Bayesian Multilevel Modeling for the Intersections of Race and Gender

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Abstract

Intersectionality is widely recognized as one of the largest contributions to the study of race and gender across the academy. However, the quantitative operationalization of intersectionality within Political Science is often unsatisfactory. I offer a method to account for the multidimensionality of identity which highlights the modifying nature of living with both different combinations of oppression, and privilege. I identify the Bayesian Multilevel Model as a superior tool to understanding intersectional dynamics in political behavior than conventional methods. By applying this method to two major published studies, I show how Bayesian Multilevel Models increase our inferential understanding of group-based heterogeneity in public opinion and political behavior. In doing so, the model better captures the interwoven nature of race and gender that often go unnoticed in Political Science research.

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Introduction

Scholars have long been interested in the influence of social identities on American politics (Berelson, Lazarsfeld and McPhee 1954; Converse et al. 1961; Dawson 1994; Kinder and Sanders 1996; Mason 2018). The salience of race during Barack Obama's presidency and the racialized and gendered politics of the Trump era have made understanding the complex nature of intersecting identities all the more important for researchers (Tesler 2016; Sides, Tesler and Vavreck 2018; Jardina 2019; Phoenix 2019).

American politics research, however, has not effectively updated the methods used to study increasingly salient intersecting identities. The leading quantitative methods for the accounting of race and gender in American politics often fall short of the theoretical understanding of their compounding nature. The discipline has made strides in recent years to overcome this methodological divide by using intersectional theory (Crenshaw 1989, 1991). But, the bulk of work on political behavior and attitudes in the United States omits the interwoven and modifying nature of race and gender–particularly as it relates to the unique experiences of women of color in the United States who face discrimination and oppression on multiple fronts.

Some of these failures surely stem from the difficulty in operationalizing intersectionality's as it requires rich contextual understandings of lived experience and working against the hegemonic norm that race and gender can be studied in isolation from each other (Simien 2007). However, there are also major methodological impediments to understanding the complex nature of intersecting identities in political behavior. In particular, there are real data limitations for quantitative scholars who study subgroups, as survey data often has too small of subsamples for intersectional analysis Frasure-Yokley (2018).

A segment of scholars such as Junn (2007), Hancock (2007*b*,*a*, 2019), McCall (2005), Weldon (2006), Simien (2007), and Spry (2018) theorize how to use intersectionality within quantitative methods. These scholars have: created frameworks for applying intersectionality quantitatively, outlined limitations of current methods, and rethought our survey methodology to better understand multidimensional identity. This work builds on the contributions of intersectional scholars' recognition that the study of political behavior and attitudes in the United States requires an intersectional understanding of identity. I depart from this work by showing there already are quantitative methods available to better capture these relationships. The focus of this piece is thus grappling with the methodological divide between quantitative methods and intersectional understandings of identity to pose new modeling tactics less theoretically limited.

This paper bridges the strides made by intersectional scholars to those made by political methodologists who have advanced their ability to account for group-based heterogeneities (Gelman and Hill 2006). This piece offers Bayesian Multilevel Models as a better option than classical regression for the study of multidimensional identities. The contemporary quantitative methods used to study multidimensional identities have shortcomings that can be addressed by Bayesian Multilevel Models, namely, sample size limitations. Bayesian Multilevel Models are designed to account for such group-based heterogeneity by estimating group-level effects, as well as incorporating prior knowledge of these groups. They are superior to classic regression in their ability to more precisely estimate unique intercepts (baseline values) and slopes (magnitudes of change). This method does so with less noise, more efficiently even with smaller sample sizes, all while giving more description of total variation explained by the model.[1] Scholars can also meaningfully engage with Bayesian methodologies by using this method including their advantage of candidly showing statistical uncertainty and reducing damage done by the p-value. Building on these methodological opportunities, this piece shows Bayesian Multilevel Models are a better option than classical regression for the study of multidimensional identities.

First, this paper will outline commonly used methods to quantitatively measure identity including: indicator/dummy variables (complete pooling), interaction terms, subgroup regressions (no pooling), and ANCOVA with Bonferroni. Secondly, I present why the

[1]Gelman and Hill outline traditional/classic regression without multilevel as OLS or Logit with only individual level effects estimates, and no group-level effects estimated.

Bayesian Multilevel Model is a superior method than conventional tactics to account for the multidimensional lived experience with privileges and/or oppression. Thirdly, this piece applies the Bayesian Multilevel Models to Klar (2018) and Sirin, Valentino and Villalobos (2016) to show that there are applications of the method within flagship Political Science journals. The paper concludes showing that researchers can use this model to recalibrate their conventional approaches to understanding the interwoven nature of identity.[2]

Operationalizing Intersectionality

Intersectionality was pioneered by Kimberlé Crenshaw in 1989 as she critiqued identity literature and White feminism for a lack of understanding of the interwoven nature of race/ethnicity, gender, and class. In particular, Crenshaw highlights how the lived experience of both racism and sexism didn't line up with the societal understanding of them being separate, and left the experiences of Black women in the shadows. Crenshaw's original intention was to explain this in terms of the legal system as an interventionist and practitioner-oriented approach. The intellectual lineage of scholars of color describing these intersections is long; however, Crenshaw coined the term and approach in a way that has been widely disseminated in academic circles and politics alike (Davis 2008; Cho, Crenshaw and McCall 2013).[3]

Americanists using intersectionality have used it to explain: the race-gendering of women of color in political institutions such as Congress (Hawkesworth 2003; Smooth 2011; Brown 2012), political behavior of women of color (Junn and Masuoka 2008; Junn 2017; Junn and Masuoka 2020; Brown 2014; Ojeda and Slaughter 2019), voting rights (Montoya 2020), interrogating U.S. democracy (García Bedolla 2007), and political atti-

[2]This paper does not deal with class as a facet of identity yet, as a third level adds an incredible amount of complexity to the estimation. In addition, many current works on intersectionality start by only working with just race and gender (Frasure-Yokley 2018; Hancock 2019). Future work will include methods that can successfully incorporate class.

[3]Scholars and activists include but are not limited to: Gloria Anzaldua, Combahee River Collective, Patricia Hill Collins, Anna Julia Cooper, Ida B. Wells, and Maria Stewart.

tudes of different racial groups of women (Frasure-Yokley 2018; Gershon et al. 2019). Researchers have also sought to apply intersectionality in the comparative context (Weldon 2006), and have created better datasets for intersectional analysis (Barreto et al. 2018).

