmental preferences, demographic information, and forest use.

These household data were used to measure each of the types of heterogeneity. Because households themselves answered these questions, we are able to accurately describe the degree of differences in assets, demographics, and preferences, rather than having to infer this information from an expert's assessment of these variables or using crude categorical measures of inequality. IFRI data at the village and forest level were used to construct measures of collective action outcomes and behaviors. We measure basal area, for example, from the biophysical data collected during the same site visit when the household interviews were conducted. Data on behavioral outcomes, the frequency of monitoring and sanctioning activities and of maintenance activities is similarly taken from that reported at the village level.

(a) *Measuring heterogeneity*

As described in the previous section, we wish to measure the effects of different types of heterogeneity on collective action. In this section we describe the four measurements we use to assess heterogeneity in the village: wealth inequality, religious heterogeneity, ethnic heterogeneity, and environmental preference heterogeneity.

(i) *Wealth inequality*

In order to assess wealth inequality at an aggregate level, such as for a community or even a country, we must have some means of first ascertaining socioeconomic conditions and status for each individual household or individual member of that larger group of people. Prior research has used socioeconomic indicators of wealth such as the type of materials from which a home is built, ownership of various goods such as televisions and radios, education level, and occupation (Vyas & Kumaranayake, 2006).[2] There is little agreement about best practices of which variables should be measured to assess socioeconomic conditions and which should be left out (Montgomery et al., 2000).

Researchers have sought to develop indexes that combine multiple indicators of wealth. Principal components analysis (PCA) is often used in this regard; it is a data reduction technique to detect components which explain the underlying variation in the multiple indicators. We use PCA to compose an index from twenty-one indicators of wealth for households sampled in a total of 23 communities in the four countries.[3] Six variables were used which indicate the amount of assets owned by the household including the number of cars, bikes, motorcycles, phones, televisions, and radios. Five variables are binary indications of the material of the house: if the walls of the house are made of mud, wood, or brick/concrete (as opposed to reeds, straw, grass, or fiber), and if the roof of the house is made of thatch or metal (as opposed to wood or tiles). A variable is included indicating the amount of cropland that the household owns privately, as well as the age, sex, and years of schooling of the household head. Categories of occupation are also included: binary indicators are included for farmers, teachers, and businesspeople (the base category is all other occupations). Finally, information is recorded on whether there was a major income shortfall from a crop failure or illness in the family. These variables are recorded on a scale of 0-2; zero indicates no such events, one indicates a moderate crisis, and two indicates a severe crisis.

To create an index for socioeconomic status we performed a PCA on these twenty-one variables for all households in each country. Factor scores from the first principal component were used to construct an index.[4] The index is formed by multiplying a variable's realized value for a household by its factor score. The index, across all households within a country has a mean equal to zero and takes both negative and positive values. Figure 1 shows histograms of this index for each country.

[FIGURE 1 ABOUT HERE]

Researchers have pointed out that such indexes may suffer from clumping or truncation issues. If there tend to be groups of households with the same asset portfolios then these households will clump together around a similar score. Truncation refers to the overall range of index scores. Without sufficient variation in the variables used in PCA, the analyst will not be able to differentiate poor and rich households. The solution to both problems appears to be to survey a wide variety of asset holdings and measure continuous indicators of wealth that disaggregate households from one another (Vyas & Kumaranayake, 2006). In Figure 1 we show that there does not appear to be clumping (the distribution of PCA scores are flat) and that for each country the PCA appears to be fairly wide-stretched, approaching close to ±5 standard deviations.

The index score, however, does not lend itself easily to interpretation. In order to facilitate interpretation, we categorize the index score into quartiles. That is, we form a variable called socioeconomic status (SES), which takes a value of one if the household is in the lowest (poorest) quartile of the PCA index score, a value of two if the household is in the second quartile, a value of 3 if the household is in the third quartile, and a value of four if the household is in the fourth (richest) quartile. Note that the socioeconomic status variable indicates the quartile in which a household belongs, given the wealth assets for other households only in our research sites within the same country. For example, a household is categorized into the poorest household in Bolivia only by comparing that household's assets with other households in sampled Bolivian communities.

