What Kind of Nationalist are You?: A Comprehensive Statistical Modeling for Understanding Public Opinion for Muslims among White Americans

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Abstract

Intergroup opinion between white Americans and Muslims in the age of Trump are barely studied in social science. Using ANES 2016 and ANES 2018 pilot data, this thesis focuses on how two of the most salient ingroup identities among white Americans inform their outgroup attitudes for Muslims: racial identity and ethnocultural nationality. The statistic tool for empirical analysis is finite mixture model that combines latent class analysis and multilevel modeling, which allows me to make more accurate estimation for both intragroup and intergroup variations than conventional methodologies. For generic evaluation for Muslims, I find that race is more salient than nationality in predicting anti-Muslim prejudice while nationality is more contingent to favoritism to Muslims. About specific stereotypes, I find the opposite patterns. In addition, I find Republican identity and education are two robust indicators for identity grouping for both generic and specific outgroup attitudes for Muslims.
Anti-Muslim agenda is a major feature of the white identity politics that marks conservatism in the age of Trump (Gorski 2019; Inglehart and Norris 2016; Jardina 2019; Kalkan 2019; Sides et al. 2019). Surprisingly, no published study examines how average white Americans’ ingroup consciousness shapes their attitudes toward Muslims although intergroup conflicts is a popular issue in political sociology and social psychology. Connecting social identity theory in social psychology (eg. Tajfel 1978) with the theory of symbolic boundaries in sociology of culture (eg. Bourdieu 1984), the central argument in this article is that when white Americans’ racial identity is not the only source to draw their intergroup boundaries with Muslims. As the dominant group in the mainstream American society, white Americans perform two contingent identities to inform their attitudes toward Muslims: race and nationality. In the American context, racial identity is associated with a power system that essentializes psychical appearances such as skin colors to draw symbolic boundaries of ingroups while national identity embodies a system that prioritizes culturally norms and values (Jeffrey 1992; Edgell et al. 2006; Edgell et al. 2019; Smith 1997).

In addition, I also examine if a given identity is more contingent in drawing symbolic boundaries between white Americans and Muslims under certain conditions. Social identity reflects individual members’ perception and knowledge of group membership (Tajfel 1978). On the one hand, group membership as a socially constructed reality is associated with many long-term social factors. For example, working-class, religiously conservative Christian, and aged white Americans tend to be high racial identifiers (Jardina 2019; Gorski 2019). On the other hand, political factors such as partisan belongings and policy ideologies may also affect the perception of ingroup/outgroup boundaries. For example, a recent study in political psychology
also indicates that the partisan polarization among average voters on Muslim issues has been consistently salient since inception of Obama’s administration (Kalkan 2019).

The empirical analysis relies on a well-established statistic tool in social science, the Finite Mixture Model or FMM (Arminger and Stein 1997; Grün and Leisch 2008; Imai and Tingley 2012). FMM suits the research questions well because it assumes that individual models are locally-based and certain observations are more systematically responsive to one theory than another (Imai and Tingley 2012). Dated research on different identity grouping using pollster data relies on conventional cluster analysis methodologies such as latent class analysis (LCA) and K-means clustering (eg. Bonikowski and DiMaggio 2016; Edgell et al. 2019). However, cluster analysis does not provide explanatory models to explain variances within each group as regression models. FMM offers an algorithm that bridges cluster analysis and regression modeling so that one can not only understand how the sample is clustered by different groups but also explain ingroup variance. Regarding the data for analysis, I draw two subsamples of non-Hispanic white population from the American National Election Studies 2016 time-series (ANES 2016) and 2018 Pilot Study (ANES 2018) respectively. I choose ANES because it is the only public accessible data including valid and robust batteries for white identification and ethnocultural nationalism as well as different continuous measures for attitudes toward Muslims such as feeling thermometers to Muslims as well as two popular negative stereotypes against Muslims: whether Muslims are disloyal and violent.

A major contribution of this study is to provide a more comprehensive understanding for white Americans’ intergroup opinions to Muslims accounting for both anti-Muslim and pro-Muslim sentiments. This work, accordingly, is also part of the growing literature on intergroup dynamics in today’s political and cultural polarization. Results of analysis reveal that on the one
hand, strong white racial identity significantly predicts anti-Muslim but not vice versa. A considerable anti-Muslim population are still attached with their high ethnocultural national identity. On the other hand, national identity is more salient in explaining generic favoritism to Muslims than racial identity while the latter is less contingent in predicting specific negative stereotypes for Muslims.

Social Identity Theory: Why Group Identity Matters?

Ethnocentrism is a ubiquitous phenomenon in all social domains, even in artificial scenarios where ingroup affiliation is randomly assigned based on trivial grounds as Tajfel (1970)’s widely known minimal group experiment. To understand the universality of ingroup identification, Tajfel and his colleagues established social identity theory (Kam and Kinder 2010). Its core argument echoes with Taylor (1989)’s work on individual identity, contending that group membership provides a communal and dialectic base on which ingroup members satisfy their psychological predisposition in looking for self-esteem as individual homo socius.

