Incorporating Class Identities in Intersectional Quantitative Political Attitudes Research

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Abstract

Class is a known determinant of political attitudes and behaviors, yet it is often overlooked in quantitative intersectional research due to challenges in operationalization. This oversight stems from two main issues: inconsistent definitions of class in survey instruments and sparse data. In this paper, we propose defining class as a context-dependent latent variable, estimated through mixture models. Traditional methods typically isolate a single socioeconomic status (SES) or subjective social status (SSS) measure as an independent variable, but mixture models integrate multiple facets of SES and SSS, identifying the component of class most pertinent the political outcome being studied. Coupled with intersectional approaches like Bayesian Multilevel Models, this framework allows for a more comprehensive representation of relevant identities in data sparse environments. We demonstrate our method with two empirical examples using 2020 American National Election Studies data, showing that the significance of SES or SSS elements varies depending on the outcome. Our results also indicate that not accounting for class in intersectional modeling leads to biased estimates. We recommend a more detailed approach such as mixture models to asses class alongside race and gender in quantitative analyses based on our findings.

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1 Introduction

Class is a critical component of social identity, and is deeply intertwined with race and gender in shaping political attitudes and behaviors according to intersectionality research (Crenshaw 1989). Despite significant strides in integrating intersectionality into quantitative research, class often remains inadequately addressed. The complexity of class as an identity—defined through socioeconomic status (SES) or subjective social status (SSS)—presents unique challenges for quantitative researchers aiming to capture its nuanced effects alongside race and gender. Unlike qualitative approaches, which can address the intersecting layers of identity in depth, quantitative work must deal with smaller sample sizes as more and more identity groups are added. It must also grapple with how to choose which measure of class will be used as an independent variable alongside race and gender. This often means class is omitted from analyses. This gap leaves researchers without robust tools to address class within an intersectional framework, risking an incomplete understanding of how these identities collectively shape outcomes.

However, the prevalence of quantitative intersectionality, both through modeling tactics and data generation, is increasing with data availability and awareness of interconnected identities (Barreto et al. 2018; Spry 2018; Much 2022; Block, Golder and Golder 2023). We aim to enter the literature alongside other scholars who are seeking to do better quantitative intersectional research, leveraging the lessons from qualitative and interpretive scholars who have long articulated the importance of class (Collective 1974). Class is also widely recognized as an important predictor of political attitudes and behaviors (Huckfeldt 1984; Jackman and Jackman 1983; Leighley and Nagler 1992).

We define class as a higher-order construct representing an individual or group's relative position in an economic-social-cultural hierarchy (Diemer et al. 2013). The concept has been measured in a myriad of ways often utilizing socioeconomic status (SES) and/or subjective social status (SSS) (Diemer et al. 2013). Most often SES is used to determine class through material circumstances by measures of occupation, income, and education

(Leighley and Nagler 1992; Goldthorpe and McKnight 2004; Leighley and Nagler 2007; Bartels 2016). Scholars that focus on SSS tend to understand it from the lens of identity and self-awareness/placement into one of the cultural definitions of class (Jackman and Jackman 1973, 1983). While class's importance to political life is ubiquitous, it remains unclear whether or not SES or SSS should be used to measure the concept. Additionally, little work has been done to prioritize methods that capture both SES and SSS in a parsimonious way.

The literature on how to measure class is reshaped by the notion of intersectionality (Crenshaw 1989, 1991; Collins 1999). Intersectionality, as articulated by Kimberle Crenshaw in 1989, attempts to show how racism, sexism, and classicism combine to generate unique lived experiences for individuals living at the intersection of marginalized groups. Originally, this was used to draw insight into how working-class Black women were overlooked in the United States legal system (Crenshaw 1989, 1991). This work was expanded to show the ways that race, sex, and class as identities shaped sociological and political phenomena (McCall 2005; Hancock 2007*b*; Weldon 2006; Simien 2007). It provides a framework for understanding lived experiences with oppressive structural power dynamics (racism, classicism, and sexism) along with a framework to articulate the nature of social identities on the individual level (Dhamoon 2011; Yuval-Davis 2015). An intersectional lens demands that class be studied in tandem with race and gender as they are multiply constituted social identities.

Our discussion is necessary, as broadly, when quantitative scholars attempt to incorporate the theory in their work from a modeling standpoint, class is often overlooked. We posit that there are two main reasons for this oversight. The first is that class can be measured in many ways within survey responses as opposed to its alternatives, race, and gender. A scholar can either use SES or SSS, but the measurement tactics will vary across different datasets. Some of the measures of SSS on their own provide skewed information about material circumstances, and different measures of SES exist across datasets.[1]

Secondly, intersectional research is always challenged with the sparsity of data and incorporating class further subsets already small datasets for racial and ethnic minorities of different genders (Junn and Masuoka 2008; Frasure-Yokley 2018; Barreto et al. 2018; Much 2022). When a scholar chooses the intersectional research paradigm and wants to include a SSS measure, it would further split the groups into the data making traditional regression tactics less suitable.

In order to overcome these barriers, we introduce the use of mixture models to serve as a wrapper around existing models as a method for including class. These models allow for flexibility in specifying the functional form of intersectionality (ex: interaction terms or multilevel models), while also providing a mechanism for determining class membership using both SSS and SES measures. These models are a form of clustering analysis that generates the probability of belonging to a group based on relevant factors and then uses that information to classify groups. This grouping can then be used to fit a multilevel model for each class identity.

In practice, this means feeding in all the relevant class measures (income, education, occupation, subjective social status, etc.) into the mixture model, which then probabilistically assigns individuals to latent class categories based on these indicators. The model simultaneously estimates the relationship between these latent class memberships and the outcome of interest (think of a relevant political outcome like vote choice). This approach allows for a more nuanced and data-driven categorization of social class that can capture complex, multidimensional aspects of socioeconomic status, rather than relying on predetermined cutoffs or single indicators.

They are designed specifically to help researchers better understand data that has group-based differences that are latent, which are concepts difficult to directly measure based on the data at hand. We argue that class fits this criteria, with no one measure being the ideal for holistically measuring class. The use of mixture models in order to uncover the distribution of groups has been used in a multitude of fields within the social sciences, as well as biological and physical sciences (McLachlan and Basford 1988; McLachlan, Lee and Rathnayake 2019). Since we can also assume that group membership is dependent on the covariates themselves, we can also uncover an equation that represents the probability of belonging to one group or the other. This enables the model to serve the dual purpose of generating estimates for prediction as well as estimates for class membership based on certain contexts. The latter is important for understanding which elements of class are salient for various outcomes—or rather represents which survey questions can appropriately be used as proxies for class for specific outcomes.

Intuitively, this approach can be connected to the fuzzy logic path of intersectionality suggested by Hancock (2007*b*). In it, Hancock claims that an appropriate way to incorporate the in-group heterogeneity of individuals resulting from intersectionality is to view identities as percentages rather than binary. This is because the identities of individuals may affect them differently due to a multitude of contextual factors—for instance, the strength of racial identity can be changed due to the racial composition of the neighborhood, or the degree to which a policy is racialized. By applying a class-based mixture model, we produce a probability of being in each class for each individual. In other words, mixture models are often imagined as a probability distribution between two discrete groups. Mathematically this is the same as saying that they are a percentage of each group. By generating estimates for individuals using the combinations of the groups represented by the probabilities, we generate a class scale. This also enables class to be defined within the context of the outcome being studied. Assuming the concept is fluid and context-dependent helps us to understand why previous research has had such a hard time pinning down the operationalization of class.

This work is situated within the intersectional research paradigm, which posits race, gender, and class are interlocked concepts and their interrelated nature should be prioritized in the research design phase (Hancock 2007*b*). We believe it is important to note that this methodology is not meant to be used to test the existence of intersectionality within separate research projects. This paper is written with the understanding that intersectionality is viewed as a paradigm or lens that informs a way of thinking about social science problems (Simien 2007; Hancock 2007*b*). That is, regardless of the size of the effects of the intersection of race, gender, and class on outcomes, their inclusion is necessary in order for models to be consistent with the lived experiences of individuals. The inclusion of class is a step toward moving models further toward reality. While using mixture models enables us to uncover elements of class that are more salient to specific outcomes, the existence of intersectionality and the importance of all three aspects are not questioned.

To illustrate the empirical applications of our approach, we apply it to two outcomes from the American National Election Study survey from 2020—thermometer scores on undocumented immigrants (Immigrant Attitudes, IA) and on the Black Lives Matter movement (BLM). These two outcomes were chosen as immigration attitudes are said to vary by class (Berg 2010; McDermott, Knowles and Richeson 2019). We additionally include Black Lives Matter attitudes as they are racially stratified and often have gender differences, therefore it is a reasonable area to introduce a class-based investigation (Azevedo, Marques and Micheli 2022). We find that, as expected, class memberships are correlated between outcomes, but not identical. For the two outcomes, we have that the salient version of class is slightly different. This approach additionally lets us understand the factors that lead to thermometer scores for each of these topics better.