In Tables 2 and 3 we report the characteristics of household wealth in each quartile of SES. The first rows in these tables show the mean socioeconomic index score constructed from the first principal component of these variables. The remaining rows show the average of each variable. For example, in Bolivia households in the poorest quartile own no cars while households in the richest quartile own, on average, 0.167 cars.

[TABLE 2 ABOUT HERE]

[TABLE 3 ABOUT HERE]

To construct a variable indicating village-level inequality we compute the standard deviation of the socioeconomic index score for all the households in a given village. We calculate this measure for all 23 villages in the sample and report the results in Table 4. In this table, each village is classified by country and an arbitrary identification number. Each village's inequality score is reported along with the mean socioeconomic conditions from all households in the village.

[TABLE 4 ABOUT HERE]

(ii) *Religious and ethnic heterogeneity*

Another source of potential heterogeneity between households is the diversity in ethnic and religious composition. Habyarimana et al. (2009) provide extensive evidence that ethnically diverse societies are less likely to engage in collective action. We form separate measures of religious and ethnic heterogeneity. Following Varughese and Ostrom (2001) we create a variable which indicates the probability that a member of one religion would meet another member of the same religion if two were chosen randomly from the village.

The indexes were constructed from the following formula:

(1)

Here, represents the proportion of those surveyed in the j^{th} ethnic group or religion. The index varies from 0 to 1. Villages with an index of 1 are completely heterogeneous; there are no two people in the village with the same religion (or ethnicity for the ethnicity index). Villages with an index value of 0 are completely homogeneous; every person they meet is of the same religion (or the same ethnicity for the ethnicity index).

(iii) *Environmental preference heterogeneity*

Environmental preference heterogeneity is calculated in much the same manner as the ethnic and religious heterogeneity measures. Each household was asked the following question: “Do you agree with the statement: ‘Forests should be protected’?” Each household head answered if they agreed with this statement (=1) or not (=0). An index was created using the formula of Equation 1. It has a similar interpretation as the probability that two randomly chose people from the village will agree on their answer to that question. This probability ranges between 0 and 1.

(b) *Measuring Collective Action*

The outcomes that we measure are based upon data gathered at the village level. That is, we are interested in how forests and user groups the communities that use the forests respond to the heterogeneity present in the households that comprise the village. Thus, this data is recorded at the village level.

(i) *Basal area*

Basal area is a measure of forest conditions which are assessed at each IFRI visit to the forest. A series of random forest plots are taken for each forest and all the trees above 10 cm in diameter are sampled and measured. Basal area is derived from measurements of stem diameter at breast height, d. Basal area for each tree is calculated as the total area covered by the tree at breast height, or $\pi \times (d^2/4)$. Total basal area for the entire forest is estimated based on the measures at each randomly selected forest plot. Basal area is often used to indicate biomass.[5] It has been used in a number of studies examining forest policy outcomes (Ostrom & Nagendra, 2006; Coleman, 2009). We use it here as a proxy for the provision of the collective good.

Our measure of basal area is normalized to account for ecological differences across country. Specifically, our measure is the proportion of basal area in a given forest to that measured in all forests of that forest type in the particular country. A value of greater than one indicates that basal area in the forest is greater than the average forest basal area for all forests sampled in that country. A value less than one indicates that basal area in the forest is less than the average forest basal areas for all the forests sampled in that country.

We wish to emphasize the importance of linking inequality measures to actual environmental outcomes. Often research is forced to rely on subjective assessments of forest conditions or to only look at changes in behavior. For most policy analysts the important question is how inequality affects a desired outcome—that forests remain intact. The IFRI data used in this study provides a relatively unique opportunity to link household inequality with biophysical outcomes.

(ii) *Monitoring and sanctioning*

Multiple groups of forest users access and use forest resources in each community. Sometimes these groups of users organize to manage the forest. Ostrom and Nagendra (2006) and Coleman (2009) found that user groups that monitor others' use of the forest and administer sanctions when rules are broke are more likely to maintain forest biomass and biodiversity. Thus, the willingness to engage in such actions is a key behavioral outcome of collective action in forest commons (Coleman & Steed, 2009).

We measure monitoring and sanctioning by evaluating the frequency with which the most active user group engages in such activities: 1—Never, 2—Occasionally, 3—Seasonally, 4—Year Round. Engaging in such activities requires individuals to invest time and resources into ensuring that other households comply with the rules.

