New Dimensions of Tolerance: A Case for a Broader, Categorical Approach

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Abstract: Most social scientific research on tolerance rests upon two assumptions: 1) that tolerance is mainly concerned with the extension of political rights, and 2) that the concept is best understood as a unidimensional continuum of attitudes that are more or less tolerant. We argue that to have a fuller understanding of tolerance, we must transcend these two assumptions to develop a concept that is multidimensional. We use latent class analysis and confirmatory factor analysis to uncover new patterns of tolerant responses to least liked groups. Our results reveal four different profiles, which describe four different approaches to objectionable groups. These are generally intolerant, politically tolerant, generally tolerant and privately tolerant. Our profiles provide a fuller, more nuanced description of tolerant and intolerant attitudes than traditional approaches. These profiles can be used to help social scientists refine existing theories on the mechanisms of tolerance.

Keywords: tolerance; social distance; latent class analysis

Editor(s): Jesper Sørensen, Kim Weeden; **Received:** March 10, 2014; **Accepted:** July 24, 2014; **Published:** November 24, 2014

Citation: Mather, Darin M. and Eric Tranby. 2014. "New Dimensions of Tolerance: A Case for a Broader, Categorical Approach." *Sociological Science* 1: 512-531. **DOI:** 10.15195/v1.a28

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MUCH of the scholarly debate on tolerance revolves around issues of conceptualization and measurement (Gibson and Bingham 1982; Harell 2010; Sullivan, Piereson, and Marcus 1982). These ongoing debates have sharpened conceptual frameworks and improved methods, thereby advancing theory and refining research results (Hurwitz and Mondak 2002). Although significant progress has been made over the past sixty years, our basic conceptions of tolerance still have important shortcomings (Harell 2010). Two notable examples include the narrow focus of the research on political considerations and a limiting methodological approach that relies heavily on additive scales. In this article we propose a new approach to tolerance that extends beyond considerations of civil liberties into the realm of personal relationships. Drawing from the social distance literature, we include measures that help us more accurately reflect the full scope of tolerant attitudes exhibited in society and not just the political. In addition, we argue for an improved methodology, demonstrating that latent class analysis provides enhanced model fit

and more nuanced results when compared to the use of traditional additive scales. Whereas traditional methods simply show that respondents are more or less tolerant, our approach demonstrates that respondents are more accurately assigned to one of four tolerance categories: *generally intolerant*, *politically tolerant*, *generally tolerant*, and *privately tolerant*. To fully understand the ramifications of this broader approach, we must begin with a review of the conceptual and operational schemes most commonly used in foregoing tolerance research.

Literature Review

The Political Nature of Tolerance

Much of the work on tolerance in the social sciences has been done by political scientists, who regularly define tolerance politically. Sullivan, Piereson, and Marcus (1982:76) assert that "political tolerance exists when respondents allow the full legal rights of citizenship to groups they themselves dislike." Other definitions vary slightly, but

they generally agree that tolerance involves a willingness to allow expressive activities and extend civil liberties to people with disliked opinions or lifestyles (Harell 2010). This approach is entirely appropriate given the focus of scholars within the political science discipline, and the results of their research have provided us with a variety of helpful insights into the nature of tolerance. However, focusing narrowly on civil liberties unnecessarily limits the potential range of social impacts of tolerant attitudes. Other, more sociological, dimensions should also be considered.

The word tolerance is derived from the Latin word *tolerare*, which means “to bear or endure.” More specifically, it is an attitude which corresponds with a willingness to put up with a person or behavior that one finds objectionable. Though it is clearly important to closely examine the issue of tolerant attitudes regarding free political expression and civil liberties, there is no reason that the concept should be limited exclusively to these activities. Frameworks for tolerance could also extend to the interpersonal level. For instance, how would one who dislikes Muslims respond if a Somali family moved next door? Would she peacefully coexist with her new neighbors? Or would her dislike lead her to become inhospitable or perhaps harassing? If more Somalis moved into the neighborhood, could it induce white flight? Or to take another example, would a person who objects to Christian fundamentalists befriend a new conservative Christian coworker, or would he alienate him and seek to undermine his reputation in the office? These brief examples demonstrate that even at the interpersonal level, tolerant or intolerant attitudes and actions have important social significance, yet the majority of the existing social science literature on tolerance ignores this aspect of it. Golebiowska’s (1996, 2000, 2001) work is among the few to conduct in-depth analyses of tolerance at both the interpersonal and civic levels, but her studies are limited to tolerance of racists and homosexuals. They also focus narrowly on the impact of stereotypic beliefs, which she shows influence tolerant responses. Though her work is helpful, more needs to be done to expand on her initiative to combine the interpersonal with traditional civic measures of tolerance.

One might expect that sociologists, who are not limited to political considerations, would have

a broader perspective on tolerance. Though there are notable exceptions (Côté and Erickson 2009; Edgell, Gerteis, and Hartmann 2006), this is not generally the case. For instance, Burdette, Ellison, and Hill (2005) provide a thorough review of the literature on tolerance toward homosexuals. Each of the ten studies in their analysis uses a civil liberties scale to measure tolerance. This emphasis on political tolerance is partially driven by the fact that these and other sociological studies on tolerance rely heavily on the General Social Survey (GSS), which measures tolerance based on whether one would allow members of various disliked groups to speak publicly, teach in a college or university, or have a book in a public library. Again, these civil liberties measures of tolerance are important, but ignoring the effects of tolerance on private, interpersonal relationships greatly limits the scope of our understanding of this issue.

Although much of the tolerance research in sociology focuses on civil liberties, another deep vein of sociological inquiry widens the scope of analysis. In the 1920s, Emory Bogardus pioneered a series of studies on social distance, which he defined as “the degree of sympathetic understanding that functions between person and person, between person and group, and between groups” (Bogardus 1959:7). In this line of research, which is widely influential to this day, scholars are concerned with the degree to which a respondent views members of a different group as acceptable or objectionable. The Bogardus (1959) social distance scale asks respondents if they would accept members of an out group as close relatives by marriage; close personal friends; neighbors on the same street; coworkers in the same occupation; citizens in my country; only visitors in my country; or would exclude them from my country. Responses are placed on a scale, and each group’s rank on the continuum provides an indication of the degree of intimacy the respondent feels toward members of that group. Results are used to determine which groups in a society are more socially close and which more distant (Parrillo and Donoghue 2005). These findings are then employed to uncover linkages between social distance and prejudice, hostility, discrimination, and other social phenomena (cf. Halperin, Pedahzur, and Canetti-Nisim 2007; Weaver 2008). Social distance theory and research is an integral

part of new theoretical developments in sociology, particularly symbolic boundaries theory (Lamont and Molnar 2002).