It is vital to note intersectional theory is also often applied outside the positivist realm, through interpretive or ethnographic methods, as these methods provide richer context (Jordan-Zachery 2007; Alexander-Floyd 2012). Intersectionality research outside of the quantitative realm is, "...a vibrant, complex body of knowledge" (Alexander-Floyd 2012). The nuance and context needed for detailed description of intersections of oppression was often more suited to methods outside of quantitative methods McCall (2005). The method proposed in this piece is derived from taking the charges of contextual richness and theoretical robustness seriously through applying Bayesian methods, and prioritizing the interwoven and modifying nature of race and gender.

For the purposes of this paper, I will first make an important distinction between intersectionality and multidimensionality, as well as clarify my use of intersectionality. In its travels, intersectionality's intellectual trajectory has morphed so that intersectionality ranges from broader interpretations which employ it as a research paradigm (Hancock 2007*a*,*b*), and more narrow interpretations that intersectionality should solely focus on the experiences of Black women and social justice projects (Alexander-Floyd 2012).

I employ Hancock's understanding of intersectionality as a research paradigm that, "...represents a set of basic beliefs or a worldview that precedes questions of empirical investigation" (Hancock 2007*a*). In addition, I leverage the claim of Simien (2007) that, "... an intersectional approach expects that such identity categories such as race, class, and gender fuse to create distinct opportunities." I use intersectionality to describe the lived experience of those who have oppression on multiple fronts of their identity, in particular with regards to race and gender. This maintains the focus of intersectionality on Black women at its most narrow, and women of color at its most general. This choice was based on facilitating research that uses intersectionality in way that is true to its "world making possibilities," (Nash 2018). Hancock also outlines the importance of looking at both the individual and structural level to be an intersectional analysis, and I show this method poses a new way to look at the individual level (Hancock 2007*a*).[4]

Multidimensionality refers to the larger scope of how race and gender operates interdependently for all individuals, not just those with multiple marginalized identities (Simien 2007; García Bedolla 2007; Spry 2018). Intersectionality exists within the multidimensionality of identity, but not all modifying identities are intersectional. This is a vital distinction as the Bayesian Multilevel Model accounts for multidimensionality (multiple forms of race and gender), as well as intersectionality within it. I then leverage the rich intellectual history of intersectionality to inform my methodological priorities, as intersectional research demands leaving intact these interwoven groups and incorporating contextualization. This modeling tactic captures multidimensionality and allows for isolation of intersectional relationships.

This understanding of intersectionality and multidimensionality guides the research questions. What are the most commonly used methods to incorporate identity into quantitative work? How can we make these methods better incorporate context and improve the status of data limitations? There are four main approaches that scholars utilize for identity, none of which pose the same utility as the Bayesian Multilevel Model.

The most commonly used approach is indicator variables. Additive understandings of intersectionality lead to a reliance on binary indicator variables to account for race and gender. Indicator variables (without interactions) only show the additional effect of being of a given gender or race on the outcome variable independent of each other, and will not reflect the interdependent effect of race and gender on an outcome. As explained by Simien, "Firmly rooted in an experience-based epistemology, [intersectionality] encompasses perspectives that maintain that such identity categories as gender, age, race, ethnicity, class, and sexuality are mutually constituted and cannot be added together (Simien

[4]Future work will hopefully include a model that elegantly includes individual and institutional predictors in tandem.

2007).” Quantitative methods can reify these artificial understandings of identity through modeling practices that do not adopt intersectional understandings. Women of color don’t operate solely through their gender or racial identity at a given moment but are constantly influenced by the two structures (Junn 2007; Hancock 2007*b*). Methods should therefore be put forth with the premise that one cannot privilege a single aspect of identity, but they are to be taken as a whole (Brown 2014). This demonstrates the clear shortcoming of indicator variables as they capture a false isolation of race or gender on their own. This is a method of complete pooling, as it combines the groups in the data, and masks group-based heterogeneity.[5] Complete pooling is troubling if the main point of study is to investigate a particular race/ethnic and gender group, and this tactic "pools" or dilutes group-based heterogeneity (Gelman and Hill 2006). This is most commonly used by scholars who are not acknowledging intersectionality.

Secondly, scholars use race and gender interaction terms (accounting for the shared effect of race and gender) in a model as an attempt to accommodate intersectional theory. It allows for the estimation of a baseline and effect value for each intersectional or multidimensional race/gender group. However, the interaction term is assuming these variables are separate uncorrelated pieces, which goes against intersectional theory (Simien 2007). Interaction effects are also noisy estimates for small sample sizes and are not ideal for estimating grouped effects (Gelman and Hill 2006). Thus, the multiplicative understanding of identity in practice falls short methodologically and theoretically as it still lacks context and has poor small sample size performance.[6]

Alternatively, subgroup regressions, (or a separate regression for each race-ethnic and gender intersection), are another method used by intersectional scholars (Frasure-Yokley 2018; Hancock 2019). This tactic lacks modeling parsimony, but accounts for the grouped

[5]There are three main ways to "pool," or combine the data: complete, no pooling, and partial pooling. Partial pooling is the happy medium. "Multilevel modeling partially pools the group-level parameters at their mean to split the difference between the two extremes of no pooling and complete pooling (Gelman and Hill 2006).

[6]The frequentist paradigm refers to traditional statistical approaches as opposed to using the Bayesian paradigm with priors. Both of these concepts will be explained in later sections.

nature of race and gender.[7] This method comes closer to incorporating intersectional theory. Within the methods community, this is called "no pooling" of groups. No pooling methods separates all groups, and a regression is run separately for each. This can lead to to overfitting issues, and it is problematic for groups with small amounts of data in each group, as the researcher is likely to get more extreme estimates (Gelman and Hill 2006).

Beyond this, no pooling has three main limitations for intersectional purposes. Most datasets do not often allow for one to subset by both race and gender and still maintain large enough sample sizes for robust statistical analysis. This was even outlined in the original discussions of intersectionality within Crenshaw's analysis of defendant experiences with the legal system. The defendants outlined in "Demarginalizing the Intersections" had trouble proving their point as data on Black women was few and far between (Crenshaw 1989). Secondly, researchers can't directly compare coefficients across multiple models, so direct comparisons of effects across race and gender subgroups are lost. Lastly, interpretation is difficult for multiple dependent variables of interest and multiple subgroups, as this requires a multitude of regressions have to be run for each subgroup and effect being measured.