(iii) *Maintenance activities*

Maintenance activities have been commonly used to assess the effects of heterogeneity (see Bardhan & Dayton-Johnson, 2007; Varughese & Ostrom, 2001). Maintenance activities imply tangible costs borne by households in collective action. Consider the incentives members of the user group face when deciding to make such investments. Once a user group member plants seeds, builds a fence, or makes some other improvement they must wait a period of time before realizing the returns from the investment. They must trust that others will behave cooperatively and not exploit their efforts to maintain the resource.

We measure maintenance similarly to monitoring and sanctioning, by evaluating the frequency with which the most active user group engages in maintenance activities: 1—Never, 2—Occasionally, 3—Seasonally, 4—Year Round.

(c) *Statistical models*

To investigate the effects of various forms of inequality on collective action as described in Section 2 and summarized in Table 1, we perform simple regression analysis of inequality on each of the three measured outcomes. Ideally, one would like to control for confounding factors or reverse causality in assessing these correlations; however, because we only have data from 21 villages on both household characteristics and our collective action measures, including additional control variables is not advisable. The analysis should be interpreted as correlates between inequality and collective action and any causal inference should be avoided.

Nonetheless, analyzing even the correlates between different sources of inequality and collective action has remained elusive because it requires that the various inequality measures be measured by aggregating household data across multiple communities and comparing it with community outcomes. This requires a substantial investment and synthesis of survey, ethnographic, and biological research. Our analysis is a first step to better understanding how inequality may be linked to measures of collective action.

We performed linear regression to test the effects of religious, ethnic, and environmental preference heterogeneity on the measures of group behavior. This is to test our expectations as outlined in Table 1. Alternatively, we regressed the outcomes on wealth inequality in a quadratic fashion; that is we include both the wealth inequality measure and the wealth inequality measure squared in the regression analysis. This is to test our hypothesis in Table 1 that the relationship between wealth inequality and environmental outcomes is U—shaped.

(d) *Results*

The results from the regression analysis are reported in Table 5 and the scatter plots, model predictions, and normally-approximated 95 percent confidence intervals are shown in Figure 2. The first thing that should be noticed from Figure 2 is that, contrary to much of previous research, all types of heterogeneity appear to have a negative effect on collective action. We do find a U—shaped relationship between wealth inequality and basal area, as expected; however the statistical analysis reported in Table 5 shows that this relationship is not statistically significant at the 0.10 level. In all other cases, the affect of heterogeneity is plainly negative or flat. That is, in no instance do we measure a positive relationship between heterogeneity of households and collective action on the commons.

[FIGURE 2 ABOUT HERE]

[TABLE 5 ABOUT HERE]

Statistically significant measures of the effects of heterogeneity are most common when assessing the collective action outcome basal area. In this case, wealth inequality is significantly negatively correlated, but the U—shaped relationship is not significant at the 0.10 level. Religious heterogeneity is significantly correlated with basal area.

For monitoring and sanctioning there are two significant correlations, the first between wealth inequality and maintenance activities—the correlation between the linear and quadratic terms are jointly significant with maintenance activities at the 0.01 level. The sign on the quadratic term is negative, although not significant, indicating that the relationship is primarily driven by a negative relationship between wealth inequality and monitoring and sanctioning. The relationship between heterogeneity of environmental preferences and monitoring and sanctioning activities is negative and significant at the 0.05 level.

For maintenance activities, wealth inequality appears to have a significant U—Shaped relationship (again, the linear and quadratic terms are jointly significant), although the actual relationship seems to be dominated by the linear, negative term. In addition, religious heterogeneity appears to be significantly and negatively correlated with maintenance activities at the 0.10 level.

4. DISCUSSION

The results of our analysis demonstrate different conclusions than those commonly reached in the literature on heterogeneity and collective action. The theoretical arguments discussed in the first section have indicated that certain types of heterogeneity are expected to have nonlinear effects on collective action, while others predict positive, negative, or ambiguous effects. The empirical literature seems to mimic this; different research has found widely different effects. Our analysis, however, indicates that all the types of heterogeneity that we measure are negatively correlated with various measures of collective action. Why does our analysis produce consistently negative results while the relevant academic literature is so inconsistent? We offer three possible explanations (a) precision of measureing heterogenuety; (b) Range of Heterogeneity measures, and (c) diverse collective action measures.