In this paper, we begin with a review of current methods of quantifying class and their limitations. We then introduce mixture models and how they have the potential to help scholars incorporate a more complete understanding of class into their work. We demonstrate the strengths of this approach through a thorough study of how individuals view undocumented immigrants and the Black Lives Matter movement. We conclude that class is, in fact, dependent on the situation, supporting our approach.

2 Approaches to Class as an Identity and Predictor

We understand class as a higher-order construct representing an individual or group's relative position in an economic-social-cultural hierarchy (Diemer et al. 2013). This reflects both socioeconomic status and subjective social status, or in other words, accounts for both the material circumstances of a person as well as their group contexts and social status based on networks and cultural norms. We take this approach to provide a holistic view of class that can then be combined with racial and gender identities to garner a full look at structural inequality and lived experience (Crenshaw 1989; Yuval-Davis 2015). Conventional wisdom has measures of SES represented by a combination of factors such as education, occupation, and family income levels (Leighley and Nagler 1992; Diemer et al. 2013). We understand SSS as defined by Jackman and Jackman (1973) with four different categories for respondents to self-ascribe; to low-income, working-class, middle-class, upper-class. Additionally, class is relegated to being a control variable, rather than a key variable of interest (Diemer et al. 2013). This is problematic as it will lead to less biased estimates, but does not investigate whether or not there is a mediating or moderation relationship between class and the variable of interest. In the research design phase, this also poses problems because there is often a superficial level of attention given to class, despite the fact that it can drastically change the evidence garnered from the research based on the way it is operationalized (Leighley and Nagler 1992, 2007).

We recognize that much work has been done to differentiate class and social status, our aim in this paper is not to enter into this conversation. Rather, our work is meant to be a broad, contemporary quantitative approach to operationalizing the spectrum of economic experiences and identities; therefore, approaching these concepts under the umbrella of class allows us to achieve this goal with more theoretical parsimony. The flexibility of our model allows us to combine these measures, and additionally accommodate other measures that we believe to be related to class such as student loans, employment status, union affiliation, and having money in the stock market.

2.1 Socioeconomic Status

Within Political Science, many have argued for the use of income as the best measure of SES in terms of predicting voting (Leighley and Nagler 1992). They argue when class is measured in terms of something like education or occupation, it seems as though the higher the class the more likely an individual is to vote. This work came on the heels of work such as Burnham (1982); Burnham and Reichly (1987); Bennett (1991) which showed a decrease in turnout from lower-class individuals. They argued if this finding were correct, it would lead to a further elite class bias in public policy. Leighley and Nagler (1992) show instead that this finding is driven by the operationalization of class rather than class itself. When measuring SES with income rather than education, turnout by class appeared stable. In this paper, we leverage the lessons learned from this piece—the influence of class is susceptible to variance based on the way it is operationalized and care needs to be taken to properly articulate its contours.

Currently, the most common approach of other scholars is to use measures of occupational prestige, or a composite measurement of these SES categories along with occupation to articulate class (Goldthorpe and McKnight 2004). These measures take into account not only the occupation but also the benefits associated with the job like income security, earnings stability, and long-term prospects. The groups in the schema are as follows: higher and lower professional and managerial classes, the "routine nonmanual class" (typically lower-grade clerical "white-collar ," the "petty bourgeoisie" (small employers and self-employed), and the "working class" (foremen and technicians, skilled, semi-, and unskilled manual workers) (Evans and Opacic 2022)." Other scholars in psychology focus on incorporating prestige and resources more robustly, which means creating an socioeconomic index (SEI) that incorporates many facets of class.

Due to the nature of the datasets we are using, we are unable to access all previously mentioned scales or indexes, we are able to accommodate occupation, income, and education as conventional measures. We additionally provide other objective measures such as student loans, money in the stock market, and being in a union. However, we are confident that whichever measures are present in the scale can be accommodated by our method of class-based mixture modeling. This paper demonstrates in particular how to use the measurements featured in one of the most widely used Political Science datasets, the American National Election Study (ANES) to fit a mixture model.

2.2 Subjective Social Status

Class consciousness and class as a social identity emerged with the work of scholars like Karl Marx who based his theories on where people were situated in the means of production (Evans and Opacic 2022). This literature is related, but distinct from measuring social status according to Weber (Weber 1968). According to Weber, social status is based on social hierarchies and cultural perceptions, while class is based on objective material realities (Chan and Goldthorpe 2007). Our work is situated with the behavioralist researchers that operationalize class through SSS survey measures as a means to predict political outcomes. Jackman and Jackman (1973, 1983) showed that class identity was a combination of the material as well as social patterns of contact that change the relationship between objective measures of SES and subjective measures and that these relationships predict relevant political outcomes. Jackman and Jackman (1973) showed that the boundaries of these class identities and patterns of contact then led to distinct out-group views and the development of class-based identity using the work of (Tajfel 1969). Our work recognizes the importance of the origins of Marx and Weber but broadly situates class as in part a social identity along the lines of Jackman and Jackman (1973, 1983) where there is a psychological attachment to the self-identified group.

The work by Jackman and Jackman (1973, 1983) led to a boom in research on the link between subjective social status and socioeconomic status. Scholars such as Evans and Kelley (2004); Sosnaud, Brady and Frenk (2013) show that the vast majority of people identify as being in the middle class despite their material realities showing otherwise.

In the American context, Sosnaud, Brady and Frenk (2013) specifically showed that this divergence in subjective and objective class varied by race and education. This research has shown a distortion between subjective measures and objective measures that could be rooted in desires to distance from segments of society such as the upper or lower class which have certain cultural connotations (Bourdieu 1984; Lamont 2002; Stuber 2006). Our modeling approach recognizes both the strength and weaknesses of SSS by accommodating the measure along with the material context.

2.3 Class and Intersectionality

Across the disputes on how to operationalize class from Marx, Weber, and beyond, intersectionality provides a method for articulating these stratifications in social positions that recognizes that class does not exist in a vacuum away from other structural oppressions (Yuval-Davis 2015). The power of intersectionality, broadly, is that it does not limit understandings of stratification to one axis of difference like class on its own, but incorporates power differentials along race and gender as multiply constituted identities (Crenshaw 1989; McCall 2005; Hancock 2007*b*; Yuval-Davis 2015). Lived experience in this context is thus a combination of material and cultural economic realities, racial and ethnic dynamics, and gender structures. Yuval-Davis (2015) argues that situated intersectionality specifically provides a comprehensive manner to studying social inequalities and class in a way that is ignored if one takes the traditional approach of Weber or Marx. We specifically define class as both a combination of SSS and SES in mixture modeling, then use an intersectional research paradigm approach to including race and gender as well (Hancock 2007*b*, 2019; Much 2022). This methodology allows the researcher to incorporate race, gender, and class quantitatively.

3 Class as a Latent Variable

Historical work has emphasized the importance of care in the way class is operationalized. While there is little doubt that class membership holds importance in a multitude of areas, findings are often difficult to accept when they can be nullified by an equally reasonable definition of class. Thus, in this paper, we recommend viewing class as a latent variable. In addition, rather than locking down a single definition of class, we argue that it is situationally dependent. An individual's class identity is dependent on a variety of factors, and in different contexts, different aspects of that identity may become more salient.

There exist many methods for uncovering latent classes, some of the most popular unsupervised methods include item response theory models (Lord 1980; Osteen 2010) , k-means (MacQueen 1967), k-modes (Huang 1997), principal component analysis (Pearson 1901) and factor analysis. In the case of class, model-based approaches take advantage of the structure of responses in a way that other, fully unsupervised methods, fail to. Individuals of different classes have different opinions, habits, and views on life, not just different characteristics. This variety in outcomes, not just observable characteristics, leads us to choose a model-based approach rather than other latent variable models such as item response models or clustering which are purely unsupervised to uncover class membership. In jointly estimating the latent class with the response variable, the coherence of the response is taken in addition to the clustering of the class-related covariates. Specifically, we are not interested simply in the clusters of class-related responses, but how they interact with the response variable in question.

Furthermore, among model-based approaches, we choose mixture models due to the "soft" classification it provides. That is, for each respondent, the mixture model provides a probability of being in each group. Rather than assigning each respondent to a class, we generate a class spectrum. This conceptualization is consistent with work done within the intersectionality field which suggests the most appropriate characterization for identity is continuous rather than binary (Hancock 2007*a*).

In our approach, we assume that there are two class-based groups for ease of understanding and parsimony. Additionally, since we are not assigning discrete class assignments, but probability measures, two classes still allows for a great deal of variability. However, this assumption is without loss of generality and the number of classes can easily be expanded within the model to large groups if needed. A large contribution of this approach is its flexibility and responsiveness to the needs of the researcher. We claim that by using a mixture model, dependent on variables related to class, we achieve the dual goal of including class in addition to uncovering, for specific outcomes, how various factors contribute to the understanding of class. Given any models for outcomes, a mixture model wrapper can be included to integrate class in the analysis.

3.1 Mixture Model Description

For respondents $i \in \mathcal{I}$, take y_i to be the outcome of interest. We claim there is an underlying latent class variable denoted as $\kappa_i \in \{1, 2\}$. These correspond to class memberships that are not explicitly observable.