Collective identity informs individuals’ behaviors in intergroup relationships (Tajfel 1981). On the one hand, identification with groups empowers people to control their own social life by providing “cognitive tools that segment, classify, and order the social environment, and thus enable the individual to undertake many forms of social action” (Tajfel and Turner 1979, p.40). On the other hand, the social classification between ingroups and outgroups cultivates a mentality connecting ingroup favoritism with outgroup derogation, which is the direct source for intergroup conflicts and negative stereotypes for outgroups (eg. Park et al. 2015). However, social identity theory does not assume intragroup variation on ingroup favoritism among individual members. According to Kam and Kinder (2010)’s classic research on ethnocentrism in the United States, the established social identity works “display little interest in differences
among individuals” but in reality “some people are very ethnocentric; many are mildly ethnocentric; and few are not ethnocentric at all” (p.24). Therefore, accounting interpersonal variation on ingroup love empowers social identity theory in understanding nativist sentiments and discrimination against immigrant minorities such as Muslims.

**Sociological Theory of Symbolic Boundaries: What Identities Matters**

Social exclusion of Muslims is nothing new to the American history (GhaneaBassiri 2010). In their widely cited article on anti-Muslim prejudices, Kalkan et al. (2009) attribute the lasting dislike to Muslims to ethnocentrism among “mainstream Americans” (p.848) who are, in their case, white Americans. Like other scholars who follow social identity theory, they fail to address the intragroup variance on ethnocentrism. However, their another finding is that they compared two patterns of otherization of Muslims among white Americans: one is racially based and another is culturally based. Analyzing data from 2004 National Election Studies with the method of factor analysis, they find that it was mainly prejudice against cultural outgroups that explains anti-Muslim sentiments. However, since recent studies on the anti-Muslim politics also find that racial resentment to Muslims has become the pivot components of anti-Muslim prejudice and behaviors (Calfano and Lajevardi 2019; Lajevardi 2017) that echoes with old-fashion Jim Crow racial resentment to blacks (Jamal 2009; Lajevardi 2017), it is not sure if Kalkan et al. (2009)’s finding still stands ten years later.

According to the literature in sociology of culture, group boundaries contains symbolic and cultural powers in creating and maintaining social order and stratification (Lamont et al. 2015). In addition, many sociologists find that majority groups utilize different symbolic tools to justify, maintain, and reproduce their dominant status and social powers (Bourdieu 1984; Collins 2019; DiMaggio and Mohr 1985). The sociological theory of symbolic boundaries is thus relevant to
understand intergroup dynamics between white Americans and Muslims because white Americans may identify themselves with not only the race group but also the cultural majority in the mainstream society.

**White Identity**

A burgeoning literature focusing on Islamophobia at the elite level contends that Muslims are new racial others to the post-9/11 America (eg. Bail 2012; Jamal 2008; Love 2019; Oskooii et al. 2019). White racism is the most studied topic in social sciences on race and ethnicity in the United States because race remains to be a dominant symbolic system in the society. Social identity theory indicates that strong ingroup identity triggers positive emotion for individual ingroup members. Therefore, to be a high white identifier one must feel good about his or her whiteness. However, it is not always easy to test the correlation between white racial consciousness and racist ideology empirically. One reason is that valid and robust measurements of white racial identity in pollster data was not available until recently (Jardina 2019). Another reason is there is a gap between average white Americans’ understanding of whiteness and social scientific conceptualization. Social scientists, especially sociologists, assume white identity as collective consciousness to maintain their racially-based privileges and status in society (eg. Bonilla-Silva 2001). Put it differently, it is racial oppression and exclusion rather than ingroup membership that defines whiteness. While some white Americans may possess the racial consciousness, most white Americans perceive their racial identity in terms of their white skin color. The gap is a major source for measurement error. It is because as the dominant race in the American society who experience little racial discrimination, a super majority of white Americans take their whiteness for granted so that they may not perform strong and visible awareness to maintain their racial status (Doane 1997). In addition, because of the invisibility of
their whiteness, Swim and Miller (1999) finds that most white Americans do not feel guilty collectively as whites for racial injustice and inequality in the society.

To fill the caveat, political scientist Ashley Jardina (2019) argues that white racial identity is latent and reactive and proposes a new scale to measure white racial identity to accordingly. The proposed measure takes both white awareness and perception of threat to their white dominance into account. Following social identity theory, her measure includes items such as salience of white identity, white pride, and white solidarity (p.58). Considering social dominance theory that majority consciousness is visible when threat from outgroup is salient (eg. Pratto et al. 1994), she also recommends items regarding perception of threat to whites such as reverse racism targeting white Americans (p.60). Multiple national representative survey such as YouGov and ANES have included certain items from the new white identity scale. Besides, recent studies in sociology and political science also support its validity and robustness, especially in understanding American public opinion in electoral politics (eg. Bonikowski et al. 2019; Perez and Deichert 2019).