Social distance research has been applied to a wide variety of contexts (see Parrillo and Donoghue 2005 and Ethington 1997 for reviews). This approach tends to be more relational than civic, emphasizing the affective nature of personal interactions instead of public or political concerns, and as such it is more commonly applied to research on prejudice and not tolerance. If, however, tolerance is a willingness to put up with a person or behavior that one finds objectionable, accepting persons from disliked groups as neighbors and coworkers would clearly fit the definition of tolerance. While the literature emphasizes the linkages between social distance and individual and institutional discrimination (Parrillo 2006), it says little about the discrimination that occurs at civic levels. The opposite is true for most tolerance research. Because these different levels are regularly considered separately, we lose the opportunity to gain a more comprehensive perspective on tolerance. For instance, individuals may discriminate against homosexuals individually and institutionally, yet feel little reason to limit their free speech rights or their ability to participate in political rallies. The opposite might be true of abortion (or anti-abortion) activists. With regard to communists, some may feel both intolerant and socially distant toward them. These distinctions are theoretically important and have significant social consequences. For this reason, we argue that our conception of tolerance is more complete if we extend it to include measures from the social distance scale along with those relating to civil liberties. In addition to providing a more comprehensive description of tolerance, we will demonstrate that combining the social distance and tolerance measures into one broad tolerance measure is better methodologically, as it produces models that fit the empirical data better than traditional methods. In the section that follows, we provide a brief overview of these traditional methodologies for studying tolerance.

The Unidimensional Nature of Tolerance

Research on tolerance is usually conducted using one of two methods. The first is based on a strat-

egy that was pioneered by Stouffer (1955). In this approach, which is used in adapted form in the General Social Survey, respondents are asked questions about tolerant responses to five diverse target groups (anti-religionists, socialists, racists, communists, militarists, and homosexuals). The second approach, developed by Sullivan, Pierson, and Marcus (1979), uses a content-controlled method. Sullivan and his coauthors argued that tolerance can only be directed toward groups that one dislikes. Thus, their method first guides respondents through a process that enables them to select their least liked group. Once this least liked group is identified, a series of free speech and civil liberties questions is asked about this group. The usual result for each of these common approaches is a scale measuring responses to varying questions about whether or not the group in question should be able to conduct rallies, run for office, teach, be free from government monitoring, and so on. Using these scales, models are developed to determine which factors might make respondents more or less tolerant.

With each of these approaches, multiple measures are used to assess one's level of tolerance for disliked groups. While these data offer researchers the opportunity to uncover nuanced patterns of responses, the preponderance of studies using these methods operationalize the concept of tolerance unidimensionally. Respondents are simply placed on a continuum of more or less tolerance depending on the number of intolerant responses that they give for their disliked groups, and the resulting scale is used for analysis. This unidimensional approach is so entrenched that James Gibson, a leading researcher in the field, has noted that any suggestion "that tolerance and intolerance do not define the end points of a continuous, unidimensional construct is a terribly important deviation from a long line of research on tolerance" (Gibson 2005a:313–14). Gibson (2005b:344) later argues that "conventional wisdom [about the unidimensional nature of tolerance] is wise and should remain conventional." We disagree. By definition the unidimensional approach provides a very narrow perspective on an issue that is complex and multidimensional. The complexities of tolerance extend beyond matters of degree as they are conceived of in the scales described above. People are intolerant for different reasons and they put up with objectionable

groups (or refuse to) in different ways. Thus, as Harell (2010) notes, we need more “conceptual room” to distinguish between different types of tolerance.

The social distance methodology is very similar in its reliance on unidimensional scales for its analysis. As we described above, respondents are presented with a series of responses to members of select groups. (Would you accept them as extended family members, neighbors, coworkers, etc.?) These responses are placed on a scale to measure the magnitude of social distance. Although, like tolerance, social distance is complex and multifaceted, it too is consistently operationalized on a single continuum (Karakayali 2009). Moving beyond the unidimensional in both of these areas can help us better theorize about people’s reasons for, and approaches to, intolerance.

In this paper, we take a step toward developing a broader, multifaceted conceptualization of tolerance by operationalizing social distance measures to add a private dimension to the conventional civic considerations. Our emphasis on uncovering the underlying multidimensionality that is often not apparent when using traditional analytical techniques follows a recent trend in other social scientific studies of political public opinion (Baldassarri and Gelman 2008) and racial demography (Maralani 2013). Using this multidimensional approach, we propose four different profiles of tolerant responses, which emerge from our analysis of the empirical data. These profiles, which are described in detail below, provide us with a new way to think about tolerance—one which breaks free from typical political constraints and adds new dimensions to the traditional unidimensional tolerance continuum. We argue that this approach opens new doors for understanding tolerance, which in turn provides new opportunities to reexamine existing theories.

Predictors of Tolerance

Conceptualizations of tolerance are important because they affect our understanding of the key predictors and outcomes of tolerant behavior. In this research we demonstrate that our multidimensional approach provides more accurate and nuanced insight into the factors that are linked to

tolerant and intolerant behavior. Prior research has uncovered correlations between tolerant attitudes and a variety of social characteristics. Age is one important predictor, with older people tending to exhibit less tolerance than younger (Cutler and Kaufman 1975; Davis 1975). Gender is also significant in that women tend to be more reluctant than men to afford civic rights to their least liked groups (Golebiowska 1999; Marcus et al. 1995). Most studies from Stouffer on have established a clear link between religion and intolerance (see Eisenstein 2006 for a review). However, Eisenstein’s (2006) recent work suggests that when relevant psychological and political predictors of tolerance are added, correlations between religion and intolerance are insignificant. Other studies have established a positive relationship between tolerance levels and education (Bobo and Licari 1989; McClosky 1964; Prothro and Grigg 1960). Finally, research has shown that tolerant responses are greatly influenced by contextual factors such as intergroup contact and perceived threat (see Schlueter and Scheepers 2010 for an extensive review of the contact and threat theory literatures); social capital development (Cigler and Joslyn 2002; Putnam 2000; Warren 2001); and macropolitical culture (Sullivan et al. 1985; Weldon 2006). These key predictors will be incorporated into our models to compare outcomes of unidimensional and multidimensional conceptions of tolerance.