Assuming κ_i, the expectation of the response variable can be expressed as:

$$\mathbb{E}[y_i] = \sum_{j \in \mathcal{J}} \pi_j f_{j,i} \tag{1}$$

where $\pi_j = Pr(\kappa_i = j)$ is the probability that individual i belongs to class j and $f_{j,i}$ is the expected outcome for individual i assuming they belong to class j.

In order to extricate respondent class and generate appropriate estimations of the outcome, we split the variables into two groups: one which determines class membership (class-determining variables) and the other which determines outcomes dependent on class (outcome-determining variables). While both groups of variables contribute to the overall outcome, the class-determining variables are not found in the outcome regression. The covariates for respondent i are thus written as (c_i, x_i) where $c_i = (1, c_{i,1}, c_{i,2}, ...)$ are the class-determining variables and $x_i = (1, x_{i,1}, x_{i,2}, ...)$ are the outcome-determining variables. Equation (1) can thus be re-written with our definitions as:

$$\mathbb{E}[y_i|c_i, x_i] = \sum_{j\in\mathcal{J}} \pi_j(\alpha c_i) f_{i,j}(\beta_j x_i). \tag{2}$$

Without loss of generality, we assume that the class function is defined by a logit link function. This can be replaced by any general linear model that maps the covariate space to the $[0, 1]$ interval. For the logit link function, we have that:

$$\log\left(\frac{\pi_1(c_i)}{1-\pi_1(c_i)}\right) = \alpha c_i. \tag{3}$$

The functional form of the class-group outcome is exogenous to the model description. The flexibility of this approach allows users to choose the class-group model they feel best represents their outcome. The outcome equations can have any form the researcher desires, so long as the equation

$$\mathbb{E}[y_i|c_i, x_i, \kappa_i = j] = f_{i,j}(\beta_j x_i) \tag{4}$$

holds. There is no restriction on the relation between $f_{i,1}$ and $f_{i,2}$, they can be different or the same, although for the case of simplicity in our examples we will have them maintain the same functional form as each other.

3.2 Empirical approach

In this section we discuss methods for fitting mixture models as well as tests to ensure robustness of solutions. This is meant to aid in the use of the method for future research. Due to the nature of mixture models, we suggest an empirical Bayes approach to fitting the model. Empirical Bayes is a tactic in which results from similar models are used in order to aid in the solving of a more complicated model.

When solving mixture models using Monte Carlo solvers, the results are more robust and solutions converge faster if weakly informative priors are supplied. It can safely be assumed that class is a clustering of various economic and social dimensions (Diemer et al. 2013). Thus, in order to provide the mixture model with an appropriate prior we recommend using a completely unsupervised clustering method on the relevant covariates as an initial guess. Specifically, we suggest k-modes, an extension of k-means which extends its use to categorical data (Huang 1997; MacQueen 1967). With the specification that $k = 2$, this assigns a group membership, g_i, of 1 or 2 to each respondent.

Once initial clusters have been uncovered, we fit a logisitic regression to the class-membership variables with the unsupervised membership values as the outcome. This takes the form:

$$Pr(g_i|c_i) = \frac{1}{1 + e^{-\tilde{\alpha} c_i}}. \tag{5}$$

The estimates $\tilde{\alpha}$, with their standard errors, serve as the priors for the class membership. The next step is to estimate probabilities of class membership given the regression results. At this point, the respondents can be split into two groups based on estimated probabilities, for instance those for whom the probability of being in a group is greater than 50%.

With these new groups, a simple regression can be run of the form:

$$y_i = f_j(\tilde{\beta}_j x_i). \tag{6}$$

The estimates for $\tilde{\beta}_j$ can then be used as the priors for the group-level coefficients β_j. With these priors in hand, the researcher is prepared to solve for the full model using Markov Chain Monte Carlo techniques.

Generally, we recommend including the exact estimates (if not shrinking the priors) in order to dial in relevant parameters for solving such as target average acceptance probability (adapt_delta in stan), max binary tree size for the NUTS algorithm (max_treedepth in stan), warmup iterations and sampling iterations. Once those solving parameters have been chosen, decrease the specificity of the priors by increasing the variance. As this goes, you may need to alter the solving parameters as well. For all the priors, we recommend including the estimate found using the above methods but at least doubling if not tripling the variance for each estimating. This decision is to decrease reliance on the prior and enable further movement when the algorithm searches the space.

3.3 Theoretical Expectations

Based on extant literature we would expect to find intersectional patterns among Americans and attitudes towards immigration and groups like undocumented immigrants. We constitute higher feeling thermometer scores for undocumented immigrants as pro-immigrant attitudes. Class-based immigration attitudes usually find that higher SES leads to more progressive immigration attitudes, with a specific focus on the role of education in increasing pro-immigrant attitudes (Espenshade and Calhoun 1993). Thus we expect higher class status to increase pro-immigrant attitudes (negative undocumented immigrants attitudes), with the biggest shifts being minority groups with higher education. With regards to race, there are divergent findings based on the racial group in question. Hispanic Americans are a heterogeneous pan-ethnic group whose immigration attitudes vary by national origin. In particular, scholars have found that Mexicans are more pro-immigrant than many other national origins (Rouse, Wilkinson and Garand 2010). Additionally, ethnic attachment and acculturation namely the importance of using Spanish, pro-acculturation values, standards of incorporation, and generational differences shape Hispanic political attitudes towards immigration, both legal and illegal. For the purposes of this paper, we expect Hispanics overall to be more supportive of undocumented immigrants as Mexicans are the dominant Hispanic group in the ANES.[2]

Economically anxious Black Americans have shown less positive views towards immigration likely due to occupation competition in some studies (Espenshade and Calhoun 1993; NEAL and Bohon 2003; Esses et al. 2010). However, other work has shown there is group-based empathy between minority racial groups because both groups have experienced racial discrimination, thus leading to more positive immigration attitudes (Sirin, Valentino and Villalobos 2016). This finding is made more compelling with work such as Carter, Wong and Guerrero (2022) which shows that Black Americans' levels of linked fate with other minority groups make is associated with more progressive immigration attitudes. We expect because of more recent research about cross-racial coalition building and group-based empathy will lead Black Americans to be more supportive of undocumented immigrants overall in comparison to White Americans (Pérez 2021*b*; Sirin, Valentino and Villalobos 2016; Carter, Wong and Guerrero 2022). White Americans are comparatively more conservative and thus also associated with less positive immigration attitudes (Burns and Gimpel 2000). We expect in particular White Americans' perceptions of immigration to be different based on partisanship, gender, and class.

We will expect that some racial groups of women will have more positive immigration attitudes than their male counterparts because of higher group-based empathy and more consistent support of the Democratic party which is more accommodating to immigration Sirin, Valentino and Villalobos (2017); Junn and Masuoka (2020). In particular, we expect Hispanic and Black women to be more supportive of undocumented immigrants compared to White women, and we expect them to be both slightly more positive towards undocumented immigrants than their male counterparts. We will expect that for certain racial groups, higher class status people will be more likely to be positive towards undocumented immigrants because of the role of education. Scholarship finds that higher educational attainment is associated with more positive immigrant attitudes (Cavaille and Marshall 2019). Additionally, we expect partisanship to play an influential role in different identity attitudes toward immigration, with Democrats being more supportive overall across other identities towards undocumented immigrants, and Republicans being less supportive. Additionally, based on extant research we expect there to be a negative relationship between age and attitudes towards undocumented immigrants with increases in age being associated with less supportive feelings.

Shifting to Black Lives Matter attitudes, we expect African Americans of both gender groups to have more positive associations with BLM, and White Americans to have lower support than African Americans (Azevedo, Marques and Micheli 2022). For White Americans, often what shapes their support for BLM is the degree they associate with their white identity and privilege, but that is beyond the scope of this paper (Cole 2020). We also expect Hispanic and Asian Americans to be more supportive than Whites of BLM which is said to be associated with increasing hate crimes against minorities and the development of shared identities as people of color (Pérez 2021*b*,*a*). As both groups are pan-ethnic identities, we expect there to be heterogeneity in support for BLM beyond the scope of this paper that centers on national origin (for both groups), and Black identity (for Hispanics) (Merseth 2018; Azevedo, Marques and Micheli 2022). Along gender lines, there are inconsistent results, but more often than not studies find that women are more likely to support BLM than men (Azevedo, Marques and Micheli 2022). We expect class to intersect in similar ways that it did in the immigration literature in the role of education higher education leading towards more progressive racial values, despite there being non-significant findings in previous studies (Azevedo, Marques and Micheli 2022). We also leverage Cohen (2004)'s work, so expect to see heterogeneity in Black Americans' support for BLM based on being in the upper or lower class status category. This literature shows that the Black middle class tends to have less support for shifting structural oppression and more of a focus on individuality which might lead them to have less support for a system-disrupting movement like BLM (Cohen 2004).

3.4 Empirical Checks

Once the priors have been set, the full model can be estimated. After estimation, there are a few key checks necessary to ensure goodness of fit. The first set is to ensure that the prior results are not too heavily influencing the final results. While the priors are useful for giving the model direction, a key point of the mixture model approach is that the dependent variable helps determine the way that class is defined. Second, like with any model, it is important to check that the fit is appropriate.