(a) *Precision of measuring heterogeneity*

One reason we find such consistent, negative relationships between heterogeneity and collective action may be that the methods we have used to measure heterogeneity are more precise than previous research. We have constructed a variety of measures of heterogeneity from household survey instruments after interviewing many households, on average 57 households per village (1311 surveys conducted across 23 villages). Some of the other research uses a small number of households to construe their measures of heterogeneity (for example Bardhan & Dayton-Johnson (2007) use 10 household per village) or use categorical data for the community as a whole, such as a high or low degree of wealth inequality (e.g. Varughese & Ostrom, 2001; Rattan, 2007). Our measures more precisely estimate the distributions of wealth because they (1) use data from many households to estimate the village-level heterogeneity, (2) take into account a wider range of assets (21 assets) for the measure of wealth inequality, and (3) use a continuous scale to rank the variance of those assets.

(b) *Wider Range of Heterogeneity*

Another reason our results may produce consistent, negative findings is because we pool data from communities in different countries and our data on inequality includes an extremely wide range of values. It may be that for any given country the effects of heterogeneity are positive, negative, or nonexistent, but that across countries, on average, these effects are negative (or U—shaped when referring to wealth inequality). Furthermore, if one examines only a small range of wealth inequality it is possible that the range examined is confined to communities with a more unequal distribution of resources.[6] If a positive effect is found it may simply represent the right side of the U—shaped relationship found for wealth inequality. For example, if in our study we had limited ourselves to only those villages that had a wealth inequality measure above 1.5, then we would find a strictly positive relationship between wealth inequality and basal area. If any given country happens to be relatively unequal in assets, then results from this country might show that the most heterogeneous communities are more likely to provide collective goods like high basal area.

To compare our study with those of others in terms of the range of values for the heterogeneity variable, we calculated a gini coeffcieint for land holdings, which is the most commonly used heterogeneity measure in the existing literature. This measure ranges from 0 (absolute equality) to 1 (absolute inequality), and in our data set the actual range is from 0.00 to 0.92. No other empirical study that we have found covers a wider range that ours.

(c) *Measurements of Collective Action*

A more fundamental reason for the discrepancy of prior results may be that previous research has usually confined itself to measuring one kind of heterogeneity and relating it to one kind of collective action outcome. The effects of heterogeneity are probably sensitive to both measures (Rattan, 2008). By including three different measures of heterogeneity and two measures of collective actopn we are able to generate results that are theoretically precise and nuanced. These improved measures on both the left-hand and right-hand side variables, allow us to distinguish and explain differences between the negative, U—shaped, and no relationships that other empirical studies have documented.

5. CONCLUSION

The study of group heterogeneity and how it affects human efforts to create collective goods for society remains one of the central areas of social science research. In this paper, we have tried to make three main contributions to this existing body of work. First, by considering a variety different types of heterogeneity and collective action outcomes, we have been able to characterize subtle nuances in the relationships between the different types of heterogeneity and collective outcomes. For example, we find that wealth inequality has a different effect on collective action when we consider behavioral collective action measures—such as monitoring and harvesting activities—than when we employ biophysical outcomes as our collective action outcome measure. The relationship is curvilinear when considering the basal area of the forest as our outcome variable, but the effect is negative when considering harvesting and monitoring activities. These divergent findings would suggest that theoretical ambiguity in the ways in which other studies often define both heterogeneity and collective action may explain why contradictory findings are so common.

Second, we demonstrate how future empirical studies may improve consistency of results. We employ a new measure of wealth inequality that goes beyond the conventional gini coefficients of either income or land holdings, both of which are problematic when trying to assess livelihood assets in informal economies. We construct this new measure by using factor analysis, creating an index of socioeconomic status of each household based on a comprehensive list of household assets that are deemed to be important for meeting household needs. Also, by comparing communities of households in four different countries with very different socioeconomic realities, our measures of heterogeneity contain a wider range of values than any other empirical study that we have found.