A less common method is ANCOVA with Bonferroni corrections, which will be outlined since it is featured in the second replication (Sirin, Valentino and Villalobos 2016). ANCOVA with Bonferroni allows the researcher to calculate least squares means and their significant differences for groups while controlling for a given covariate's variation contribution. It broadly is a method for comparing subgroup differences. However, ANCOVA lacks intersectional compatibility as not even interactions can be included in this framework. Overall, it lacks the ability to account for more complicated intersectional relationships, only shows differences rather than effect sizes, and lacks contextual richness that can be incorporated in Bayesian methodologies.

Bayesian Multilevel Models provide an intuitive way to solve the problems posed by the

[7]Parsimony means simplicity, and models that are simple ease interpretability. It is a desired aspect of a statistical model.

aforementioned methods. In one single model, we can produce an intercept and slope that are relative to the intersections of race and gender, that reduces noise and overfitting risk, maintains comparisons between groups, and gives more information as to the influence of intersectionality. The next section will outline why Bayesian Multilevel Models are a superior tool than current methods.

Bayesian Multilevel Models for Intersectional Analysis

Multilevel Models (MLMs) are used in order to accommodate related groups in data. Multilevel Models can be fit in both Bayesian and frequentist frameworks; however, utility garnered by Bayesian frameworks make it a superior choice if possible. A classic example of Multilevel Models is using data of students in classrooms (Gelman and Hill 2006; Peugh 2010), where a study that is analyzing these students does not account for the effect of a given classroom, thus missing an integral component of the student's academic life. Without accounting for the effect that a given classroom (or group) likely has, a unique trend that holds across students in that classroom is missed. In the case of this piece, the classrooms are the intersections of race and gender. The effects of these identities are a result of unique experiences based on multidimensional identities. For intersectionality, structural oppression (patriarchy and systemic racism) is interwoven and modifying, which creates unique group-level effects for women of color in many political outcomes. Multidimensionality also demonstrates that identities with some level of privilege (via race or gender) also have unique lived experiences. To account for these related structures in the data, the multilevel model calculates individual level effects (the traditional main effects of a regression model), and group-level effects (also called random or mixed effects) which vary across individuals in the sample according to group. These group-level effects capture the naturally occurring patterns that result from the unique impact of the classrooms, or in this case, race and gender combinations. The general form of the individual level effects formula (at the individual level) is featured below, where *i* represents a given individual, and *j* represents the group.

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + \epsilon_{ij}$$

Where the multilevel model differs is the estimation of group specific effects for both the intercept β_{0j} and the coefficients β_{1j} through partial pooling, which weights the group estimates with the individual level estimates. In other words, partial pooling uses the overall average for the individual level to inform group-level estimates (Gelman and Hill 2006). The multilevel model also measures residual error terms at the group-level u_{oj}. Those formulas are shown below. In this example, we can estimate the group effect (*j*) across different coefficients of interest β (slope β_{0j} and coefficients β_{1j}), using the grand mean γ_{00}, deviation from the grand mean in the second level γ_{10}, and group specific means γ_{01}, γ_{11}. The group-level intercept is β_{0j} and the slope is β_{1j}.

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(X_{ij}) + u_{oj}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(X_{ij}) + u_{oj}$$

For our purposes, I specify the models to have individual level effects, and a grouping variable for each race and gender combination to find specific group-level effects (by method of partial pooling).[8] Multilevel modeling poses utility for intersectionality without Bayesian methods; however, I will propose Bayesian methods as they allow for further context to be built into modeling practice. Bayesian theorem is as follows (Clark 2018):

$$posterior \propto prior * data$$

[8]The grouping variable is a factor which, for example, has separate levels for Black women, Black men, Latinas, and Latinos, and White Women and White men. The researcher could enumerate other groups of interest if desired. Multidimensional groups are specified in *one* grouping variable to maintain their interwoven effects.

$$updated\,belief = prior * current\,evidence$$

Each portion of the Bayesian equation is posed in the context of distributions of values, which is a critical component of Bayesian theory as opposed to frequentist theory. Given this, I will estimate individual level and group effects as distributions rather than just point estimates (as in classical regression) through Stan programming and MCMC sampling in the *brms* package Bürkner (2017).

An in depth explanation of Bayesian methods will not be given here.[9] However, it is important to note that Bayesian methods garner more context than traditional regression (frequentism), as it estimates "Truth" as a distribution of values, rather than a single point estimate. This provides a more nuanced understanding of the "True" relationship being explored as compared to the frequentist paradigm (Gelman et al. 2013). This falls in line with contemporary critiques of the use of frequentist statistical significance, and the Bayesian alternatives which are more candid about estimate uncertainty (Wasserstein and Lazar 2016).

Further, we can incorporate our previous understandings of "Truth" through our prior distribution, which creates results bound in theoretical or empirical context. This includes future work done on the subjects in the replications, in which these posteriors can be used as future priors, thus creating situated knowledge and context of intersectional political experiences. Bayesian researchers have also posed its utility for deeply contextual relationships (Western and Jackman 1994; Humphreys and Jacobs 2015). These two components make Bayesian methods a more suitable alternative for intersectionality and multidimensionality.

I show the Bayesian Multilevel Model has five main advantages. First, Bayesian methods do not require as large of sample sizes as no pooling approaches because of their estimation tactic (MCMC sampling). Sample sizes have long been an obstacle of researchers who do quantitative intersectional work including, for Crenshaw herself, who ran into

[9]For an introduction to Bayesian methods see Gelman et al. (2013), and Clark (2018).

issues of sample sizes of Black women being too small for robust statistical analysis (Crenshaw 1989). Surveys such as the American National Election Survey (ANES) (which is the longest standing and most well-known American election survey) has very small sample sizes of intersectional race and gender groups. It will likely be the case that multidimensional identity sample sizes will continue to be small in the foreseeable future, and these granular studies of identity will always require sample size subsetting. Therefore different modeling tactics need to be explored, such as Bayesian frameworks, which operate better with small sample sizes (Gelman and Hill 2006).

Next, partial pooling gives more precise results than other pooling methods, particularly when there is a small sample size in a given group. The estimate garnered by partial pooling is more efficient than the relatively noisier no pooling, and complete pooling (the most common method) ignores important patters of group-based heterogeneity. Multilevel Models allow for the researcher to prioritize heterogeneity, as needed for intersectionality and multidimensional identity research. The interwoven nature of race and gender is a vital feature of the data, and should not be "pooled" away, or treated as an *ad hoc* correction with controls.