The first checks are to ensure that there is an amount of certainty in the class estimates. This is done in a few ways. First, confirm that the distributions of the estimated class have high densities at 0 and 1. If this is not the case, there can be issues from having essentially an empty set. Second, since we are confident that measures of the class should be correlated, confirm that there is a positive correlation between class as found using the unsupervised method and class as estimated after the mixture model has been fit. Finally, it is important that the coefficients of the class-determining variables are not identical between the mixture model and the fit from the unsupervised model (which provided the priors). If these are identical, that is evidence that the outcome did not effect the class definitions and we are simply using the unsupervised model.

Classic ways to confirm the appropriateness of a model include root mean square error, expected predictive accuracy, and visual confirmations. Given many of the outcomes studied in relation to class—for instance, the propensity to vote, views on subjects, etc.—are noisy, we do not expect there to be a significant improvement in fit from this method. The major benefit of this model is that it is theoretically consistent and provides insight into the effects as well as a definition of class in different contexts. However, it is important that the mixture model does not perform worse than a non-mixture version of the same model.

4 Empirical Results

For our empirical confirmation of this methodology, we use the American National Election Studies Survey (ANES) from 2020. As our outcome variables, we look at the thermometer scores for undocumented immigrants (Immigrant Attitudes, IA) as well as Black Lives Matter (BLM). In each of these questions, respondents are asked how they would rate each group from 0 to 100. We choose to look at two different outcomes within the same survey to display how the latent class variable is context-specific. These questions were chosen since they were thought to have a higher probability of clear class-related variation.

For our model, we use the two thermometer ratings as the outcome variables. For the class-determining variables, we set $c =$ (college, family income, remaining student loans, employment status, union affiliation, money in stock market, occupation type). The variables college, remaining student loans, union affiliation, and money in the stock market are binary. Occupation type and employment status are categorical with 9 and 7 groups, respectively (details can be seen in Appendix A). In the survey, income is represented as a series of bins, to convert this value to a continuous variable we assign the income value as the low end of the bin the respondent belongs to. In addition, the income values are centered around the mean and represented in the 10's of thousands in order to generate coefficients of reasonable magnitudes.

For the outcome-determining variables, we have $x =$ (7 point party identification, gender, race, age). Age and party identification are represented as zero-centered continuous and categorical variables respectively, while gender and race are just categorical. The full options for each of these variables can be seen in the Appendix A. The functional form we use for $f_{i,j}$ is a multilevel model with groupings based on gender and race combinations and random effects for both intercept and age depending on these groupings. There are additionally fixed effects for the intercept, age, and party identification. Party identification is the only outcome-dependent covariate thought to be independent of intersectional group. The ANES for 2020 had a total of 8,280 respondents. Of these, 5,831 of the respondents had valid responses to all of the variables used. This is the subset of data used to test our approach.

4.1 Fit Checks

As described in 3.2, we first generate the priors for the class coefficients as well as outcome coefficients before running the full model. Before analyzing the results, we first run through the empirical checks recommended in 3.4. First, we confirm that all versions of the clustering result in groups with respondents belonging to each, the density plot in Figure 1. It is clear that not only do all estimates break the respondents into two relatively certain groups, but the groupings are not identical. This suggests that there is information learned from the utilization of the response variable in the model. In the correlation plots it is clear that for both mixture models and the original clustering, there is a positive correlation between membership classifications. This is what we are hoping to see as we don't expect class to be completely different in different situations, we simply expect some aspects to be more important.

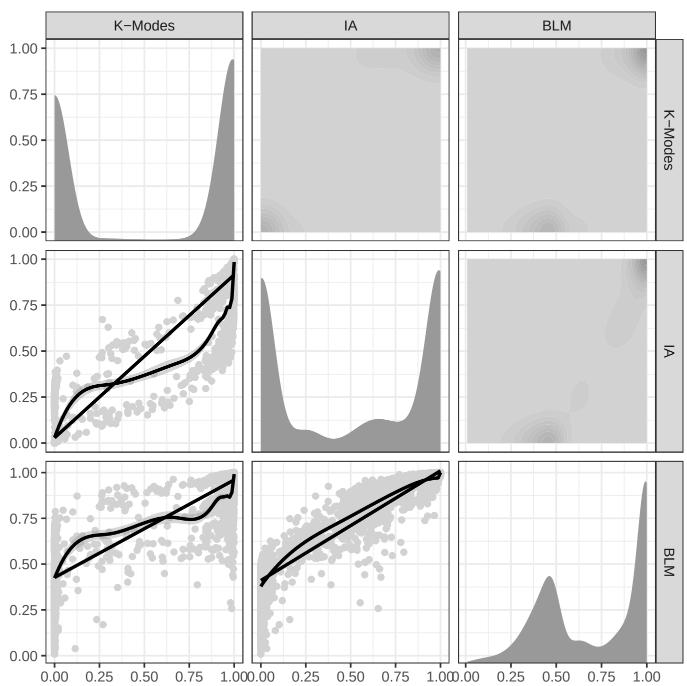

Figure 1: Predicted probabilities of class membership for undocumented immigrants, BLM and K-modes models. The diagonals show the density of the predicted membership by model. The lower triangle shows the point estimate for the dataset and a generalized linear fit for the correlation (red) as well as a best linear fit (black). The upper triangle shows a heat map of the same information.

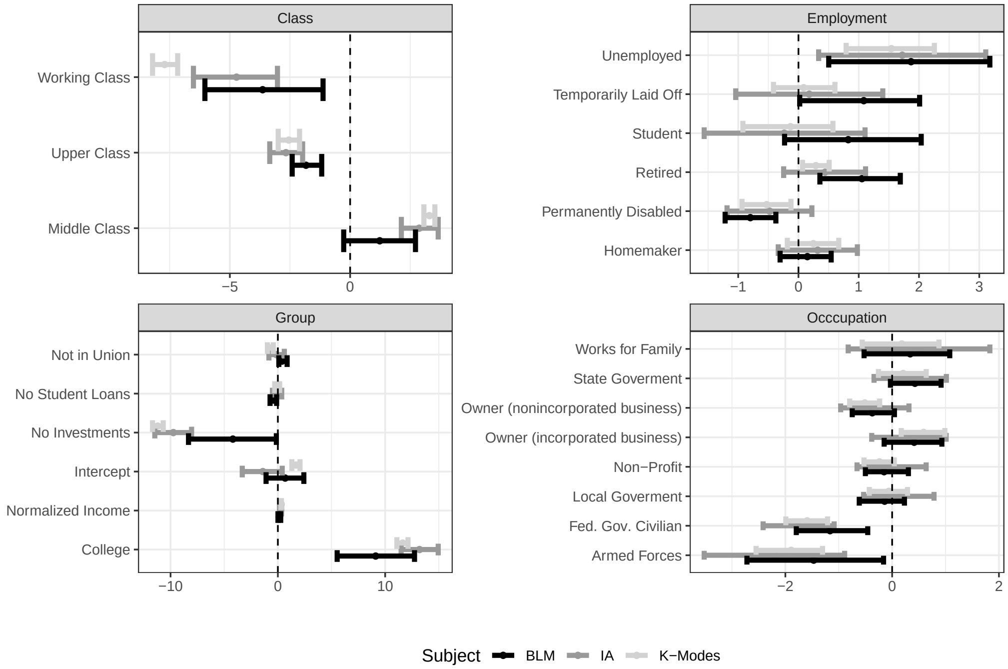

Figure 2: Predicted coefficients for class-determining covariates assuming class is split my K-modes or uncovered using a mixture model using the undocumented immigrants or BLM thermometer as the output.

In order to further confirm this takeaway, we next compare the coefficients estimates from the original k-modes clustering and the two mixture models. It can be seen in Figure 2 that the estimated coefficients are different between the priors and the two mixture models. These results show that there was enough strength from the outputs to move the estimates of the class differentiators from their priors to alternative areas. In addition, this was a different addition for the two models.

To analyze the fit of the model, we compare the results to a non-mixture version of the same model. This can be thought of as a mixture model where $\pi_i = 1$ for all i. We call this model the "single class" model as compared to the mixture model. The root mean squared error when undocumented immigrants is the outcome is 23.98 for the single class model and 23.85 for the mixture model, an improvement but an insignificant one. Similarly, the BLM error is 25.02 and 24.81 for the single and mixture model, respectively. We next look at the expected predictive accuracy of each model using leave-one-out cross-validation.

For both outcome variables, the mixture model performs better than the single class model with a difference in expected log pointwise predictive density (elpd) of 73.7 (standard error 14.1) for the BLM outcome and 39.3 (Standard error 10.9) for the undocumented immigrants outcome. Given these checks, we can feel confident that the model is appropriately estimating both class and the outcomes. We can now move on to analyzing the results.

4.2 Outcome Analysis

With the confirmation that the model has been appropriately fit, we now turn to analyze the results. There are two sets of analyses that can be done. The first is how class is understood in each context while the second is how the outputs respond to class. We first look at the definition of class and this will be followed by an analysis of the outcomes.