National Identity

Another salient collective identity among white Americans in Muslim politics is American nationality. As many sociologists argue that white Americans have already normalized their whiteness with the American nationhood, American nationality for everyday Americans have been not always based on skin-color. Take the long history of social exclusion for Irish Catholic and Jewish Americans for example. In her elaboration on anti-Muslim rhetoric during the 2016 election, Braunstein (2019) finds that Republican candidates keep framing Muslims as “outsiders, enemies, and others” to the American nationhood to justify their anti-Muslim agenda. Ethnographic studies also contend that acculturation of Muslims is still a lingering social issue
with significant political influence that concerns many average Americans nowadays (Ahmed 2011; Skerry 2011). In addition, recent studies on Christian Nationalism (Whitehead et al. 2018; Whitehead and Perry, 2020) find that on the one hand Islamophobia is significantly predicted by Christian nationalism that advocate the American nation should follow Christian values; on the other hand, Christian nationalism is not limited to conservative white Americans. All these findings echo with Walzer (1990)’s observation that even exclusive nativist sentiments need to be justified in political and cultural arguments rather than racialized terms.

Unlike the case of white racial identity, there is an established tradition in social science on how to measure American national identity in pollster data. According to Bonikowski (2008)’s detailed review, there were 31 national representative pollster datasets including General Social Survey with either single items or high-quality scales measuring patriotism, national identity, and related nationalist attitudes. In general, three dimensions are necessary to measure national ingroup identity comprehensively: national awareness, national membership, and national pride or patriotism (eg. Bonikowski and DiMaggio 2016; Citrin et al. 1994; Citrin et al. 2001).

But the interpretation for national identity can be ambiguous if we focus on the strength of national attachment only. First, it is because Americans have multiple nationalist traditions in defining American nationality whereas the heterogeneity is hard to measure in the mass opinion data. Using LCA, Bonikowski and DiMaggio (2016) find there are four latent nationalist groups using GSS 2004 data, including two groups with high national identity—“ardent nationalists” and “creedal nationalists”, and two with relatively low national identity—“restrictive nationalists” and “the disengaged”. Since they are all latent groups, it is almost impossible to build indices to capture them independently. Second, pollster data always measure two national identities together with one item. Using 1992 National Election Studies data, for example, Citrin
et al. (1994) locate three pairs of nationalist traditions: cosmopolitanism versus nativism, individual liberalism versus ethnic pluralism, and ethnoculturalism versus multiculturalism. On the one hand, they are exclusive conceptually. On the other hand, each pair is designed to be measured together in a single scale. For example, in one item measuring the importance of speaking English to the American identity, available options range from “extremely important” to “not important at all”. Cirtin and his colleagues interpret extreme important as a sign for nativism and not important at all as one for completionism. Given the complexity in measuring nationality, this article only focuses on ethnocultural nationalism in order to have an interpretable and straightforward measure for national ingroup identity that shapes white Americans’ perception for Muslims. As opposed to other national identities, ethnocultural nationality is relatively more relevant in Muslim issues because it advocates that America should be ethnoculturally homogeneous nation so that outsiders who are foreign-born immigrants and follow different norms and values that are strange to the mainstream American society should be socially excluded. Accordingly, the opposite half on the ethnocultural nationality scale measures a different nationality that celebrate America’s multicultural nationality.

**Sociological Explanation for the Identity Grouping: How Identities Matter and Why?**

The next question is under what condition which identity matters in shaping a white American’s attitude toward Muslims. In this article I focus on four major indicators in drawing ingroup/outgroup boundaries in the literature on ethnocentrism (Kam and Kinder 2010): age, education, partisan affiliation, and religious belonging. First is age. For socially ascribed identities such as race and gender, age may be a good indicator for the salience of identity because group identification is positively associated with the longevity of group membership (Campbell et al. 1960). For example, Jardina (2019) finds that high white identifiers are in
average older than low white identifiers. Second is education. High education predicts high levels of intellectual sophistication, social and cultural capitals, and toleration and open-mindedness (Bobo and Licari 1989). In addition, because national identity requires more cultural capitals than racial identity (for example, it needs certain level of knowledge about the nation’s history), one can assume that better educated white Americans are less likely to appeal to racial identity in justifying their political opinion. I do not include gender because literature on anti-Muslim prejudice has shown there is not significant different across gender groups (Kalkan 2019).

Previous research also argues that party identification has impact on people’s ethnocentrism (Kam and Kinder 2010). However, recent literature on electoral politics does provide a straightforward guidance in understand white identity grouping before Muslim issues. On the one hand, Grossmann and Hopkins (2016) find that the Republican party has become a vehicle of new conservative movement that claims to protect the symbolic purity of American traditionalism, from which Muslims and many cultural minorities are excluded. One may argue that cultural identity may be more salient than racial identity for white Republicans. On the other hand, Barber and Pope (2019) observe that both loyalty to Trump and self-claimed conservatism have greater decisive impact on the Republican identification than de facto conservative ideologies. Given Trump symbols Islamophobia and racism in public discourse, one can also assume that racial identity matters more.