Thirdly, I can estimate new quantities such as the ICC, which are helpful to scholars who care about group-based heterogeneity, i.e. identity scholars. The ICC is a percentage that shows how much of the total variation explained by the model can be attributed to the grouping variable specification. It "ranges from 0 if the grouping conveys no information to 1 if all members of a group are identical"(Gelman and Hill 2006). This measure provides utility to intersectional scholars as they now have insight into how influential race and gender are in accounting for explained variation in the model. Researchers should care about explaining variation, as it reflects how well the model the researcher specified is performing in uncovering the underlying relationships.[10]

[10]The appropriateness of the ICC can vary by whether a researcher employs Bayesian or frequentist frameworks (under certain non-linear Bayesian frameworks a substitute must be used), so it is important to check for the appropriateness of the ICC in special circumstances. However, ICC can be found in both Bayesian and frequentist work.

The fourth reason is Bayesian Multilevel Models are more accessible to scholars now than they have been in the past. Previously, they required lengthy package and syntax knowledge of (but not limited to): BUGS, JAGS, or Stan programming.[11] These skills were needed beyond learning Bayesian methods, which are not as widely accessible as frequentist pedagogy. The "brms" package is one of a few R based programs that interfaces with R to create multilevel model Stan code for you without needing to learn Stan (Bürkner 2017).[12] Brms allows more substantive researchers to fit appropriate Bayesian models for their research with greater ease. This step towards accessibility can be utilized by scholars of race, gender, and intersectionality.

Lastly, Bayesian methods allow intersectional scholars to utilize priors based on intersectional context. Bayesian methods with priors based on knowledge with lived experience with intersectionality will better inform multidimensional group heterogeneities than frequentist frameworks. Critical race and feminist scholars, as well as race and gender scholars, have long acknowledged the persistent salience of racism and sexism's influence on political behavior and attitudes. Therefore, this epistemology of acknowledging intersectional forms of oppression and multidimensional identities can be built into model specification. Priors in this paper are garnered by specifying weak normal priors for individual level effects, and then utilizing a LKJ correlation prior for the group effects. Defining the LKJ prior (which allows for correlations between the levels of the grouping variable) helps build in context of the interrelated nature of race and gender as implied by multidimensional identity research. [13]

Below I feature a table which provides an overview of the conventional methods in comparison to the Bayesian Multilevel Model. While the equation is more complicated, it is a small price to pay for increasing small sample size performance, minimizing noise and

[11] See MCMC Pack, RCPP, Bayes M.

[12] Also see rstanarm.

[13] I use this as recommended by the Stan developers for grouping variables that have more than one level per grouping factor. Researchers can also specify group-level priors priors individually (for each race gender intersection). This requires working directly in Stan, and not brms, which poses an accessibility trade-off. It is a more involved (less accessible) process, but adds additional context called for by intersectional theory.

overfitting issues, providing new variation terms, and incorporating prior context.

Table 1: Methods Comparisons

Method	Equation	Benefits	Drawbacks
Indicator - Complete Pooling	$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon_i$	- Accessibility to academic community - Race and gender are in the model	- Additive understanding of identity - Masks intersectional effects by missing effect differences between groups - Violates that variables are separate uncorrelated pieces - Lacks contextual richness
Interaction	$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 * X_2 + \epsilon_i$	- Effects for race/gender groupings are given	- Violates that variables are separate uncorrelated pieces - Noisy estimate with smaller n - Lacks contextual richness
No Pooling	$Y_{Group1} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon_i$ $Y_{Group2} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon_i$	- Group level effects that are less noisy than interaction term - Accounts for group heterogeneity as a vital feature of data	- Potential for overfitting - Loss of direct comparisons - Difficult interpretation across multiple DV's - False discovery rate - Small sample size - Lacks contextual richness
ANCOVA	$Y_{ij} = \mu_i \beta(X_{ij} - \bar{X}) + e_{2ij}$	- Simplicity for either race or gender - Shows subgroup differences	- Does not scale up well for more complicated analysis - Shows difference not effects - Lacks contextual richness
Bayes MLM	$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + \beta_{2j} X_{ij} + \epsilon_{ij}$ $\beta_{0j} = \gamma_{00} + \gamma_{01}(X_{ij}) + u_{oj}$ $\beta_{1j} = \gamma_{10} + \gamma_{11}(X_{ij}) + u_{oj}$ $\beta_{2j} = \gamma_{20} + \gamma_{22}(X_{ij}) + u_{oj}$	- Minimizes noise - Minimizes the potential for overfitting - Avoids missing important patterns with complete pooling - New Ways to Explain Total Variation and Group Variation - Small sample size performance - Informative priors increase contextual richness	- Lack of accessibility from complicated model

Expectations

In this section I will detail: when Multilevel Models are expected to highlight intersectionality, the interpretation of Bayesian Multilevel Model outputs in this paper, and the empirical expectations of each replication. The Bayesian Multilevel Models will preform particularly well in instances where group-based heterogeneity exists and there are small sample sizes in groups. At the broadest level, questions of political attitudes and behaviors that address identity with intersectional subgroups in the sample should actively try to account for group-based heterogeneity in their modeling practices. Further, data limitations are pervasive for minority group analysis, so the combination of the salience of intersectionality in identity politics and the real constraints of subgroup analysis make the Bayesian Multilevel Model a superior choice over conventional methods.

This heterogeneity in the context of intersectionality theory exists for Black women, and women of color, as a result of the uniqueness of those who experience multiple forms of oppression due to race and gender. In particular, research that treats gender as a monolith falls into traps of over generalization. White women and Women of Color's lived experience often differ drastically due to this unique positionality, so research of this manner will likely benefit from an intersectional method (Diamond and Hartsock 1981). This logic can be extended to multidimensionality, as the modifying nature of race and gender exists when privilege is present, so group-based heterogeneity need be accounted for in many other research avenues, particularly for Men of Color and White women. Replications were chosen as tactic to demonstrate that major contributions to Political Science research can be strengthened to include multidimensional accounts of identities. These replications provide both substantive improvements and rigorous new modeling tactics.

In these replications, we will see this method show intersectionality and multidimensionality best when there is a matching between the theoretical expectation of subgroup difference and an empirical opportunities (the data). This section details the empirical expectations (what the output will look like) when intersectionality and multidimensionality matter in a given model. In the Data and Methods Section, I will lay the foundations for why theoretically we should see the full scope of identity play a role in these two papers.