In order to understand how class is determined in each situation we return to Figure 2. With these results, we can see how class differs in the three contexts: naive k-modes, BLM and undocumented immigrants. For the SSS measures, in which we look at how people self-identify, the mixture model-derived coefficients show them as less differentiating than the k-modes based prior. There is no statistical difference in class membership between those who identify as upper and lower class while the positive and negative effects of middle and working class, respectively, are smaller. There are also differences between the two mixture models. While the impact of being an investor is similar for the k-modes model and undocumented immigrants mixture mode, the importance is smaller when the model is based on feelings towards BLM. Finally, in some cases all three models have starkly different results, for returned individuals there is no difference between working individuals and retired individuals, but for the undocumented immigrants mixture model being retired is indicative of more likely having a higher class status and for BLM it is even more likely. This supports our theory that for different outcomes, the salient factors of class are different.

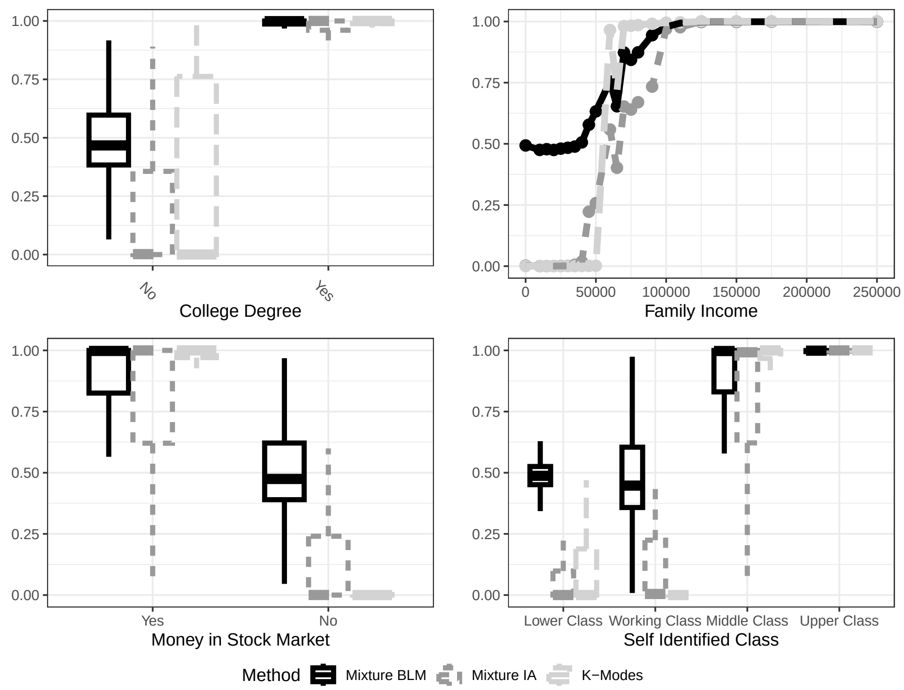

Figure 3: The estimated class membership when the data is split by a subset of the class-dependent covariates. 1 refers to a 100% probability of having a higher class status while 0 refers to a 100% probability of belonging to the lower class.

Due to the categorical nature of the covariates, the coefficients themselves are a bit difficult to interpret. As a result, we additionally look at the differentiation between the clusters through their expectation in group membership. We cut the data by each covariate and look at the estimated membership for each clustering method. These results can be seen in Figure 3. We see that many of the categories imply a stronger group membership in one direction or the other—for instance, college education implies a higher class status and as does higher income levels. However, the strength of these movements is different between models. Self-identified class is significantly less predictive in the BLM model than in the other two, and in both mixture models the income gradient is less stark. In addition, the transition from low to higher class status within income happens earlier in the BLM model than in the other two.

We conclude that while there are certain factors that undoubtedly are indicators of class membership—a higher income correlates with higher class status, as does a higher level of education—class is topic dependent. With this new understanding of class, we can delve into the conclusions that can be drawn from the sub-regressions.

4.3 Substantive Interpretation

Substantively, our results comport with extant literature showing relationships between identity and racially charged political attitudes. We also provide additional intersectional nuance. Using feeling thermometers from the 2020 ANES, we show that not taking class into account from an intersectional perspective over and understates effects across intersectional groups in Figure 4. The pooled class in black reflects a multilevel model random effect where the class is not taken into account. The two shades of grey show the higher and lower class grouping effects from the mixture model. In the case of BLM, we see that often the multilevel model on its own pools away class-based variation. For example, as age increases higher class status Black women are less supportive of Black Lives Matter as opposed to lower class status Black women, and the pooled effect would understate the degree to which age impacts higher class status Black women's level of support towards BLM. Another stark example is lower and higher-class status white women, whose age effect is drastically understated in the pooled class context.

For undocumented immigrants attitudes, our work shows that the pooled measure of class overstates the degree to which age impacts higher class status individuals across racial and ethnic groups, and particularly for men. Black women show little difference in their age effect across intersectional identities; however, Black men have class based heterogeneity across age pooled away when class is not addressed properly. Hispanics in the sample show different age effects based on gender and class, with higher class status Hispanic men being the least supportive to undocumented immigrants, with the pooled estimate understating the class effect for both groups. Interestingly, Hispanic women's pooled average is similar to high class status women, but the pooled average understates

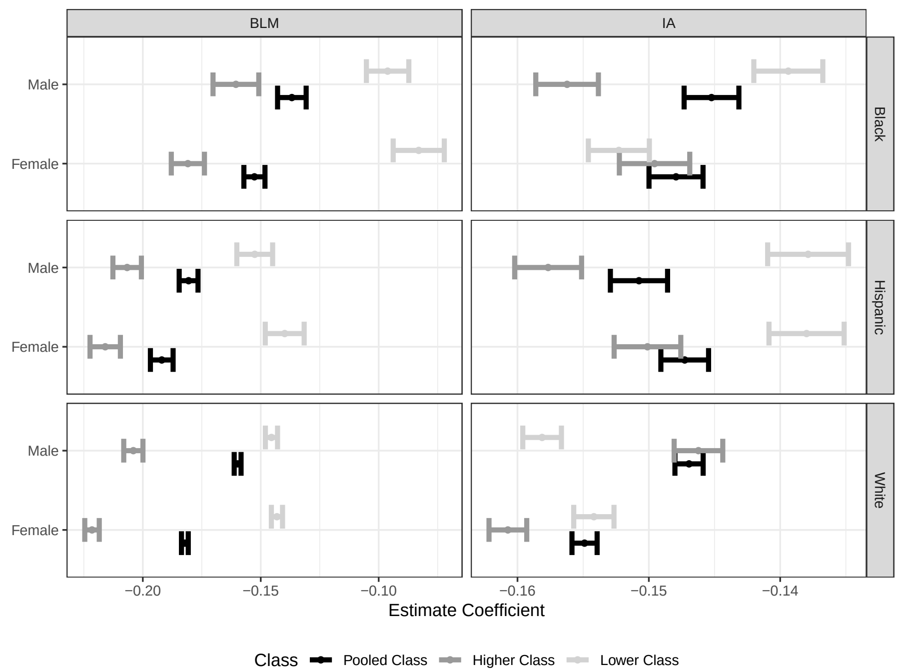

Figure 4: Random effects for age for each model.

the degree to which lower class status women have warm feelings towards undocumented immigrants. For white indiviudals, there is some degree to which the pooled method can uncover class difference, but lacks it across both groups. White women's pooled estimate is similar to lower class status white women, but understates the degree to which White women have negative feelings towards undocumented immigrants. The same is true for higher class status white men whose pooled estimate is similar, but the lower class status category's negative feelings are drastically understated. Overall, the method more often than not uncovers interesting substantive class based heterogeneity in the age effect across both BLM and undocumented immigrant attitudes as shown by the gaps between the mixture model effects and the pooled class effects.

We can additionally show this by looking at the slopes for age on the undocumented immigrants and BLM feeling thermometers along with party identification. In Figure 6 we address race, gender, class, party identification, and age's impact on undocumented immigrant attitudes. We isolate only strong partisans and independents for this analy-

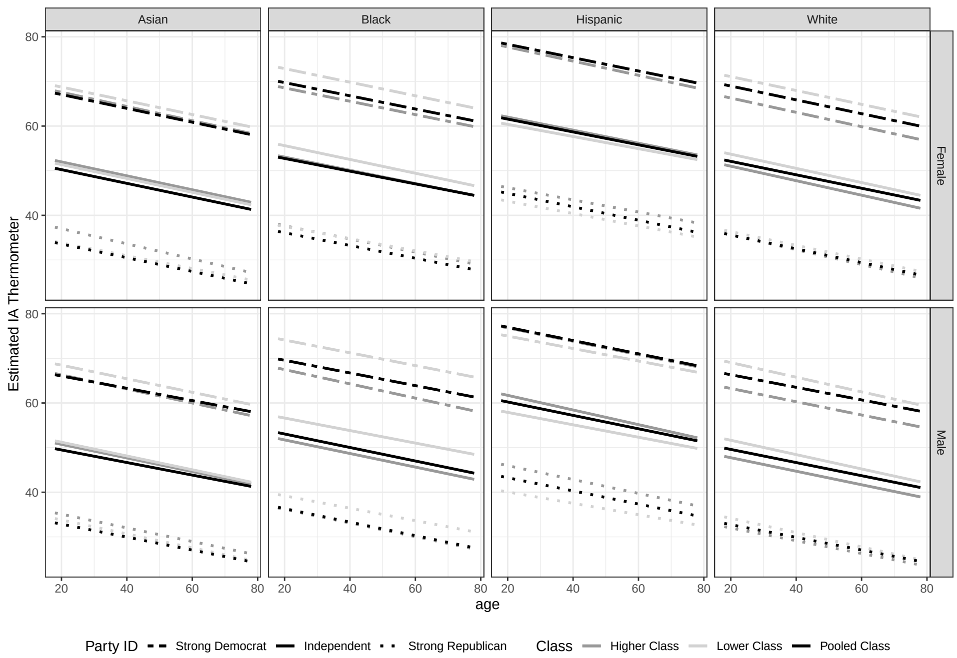

Figure 5: Expected undocumented immigrants thermometer values for strong partisans and independents split by race and gender.

sis. Among Democrats, there is clear class heterogeneity for Black and White Americans. Black women in the lower class status category are on average more warm towards undocumented immigrants across age. Higher class status Black women are less positive towards undocumented immigrants across age. Black men show clearer class based difference with higher income. Lower class status White Democrats, both men and women, are on average more positive towards this group than higher class status Whites.