Religious identity also has uncertain effects on the identity grouping. Social scientists have repeatedly shown that white evangelicals are hard-core Trump loyalists (Froese et al. 2017; Pew 2016). To understand the political division between evangelicals and other religionists, Davidson and Pieper (2019) find that evangelicals and religious nones share opposite political habitus and
ideologies. Since the 1970s, the belief in a Christian American nation has been a core tenet among born-again evangelicals (Brint and Schroedel 2009). Although the cultural dominance of white evangelical is declining recently (Jones 2016), some sociologists argue that Trump’s election symbolize a new social movement of white Christian nativism to which Muslims, as well as Mexican immigrants, are two major others (Gorski 2019; Whitehead et al. 2018). It is thus not easily to assume that evangelical belonging is more associated with racial identity than national identity. Taken together, I propose four interdependent hypotheses as below:

*Hypothesis 1*: The strength of white racial identity is positively associated with the anti-Muslim attitudes;

*Hypothesis 2*: The strength of ethnocultural nationality is positively associated with the anti-Muslim attitudes;

*Hypothesis 3*: The strength of multicultural nationality is positively associated with the pro-Muslim attitudes;

*Hypothesis 4*: The probability of accepting racial identity as opposed to national identity is significantly associated with the strength of Republican identification, born-again Protestant belonging, and age, and education;

**Data**

To study the public opinion for Muslims in the Trump era, time contingency is the priority in data selection. Few national representative public opinion data collected since Trump’s election are publicly accessible except General Social Survey (GSS) and American National Election Studies (ANES). As opposed to GSS, ANES datasets provide more measurements for political beliefs, behaviors, belongings, and policy preferences. In addition, ANES is also known for many modules to study intergroup relations such as white identity battery and immigrant battery that are not available in GSS and other sources. Data for analysis in this project, therefore, come from two ANES datasets: ANES 2016 Time Series Post-Election and ANES 2018 Pilot Study.
The ANES 2016 Time Series dataset is a national representative panel data including a probability sample which was randomly taken from a of voting age American citizens. The data was released in May 2017 and collected in two waves. The pre-election wave was collected between September 7 and November 7, 2016 and the post-election wave was collected since November 9, 2016 till January 8, 2017. The data collection is of two modes: face to face interview and internet mode. Overall the sample includes 4271 observations who finished pre-election survey and 3649 finished both pre-election and post-election surveys. Because my targeted subsample is white Americans only and certain items for analysis are only available in the post-election survey, I draw a subsample accordingly that reduce the sample size to 2631 including non-Hispanic white respondents only. The ANES 2018 Pilot Study is a non-probability cross-sectional national representative survey conducted online using the YouGov panel during December 6 and December 19, 2018. The YouGov panel has a huge pool of over one million volunteer respondents who take survey for redeemable points for gift cards. The sample design is relatively simple. The sample weighting matches with both 2016 American Community Survey (ACS) sample by gender, age, race, and education by the U.S. Census Bureau and YouGov matching for 2016 presidential candidate choice, gender, age, race, and education. The original sample includes 2500 respondents who are U.S. citizens and at least 18 years old in total, with a subsample of 1854 non-Hispanic white observations.

With regard to the missing data, in ANES 2016 the missing data points only constitute less than eight percent of the whole sample for analysis and in ANES 2018, less than five percent. Therefore, I choose listwise-delete method to handle the missing data in order to reduce the computation burden without compromising the accuracy of estimation (Allison 2001; Schafer 1997).
Dependent Variables

Following previous research on anti-Muslim opinion (Kalkan et al. 2009) and ethnocentrism in public opinion (Kam and Kinder 2010) using ANES data, I choose three dependent variables for outgroup attitudes toward Muslims using ANES 2016: one is feeling thermometer to Muslims and another two are on negative stereotypes against Muslims: whether Muslims are violent or peaceful and patriotic or peaceful. As a pilot survey for the 2020 ANES Time-Series, ANES 2018 only have feeling thermometer. In the public opinion literature, feeling thermometer is a widely used to measure public evaluation for a given social group, public figure, and issue since the 1964 ANES survey (Zaller 1992; Lavrakas 2008). In addition, some psychological studies also compare feeling thermometers for different social groups to measure intergroup social distance (Bleich et al. 2018). The thermometer measure asks respondents to evaluate certain people or groups in single items willingly (Weisberg and Rusk 1970). In the ANES 2016 and 2018, respondents were asked “How do you rate Muslims” and to report their evaluation for Muslims on a scale from 0 to 100, where 0 means very cold feeling, 50 represents neutral attitudes, and 100 denotes very warm feeling. In one word, feeling thermometer provides a robust and sensitive enough measurement for public attitudes for Muslims.