Interpreting Bayesian Multilevel Models require combining the principles of the multilevel model, garnering individual level and group-level regression effects, and Bayesian methods, which give outputs in terms of a distribution of estimates for any specified covariate (β). Through Stan programming which uses MCMC sampling, the model estimates individual level and group-level effects many times (called iterations), to create a distribution of estimates for a covariate at each level.[14] These distributions of estimates are often displayed as density plots to show the median estimate over the many iterations, which is then used as the point estimate in tables. The density plots can also be used to show significant differences in group estimates, as the total iterations for a baseline subgroup can be subtracted from another group of interest to see the similarity in the total interval estimates. These difference between the two distributions are plotted in a new distribution

[14]The complexities of Stan using MCMC sampling is beyond the scope of this paper. Further information can be found in Carpenter et al. (2017).

where zero on the x-axis reflects no difference between the groups, and values on either side reflect the magnitude of difference between groups. The y-axis for all density plots is the % of the posterior that falls into that estimate. For the tables, both individual level and marginal group-level effects are featured, as the group-level effect can be added to the individual level effect to get the specific group estimate.

In the case of this paper, I will feature density plots and tables. In instances where I feature density plots, I will use a combination of total iteration density plots, where the plot shows all the group-level effects over the iterations (I use 3,000) and how often those estimates occur, and difference densities where a subgroup's distribution is taken as the baseline and is compared to other subgroup's distribution. When intersectionality or multidimensionality shines in this modeling technique, the density plots for the different subgroups in the total iteration density plots will be centered around different estimates from each other and potentially have different shapes, and for the difference density plots, the distributions will be centered away from zero. Additionally, in instances where the Bayesian Multilevel Model is performing well, the tables will show distinct group-level effects beyond the individual level (the significant differences gained through plots), and an ICC which demonstrates that the grouping variable contributes to the overall variance explained. The table used reflects individual level effects (i.e. effects not taking group into account), and group-level effects, or the marginal effect that group has on an intercept or covariate. Both feature credible intervals which determine the likelihood of a value to fall with a certain level of probability (95% in this case).

Data and Method

Klar's 2016 piece "When Common Identities Decrease Trust: An Experimental Study of Partisan Women"; and Sirin, Valentino, and Viallobos's 2016 piece "Group Empathy Theory: The Effect of Group Empathy on US Intergroup Attitudes and Behavior in the Context of Immigration Threats," were chosen as each employs conventional methods for understanding the role of race or gender.[15] Klar employs conventional regression tactics with interaction terms to understand gender's role on candidate trust and how it varies along partisan lines, and Sirin, Valentino, and Villalobos utilize ANCOVA with Bonferroni corrections to denote racial differences in group empathy. While their results are quite important in and of themselves we can build on these findings by incorporating intersectional methods and perspectives that account for the interwoven nature of race and gender.

In an important contribution to the study of partisan women in the U.S., Klar argued that the shared identity (womanhood) does not overcome partisan differences. Main findings include that, "opposing partisans who share the superordinate identity of being a woman will not reduce their intergroup biases (Klar 2018)." In an experimental setting, Klar shows level of trust in an out-party candidate actually decreases when gender is primed (candidate being a woman or speaking on a woman's issue). Overall, she shows women are more distrusting of an out-party woman than a similarly situated man. The sample has 1,760 respondents and was administered by Survey Sampling International in March of 2017. The dependent variable of interest, trust in a candidate, is measured on a seven point scale from do not trust at all (1) to trust very much (7).

To expand this work, I interject race should be taken into account when analyzing candidate trust, partisanship, and womanhood. Klar provides a necessary interjection in the use of the common in-group identity model (CIIM), which states that salient superordinate identities reduce intergroup bias (Gaertner et al. 1993). Klar elegantly details how womanhood as an superordinate identity is not conceived uniformly, which leads to her argument that this difference in conception causes women to express more bias to out-party women more than they do out-party men. While a worthy interjection, I pose that race is a fundamental component of understanding what "woman" is as an analytic category, and can explain why womanhood is not a cohesive shared experience across all groups

[15] They were published in the AJPS and JOP respectively, and represent major contributions in top Political Science journals.

Hawkesworth (2006). Further, research on race and partisanship has shown that race is becoming increasingly aligned with political parties and must be considered when looking at current partisan dynamics (Mason and Wronski 2018; Westwood and Peterson 2020).

For these reasons, and based on intersectionality theory, I expect that women of different race ethnic groups will relate to candidate trust differently. In particular, since the race of the candidate is not included in the vignette, I hypothesize that women in these racial groups may perceive what that candidate looks like differently, where Black women and Latinas may perceive a candidate of their own group more favorably at a baseline level (McConnaughy et al. 2010; Stout 2018).

As an inital proof of concept, I use Klar's dataset which does contain information on race (White, Black, Hispanic), and use an interaction term in her original findings using conventional OLS regression. There appears to be a heterogeneous effect by race where Women of Color show higher levels of trust than their White counterparts.[16] If this theory holds with my method, the results (with Black women as the baseline) will show significantly different distributions between Black women and White women (e.g. distribution centered away from zero), showing that their baseline relationship with candidate trust is fundamentally different. The relationship between Black women and Latinas is less clear, but if the distributions are similar (centered closer to zero), women of color have similar baseline levels of candidate trust, and if they are not similar, there is a heterogeneous baseline of candidate trust across these racial groups. Lastly, the Bayesian Multilevel Model should have a relatively large ICC, which means grouping variable (multidimensional race/gender intersections) makes an impact in explaining the total variation.

The second replication, "Group Empathy Theory: The Effect of Group Empathy on US Intergroup Attitudes and Behavior in the Context of Immigration Threats" by Sirin, Valentino, and Villalobos (2016) made important contributions to the study of empathy's effect on issues of race and immigration by using their novel group empathy theory and

[16] This analysis can be found in the Appendix in Table A-1.

measures. It shows that there are racial differences in feelings of out-group empathy between People of Color and White individuals as well as establishing that People of Color exhibit greater levels of group empathy for specific immigration attitudes than White individuals. According to the authors, the dataset is a "two-wave national survey experiment with 1,799 participants consisting of a randomized sample of Anglos and randomized, stratified oversamples of African Americans and Latinos." They measure group empathy with their Group Empathy Index (GEI) which is a 14 item battery of questions scaled from 1 to 5, with 1 showing less group empathy, and 5 showing higher levels of group empathy. They analyze group empathy and policy with respect to undocumented immigrants, and immigrants from different racial groups. The measures are then taken from a 5 point scale, and transformed to a 0-1 scale by the authors. The authors use ANCOVA with Bonferroni correction to show subgroup differences.