Looking at Hispanic men and women Democrats, we see that among strong Democrats increases in age are associated with decreases in support for undocumented immigrants; however, there is not clear class based heterogeneity aside from a small margin in less warm feelings across age for lower class status Hispanic men. Asian Americans that identify as Democrats, their pooled estimate uncovers the high class status group well, showing less positive feelings towards undocumented immigrants as age increases, and there is a slight increase across age for lower class status people in that racial group. Other interesting findings include that for White men who are strong Republicans, there is little to no class effect on age and this immigration attitude, as shown by the dotted lines being on top of each other.[3] They along with Asian American men in the party have some of the lowest feeling thermometer ratings.

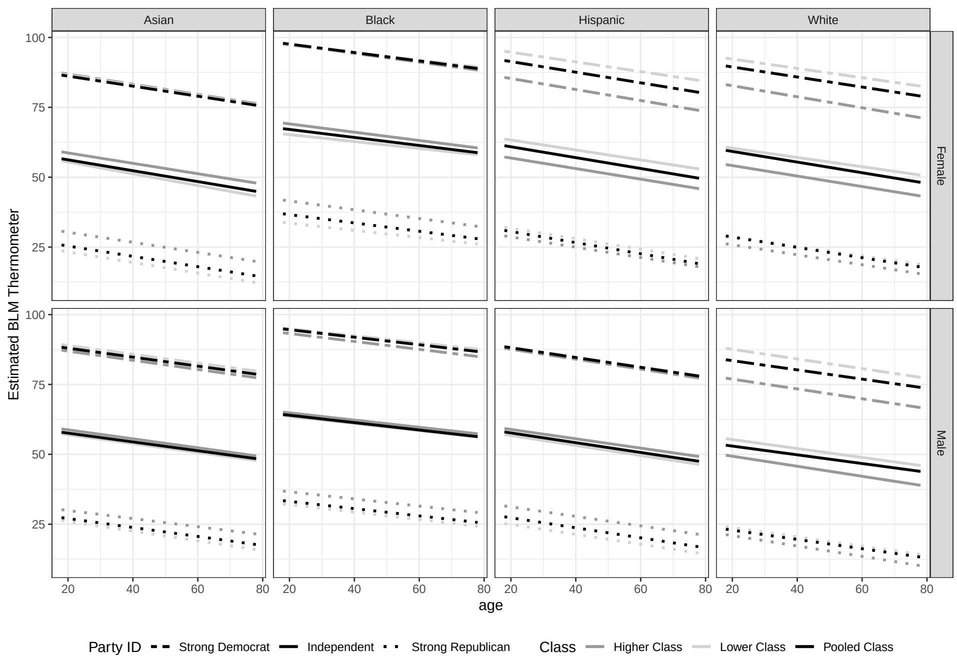

Figure 6: Expected BLM thermometer values for strong partisans and independents split by race and gender

With regards to BLM attitudes, strong Democratic Black men and women both have decreasing support for BLM as age increases, but are overall very supportive. The pooled class method in this instance controlling for race and party is less distinct, as the pooled effect looks similar to the mixture methods. Hispanic Democrat women have a clear class effect, with lower class status group being much more supportive accross age towards the BLM movement. This finding does not hold for Hispanic men, whose pooled measure captures class effects. White Democrats from lower class status groups are more supportive than higher class status Democrats, and this effect happens at a slightly higher margin across age for women than it does for men. Asian Americans across race, gender, party, and class have similar effects so the pooled estimate for age accounts for BLM attitudes. White low class status Republicans have the lowest effects across age, and this effect is consistent across gender. [4] Black independent men and women do not demonstrate a clear class effect. Independent groups that show class effects are Hispanic women who have higher rates of support for BLM if they are in the lower class status category. White independents show similar trends to Democrats, but just at a much lower level of support. Overall, Figure 6 shows that a researcher could easily overstimate support for BLM for higher class status across ages, and underestimate support for lower class status individuals depending on the racial group and partisan identification.

5 Discussion and Conclusion

Class is widely recognized as a significant factor impacting individuals' political behavior and opinions. However, there has been a lack of consistency in existing research on the best way to approach estimating and utilizing class in quantitative models. Additionally, intersectionality poses that race, gender, and class need to be considered together when studying sociopolitical identities, but often only race and gender are addressed. These issues have led to researchers to present contradictory results on the impact of class in various situations or leave the important impact of class unexplained. In this paper, we recommend treating class as a context-dependent latent variable that can be recovered using mixture models. This mixture model can then be combined with the desired intersectional modeling tactic like multilevel models in our case. We defend this approach from a theoretical standpoint and using empirical evidence.

Methods for measuring class are generally split into two categories—socioeconomic status (SES) which is measured as some combination of material circumstances and subjective social status (SSS) which relies on individuals' self-identification. Researchers make informed decisions on what is the best measure for the outcome they are studying. In this paper, we introduce using the information provided by the outcome variable to help untangle the definition of class. Rather than relying on intuition, which has the potential to propagate biased thinking, our method has the ability to include all available contributors and uses the outcome information to determine the weighting of the aspects. This approach is able to seamlessly weave in measures of both SES and SSS into a single bespoke parameter.

In our two empirical examples, we look at thermometer ratings for undocumented immigrants and BLM using the 2020 ANES. We find that the definitions of class in each case, while strongly correlated, are non-identical. In the context of undocumented immigrants not having money in the stock market is a strong indication of belonging to the lower class status group, while this relationship is less strong in the context of BLM. In contrast, not having a college degree is a much stronger indication of being in the lower class status for BLM than for undocumented immigrants. These results show that class is in fact context-dependent, and also provides insight into which aspects differentiate classes in the case of BLM and undocumented immigrants.

The substantive results also comport with existing literature on racialized political phenomena. We find that overall individuals with higher class status have less change in their opinions as they age compared to their lower class status counterparts. However, the opinions of those with higher class status are much more affected by party identification than equivalent individuals with lower class status. For the most part, the results of the pooled class model split the results of the two class extremes. This means that traditional models are likely to skew the results towards the larger class group displayed in the data.

In reducing the subjectivity of class we are able to ameliorate the bias introduced through researcher intuition. Additionally, by accepting that class is not a clearly defined concept, we can exploit the myriad of ways it is operationalized to come up with a holistic approach. We allow the definition to change with the outcome variables which allows for a whole new realm of study. This technique opens doors to work on how class is experienced by individuals as well as the effects of class on outcomes.

Endnotes

[1]While valuable to show perceived social class status (SSS), many working-class individuals often inflate their class status, and upper-middle-class individuals deflate it (Jackman and Jackman 1983; Sosnaud, Brady and Frenk 2013).

[2]In the 2020 ANES around 40% of Hispanic respondents say most of their family is from Mexico.

[3]We will not address Black and Hispanic Republican groups because of sample size constraints.

[4]Due to sample size constraints we will not further interrogate racial and ethnic minority strong Republicans.

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A ANES Details

All of the variables came from either (1) direct questions asked in the ANES, (2) summary questions reported by the ANES, or (3) summaries based on questions in the ANES. We eliminated respondents who had incomplete answers to any of the variables needed for either analysis. For each subject we list out how many respondents had each type of inapplicable response. In total, we are left with 5,662 of the original 8,280 respondents or 68%.

Race — determined by ANES combination outcome variable:

V201549x:

-9. Refused

-8. Don't know

1. White, non-Hispanic
2. Black, non-Hispanic
3. Hispanic
4. Asian or Native Hawaiian/other Pacific Islander, non-Hispanic alone
5. Native American/Alaska Native or other race, non-Hispanic alone
6. Multiple races, non-Hispanic

Individuals who responded with Refused (-9) or Don't know (-8) were excluded from the analysis. This includes a total of 96 (1.16%) and 6 (0.07%) respondents respectively.

Gender — explicitly asked in the survey:

V201600: What is your sex?