Furthermore, unlike feeling thermometer, negative stereotypes measure specific cognitive perceptions for outgroups. As Allport (1954) suggests, stereotypes provide an efficient but also rough and unrefined way for individuals to process information and simplify social reality. In addition, stereotypes rely on moral and characteristic judgments so that they include both emotional and cognitive elements. In a nutshell, negative stereotypes to outgroups are also good measures for outgroup evaluation. Common stereotypes in pollster data include componence (Park et al. 2015), industriousness, trustworthiness (Brewer and Campbell 1976), violence and
disloyalty (Brewer 2007), and so on. With regard to the two Muslim stereotypes that Muslims are violent and disloyal, ANES 2016 asks respondent “where would you rate Muslims in general on this scale” and available options are from 1 “Peaceful” to 7 “Violent” and 1 “Patriotic” to 7 “Unpatriotic” respectively.

**Independent Variables**

In order to measure the two forms of collective identities, I build up two indices respectively. First, following Jardina (2019), I build a six-item white identity index with ANES 2016 and three-item one with ANES 2018. The 6 items from ANES 2016 includes three items available for white respondents only and three are available for the whole sample. The three white only items are: “How important is being White to your identity”, “How important is it that whites work together to change laws that are unfair to whites?”, “How likely is it that many whites are unable to find a job because employers are hiring minorities instead?” The original answer options ranges from 1 “extremely important/likely”, to 5, “not at all important/likely”. The rest three items are about whether one perceive whites are violent, hardworking, and being discriminated. For the first two stereotype items, answers range from 1-7 where 1 represents whites are peaceful/violent respectively. For the last item, it asks respondents “how much discrimination is there in the U.S against whites” and available options range from 1 “A great deal” to 5 “Not at all”. The three-item index using ANES 2018 only includes the first three white-only items (reversely coded to be consistent with ANES 2016). Finally, using the *alpha* syntax in STATA 16, I generate two white identity indices by taking the mean of the z-scores after the standardization of the three items and the scale is with a 0.66 Cronbach-α for the six-item index and 0.69 Cronbach-α for the three-item index. In general, lower score on each index represents
higher white racial identification in terms of white awareness, solidarity, perception of threat, and white favoritism.

Second, I build an ethnocultural nationalism index using six items from ANES 2016 as well. The first four items measure ethnocultural consciousness by asking respondents how important they think “to be truly American” needs “to have been born in U.S.”, “to have American Ancestry”, “to speak English”, and “to follow America’s customs/traditions” and options range from 1 “very important” to 4 “not important at all”; One item is about the salience of American identity and options range from 1 “extremely important” to 5 “not at all important”; additionally, one perception of threat item is also included which asks respondents if they agree that “America’s culture is generally harmed by immigrants” and answers range from 1 “Agree strongly” to 5 “disagree strongly”. I also use the alpha command in STATA 16 to generate a standardized index with a 0.81 Cronbach-α. In ANES 2018 the only corresponding item for me is one that measures respondents’ attitudes for cultural diversity as measurement for ethnocultural nationality sentiments. The ANES question asks respondents: “On balance, do you think having an increasing number of people of many different races, ethnic groups and nationalities in the United States makes this country a better place to live, a worse place to live, or does it make no difference?” and gives them options from 1 to 7 where 1 denotes a lot worse and 7, a lot better. To be consistent with the ANES 2016 index, I reversely rescale the range to -3 to 3 as well so that low score refers to high ethnocultural national identity.

Finally, with regard to predictors for the identity grouping, I use age, education, partisan affiliation, and born-again Protestant identity as four concomitant variables. There is little different between ANES 2016 and 2018 datasets. First, age is mean-centered to have a meaningful zero because the original age starts at 18. Second, I recode education by collapsing
“2-year college” and “some college” to some college and rescale the range from 1 to 5 to 0 to 4. Third, for the Republican identification, I rescale the range from 1 to 7 to -3 to 3 where -3 means “Strong Democrat”, 0 denotes “Independent”, and “3” represents “Strong Republican”. Last, I generate a born-again Protestant identity if respondents report “yes” to the item “Do you consider yourself to be ‘born again’?” and “Protestant” on “What is your present religion, if any?”. Table 1. presents the descriptive statistics.

[INSERT TABLE 1. HERE]

**Methodology**

This article argues that white Americans not only perform diverse strength of ingroup favoritism but also have two heterogeneous ingroup/outgroup boundaries—race and nationality in shaping their attitudes toward Muslims. In addition, following Edgell et al. (2019) and Bonikowski and DiMaggio (2016), identity grouping in pollster data is latent rather than manifested. Accordingly, rationale behind the selection of methodology is twofold. First, the proposed theoretical assumption suggests a conditional multilevel data structure of the attitudes for Muslims because different identity ingroups are responsive to ingroup identifications locally. Second, the identity grouping is associated with multidimensional social facts including age, education, partisan affiliation, and religious belonging. An appropriate method to test the four hypotheses, therefore, should be matching with the mixture data structure as well as account for the interdependence in between the four proposed hypotheses.