Third, our most striking finding in substantive terms is that our analysis of forest communities fails to find any support for Olson's hypothesis that heterogeneity has a positive effect on human cooperation. In fact, all of the relationships that are statistically significant—three in total—indicate that heterogeneity has an overwhelmingly negative effect on collective action. We believe that the observed negative effects of the three different types of heterogeneity are related to the challenge of creating a cooperative environment in communities that have members with highly diverse asset endowments, ethnicities, cultural and religious beliefs, as well as environmental preferences. As noted by previous studies, economic social inequalities can produce social resentment and low levels of trust among group members, which in turn may reduce the likelihood of communities to organize collectively.

Finally, a word of caution seems warranted. One of the admitted shortcomings of this study is its small sample size. Although we carried out several robustness checks -- all of which suggest that the findings are robust and not sensitive to outliers -- it would be wise to interpret these results in light of the relatively small number of observations. As we, and other IFRI scholars, continue our project to collect more data on more households in more forest communities, we will be able to conduct more rigorous tests of the purported relationships.

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TABLES

Table 1. *Theoretical expectations on how heterogeneity affects collective action*

		Types of Heterogeneity		
		Economic	Ethnic/ Religious	Environmental Preferences
Measures of Collective Action	Outcomes (Basal Area)	U-shaped[1]	Negative[3]	Negative[5]
	Group Behavior (Maintenance Activities and Rule Enforcement)	Ambiguous[2]	Negative[4]	Ambiguous[6]

Notes: Theoretical expectations abound in the literature and numerous papers could be cited for each hypothesized relationship. Representative views of theory are found in the following: [1]Dayton-Johnson and Bardhan (2002); [2]Baland and Platteau (1999); [3]Habyarimana et al. (2007); [4]Henrich (2009); [5]Hardin(1982); [6]Kurien and Dietz (2004).

Table 2. *Mean wealth characteristics by socioeconomic status quartile for Bolivia and Kenya*

	Bolivia				Kenya			
Variable	Poorest	Second	Third	Richest	Poorest	Second	Third	Richest
Socioeconomic Index Score (from PCA)	-1.504	-0.790	-0.097	2.457	-2.506	-0.795	0.731	2.601
No. of Cars	0.000	0.000	0.000	0.167	0.000	0.026	0.038	0.321
No. of Bikes	0.108	0.270	0.514	0.556	0.924	0.756	0.513	0.359
No. of Motorcycles	0.000	0.000	0.108	0.111	0.013	0.013	0.038	0.077
No. of Phones	0.108	0.135	0.486	0.083	0.430	0.667	1.000	1.872
No. of TVs	0.000	0.027	0.243	0.500	0.000	0.090	0.282	0.936
No. of Radios	0.838	0.892	0.838	1.111	0.797	1.141	1.218	1.526
Walls of mud	0.189	0.270	0.189	0.028	0.975	0.872	0.244	0.013
Walls of wood	0.784	0.622	0.568	0.056	0.000	0.026	0.487	0.692
Walls of brick/concrete	0.000	0.000	0.081	0.889	0.000	0.064	0.256	0.295
Roof of thatch	0.757	0.270	0.162	0.083	0.861	0.115	0.026	0.000
Roof of metal	0.216	0.541	0.486	0.556	0.139	0.859	0.974	0.987
Hectares of Cropland	2.697	3.024	3.392	7.917	0.839	0.686	0.645	24.738
Age	51.595	41.622	40.216	46.000	48.557	51.333	47.449	44.577
Sex	0.162	0.081	0.081	0.083	0.367	0.385	0.218	0.179
Education	2.838	5.243	6.622	11.333	5.861	6.333	7.103	10.974
Farmer	0.892	0.811	0.486	0.694	0.759	0.731	0.821	0.423
Teacher	0.000	0.000	0.000	0.111	0.000	0.026	0.026	0.192
Businessperson	0.000	0.000	0.000	0.056	0.038	0.077	0.064	0.051
Migrated?	0.405	0.378	0.459	0.583	0.354	0.244	0.295	0.205
Crop Failure	1.676	1.351	1.162	1.139	1.329	0.962	0.821	0.410
Major Illness	0.838	0.622	0.541	0.611	1.076	0.936	0.500	0.269
Observations	37	37	37	36	79	78	78	78

Table 3. *Mean wealth characteristics by socioeconomic status quartile for Mexico and Uganda*