Data, Methods, and Variables

Data

The data for this study is taken from the Henry Institute National Survey on Religion and Public Life, a nationwide phone survey of 3,002 Americans conducted in April 2008. Households were selected for participation in this survey using random-digit dialing (RDD). One adult respondent was selected at random within each household. Surveys were conducted in Spanish if requested by the respondent. The data were weighted to match the gender, race, and age distribution of the United States and to account for survey design characteristics, including non-response. All reported analyses use these survey weights.

The response rate¹ for the Henry survey was 30 percent, a rate that compares favorably with what most recent national RDD-based studies have been able to achieve (CMOR 2003). When deciding on an acceptable response rate, the most important consideration is the potential for nonresponse bias. The limited research on this issue reveals few differences between higher response rate (51 to 60 percent) and lower response rate (27 to 36 percent) RDD surveys on standard measures when standard sampling and survey techniques are employed (Keeter et al. 2000). Moreover, RDD surveys, conducted with standard sampling and survey techniques, yield samples not significantly different from high response rate government surveys (Pew Research Center for People and the Press 2004). While new research is beginning to evaluate different survey designs that address concerns about noncoverage, including households with no phone or no landline phone (Link et al. 2008), the methods used for this study conform to conventional approaches and results.

Methods

Identifying Least Liked Group

One section of the Henry survey focuses on the issue of political and social tolerance. Using methods adapted from Sullivan, Piereson, and Marcus (1982) and Eisenstein (2004), this survey first led respondents through a series of comparative questions to help them identify their least liked group (LLG). Respondents were also given the opportunity to name a group that was not listed in the comparative categories. In the course of our analysis, we reclassified as many of these individually selected groups as was reasonably possible. For instance, if a respondent selected the Ku Klux Klan as their LLG, we recoded their LLG as being “Racists.” Other individually selected groups occurred frequently enough that we added them as categories in Table 1, including liberals, conservatives, criminals, and politicians. The “other” category includes those who selected unique groups as their least liked group. Table 1 provides a list of the LLGs along with descriptive statistics for each.

¹We use the AAPOR Response Rate 2 calculation to report the response rate (AAPOR 2011).

After they identified their LLG, respondents were asked if these groups should be allowed certain civil liberties, or if they would personally associate in different ways with members of this group. The first three questions correspond to increasing levels of political influence for the LLG—the ability to hold public rallies and demonstrations, to make political speeches in public, and to hold positions of political authority. The next question pertains to permitting members of the LLG to teach in public schools, another common measure in tolerance research. Finally, the last two questions place the LLG in increasing degrees of personal proximity, asking respondents if they would have the LLG as a neighbor or a friend.² This extends the tolerance measures into areas that are more commonly addressed in the social distance literature. In order to simplify the subsequent analysis, we collapsed the response categories into a dummy variable that was coded 1 if the respondent somewhat or strongly agreed with the statement and 0 if they disagreed or had no opinion.³ Table 2 provides a description of respondents’ answers to each of these questions.

Latent Class Analysis

Thus far, methodologically, we have followed the standard procedure for assessing tolerance. From here, researchers would normally construct a continuous scale of the questions in Table 2 using additive scaling, factor analysis, principal components analysis, or some other technique, and the resulting scale would be used to compare the degree to which different respondents are tolerant or intolerant. This is the point where our approach differs from the standard procedure. We argue that by creating a single scale of the responses to the items in Table 2, and by conceptualizing political and social tolerance as unrelated scales to be investigated separately, we miss an opportunity to uncover divergent patterns of responses.

²An additional question asked if members of the LLG should have their right to petition in court limited. We dropped this variable from our analysis because there was very little variation in responses to this variable across our latent classes and so it is not useful for measuring variations in tolerance.

³Results of the latent class analysis using the full ordinal variable (available upon request) are substantively identical to the results presented below but are more difficult to interpret and so are not presented here.

Table 1: Descriptive Statistics for Least Liked Groups

Which of these groups do you like least?	%
Racists	29.16
Radical Muslims	19.57
Favor Military Rule	7.59
The U.S. Communist Party	7.39
Atheists	6.52
Homosexual Activists	4.53
Anti-abortion Activists	3.53
Christian Fundamentalists	2.53
Radical Environmental Activists	2.13
Criminals	1.46
Politicians	0.93
Liberals	0.80
Conservatives	0.80
Other	3.93
Don't know/refused	9.06
Total	100.00

Our method seeks to give a fuller account of the variation in how respondents answered these questions by using latent class analysis (LCA)⁴ to find compositional patterns in tolerant responses to objectionable groups. LCA is a statistical method that investigates whether a set of unobserved classes can account for the association among cross-classified indicator variables⁵ (Clogg and Goodman 1984; McCutcheon 1987; Vermunt 2010). In other words, LCA postulates that variations in a series of related indicator variables can be well represented by a few unobserved latent classes. Typically, the categorical responses

⁴LCA is not a new technique, having been developed in 1950 by Lazarsfeld and made applicable in practice by Goodman (1974), who developed an algorithm for obtaining maximum likelihood estimates of the model parameters. However, it has only become widely used in the social sciences in the past decade (Hagenaars and McCutcheon 2002). Today, it is considered part of a broader set of methods often referred to as finite mixture modeling (McLachlan and Peel 2000).

⁵Latent class models are fit to the data using the Newton-Raphson algorithm for maximum likelihood estimation. There are three potential problems with using this algorithm: the possibility of nonidentified parameters, the presence of local maxima, and the occurrence of boundary solutions. We avoided these problems by including more than five indicator variables, estimating models with different sets of random starting values, and close examination of the results to check for boundary solutions (Vermunt and Magidson 2004).

are assumed to be independent given class membership (Lazarsfeld and Henry 1968; Vermunt 2010).