All things considered, I choose Finite Mixture Model (FMM) to test the four hypotheses simultaneously. FMM is sufficiently discussed and well-established in statistical literature (eg. Gordon and Smith 2004; Grün and Leisch 2007, 2008; Fruhwirth-Schnatter 2007). FMM suits the analysis well for two reasons. First, instead of building up global models that explain
variances among all observations as conventional regression modeling does, FMM provides a
more flexible and comprehensive parametric modeling approach by confating multilevel
modeling with latent class analysis. FMM assumes that each observation is consistent with one
of the M number of models to be tested so that observations are grouped by models. Therefore,
each model is locally applicable. Second, regarding the latent group prediction, FMM can also
include the probability model for grouping so that one can estimate which observations are
consistent with which models in particular (Arminger and Stein 1997; Imai and Tingley 2012).
Last, the probability model’s calculation is simultaneous with that for locally based models.

Formalization of FMM, therefore, includes two components: first, a latent variable \( Z_i \) is
necessary to predict by which theory observation \( i \) is explained because we have no prior
knowledge about the pairing between observation and theory; second, the model also needs to
have key independent variables derived from individual theories, therefore, the formal model for
FMM is as below (Fox 2015; Imai and Tingley 2012)

\[
Y_i | X_i, Z_i \sim f(Y_i | X_i, \theta_i) \quad (1)
\]
where \( \theta_i \) denotes to a vector of coefficients for each variable and \( i \) ranges from 1 to N. Due to
the mixture data structure, traditional OLS estimation no longer fits. The appropriate algorism
should be Maximum Likelihood given the large-N sample. In addition, to get the maximum
likelihood estimate, the algorithm is Expectation-Maximization (EM), a two-step interactive
algorithm that include exception and maximum steps (Dempster et al. 1997). Assuming the
independence among individual observations in given sample, the likelihood estimation algorism
is as below:

\[
L_{obs}(\Theta, \pi | \{X_i, Y_i\}_{i=1}^N) = \prod_{i=1}^N \pi_i f_i(Y_i | X_i, \theta_m) \quad (2)
\]
where \( \pi_i \) is the probability for each observation \( i \) when \( Z_i = m \), \( \Theta \) is a set for all model parameters and \( \Pi \) is the combination of all probabilities for all models. In the case of this research, we also need to construct a concomitant probability model for \( \pi_i \) that is dependent on the grouping variables. Given we only have two identity groups in theory, the probability model is as below:

\[
\Pr(Z_i = m | W_i) = \pi_m(W_i, \psi_i) \tag{3}
\]

where \( W_i \) = a set of grouping variables and \( \psi_i \) is the vector of parameter for the variables.

### Results

In this section, I apply the proposed FMM approach to examine the relationship between attitudes for Muslims and ingroup identification among average white Americans. Since dependent variables are continuous and we only have two theories, for hypothesis 1, 2, and 3 I construct two Gaussian models and for the hypothesis 4, a probability model and the algorism I choose is logistic regression because of its binary outcome. Following lists the three models:

For hypothesis 1: \( f(Y_i | X_i) = \beta_0 + \beta_1 \text{ white identification}_i \)

For hypothesis 2 and 3: \( f(Y_i | X_i) = \beta_0 + \beta_1 \text{ ethnocultural national identity}_i \)

For hypothesis 4: \( \pi_w(W_i) = \logit^{-1}(\beta_0 + \beta_j \text{ identity grouping variables}_j) \)

where \( w \) in model 3 refers to white racial identity, \( j \) represents given variables and \( i \) denotes to particular observations.

I estimate this model using a R package, `flexmix` (Leisch 2004), in a similar fashion with Imai and Tingley (2012). As STATA 16 also include a package, `fmm`, to do FMM modeling, I find it less flexible and not as transparent on presenting the calculation results for individual steps as the R package. Table 2 includes FMM estimate results on feeling thermometer to Muslims in ANES 2016 and 2018 independently. First, local modeling results based on ANES
2016 matches expectations of hypothesis 1 and 2. For racially identified white Americans, one standard deviation increases in their white identification significantly decreases 18.25 units in their warm perception for Muslims while for ethnocultural identifiers, one unit increase in their ethnocultural nationality decreases 15.4 units. Second, the probability modeling results partially support hypothesis 4 that only education and partisan affiliation matter. For the partisan identity, one unit increase in the strength of Republican identification increases the odds ratio for belong to the racial identity group as opposed to nationality group by 0.87. For education, one unit increase in the received formal education decrease the odds ratio by 0.32. Similar patterns exist in results on ANES 2018 with one exception. The coefficient estimate for born-again Christian identity is significant in the probability model. It interprets that being a born-again Christian increases the odds ratio of being a racial identifier by 1.83.