	Mexico				Uganda			
Variable	Poorest	Second	Third	Richest	Poorest	Second	Third	Richest
Socioeconomic Index Score (from PCA)	-2.494	-0.043	0.838	1.740	-2.209	-0.624	0.596	2.237
No. of Cars	0.190	0.381	0.429	0.805	0.000	0.000	0.000	0.023
No. of Bikes	0.095	0.095	0.238	0.439	0.257	0.526	0.462	0.877
No. of Motorcycles	0.048	0.048	0.048	0.073	0.000	0.000	0.047	0.135
No. of Phones	0.262	0.167	0.357	1.049	0.029	0.006	0.228	0.544
No. of TVs	0.786	0.976	1.071	1.390	0.006	0.029	0.012	0.047
No. of Radios	0.548	0.643	0.595	0.585	0.480	0.778	0.795	1.029
Walls of mud	0.643	0.048	0.000	0.000	1.000	0.959	0.404	0.029
Walls of wood	0.238	0.143	0.000	0.000	0.000	0.000	0.012	0.006
Walls of brick/concrete	0.071	0.810	1.000	1.000	0.000	0.012	0.573	0.965
Roof of thatch	0.310	0.000	0.000	0.000	0.585	0.018	0.000	0.000
Roof of metal	0.310	0.738	0.929	1.000	0.398	0.959	0.977	0.994
Hectares of Cropland	2.232	2.013	1.855	1.932	1.781	1.487	1.053	1.375
Age	51.452	52.262	51.310	51.610	45.339	44.181	49.064	42.053
Sex	0.071	0.071	0.095	0.195	0.333	0.094	0.316	0.082
Education	6.881	6.762	7.024	7.171	3.357	5.146	4.877	7.257
Farmer	0.905	0.857	0.762	0.463	0.901	0.930	0.801	0.538
Teacher	0.071	0.000	0.000	0.024	0.000	0.000	0.006	0.058
Businessperson	0.000	0.048	0.024	0.098	0.035	0.000	0.070	0.123
Migrated?	0.833	0.857	0.548	0.366	0.228	0.070	0.088	0.018
Crop Failure	0.500	0.452	0.310	0.268	0.503	0.374	0.339	0.351
Major Illness	0.357	0.524	0.405	0.561	0.836	0.608	0.749	0.743
Observations	*42*	*42*	*42*	*41*	*171*	*171*	*171*	*171*

Table 4. *Village inequality and socioeconomic index scores*

Village ID	Village Inequality	Mean Socioeconomic Index Score
Bolivia 14	0.467	-0.428
Bolivia 15	1.052	1.016
Bolivia 16	0.568	-0.561
Bolivia 4	0.323	-0.988
Bolivia 6	1.238	0.472
Kenya 11	0.774	1.507
Kenya 16	0.775	-1.539
Kenya 5	0.806	0.600
Kenya 8	0.729	-1.146
Mexico 5	0.783	0.875
Mexico 6	0.930	-1.127
Mexico 7	0.648	0.275
Mexico 8	0.793	-2.564
Mexico 9	0.579	-0.956
Uganda 11	0.846	0.949
Uganda 16	0.791	-0.911
Uganda 2	0.928	0.542
Uganda 20	0.907	1.072
Uganda 22	0.956	0.021
Uganda 23	1.209	-0.695
Uganda 26	0.608	-1.714
Uganda 27	0.821	-1.127
Uganda 28	0.871	0.308

Notes: ID numbers are arbitrarily assigned to a particular village within a country

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Table 5. *The estimated effects of heterogeneity on collective action*