Two types of parameters are estimated in LCA analysis. The latent class probabilities identify the relevant prevalence of each latent class. While this parameter can be thought of as the percentage of cases in each latent class, a more accurate analogy would be a mixture or density model, such that each respondent contributes some information to each latent class. The conditional item probabilities are specific to a given class and are the probabilities of observing that specific characteristic in each latent class (McCutcheon 1987; Nylund, Asparouhov, and Muthen 2007; Vermunt 2010). We used the maximum likelihood estimation in Latent Gold 5.0 to maximize the log likelihood function specified by Vermunt and Magidson (2004).

Determining the number of latent classes that best fit the data is an issue that has not been well resolved in the literature (Nylund et al 2007). A variety of simulation studies indicate that the Bayesian Information Criterion (BIC) is the best statistic for deciding between different numbers of latent classes in mixture modeling (Vermunt and Magidson 2004; Nylund et al. 2007). The BIC balances improvement in the likelihood caused by adding additional groups with a penalty for

Table 2: Descriptive Statistics for Least Liked Groups

Variable	% agreeing
LLG Allowed to Publically Demonstrate	42.14
LLG Allowed to Make a Political Speech	45.06
LLG NOT Banned from Political Office	46.02
LLG Teach in Public Schools	21.47
Would Have LLG as a Neighbor	33.48
Would Be Friends with LLG	30.70

this addition. Unlike some other applications, the smallest BIC score indicates the best-fitting model to the data in LCA when using Latent Gold 5.0. We also use the metric developed by Kass and Wasserman (1995) to determine the probability that each number of groups is the correct model from a set of competing models. A recent simulation study by Nylund et al. (2007) indicates that a bootstrap likelihood ratio test (BLRT), which uses bootstrapped samples to estimate the distribution of the log likelihood difference test statistic comparing two models, may equal or exceed the performance of BIC in LCA. Therefore, we also present the BLRT, with a p-value less than .05 indicating a significant improvement in model fit. The model fit statistics are presented in Table 3. The model that best fits the data, using both the BIC and BLRT, is the model with four latent classes.

As we describe in detail below, our finding that a fourclass model is the best fit to the data indicates that tolerance, as measured here, is not a unidimensional concept that can be measured by traditional OLS regression or the two-equation approach of a zero-inflated negative binomial model (Mondak and Sanders 2005). Instead, our analy-

sis shows that tolerance is a categorical concept in which people respond to questions measuring tolerance in four different ways. We also briefly use confirmatory factor analysis because it, along with the related method of principal components analysis, is often used to construct the unidimensional tolerance scales described above. Confirmatory factor analysis uses the common variance-covariance characteristics of a set of observed variables to test the validity of an underlying hypothesized theoretical construct (latent variables) (Schumaker and Lomax 2010). We use it below to highlight that a unidimensional scale is not a good fit to the data and that a two-dimensional classification of political tolerance and social tolerance needs to account for the strong relationship between the two concepts.

Finally, we link the latent class model to explanatory variables or covariates to estimate how membership in the latent classes varies along key lines. We compare these models with a linear regression in which the dependent variable is a linear measure of tolerance constructed as an additive scale, in which high scores are related to more tolerant attitudes. We do this in order to demonstrate the consequences of using the cate-

Table 3: Descriptive Statistics for Least Liked Groups

Number of Clusters	# of Params.	Log-Likelihood	LL Difference (Bootstrap)	BLRT (Bootstrap P-Value)	BIC	Probability Correct Model
1	9	-5108.18	—	—	10259.54	0.00
2	19	-4624.93	—	—	9343.39	0.00
3	29	-4548.80	152.26	0.00	9241.50	0.00
4	39	-4497.95	101.69	0.00	9190.17	1.00
5	49	-4493.06	9.78	0.32	9230.76	0.00
6	59	-4487.58	10.97	0.15	9270.16	0.00

gorical approach proposed in the previous section by comparing the results of latent class regression models and linear regressions using the same set of independent variables. Table 4 provides a description of, and the descriptive statistics for, the explanatory variables used in this analysis.⁶ The independent variables include demographics (gender, marital and parental status, race, socioeconomic status), religious affiliation and belief, political affiliation, membership in a civic organization, living in a large or diverse county, and the extent to which the individual believes their LLG will gain power in American society, pose a threat to society, and pose a threat to their family. These variables are included because prior research indicates their importance for understanding tolerance, as described above.

In general, the latent class model is linked to covariates using a three-step process.⁷ First, a latent class model is built for a set of indicator variables, as we have done above. Second, respondents are assigned to latent classes based on their posterior class membership probability (PCMP), or the probability of belonging to each latent class based on their observed pattern of responses. The two most widely used partitioning methods are modal assignment, in which respondents are assigned to the single latent class for which their PCMP is the largest, and proportional assignment, in which the respondents' information is assigned to a latent class in proportion to the

PCMP for that class. Modal assignment is the simplest but introduces classification error into the model, while proportional assignment is less statistically efficient but has little classification error (Vermunt 2010). Third, a standard multinomial logistic regression model is estimated using the assignment of respondents to latent classes as the dependent variable.

This three-step process is widely implemented by researchers using LCA. However, the three-step process has been shown through a series of statistical simulations to seriously underestimate relationships between covariates and class membership, especially when classification error is high (Bolck, Croon, and Hagnaars 2004; Vermunt 2010). Vermunt (2010) develops a three-step maximum likelihood approach using the first two steps described above. In the third step, however, the assignment probabilities serve as a single response variable with known measurement error probabilities. Simulations show that this approach yields more accurate estimates of both the coefficients and the standard errors, particularly when used with modal assignment. This method is also easily implemented in LCA software. Therefore, we use this method with modal assignment in the analysis that follows.

Results

Is Tolerance Unidimensional, Multidimensional, or Categorical?