-9. Refused

1. Male
2. Female

Individuals who responded with Refused (-9) were excluded from the analysis. They made up a total of 67 (0.8%) respondents.

Age — determined by ANES combination outcome variable:

V201507x:

-9. Refused

80. 80 or older

Individuals who responded with Refused (-9) were excluded from the analysis. They made up a total of 348 (4.2%) respondents.

Party ID — determined by ANES combination outcome variable:

V201231x:

-9. Refused

-8. Don't know

1. Strong Democrat
2. Not very strong Democrat
3. Independent-Democrat
4. Independent
5. Independent-Republican
6. Not very strong Republican
7. Strong Republican

Individuals who responded with Refused (-9) or Don't know (-8) were excluded from the analysis. This includes a total of 31 (0.4%) and 4 (0.05%) respondents respectively.

College — generated from a question

V201510: What is the highest level of school you have completed or the highest degree you have received?

-9. Refused

-8. Don't know

1. Less than high school credential

2. High school graduate - High school diploma or equivalent (e.g. GED)

3. Some college but no degree

4. Associate degree in college - occupational/vocational

5. Associate degree in college - academic

6. Bachelor's degree (e.g. BA, AB, BS)

7. Master's degree (e.g. MA, MS, MEng, MEd, MSW, MBA)

8. Professional school degree (e.g. MD, DDS, DVM, LLB, JD)/Doctoral degree (e.g. PHD, EDD)

95. Other SPECIFY

Individuals who answered 1-5 were labeled as not having attended college (4502, 54.4%) and individuals who answered 6-8 were labeled as having attended college (3647, 44%). Individuals who responded with Refused (-9), Don't know (-8), or Other (95) were excluded from the analysis. This includes a total of 33 (0.4%), 1 (0.01%), and 97 (1.2%) respondents respectively.

Income — determined by ANES combination outcome variable:

V201617x: Please choose the answer that includes the income of all members of your family during the past 12 months before taxes.

-9. Refused

-5. Interview breakoff (sufficient partial IW)

1. Under $9,999

2. $10,000-14,999

3. $15,000-19,999

4. $20,000-24,999
5. $25,000-29,999
6. $30,000-34,999
7. $35,000-39,999
8. $40,000-44,999
9. $45,000-49,999
10. $50,000-59,999
11. $60,000-64,999
12. $65,000-69,999
13. $70,000-74,999
14. $75,000-79,999
15. $80,000-89,999
16. $90,000-99,999
17. $100,000-109,999
18. $110,000-124,999
19. $125,000-149,999
20. $150,000-174,999
21. $175,000-249,999
22. $250,000 or more

Individuals who responded with Refused (-9) or Interview breakoff (-5) were excluded from the analysis. This includes a total of 584 (7%) and 32 (0.4%) respondents respectively.

Student loans — explicitly asked in the survey:

V202562: Do you currently owe money on student loans, or not?

-9. Refused

-7. No post-election data, deleted due to incomplete interview

-6. No post-election interview

-5. Interview breakoff (sufficient partial IW)

1. Yes

2. No

Individuals who responded with Refused (-9), No post-election data (-7), No post-election interview(-6) or Interview breakoff (-5) were excluded from the analysis. This includes a total of 16 (0.2%), 77 (0.9%), 754 (9%), and 103 (1.3%) respondents respectively.

Employment Status — determined by ANES combination outcome variable:

V201534x:

-2. Refused/Don't know/Inapplicable

1. R working now (if also retired, disabled, homemaker or student, working 20 or more hrs/wk)

2. R temporarily laid off

4. R unemployed

5. R retired (if also working, working <20 hrs/wk)

6. R permanently disabled (if also working, working <20 hrs/wk)

7. R homemaker (if also working, working <20 hrs/wk/incl non-workg rs both homemaker and student)

8. R student (if also working, working <20 hrs/wk)

Individuals who responded with Refused/Don't know/Inapplicable (-2) were excluded from the analysis. This includes a total of 57 (0.7%) of respondents.

Socioeconomic Class — explicitly asked in the survey:

V202352: How would you describe your social class? Are you in the lower class, the working class, the middle class, or the upper class?

-9. Refused

-8. Don't know

-7. No post-election data, deleted due to incomplete interview

-6. No post-election interview

-5. Interview breakoff (sufficient partial IW)

1. Lower class

2. Working class

3. Middle class

4. Upper class//

Individuals who responded with Refused (-9), Don't know (-8), No post-election data (-7), No post-election interview(-6) or (-5) Interview breakoff were excluded from the analysis.

This includes a total of 25 (0.3%), 2 (0.02%), 77 (0.9%), 754 (9%) and 53 (0.6%) of respondents respectively.

Occupation — explicitly asked in the survey:

V201529: Which one of the following best describes your employment?

-9. Refused

-1. Inapplicable

1. For-profit company or organization

2. Non-profit organization (including tax-exempt and charitable organizations)

3. Local government (for example: city or county school district)

4. State government (including state colleges/universities)

5. Active duty U.S. Armed Forces or Commissioned Corps

6. Federal government civilian employee

7. Owner of non-incorporated business, professional practice, or farm

8. Owner of incorporated business, professional practice, or farm

9. Worked without pay in a for-profit family business or farm for 15 hours or more per week

Individuals who responded with Refused (-9) or Inapplicable (-1) were excluded from the analysis. This includes a total of 181 (2%) and 234 (2.8%) of respondents respectively.

Union Affiliation — explicitly asked in the survey:

V201544: Do you or anyone else in this household belong to a labor union or to an employee association similar to a union?

-9. Refused

-8. Don't know

1. Yes
2. No

Individuals who responded with Refused (-9) or Don't know (-8) were excluded from the analysis. This includes a total of 39 (0.5%) and 4 (0.05%) of respondents respectively.

Stock market investor — explicitly asked in the survey:

V201606: Do you personally, or jointly with a spouse, have any money invested in the stock market right now - either in an individual stock or in a mutual fund?

-9. Refused
-8. Don't know
-5. Interview breakoff (sufficient partial IW)
1. Yes
2. No

Individuals who responded with Refused (-9), Don't know (-8) or Interview breakoff (-5) were excluded from the analysis. This includes a total of 179 (2%), 641(7.7%) and 11 (0.1%) of respondents respectively.

Outcome variables — we looked at two outcome variables. We differentiate them throughout the paper by refering to them as the two "subject matters". The options are ICE and BLM. Both come from explicit questions in the survey with the same outcome structure. The questions are:

ICE — *V202182*: How would you rate: The Immigration and Customs Enforcement (ICE) agency

BLM — *V202174*: How would you rate: Black Lives Matter movement

The outcome options are a scale from 0-100 or:

-9. Refused

-7. No post-election data, deleted due to incomplete interview

-6. No post-election interview

-5. Interview breakoff (sufficient partial IW)

-4. Technical error

998. Don't know

999. Don't recognize

All respondents who responded outside of 0-100 for either scale were removed from both analysis. The table below notes the number and percentage of each type of response for each subject.

	IA		BLM	
Responses	Number	%	Number	%
-4	1	0.01	1	0.01
-5	87	1.05	14	0.17
-6	754	9.11	754	9.11
-7	77	0.93	77	0.93
-9	269	3.25	86	1.04
998			2	0.02
999			2	0.02
0-100	7092	85.65	7344	88.70

Table 1: Number and percent of respondents who responded in each of the eliminated category or were kept in the analysis (0-100).

B Stan Implementation

We run all analysis in Stan using the BRMS frontend in R (Bürkner 2017, 2018). In order to generate the prior for the class specification we first run K-Modes on the class relevant covariates using the 'klaR' package in R (Weihs et al. 2005). The income level is changed to the numerical value of the lower end of the bin. Income_norm refers to that value divided

Race	Gender	Strong Democrat	Not very strong Democrat	Independent Democrat	Independent
Asian	Female	25	20	9	9
Asian	Male	19	21	15	13
Black	Female	180	46	36	22
Black	Male	91	19	22	19
Hispanic	Female	71	48	42	38
Hispanic	Male	48	31	32	37
Multiple Race	Female	22	19	25	14
Multiple Race	Male	16	9	14	17
Native American	Female	5	4	5	10
Native American	Male	9	4	6	19
White	Female	606	213	246	174
White	Male	373	176	265	186

Race	Gender	Independent Republican	Not very strong Republican	Strong Republican
Asian	Female	6	5	6
Asian	Male	8	13	10
Black	Female	7	4	5
Black	Male	7	8	5
Hispanic	Female	13	15	23
Hispanic	Male	32	19	33
Multiple Race	Female	9	2	12
Multiple Race	Male	17	5	11
Native American	Female	6	5	6
Native American	Male	10	3	10
White	Female	207	263	511
White	Male	276	255	532

Table 2: Distribution of respondent party identification based on race and gender

by 10,000. This is done in order to place it on a more appropriate scale when compared to the rest of the covariates. Given the dataframe “anes_2020“, the original split is done as:

```
anes_2020 <- anes_2020 %>%
  mutate(group_class = kmodes(as.matrix(anes_2020 %>%
  dplyr::select(college,
                income,
                loans,
                employ,
```

```
              Class,
              occupation,
              union,
              investor)),
            2)$cluster - 1)
```