Given the scope of their dataset, this work can be expanded to account for multidimensional identities, and include gender as more than a control with ease. The dataset includes both women and men in the following groups: Black, Latina(o)s, and White individuals. In other work establishing the relevance of Group Empathy Theory for Political Science, the authors found significant differences between men and women and their propensity for group empathy, namely, that women show higher levels of group empathy than their male counterparts (Sirin, Valentino and Villalobos 2017). I interject an expansion here to include women substantively. I revised the ANCOVA and split groups by both race and gender to garner significant differences by multiple identity groupings.[17] There is no clear pattern by both race and gender across treatments, but there are heterogeneous average responses in the groupings. Again, I will employ the Bayesian Multilevel Model to this work to account for the relationship of multidimensional identities on group-based empathy.

Starting with the posteriors for all groups, I will compare the distributions to deter-

[17] The original and revised ANCOVA are in the Appendix A-2, A-3.

mine if there are patterns different than the initial findings. If the initial findings of the authors hold, distributions for People of Color (both men and women) will overlap each other (e.g. be centered on similar estimates and have near identical shapes), and White individuals in the sample's distributions will overlap each other. This would show that group empathy towards undocumented immigrants in this experimental setting is divergent for People of Color and White individuals while taking into account the intersectional and multidimensional effects of race and gender. The converse is true if my expectations hold. In that case, there will be heterogeneous distributions across different race/gender groupings (e.g. not centered on similar estimates and/or have different shapes). Similar to the Klar replication, I expect this model to show intersectionality in the difference densities (with Black women as the baseline) if the results show significantly different distributions between Black women and other subgroups (e.g. distribution centered away from zero). This result would show that Black women's baseline group empathy towards undocumented immigrants is fundamentally different than other subgroups. Lastly, I will interrogate the ICC to determine the usefulness of the grouping variable as a relatively large ICC denotes grouping variable impact.

To reiterate model specifications for ease of interpretation, these models for both replications reflects the individual level effects across the whole sample, and group-level effects for a given race and gender group. For each paper, an intersectional grouping variable was specified to denote what race and gender groups were being analyzed. With respect to Klar, I specify a grouping variable which estimates unique effects for Black women, Latinas, and White women. With regards to Sirin, Valentino, and Villalobos, I define a grouping variable for Black women and men, Latina(o)s, and White women and men. I also enumerate weak normal priors on individual effects, cauchy for standard deviations of the group effects, and an LKJ correlation prior of 0.6 (Klar) and 0.8 (Sirin) for the grouping variable.

Replication 1: Klar Results

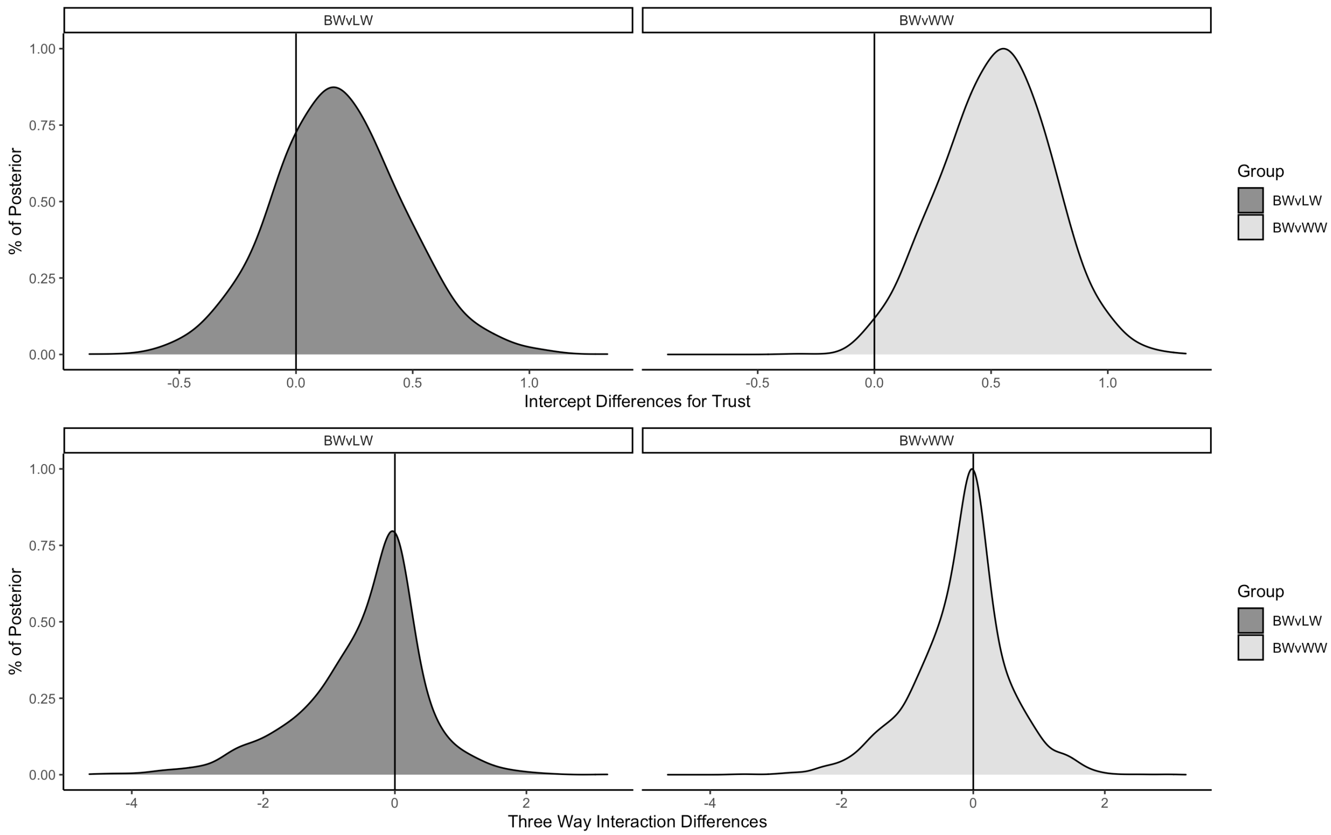
The Bayesian Multilevel Model is estimated and the distribution of the posteriors for the group-level effects are shown in Figure 1. I feature the intercept (baseline level of candidate trust) as well as Klar's coefficient of interest, the three way interaction between woman candidate, being of a different party, and a woman oriented policy prime. Both posterior distribution plots featured in this replication are significant difference distributions.