Table 5 provides the results of our latent class analysis. The column on the left lists the various responses to questions about tolerant responses toward the LLG. The bottom rows of the table show two measures of model adequacy: the average PCMP of cases that were assigned to that class based on modal assignment and the percentage of assigned cases with PCMPs greater than 0.90. The relatively high probabilities for each latent class indicate that using modal assignment is unlikely to introduce substantial measurement error. The remaining columns describe each of the latent classes that were derived from our analysis. We have named these classes *generally intolerant*, *politically tolerant*, *generally tolerant*, and *privately tolerant*. These labels describe the

⁶Missing data on many of the independent variables was imputed using hotdeck imputation for categorical variables and regression-based imputation for continuous variables. Our imputation used all the other variables in the model, as is typical (Graham 2009). The average amount of data imputed was 1 percent and never exceeded 5 percent. We would have preferred to use multiple imputation because it has better statistical properties (Little and Rubin 2002). However, multiple imputation is not available in Latent Gold or other programs that can perform a latent class analysis with covariates. Therefore, we use the single imputation methods in order to avoid discarding cases with missing values. We did not impute missing data on the variables used to generate the latent classes.

⁷An alternative approach is the simultaneous estimation of the latent class model of interest with a logistic regression model in which the latent classes are related to a set of covariates (Clogg 1981; Vermunt 1997; Yamaguchi 2000). This one-step approach has a number of disadvantages, including model-building problems, needing to reestimate and refit the latent class model whenever a covariate is changed, and an incompatibility with the logic of applied, collaborative research (Vermunt 2010).

Table 4: Descriptive Statistics of Independent Variables

Independent Variable	Description of Variable	Mean or %	S.E.
Female	Female Dummy Variable (1 = Female, 0 = Male)	45.11%	—
Age	Age of respondent in years (Range: 18 to 92)	40.54	1.01
Married	Respondent is married or cohabiting (0=Single, divorced, separated, or widowed)	46.94%	—
Child under 18 in HH	Respondent has one or more children under 18 currently living in their household (1 = One or more children under 18 in the household)	73.15%	—
Black	Respondent is African American	16.43%	—
Hispanic	Respondent is Hispanic	13.32%	—
Education	Highest level of education completed (1 = 8th grade or less to 7 = Graduate School)	3.09	0.09
Income	Family income in 2007, before taxes (1 = Under \$15,000 to 8 = \$100,000)	3.17	0.10
Conservative Protestant	Respondent attends or prefers a church that is part of a conservative Protestant denomination	27.05%	—
Catholic	Respondent attends a Catholic church or claims a religious preference for Catholic	18.49%	—
No Religious Affiliation	Respondent claims not religious affiliation, to not be a believer, or be atheist or agnostic	15.03%	—
Religious Saliency	Respondent considers religion to a very important part of their life	71.07%	—
Republican	Respondent is a Republican (0=Democrat)	22.07%	—
Independent	Respondent is an Independent (0=Democrat)	44.30%	—
Member of Civic Org.	Respondent belongs to one or more civic organizations	52.36%	—
County Population Density	County population density per square mile, in 2000. (Source: Mapping Census 2000: The Geography of U.S. Diversity)	1295.85	181.80
County Diversity Index	County diversity index, calculated as an index of dissimilarity between 8 racial groups, in 2000. (Source: Mapping Census 2000: The Geography of U.S. Diversity)	0.36	0.01
LLG is Likely to Gain Power	Respondent believes that the LLG is likely to gain power in the United States	26.27%	—
LLG is a Threat to Society	If LLG gained power in the United States, they would pose a danger to our society	84.87%	—
LLG is a Threat to My Family	If LLG gained power in the United States, they would pose a danger to my family	73.61%	—

Note: Results are weighted to match the gender, race, and age distribution of the United States and to account for survey design characteristics.

Table 5: Latent Class Analysis of Profiles of Tolerance

	Latent Class			
	Generally Intolerant	Politically Tolerant	Generally Tolerant	Privately Tolerant
Latent Class Probability (%)	42.30	22.83	20.90	13.97
Conditional Item Probability:				
Allowed Free Assembly (%)	11.33	82.05	86.62	4.31
Allowed to Make a Political Speech (%)	11.85	92.63	80.80	13.50
NOT Banned from Political Office (%)	15.15	72.37	80.13	46.74
Would Have as A Neighbor (%)	5.92	10.57	85.84	76.44
Would Be Friends With (%)	12.10	14.92	60.53	67.53
Teach in Public Schools (%)	7.13	25.93	53.81	8.55
Model Adequacy:				
Average Posterior Class Membership				
Probability	0.98	0.86	0.88	0.79
% of Posterior Class Membership				
Probabilities < .90	74.14	47.97	57.77	45.10

Note: Cases were classified into a class following a modal assignment rule.

distinct differences that we observe in the four profiles.

We call the most prevalent latent class, with an expected probability in the population of 42 percent, the *generally intolerant* profile. Respondents in this group are highly unlikely to be in favor of granting members of their LLG the right to publicly demonstrate (only 11 percent would allow it), make a political speech (only 12 percent would allow it), or the right to hold public office (only 15 percent would not ban them from office). In addition, 93 percent of respondents in this group believe that members of their LLG should not be allowed to teach in public schools. Finally, the vast majority of respondents in this generally intolerant group would not want members of the LLG as neighbors or friends.

The second most prevalent profile is the *politically tolerant* profile. While this group is generally permissive of their LLG in the civic realm, they would prefer to hold them at arm's length personally. A relatively high percentage in this group would allow members of their LLG to publicly demonstrate, make a political speech, and hold elected office. However, only a quarter of the members of this profile would permit individuals from their LLG to teach in schools and even fewer would have them as neighbors or friends. Our findings here highlight the distinctiveness

of political tolerance, which can be contrasted with the private tolerance listed below. It is also important to note that research techniques which rely strictly on political measures could easily classify members of this group as highly tolerant, missing the intolerance that they demonstrate in the private realm.

We identify the third profile as the *generally tolerant* profile. On the whole, respondents in this profile are willing to afford members of their LLG a broad range of political rights while also being open to associating with them on a more personal level. While their support for allowing members of their LLG to teach in public schools is only 53 percent, this level of support is much higher than that of any other profile in the list. Because our multidimensional approach is less conceptually stringent than the traditional unidimensional approach, we can call attention to a segment of the population that is generally willing to put up with objectional groups in a wide variety of ways, without missing a result that fits the theoretical notion that even the most tolerant among us are often intolerant in some way.