	Basal Area	Basal Area	Basal Area	Basal Area
Wealth Inequality	-2.318*			
	(0.96)			
Wealth Inequality Squared	0.755			
	(0.35)			
Religious Heterogeneity		-1.432**		
		(0.39)		
Ethnic Heterogeneity			-0.672	
			(0.66)	
Environmental Preference Heterogeneity				-1.184
				(0.56)
Constant	2.753**	1.272***	1.309**	1.279***
	(0.54)	(0.12)	(0.24)	(0.14)
R-Squared	0.116	0.141	0.103	0.087
F	3.704	13.227**	1.039	4.418
N	21	21	21	21
	Monitor and Sanctions	**Monitor and Sanctions**	**Monitor and Sanctions**	**Monitor and Sanctions**
Wealth Inequality	-0.190			
	(2.97)			
Wealth Inequality Squared	-0.157			
	(1.39)			
Religious Heterogeneity		-1.703		
		(1.28)		
Ethnic Heterogeneity			-0.017	
			(0.81)	
Environmental Preference Heterogeneity				-1.668**
				(0.52)
Constant	3.102*	2.744**	2.529**	2.796***
	(1.24)	(0.55)	(0.44)	(0.36)
R-Squared	0.025	0.032	0.000	0.028
F	86.505***	1.774	0.000	10.324**
N	21	21	21	21
	Maintenance	**Maintenance**	**Maintenance**	**Maintenance**
Wealth Inequality	-1.644			
	(2.73)			
Wealth Inequality Squared	0.282			
	(1.22)			
Religious Heterogeneity		-2.890*		
		(1.00)		
Ethnic Heterogeneity			-0.162	
			(0.71)	
Environmental Preference Heterogeneity				0.002
				(0.66)
Constant	3.932**	2.613***	2.292**	2.238**
	(1.06)	(0.44)	(0.61)	(0.53)
R-Squared	0.074	0.116	0.001	0.000
F	14.018**	8.314*	0.052	0.000
N	21	21	21	21

Notes: Standard Errors, cluster on country, in parentheses. Two-tailed hypothesis tests: * p<0.10, **p<0.05, ***p<0.01.

FIGURES

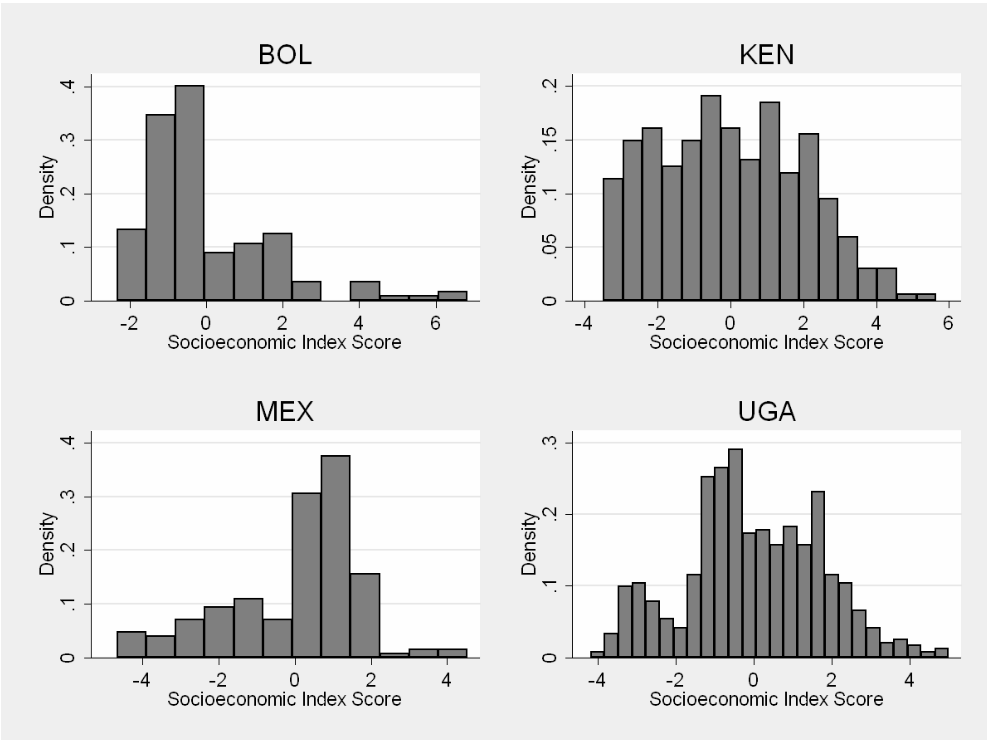

Figure 1. *Socioeconomic scores from the first principal component of the variables used to assess socioeconomic conditions and inequality.*