More specifically, Figure 1 uses Black women as the baseline, and shows the difference between their posterior distribution and the other subgroups in the sample.[18] The top plots in Figure 1 show differences in posterior distributions between Black women's baseline (intercept) values of trust towards a candidate with respect to other subgroup. The bottom row shows significant differences in posteriors between Black women's treatment variable (differing party and two gender primes) and the other subgroups. Black women were chosen as the baseline as the focus is on intersectional oppression.

[Figure 1 About Here]

[18]It is important who the researcher chooses as the baseline for intersectional research, as intersectionality places an explicit focus on Black women and women of color.

Figure 1: Klar Posterior Distributions for Group-Level Intercept and Treatment



Note: The x-axis denotes the point estimates of the posterior, and the y-axis denotes the % of the posterior at that point estimate. BW denotes Black women, WW denotes White women, and LW denotes Latinas.

Starting at the intercept, it becomes clear that beyond what the original analysis shows looking at just gender, race is operating very differently for certain subgroups. As I outlined in my expectations, Black women's baseline level of trust in a candidate is starkly different than that of White women's (light grey curve showing little overlap with zero horizontal line).[19] This shows White women who experience privilege on the basis of race show lower levels of baseline trust compared to Black women, who show higher levels of baseline trust. Black women's intersectional experience leads to different baseline levels of trust for candidates than White women, and some difference with Latinas who are slightly less trusting (dark grey curve). This effect is likely due to the lack of race treatment in this

[19] See Table 3 for group point estimates, which is the basis of this determination.

experiment, which allowed women of color to fill in what that candidate looked like for themselves. Literature on trust with race/ethnic groups show that descriptively representative candidates garner higher levels of trust with in-group race/ethnic candidates.

The bottom plots show the treatment variable group posteriors. The treatment variable in this case has a similar effect across subgroups when Black women are the baseline. group-level differences (bottom right) show that the effect of being a different party and two gender primes (woman's issue and woman candidate) operate very similarly for all three groups of women (despite slightly more skewness with Black women and Latinas). This, along with the context of the differing baselines, demonstrates that the underlying theory of candidate trust for women and partisanship operates differently by race.

[Table 2 About Here]

Table 2: Klar Replication Bayesian Multilevel Model Individual and Group Level Effects

Population Level Effects		
Predictors	*Estimates*	*Credible Interval*
Intercept	4.22	-1.27 – 9.81
Woman Candidate	0.14	-3.08 – 4.03
Different Party	-0.47	-4.80 – 7.28
Women's Issue	0.57	-3.75 – 11.06
Woman Candidate * Different Party	-0.15	-5.01 – 7.63
Different Party * Women's Issue	0.86	-5.66 – 5.86
Woman Candidate * Women's Issue	0.37	-7.05 – 5.63
Woman Candidate * Different Party * Woman's Issue	-1.13	-8.41 – 12.76
Observations		1556
Marginal R2 / Conditional R2		0.121 / 0.132

Group Level Effects						
Predictors	*Black Women*	*CI*	*Latina*	*CI*	*White Women*	*CI*
Intercept	0.326	-1.205 - 2.015	0.145	-1.423 - 1.837	-0.414	-1.974 - 1.228
Woman Candidate * Different Party * Woman's Issue	-0.283	-2.526 - 1.383	0.188	-1.636 - 2.365	-0.09	-2.152 - 1.612
Within Group Variance	2.73					
ICC	0.59					
N int	3					

Table 2 shows both the individual level effects for our Bayesian Multilevel Model (which can be interpreted similarly to the coefficients estimated in classical regression), and group-level effects for each subgroup. For example, a researcher would interpret 4.22 as the point estimate of the intercept (the median of the posterior distribution) which reflects the baseline level of trust across the whole sample (the individual level). Credible intervals are estimated instead of confidence intervals for Bayesian models, and denote the percent of certainty (95% certain) a value falls within the specified range.

To get the point estimate for the specific group, the group-level effect is added to the individual level effect. The group-level intercept for Black women, 0.326, is added to the individual level intercept of 4.22, which gives the group-specific intercept, 4.546.[20] This can be done for any of the subgroups in the multidimensional grouping variable for the intercept and the three way interaction. As previously mentioned in the model explanation section, this group specific effect is less noisy than an interaction of race and gender with small sample sizes, and runs less risk of overfitting via no pooling methods.

Further, according to expectations, we see a relatively high ICC. Our grouping variable is explaining 59% of total explained variation, showing the substantial contribution of intersectionality and multidimensionality with this modeling tactic. Lastly, we increase our adjusted/conditional R^2 (measure of candidate trust with respect to our coefficients, penalizing for additional variables) from 7.77% to 13.2% through this modeling tactic. Overall, this replication made both substantive and methodological contributions. I expanded the original piece by incorporating intersectional differences of candidate trust while using a more appropriate and better performing method to study multidimensional identities.[21]