The last profile is the smallest of the four, with an expected probability of about 14 percent. This profile we call *privately tolerant*. Members of this latent class are quite likely to accept members of the LLG as neighbors and friends, but they

Table 6: 2 × 2 Table of Tolerance

		Political Tolerance	
		Low	High
Private Tolerance	High	Privately Tolerant (14%)	Generally Tolerant (22%)
	Low	Generally Intolerant (42%)	Politically Tolerant (22%)

Note: Cases were classified into a class following a modal assignment rule.

are unwilling to allow them to publicly demonstrate, make a political speech, hold office, or teach in public schools. This profile was a surprising discovery, one which we think deserves more scholarly attention to determine what might prompt respondents to support withholding basic civil rights from a group of people that they are quite willing to associate with as friends and neighbors.

These profiles, which represent very different patterns of responses toward members of objectionable groups, provide a broader perspective on Americans' attitudes toward tolerance. The first thing that stands out in looking at these profiles is the relatively high numbers of Americans who are generally intolerant or who are willing to deny members of their LLG even basic civil rights. This group is roughly twice the size of any other profile. At the other end of the spectrum, a much lower percentage of Americans tend to be tolerant across all of the measures that were included in our analysis.

In addition to considerations about the quantitative distribution of tolerant responses, which corresponds to a more traditional understanding of the concept, our analysis reveals a qualitative distinction between those whose tolerance has a more political orientation and those whose tolerance is more private. These are unique approaches to tolerance that would be missed using the traditional methods. In fact we argue that each of these approaches—generally tolerant, politically tolerant, generally intolerant, and privately tolerant—have differences that extend beyond matters of degree to matters of form and substance. Each profile expresses a very different response to an objectionable group, and each re-

flects a different attitude toward those who are disliked. If we continue to adhere to a unidimensional concept of tolerance, which focuses specifically on political or social distance measures, we miss these important distinctions.

It could be argued that rather than representing categorical differences in approaches to tolerance in the population, we are simply capturing two different dimensions of tolerance—political tolerance and private (social) tolerance or distance. This can be visualized in a simple two-by-two table, as in Table 6. On first blush, a confirmatory factor analysis of our variables, shown in Figure 1, partially supports this claim. We first attempted a factor analysis in which all of the variables were indicators of a single latent factor of tolerance, analogous to the unidimensional scaling approach. This resulted in a poor fit to the data (normed chi-square: 26.64; RMSEA: 0.141; CFI: 0.796). As can be seen in Figure 1, a two-factor model that has a political tolerance factor and a private/social tolerance factor is a good fit to the data. However, the political tolerance and private tolerance latent factors are not orthogonal to each other, as has been claimed in the literature (Sullivan et al. 1982). Instead, they are significantly and relatively strongly correlated with each other (0.44). This correlation means that they cannot be treated as fully separate concepts but instead are related to each other and need to be analyzed and understood as such. There are multiple ways to accommodate this correlation in analysis, including structural equation models or our chosen method of latent class analysis.

Collectively, these findings highlight the categorical nature of the concept of tolerance. As

Figure 1: Confirmatory Factor Analysis of Tolerance Variables

described above, some individuals are tolerant on political indicators and intolerant on private indicators, while others are intolerant on political indicators and tolerant on private indicators. But the political and the private are not independent dimensions that can be considered apart from each other. Rather they are strongly correlated. Some individuals are generally intolerant on all of the indicators, while others are generally tolerant on all indicators. In short, these are distinct yet related measures of tolerance.

What are the Empirical Implications of a Categorical Approach?

The second major section of our analysis demonstrates the relative utility of the categorical approach by comparing it to an analysis using the more traditional, scaled method for studying political tolerance and social distance/private tolerance. This is important because the categorical approach uses a more complex methodology to measure tolerance. We show that this increase in complexity is empirically justifiable in two ways. First, we compare equations estimating standard measures of tolerance and our categorical tolerance measure using various demographic, religious, political, and social context variables. Second, we use different measures of tolerance

to estimate various outcomes. Taken together, these analyses demonstrate that our categorical approach is empirically preferable to a traditional orthogonal understanding of political tolerance and social distance.

The first analysis is shown in Table 7. On the left is a more traditional method of estimating tolerance, using linear regression with a standard political tolerance scale, a private tolerance scale, and a scale that adds both political and private tolerance as dependent variables. On the right are the results for the same variables using the maximum likelihood-based correction method proposed by Vermunt (2010). The results of this method can be interpreted like a standard multinomial logistic regression comparing odds ratios for the generally intolerant class to the other three classes. In general, while the approaches have some similar results, the categorical approach to measuring tolerance yields a more nuanced understanding of who is tolerant and who intolerant. For instance, the approaches produce similar results for the female, married, education, income, and Conservative Protestant variables. On other measures, however, the categorical approach reveals more nuanced patterns of findings. In particular, in the linear regressions, respondents who believe that the LLG is a threat to society and their family are less likely

Table 7: Estimating Tolerance by Demographic, Religious, Political, and Social Context Variables