Table 2 also sheds light on the hypothesis 3. Intercept coefficient estimates in Model 1 and 2 refer to the conditional means of the feeling thermometer in individual local models. Combining them with the coefficient estimates for independent variables, one can locate application range of each model. The conditional means of feeling thermometer for the ethnocultural identity model is 58.44 using ANES 2016 and 50.73 using ANES 2018, as opposed to the conditional means for the racial identity model 35.27 and 34.96 respectively. It means that ethnocultural identity model have more explanatory power among those who are pro-Muslims than the racial identity model.

[INSERT TABLE 2 HERE]

Table 3 presents results on the two negative stereotypes against Muslims: violence and disloyalty using the ANES 2016 subsample. Like local modeling results in Table 2, both white racial identity and ethnocultural nationality predict anti-Muslim opinion significantly which
support hypothesis 1 and 2. As to the probability modeling results, the two stereotypes show different patterns. Age does not matter in predicting the identity grouping probabilities in the case of Muslim violence stereotype but matter in the other case. Surprisingly, born-again Christian identity are not significant in both cases. With regard to the hypothesis 3, Table 3 also show the opposite patterns with these in Table 2 that marginal effects of explanatory power of the ethnocultural nationality model decrease drastically to understand positive perceptions for Muslims in both cases in Table 3.

[INSERT TABLE 3 HERE]

Figure 2 includes four histogram plots that straightforwardly visualize how the samples for analysis are clustered according to posterior probability estimations for the identity grouping, that each observation is consistent with each identity. As in Table 2 and 3, Figure 2 partially support hypothesis 3 with regard to the prediction of pro-Muslim attitudes. The top two plots on feeling thermometer for Muslims show that pro-Muslim white Americans are less likely to be racial identifiers than to be nationality identifiers while most anti-Muslim whites are racial identifiers. However, the bottom two plots show the opposite pattern. For Americans who perceive Muslims are less violent and disloyal, their white identity is at least no less salient than their national identity. And for those who have negative perceptions for Muslims, their racial identity is far less important than the ethnocultural identity. It is also worth noting that plots in Figure 2 also indicate that it is hard to tell which identity is more salient for those who are neither pro-Muslim nor anti-Muslim white Americans. Partly, the clustering visualization results are resonating with findings by Kalkan et al. (2009) that ethnocentrism against cultural outsiders remains to be a significant indicator in interpreting anti-Muslim stereotypes. Besides, all plotting
results match Jardina (2019)’s observation that racially discriminatory white Americans constitute only a small section in the white population.

In addition, inconsistency between results in Table 2 and 3 implies that the conventional wisdom on the racialization of Muslims in the American public discourse is not a simple story because national identity is still contingent and salient common in connective with negative stereotypes for Muslims. Realistic conflict theory (Brewer 1999; Ciftci 2002) suggests that intergroup conflicts are major reasons for strong ingroup attachments. Certainly, in the case of Muslim attitudes the perceived threat to Muslims triggers more nationalist concern among white Americans than racist sentiments. Although sociologists of race and ethnicity may argue that otherizing Muslims as national outsiders still indicated structured racism such as color-blind racism (Bonilla-Silva 2001), it is also hard for empirical testing using national representative data, which is, therefore, beyond the perceptive of this article.

Conclusion and Discussion

Building on the social identity theory in social and political psychology and the theory of symbolic boundaries in sociology of culture, the first contribution of this thesis is to provide an interdisciplinary framework in understanding mass opinion on Muslims and intergroup dynamics between white Americans and Muslims, which is of undeniable political consequences in the contemporary electoral politics. The second contribution is about methodology. With FMM, this article provides a more balanced and comprehensive way to model attitudes toward Muslims. As opposed to the conventional methods in the related literature, FMM has two advantages methodologically. First, it prevents the bias of “groupism” derived from traditional cluster analysis that takes little intragroup variation into account. Second, it prevents the ignorance of
intergroup variance that conventional regression models fail to address. For example, this article finds that although low racial identity may also significantly predict pro-Muslim attitudes, it only explains a super minority of pro-Muslim white population, which significantly limit the generalization ability if we only exam the association between white identity and attitudes for Muslims with a global parametric model only. Findings in this study also echo with the social identity theory that identities provide solid moral and psychological foundation for individual ingroup members (Tajfel 1978). If social reality is constructed as Berger (1967) argues, of course different social identities will generate different sociological imagination and perceptions about the surrounding social facts.