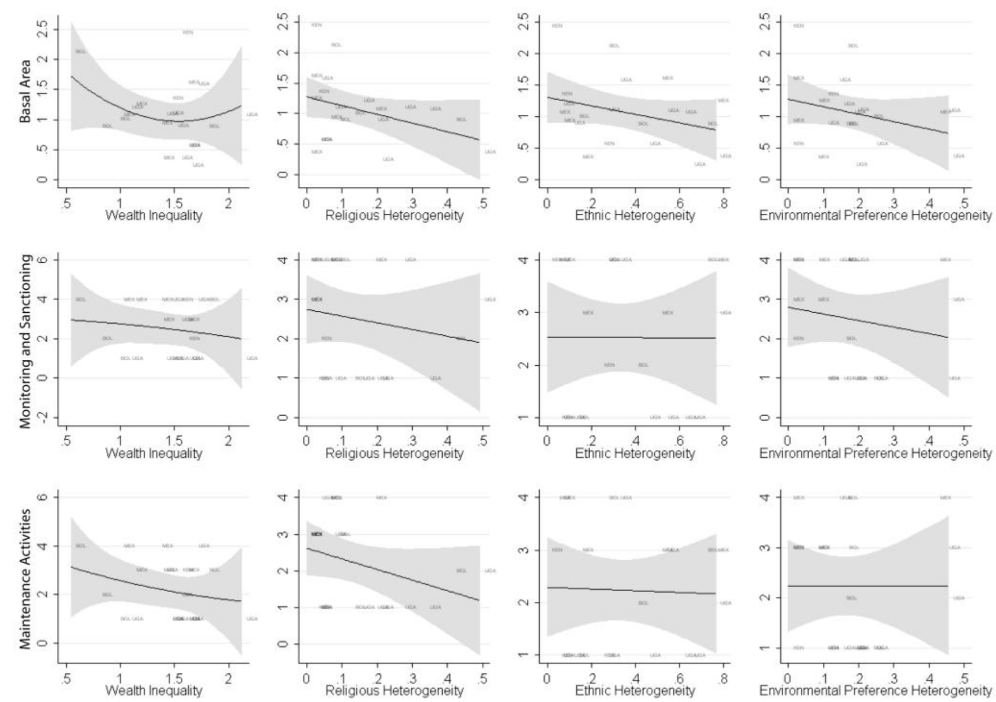

Figure 2. *Quadratic (wealth inequality) and linear (religious, ethnic, and environmental preference heterogeneity) predictions with scatterplots of inequality and collective action outcomes (basal area, monitoring and sanctioning, maintenance activities).*

ENDNOTES

[1] Notable exceptions are Poteete and Ostrom (2005), Naidu (2009), Varughese and Ostrom (2001).

[2] Income data is often preferred by economists, however McKenzie (2005) argues that,

> "…there are a number of theoretical questions of interest in which wealth inequality is more important than consumption or income inequality, so an asset-based inequality measure may be preferred in empirical tests of these theories. Moreover, the use of asset indices avoids many of the problems of recall bias, seasonality and mismeasurement that can occur with income and consumption based measures of inequality. There are therefore both theoretical and practical reasons why an asset indicator approach to inequality should be of interest."

[3] The number of indicators in this study, 21 is right within the range of those surveyed by Vyas and Kumaranayake (2006) who find studies using anywhere from 10-30 indicators. In addition, data on access to electricity, water, and sewerage were not included following MacLean (2009) who finds that such measures correlate more with geographic charectristics and seem more reflective of a broader infrastructural poverty than any particular household's poverty.

[4] The first principal component, that which explains the greatest variation among variables, is assumed to be reflective of the long-run wealth of the household (Houweling et al., 2003). Other authors have considered other components but found them to be theoretically difficult to interpret (McKenzie, 2005). In addition, higher order components are by definition orthogonal to the first principal component and thus any regression-based estimation will be robust to inclusion of these indexes as additional explanatory variables (see Filmer and Pritchett, 2001).

[5] See Husch et al., 2003, p. 236-8 for an explanation of Basal Area calculations.

[6] Prior research has usually focuses on villages within a similar geographic area (Varughese and Ostrom, 2001; Bardhan and Dayton-Johnson, 2007). It is difficult to make direct comparisons of our range of values. Wealth inequality, for example, has been measured in most studies as confined to a single asset such as land holdings (e.g. Molinas, 1998; Bardhan and Dayton-Johnson, 2007) or irrigated area (Kurian and Dietz, 2004). Similarly, while some studies such as Varughese and Ostrom (2001) calculate ethnic and religious heterogeneity similarly to our measures, they then divide the variable into categories for analysis.