	Panel A: Linear Regression			Panel B: LCA with Covariates (Ref: Generally Intolerant)		
	Political Tolerance Scale	Private Tolerance Scale	Tolerance Scale	Politically Tolerant	Privately Tolerant	Generally Tolerant
Female	−0.20 [†] (0.00)	−0.04 (0.08)	−0.05* (0.02)	0.64 [†] (0.18)	1.06 (0.22)	0.70 (0.18)
Age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	1.00 (0.01)	1.00 (0.01)	1.01 (0.01)
Married	−0.17* (0.08)	−0.02 (0.09)	−0.04* (0.02)	0.64* (0.20)	1.09 (0.24)	0.65* (0.20)
Child under 18 in HH	−0.03 (0.10)	−0.20 (0.10)	−0.02 (0.02)	1.30 (0.23)	0.98 (0.27)	0.75 (0.22)
Black	−0.23 (0.16)	0.29 (0.18)	−0.02 (0.04)	0.32* (0.52)	1.57 (0.42)	1.06 (0.37)
Hispanic	−0.16 (0.17)	0.27 (0.18)	−0.02 (0.04)	0.53 (0.44)	1.99 (0.38)	0.64 (0.39)
Education	0.20 [†] (0.03)	0.02 [†] (0.03)	0.04 [†] (0.01)	1.43 [†] (0.07)	1.05 (0.08)	1.31 [†] (0.07)
Income	0.05* (0.02)	−0.03 (0.03)	0.01 (0.01)	1.12* (0.06)	0.92 (0.07)	1.09 (0.06)
Conservative Protestant	−0.20 [†] (0.09)	−0.09 (0.10)	−0.04 (0.02)	0.52 [†] (0.23)	0.80 (0.27)	0.83 (0.23)
Catholic	−0.14 (0.10)	−0.08 (0.11)	−0.03 (0.03)	0.63* (0.24)	0.89 (0.30)	0.88 (0.25)
No Religious Affiliation	0.09 (0.15)	0.02 (0.15)	0.02 (0.04)	1.11 (0.34)	0.92 (0.45)	1.26 (0.33)
Religious Saliency	−0.10 (0.10)	−0.13 (0.11)	−0.02 (0.02)	1.15 (0.24)	1.07 (0.30)	0.71 (0.23)
Republican	0.03 (0.09)	−0.15 (0.10)	0.02 (0.02)	1.20 (0.23)	0.67* (0.29)	1.27 (0.24)
Independent	0.04 (0.09)	−0.13 (0.10)	0.03 (0.02)	1.34 (0.22)	0.76* (0.27)	1.30 (0.21)
Member of Civic Org.	0.11 (0.08)	0.04 (0.08)	0.02 (0.02)	0.91 (0.19)	0.90 (0.22)	1.51* (0.19)
County Population Density	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
County Diversity Index	0.06 (0.20)	0.14 (0.21)	0.02 (0.05)	0.55 (0.49)	0.76 (0.60)	1.46 (0.49)
LLG is Likely to Gain Power	−0.02 (0.08)	−0.10 (0.09)	−0.01 (0.02)	0.70 (0.20)	0.50 [†] (0.26)	0.86 (0.20)
LLG is a Threat to Society	−0.27* (0.11)	−0.72 [†] (0.13)	−0.07* (0.03)	1.42 (0.34)	0.47 [†] (0.30)	0.63 (0.28)
LLG is a Threat to My Family	−0.21* (0.09)	−0.52 [†] (0.10)	−0.06* (0.02)	0.72 (0.24)	0.47 [†] (0.26)	0.46 [†] (0.23)
Constant	2.36 (0.27)	3.39 (0.30)	0.34 (0.07)	0.17* (0.69)	0.80 (0.79)	0.39 (0.66)

Note: LCA estimates in Panel B estimated using ML Method. Cell entries in Panel A are coefficient estimates; in Panel B, Odds Ratios. Standard errors are in parentheses.

[†] $p < 0.01$; * $p < 0.05$.

to be tolerant across all the measures. The categorical approach adds nuance in showing that respondents who believe that the LLG is a threat to society and their family are less likely to be generally tolerant or privately tolerant, but are no more or less likely to be politically tolerant.⁸ The latent class models allow us to uncover relationships that were hidden by using a standard additive scale with OLS regression. For example, African Americans and Catholics are less likely to be politically tolerant than generally intolerant. In addition, Republicans and political independents are less likely to be privately tolerant than Democrats. Being a member of a civic organization is associated with being more generally tolerant of one's LLG. Private tolerance is generally associated with believing that the least liked groups are unlikely to come to power.

Regardless of the estimation technique, the results in Table 7 reveal that there are important insights to be gained from considering public and private tolerance as interrelated ideas. Three sets of variables in the LCA provide demonstrative examples. First, results show that Conservative Protestants and Catholics are each less likely to be politically tolerant than generally intolerant when compared to people from other religions. This suggests that the concerns that members of these religious traditions have about their least liked groups are significant enough that they are more likely than others to deny political and civil rights to the people they oppose. These findings demonstrate that religious tradition is an important indicator of tolerant attitudes, contrary to Eisenstein (2006), who argues that a more universal model of religion is appropriate. Findings for the Republican and Independent variables provide another interesting distinction. These results show that members of these two parties are less likely to be privately tolerant than members of the comparison group (Democrats). This indicates that when compared to Republicans and Independents, some Democrats are more accepting of difference in their personal lives while maintaining a willingness to limit the potential impact that members of an LLG may have in the

political and social realm. This finding is unique to our analysis, and we cannot identify a similar set of findings in the tolerance or social distance literature. Finally, many studies have shown the positive effect of volunteering and education on political tolerance (Sullivan et al. 1982). Our study shows that these factors alone are most positively associated with tolerance across the board, increasing the likelihood that someone will be generally tolerant.

The second analysis is shown in Table 8. In this analysis, we use the different tolerance measures, along with the set of various demographic, religious, political, and social context variables used in the previous analyses, to predict three outcomes. First, respondents were asked the extent to which they agreed with the statement, "Society shouldn't have to put up with those who have political ideas that are extremely different from the views of the majority." Second, respondents were asked how much they agreed with the statement, "No matter what a person's political beliefs are, he or she is entitled to the same legal rights and protections as anyone else." Finally, we assess the extent to which tolerance affected voting patterns in the 2008 presidential race. These variables are widely used in the tolerance literature, although there is debate on whether they are outcomes or predictors of tolerance (Gibson 2013). In Table 8, we predict these dependent variables using standard additive scales for political and private tolerance. (We also tried including an interaction between these two additive scales as well as an additive scale of all the tolerance measures. These two variables were never significant and so are not shown here.) We then predict these dependent variables using a categorical variable that modally assigns respondents to one of the four dimensions of tolerance. In these models, the generally intolerant are the reference group.

In the models in Table 8, we are primarily interested in the extent to which our categorical measure of tolerance produces a better fit to the data by capturing a greater share of the variance in the dependent variable or correctly classifying a greater proportion of cases. In this regard, our models do quite well. Across all the equations, the adjusted r-squared, pseudo r-squared, and percentage of cases correctly classified is larger in the models that include the categorical measure. The magnitude of the change is not huge, but

⁸We developed models that did not include these attitudes as predictors, in order to ensure that including them did not mediate the effect of other variables. Models with and without these attitudes had substantively similar findings.