The class priors are then found running a logisitic model on the group_class variable and the same covariates:

```
class_fit <- brm(bf(group_class ~ 1 +
                                  college +
                                  income_norm +
                                  loans +
                                  employ +
                                  Class +
                                  occupation +
                                  union +
                                  investor),
                 family = bernoulli(link = "logit"),
                 anes_2020 ,
                 control = list(adapt_delta = 0.92,
                                max_treedepth = 12),
                 warmup = 4000,
                 iter = 5000,
                 seed = 1234,
                 chains = 4,
                 cores = 4)
```

We then run the un-mixed regression for each output variable split into groups when

Parameter	Mean	Estimated SD
Intercept	1.2	0.4
College		
Yes	9.0	0.5
Income Norm	0.2	0.0
Student Loans		
No	-0.1	0.3
Employment Status		
Temporarilylaidoff	-0.1	0.5
unemployed	0.7	0.9
retired	0.0	0.3
permanentlydisabled	1.0	0.7
homemaker	0.8	0.6
student	1.6	1.2
Class		
WorkingClass	-6.5	0.5
MiddleClass	2.3	0.3
UpperClass	-1.1	0.5
Occupation		
Non-profit	-0.4	0.3
LocalGov	0.3	0.4
StateGov	0.2	0.5
ArmedForces	-1.2	0.9
FedGovCivilian	1.0	0.8
OwnernonMincorporated	0.1	0.4
Ownerincorporated	0.9	0.5
Workforfamily	0.9	0.9
Union Affiliation		
No	-0.1	0.3
Investor in Stock Market		
No	-9.3	0.5

Table 3: Estimated mean and standard deviation for logit of k-mode class on class covariates as well as the standard deviation for the priors given to the final response.

the estimated class is less than 50% or above 50%. For example, for the ICE model and the class represented by 0 we would have the command:

```
IA_group_0 <- brm(bf(therm_IA ~ 1 +
                                age +
                                pid7 +
                                (1 + age||intersectional)),
```

```
anes_2020 %>% filter(Estimate <= 0.5),
seed = 1234,
control = list(adapt_delta = 0.95,
               max_treedepth = 12),
warmup = 3000,
iter = 4000,
prior = c(set_prior("normal(0,50)", class = "sd"),
          set_prior("normal(0,50)")),
chains = 4,
cores = 4)
```

All of the solving parameters are consistent for each of the four regressions. The estimated means and standard deviations can be seen in Table 4. Once these values have been found, we use the estimates to set the prior and increase the prior standard deviations in order to give the model more freedom. We set all priors to be normal. The R code for each of the final regressions can be seen below.

	IA				BLM			
	Estimate $\geq$ 50%		Estimate $\leq$ 50%		Estimate $\geq$ 50%		Estimate $\leq$ 50%	
	mean	sd	mean	sd	mean	sd	mean	sd
Fixed Effects								
Intercept	30.33	1.81	29.01	2.56	61.27	2.56	64.49	2.68
age	0.38	0.04	0.45	0.04	-0.16	0.04	-0.19	0.04
pid7	7.67	0.18	6.57	0.24	-10.74	0.18	-9.47	0.26
sigma	22.92	0.28	25.36	0.36	23.05	0.29	27.26	0.40
Random Effects (sd)								
Intercept	2.42	1.57	5.40	2.14	5.75	2.23	5.52	1.98
age	0.04	0.03	0.06	0.04	0.06	0.05	0.05	0.04

Table 4: Estimates from models when artificially split into two groups

```r
priors_class <- c(
  prior(normal(  1.19,  2), Intercept                        , dpar = theta1),
  prior(normal(  9.01,  2), b, coef =  collegeYes                        , dpar = theta1),
  prior(normal(  0.21,   0.12), b, coef =  income_norm                        , dpar = theta1)
  prior(normal( -0.05,  1), b, coef =  loansNo                           , dpar = theta1),
  prior(normal( -0.12,2.4), b, coef =  employTemporarilylaidoff          , dpar = theta1),
  prior(normal(  0.70,3.6), b, coef =  employunemployed                  , dpar = theta1),
  prior(normal(  0.02,1.2), b, coef =  employretired                     , dpar = theta1),
  prior(normal(  0.99,2.8), b, coef =  employpermanentlydisabled         , dpar = theta1),
  prior(normal(  0.80,  2), b, coef =  employhomemaker                   , dpar = theta1),
  prior(normal(  1.57,  4), b, coef =  employstudent                     , dpar = theta1),
  prior(normal( -6.55,  2), b, coef =  ClassWorkingClass                 , dpar = theta1),
  prior(normal(  2.33,1.2), b, coef =  ClassMiddleClass                  , dpar = theta1),
  prior(normal( -1.10,  2), b, coef =  ClassUpperClass                   , dpar = theta1),
  prior(normal( -0.39,1.2), b, coef =  occupationNonMprofit              , dpar = theta1),
  prior(normal(  0.29,1.6), b, coef =  occupationLocalGov                , dpar = theta1),
  prior(normal(  0.16,  2), b, coef =  occupationStateGov                , dpar = theta1),
  prior(normal( -1.20,  4), b, coef =  occupationArmedForces             , dpar = theta1),
  prior(normal(  1.04,2.8), b, coef =  occupationFedGovCivilian          , dpar = theta1),
  prior(normal(  0.09,1.6), b, coef =  occupationOwnernonMincorporated, dpar = theta1),
  prior(normal(  0.87,  2), b, coef =  occupationOwnerincorporated       , dpar = theta1),
  prior(normal(  0.93,3.6), b, coef =  occupationWorkforfamily           , dpar = theta1),
  prior(normal( -0.12,1.2), b, coef =  unionNo                           , dpar = theta1),
  prior(normal( -9.37,  2), b, coef =  investorNo                        , dpar = theta1))

priors_IA <- c(
  priors_class,
  prior(normal(  2.46,   3), sd , group = intersectional, coef = Intercept, dpar = mu1),
  prior(normal(  0.04,  0.06), sd , group = intersectional, coef = age      , dpar = mu1),
  prior(normal( 30.35,  4), Intercept    , dpar = mu1),
  prior(normal(  0.38,  0.08), b , coef = age           , dpar = mu1),
  prior(normal(  7.68,  0.4), b , coef = pid7          , dpar = mu1),
  prior(normal( 22.92,  0.6),  sigma1),
```

```
  prior(normal(  5.49,  5 ), sd ,group = intersectional, coef = Intercept, dpar = mu2),
  prior(normal(  0.06,  0.08), sd , group = intersectional,coef = age      , dpar = mu2),
  prior(normal( 29.15,  5 ), Intercept    , dpar = mu2),
  prior(normal(  0.45,   0.1), b , coef = age           , dpar = mu2),
  prior(normal(  6.58,0.5), b , coef = pid7           , dpar = mu2),
  prior(normal( 25.36,0.7),  sigma2))

priors_BLM <- c(
  prios_class,
  prior(normal(  5.73,  5), sd ,group = intersectional, coef = Intercept, dpar = mu1),
  prior(normal(  0.06,  0.08 ), sd , group = intersectional,coef = age      , dpar = mu1),
  prior(normal( 61.24,   5), Intercept    , dpar = mu1),
  prior(normal(  -0.16, 0.08), b , coef = age           , dpar = mu1),
  prior(normal( -10.74,   0.4), b , coef = pid7          , dpar = mu1),
  prior(normal( 23.05,   0.6),  sigma1),
  prior(normal(  5.73, 4), sd ,group = intersectional, coef = Intercept, dpar = mu2),
  prior(normal(  0.05,     0.1), sd , group = intersectional,coef = age      , dpar = mu2)
  prior(normal( 64.45,     6), Intercept    , dpar = mu2),
  prior(normal(  -0.19,   0.1), b , coef = age           , dpar = mu2),
  prior(normal( -9.48,    0.5), b , coef = pid7          , dpar = mu2),
  prior(normal(  27.26,   0.8 ),  sigma2))
```

We finally, are able to run the two main regressions:

```
  out_IA <- brm(bf( therm_IA ~ 1 +
                         age +
                         pid7 +
                         (1 + age||intersectional),
             theta1 ~ 1 +
             college +
             income_norm +
             loans +
             employ  +
             Class +
             occupation +
```

```
        union +
        investor),
    family = mixture(gaussian(link = "identity"),
                     gaussian(link = "identity")),
    anes_2020,
    seed = 1234,
    control = list(adapt_delta = 0.95,
                   max_treedepth = 12),
    warmup = 4000,
    iter = 5000,
    chains = 4,
    cores = 4,
    prior = priors_IA)

out_BLM <- brm(bf( therm_BLM ~ 1 +
age +
pid7 +
(1 + age||intersectional),
          theta1 ~ 1 +
          college +
          income_norm +
          loans +
          employ  +
          Class +
          occupation +
          union +
          investor),
      family = mixture(gaussian(link = "identity"),
                       gaussian(link = "identity")),
      anes_2020,
```

```
seed = 1234,
control = list(adapt_delta = 0.95,
               max_treedepth = 12),
warmup = 4000,
iter = 5000,
chains = 4,
cores = 4,
prior = priors_BLM)
```