Limits in this study is as obvious as its contributions. The first one is theoretical. Because this article focuses on the individual level in the American society, it fails to address many important social systems and institutions at macrolevel such as social stratification based on race and religion. The second one is methodological. Although this article proposes a new modeling method for empirical testing intergroup opinion, it does not necessary produce unbiased and more accurate estimation for understanding how white Americans justify their sentiments for Muslims because secondary data like ANES that are not particularly designed for the research. As the result, it constrains the range of generality of the findings. Therefore, although the theory in this article makes a causal argument that different ingroup love causes different outgroup attitudes, because the data I use are cross-sectional essentially, I cannot make strong argument on the validity of the causation claims. In a nutshell, although my results provide an innovative way for understanding intergroup dynamics using pollster data, the listed flaws for future research to address.
<table>
<thead>
<tr>
<th>DVs</th>
<th>ANES 2016 (N=2631)</th>
<th></th>
<th>ANES 2018 (N=1854)</th>
<th></th>
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<td>SD</td>
<td>N</td>
<td>Mean/Percent</td>
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<td>1.68</td>
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<tr>
<td>Whites Should Work Together</td>
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<td>Whites Can’t Get Job Because of Minorites</td>
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<td></td>
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<td>To Have American Ancestry</td>
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<td>To Follow American Customs/Traditions</td>
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<td>2631</td>
<td>19.69%</td>
</tr>
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**Notes:** 1. Age in this table is not mean-centered yet so it starts from 18.
## Table 2. Parameter Estimates and Their Standard Errors from the Finite Mixture Model on Feeling Thermometer to Muslims\(^1\)

<table>
<thead>
<tr>
<th></th>
<th>ANES 2016 (N=2468)</th>
<th>S.E.</th>
<th>ANES 2018 (N=1808)</th>
<th>S.E.</th>
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</tr>
<tr>
<td>Intercept</td>
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<td>2.02</td>
<td>34.96***</td>
<td>3.00</td>
</tr>
<tr>
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<td>18.25***</td>
<td>2.04</td>
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<td>1.56</td>
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<tr>
<td><strong>Model 2</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.76</td>
<td>50.73***</td>
<td>1.56</td>
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<tr>
<td>Ethnocultural Nationality</td>
<td>15.40***</td>
<td>0.78</td>
<td>10.61***</td>
<td>0.67</td>
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<tr>
<td><strong>Model 3 (Logistic)</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
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<td>0.36</td>
<td>0.45</td>
<td>0.44</td>
</tr>
<tr>
<td>Age(^2)</td>
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<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Education</td>
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<td>1.04**</td>
<td>0.33</td>
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<td>0.63</td>
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</tbody>
</table>

**Notes:** 1. All models are unweighted; 2. Age is mean-centered; 3. \(<0.05, \text{**}<0.01, \text{***}<0.001\)
### Table 3. Parameter Estimates and Their Standard Errors from the Finite Mixture Model on Negative Stereotypes for Muslims

<table>
<thead>
<tr>
<th></th>
<th>Muslims are Violent (N=2468)</th>
<th></th>
<th>Muslims are Disloyal (N=2468)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>Coef.</td>
<td>S.E.</td>
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<td></td>
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</tr>
<tr>
<td>Intercept</td>
<td>3.04***</td>
<td>0.07</td>
<td>3.00***</td>
<td>0.08</td>
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<tr>
<td>White Racial Identity</td>
<td>0.98***</td>
<td>0.10</td>
<td>0.58**</td>
<td>0.12</td>
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<td><strong>Model 2</strong></td>
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</tr>
<tr>
<td>Intercept</td>
<td>4.45***</td>
<td>0.06</td>
<td>4.97***</td>
<td>0.06</td>
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<td>0.06</td>
<td>-1.27***</td>
<td>0.06</td>
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<tr>
<td><strong>Model 3 (Logistic)</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
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<td>0.29</td>
<td>-1.26***</td>
<td>0.24</td>
</tr>
<tr>
<td>Age</td>
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<td>0.004</td>
<td>0.01*</td>
<td>0.004</td>
</tr>
<tr>
<td>Education</td>
<td>0.19*</td>
<td>0.09</td>
<td>0.22**</td>
<td>0.08</td>
</tr>
<tr>
<td>Partisan Affiliation</td>
<td>-0.35***</td>
<td>0.05</td>
<td>-0.36***</td>
<td>0.04</td>
</tr>
<tr>
<td>Born-Again Christian</td>
<td>-0.27</td>
<td>0.20</td>
<td>-0.28</td>
<td>0.17</td>
</tr>
</tbody>
</table>

**Correlation Coefficients**: 0.58 0.69

**Notes**: 1. All models are unweighted; 2. Age is mean-centered; *<0.05, **<0.01, ***<0.001
Figure 1. Histogram Plots for Identity Group Clustering

- **Feeling Thermometer for Muslims (ANES 2016)**
  - Count
  - Identity Grouping: National Identity, White Identity

- **Feeling Thermometer for Muslims (ANES 2018)**
  - Count
  - Identity Grouping: National Identity, Racial Identity

- **Muslims Violence (ANES 2016)**
  - Count
  - Identity Grouping: National Identity, Racial Identity

- **Muslim Disloyalty (ANES 2018)**
  - Count
  - Identity Grouping: National Identity, Racial Identity
Reference