Table 8: Using Different Tolerance Measures to Estimate Various Outcomes

Variable	Oppose Extreme Political Ideologies (OLS Regression)		All Are Entitled To Legal Protections (OLS Regression)		Voted for Obama in 08 (Logistic Regr.)	
	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Additive and Interactive Tolerance						
Political Tolerance Scale	−0.34 [†] (0.03)	−0.06 (0.04)	0.06 [†] (0.02)	0.05* (0.02)	1.19* (0.07)	1.10 (0.10)
Private Tolerance Scale	0.03 (0.03)	0.00 (0.03)	−0.02 (0.02)	−0.03 (0.02)	0.93 (0.06)	1.04 (0.09)
Constant	3.01 [†] (0.10)	3.03 [†] (0.30)	4.58 [†] (0.06)	4.84 [†] (0.18)	0.54 [†] (0.21)	1.69 (0.90)
Adjusted R^2	0.08	0.17	0.01	0.01		
Pseudo R^2					0.01	0.37
% of Cases Correctly Classified					54.52	75.44
Panel B: Categorical Tolerance						
Politically Tolerant	−0.77 [†] (0.10)	−0.57 [†] (0.11)	0.15* (0.06)	0.16* (0.07)	1.12* (0.20)	1.49* (0.31)
Generally Tolerant	−0.86 [†] (0.10)	−0.68 [†] (0.11)	0.17 [†] (0.06)	0.15 [†] (0.06)	1.24* (0.20)	1.29* (0.32)
Privately Tolerant	−0.09 (0.11)	−0.15 (0.13)	−0.05 (0.07)	−0.04 (0.08)	1.31* (0.26)	1.42* (0.38)
Constant	2.58 [†] (0.06)	2.72 [†] (0.29)	4.62 [†] (0.03)	4.83 [†] (0.17)	0.70 (0.13)	2.33 (0.88)
Adjusted R^2	0.12	0.22	0.03	0.03		
Pseudo R^2					0.07	0.42
% of Cases Correctly Classified					59.90	82.36

Notes: See tables S1 and S2 in Supplemental materials for tables containing control variables. Cell entries for OLS regressions are coefficients; for logistic regressions, Odds Ratios. Standard errors are in parentheses.

[†] $p < 0.01$; * $p < 0.05$.

likelihood ratio tests of the models show that the categorical measure produces a significantly better fit to the data. A secondary consideration is whether the tolerance measures are mediated by the inclusion of other variables in the model. In this as well, the categorical measures win out. For both the first and third models, the additive scale of tolerance is fully mediated by other variables, but the categorical indicators remain significant even with the inclusion of additional variables.

Taken together, these two sets of analyses show that our categorical measures produce a clearer understanding of the underlying multidimensional

dimensionality in attitudes, yield a more nuanced result when associated with predictors of interest, and provide a better fit to various outcomes. These findings reinforce our broader point that tolerance, political tolerance, and private tolerance/social distance are related concepts that should not be explored in isolation.

Discussion and Conclusion

In this paper, we develop a broader, multifaceted conceptualization of tolerance which operational-

izes traditional tolerance measures along with social distance measures to uncover four distinct categories of tolerant attitudes. The first category, which we call generally intolerant, is made up of people who are highly unlikely to grant civil liberties to or personally associate with members of their LLG. The second group, dubbed politically tolerant, is willing to extend civil liberties to their LLG but is unwilling to associate with them as neighbors or friends. Third, respondents in the generally tolerant profile are both willing to afford members of their LLG a broad range of political rights and open to associating with them on a more personal level. Finally, the privately tolerant category is made up of people who are likely to accept members of the LLG as neighbors and friends but are generally unwilling to offer them a number of civic freedoms. These profiles represent very different patterns of responses toward members of objectionable groups that cannot be accounted for using traditional methods for studying tolerance. In addition to providing a clearer conceptual depiction of people's tolerant responses, our approach produces models that allow for a more nuanced understanding than the traditional approach using linear scales.

The findings from our research make an important contribution to the study of tolerance and social distance. First, by uncovering new categorical patterns of tolerant responses to objectionable groups, we have provided a fuller picture of tolerant and intolerant attitudes that is more nuanced and complex than the traditional unidimensional approach in both the tolerance and social distance literatures. We have shown that intolerance is not just a matter of degree; instead, there are important differences of form and substance that need to be accounted for in ongoing research. These differences have implications for our understanding of people's varied approaches to tolerating their LLG.

Second, we make a theoretical and methodological argument that political tolerance and private tolerance are tightly related concepts that should not be explored in separate literatures, as they have been up until now. Instead, our results point to the existence of subcategories of both public and private tolerance along with broad categories of tolerance and intolerance that combine them both. These interrelated ideas, and

the nature of their relationship, warrant further exploration and elaboration.

Third, our full regression models have provided insight into the demographic, religious, and political composition of the four tolerance profiles. Although our models provide a clear initial description of these profiles, they could be expanded to explore other theoretical questions such as: What other types of people might fit into each of the profiles? Why do they fit into their respective profiles? Does it have something to do with the nature of their LLG or the threat that they perceive from them, or is it related to other factors? What impact do these different approaches to tolerance have on political and social interactions? These are important questions to pursue in future research.

Our regression analysis also demonstrated that there are important insights to be gained from considering public and private tolerance as interrelated ideas. In particular, they add nuance to our understanding of specific religious and political approaches to tolerance and provide evidence for the broad impact that education and volunteering have on tolerant responses. Although these were not specifically addressed in detail in the discussion above, our models showed that a categorical approach can also provide new insight into the effects that gender, marriage, income, and race can have on tolerance.

Finally, ongoing research should address an important limitation of this study. Our dataset included only six potential tolerant responses to an LLG, including just two items from the social distance literature. Future research could provide more and different options, which may reveal other categorical distinctions that can generate new conceptualizations of tolerance. Additionally, there may be other ways to explore correlations and distinctions in tolerance responses. For instance, Harell (2010) takes another approach by distinguishing between people who are intolerant of hate groups and those who are intolerant of other types of objectionable groups.

Tolerance is a complex and multifaceted issue. Although social scientists have done much in the last sixty years to delineate the concept and describe its antecedents, more can be done to refine and expand our understanding. This article points in potentially promising directions

by focusing attention on the possibility of using categories instead of unidimensional scales for studying tolerance.

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Acknowledgements: This research was generously supported by a grant from the Henry Institute. The authors are grateful for feedback received during presentations at the American Sociological Association annual meetings, Midwest Sociological Society, and the Moberg Conference on Sociological Perspectives on Reconciliation.

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