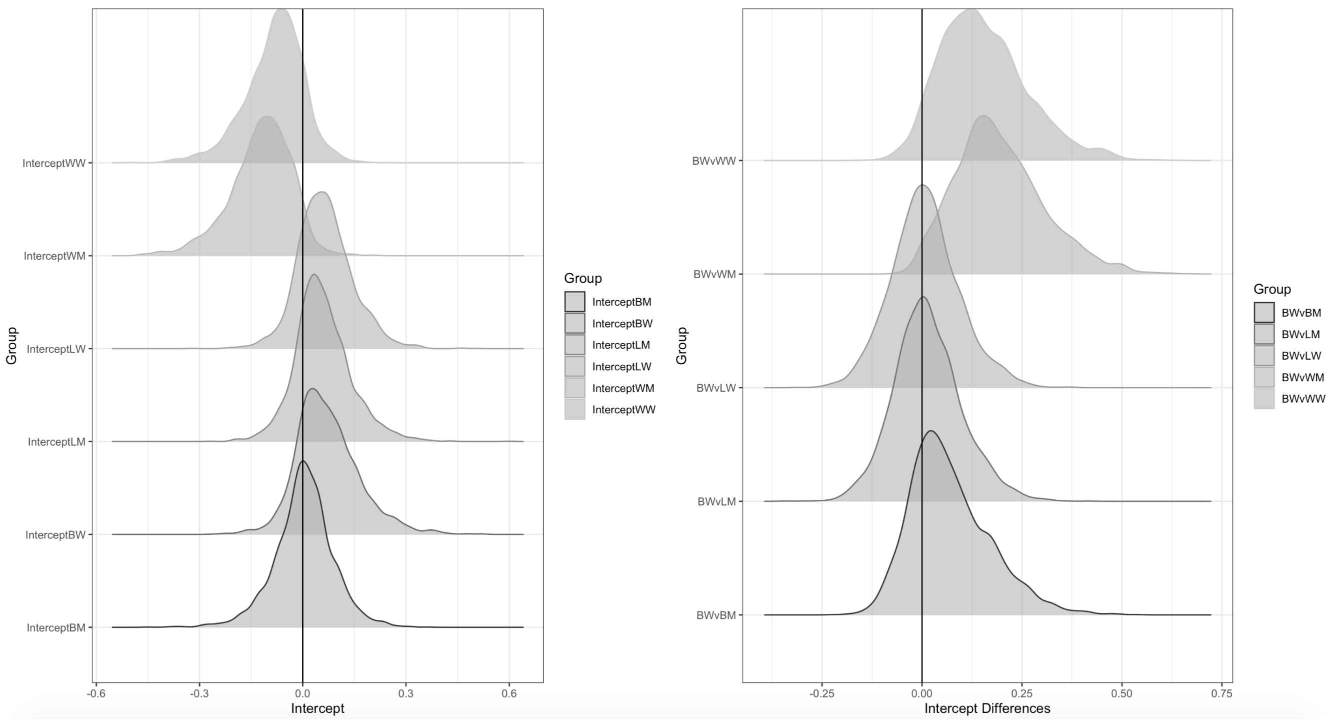
Replication 2: Sirin, Valentino, and Villalobos Results

The Bayesian Multilevel Model is estimated for Sirin, Valentino and Villalobos (2016) and the posterior distributions for each group-level intercept are shown in Figure 2. The covariates in the original model are considered more as "controls" rather than independent variables of interest, so the posterior distributions discussed for Sirin, Valentino and Villalobos (2016) will be group-level intercepts only, and not group-level-intercepts in addition to a covariate of interest as was done in the Klar replication.

[20] Group-level effects show descriptors of variation related to the grouping variable (a factor with three levels for Black women, White women, and Latinas). The ICC is the percent of total variance due to clustering (ranges 0-1).

[21] The results were compared to the conventional tactic via Leave One Out (LOO) cross validation.

Figure 2: Sirin Posterior Distributions Group Level Intercepts - Empathy for Undocumented Immigrants



Note: The x-axis denotes the point estimates of the posterior, and the y-axis denotes the % of the posterior at that point estimate. BM and BW denotes Black men and women, LM and LW denote Latinos and Latinas, and WM and WW denote White men and women.

The top plot in Figure 2 reflects the distributions for each multidimensional group's intercept values of group empathy towards undocumented immigrants. The bottom row takes Black women as the baseline, and shows the difference between their distribution and the other multidimensional groups in the sample. Black women were chosen as the baseline based on prioritizing intersectionality. However, if a researcher wanted to examine other multidimensional identity groups, they could analyze them through the same method of choosing a different baseline.

The top row shows that there are very similar posterior distributions for People of Color with regards to group empathy for undocumented immigrants. White men and White women show less group empathy than People of Color at similar rates to each other, with White men's median value being slightly less empathetic than that of women. This supports the original findings of Sirin, Valentino and Villalobos (2016) and not the expectations set forth in the previous section. To analyze significant differences, distributions of posteriors are subtracted from Black women's distribution (bottom row). Distributions centered around zero reflect little difference, and distributions with less overlap with zero reflect more difference with Black women. This shows White men and women's estimates are different from Black women at similar rates, and show less group empathy. This further backs original conclusions by the authors.

Featured below is the table for the individual and group-level effects for the group empathy towards undocumented immigrants (Table 3). As previously mentioned, the covariates featured in the individual level part of table are to be interpreted similarly to traditional regression effects. To get the point estimate for the specific group, the group-level effect is added to the fixed effect.[22]

[Table 3 About Here]

[22]Group-level effects show descriptors of variation related to the grouping variable (a factor with six levels for Black women, Black men, White women, White men, and Latina(o)s.) The ICC is the percent of total variance explained by the model that is due to clustering (ranges 0-1).

Table 3: Sirin Replication Bayesian Multilevel Model Individual and Group-Level Effect

Population Level Effects		
Predictors	*Estimates*	*Credible Interval*
Intercept	0.26	0.10 – 0.40
Age	0.04	-0.11 – 0.17
Education	0.10	-0.04 – 0.26
Ideology	0.18	0.09 – 0.28
Metropolitan	0.02	-0.04 – 0.08
Income	-0.03	-0.10 – 0.05
Catholic	0.05	-0.04 – 0.13
Observations		1770
Marginal R2 / Conditional R2		0.039 / 0.118

Group Level Effects							
Predictors		*Black Women*	*Credible Interval*	*Latinas*	*Credible Interval*	*White Women*	*Credible Interval*
Intercept		0.072	-0.084 - 0.285	0.0646	-0.084 - 0.236	-0.082	-0.281 - 0.069
		Black Men	*Credible Interval*	*Latinos*	*Credible Interval*	*White Men*	*Credible Interval*
		0.003	-0.179 - 0.172	0.058	-0.093 - 0.244	-0.121	-.327 - 0.026
Within Group Variance	0.08						
ICC	0.33						
Number of Groups	6						

To find the group-level effect for Black women, the intercept for Black women (in the undocumented immigrant question) is 0.072, which is added to the fixed effect intercept of 0.26, to give group specific effect of 0.332. This can be done for any of the subgroups in the multidimensional grouping variable for their intercept. With regards to the ICC, the total variation explained by the model, 33% is attributed to multidimensional identities. This comports with our expectation that the groupings matter; however, the lack of clear racial *and* gender differences garners a smaller ICC than that of the Klar model which had both.

The Bayesian Multilevel Model provided more nuanced and accurate depictions of intersectional group empathy.[23] The contributions made by the authors were bolstered by this approach, showing that even taking intersectionality and multidimensionality into account, People of Color generally are more empathetic than White individuals. It shows the salience of race given White women, despite experiencing an axis of oppression with their gender, do not experience higher level of out group empathy with regards to immigration. The Bayesian Multilevel Model also showed more nuance in the impact of intersectionality's explanatory power with the ICC.

Conclusion

There is much work to be done to use and operationalize intersectionality methodologically. As Simien astutely observed, "Political scientists must construct new theories and methodological approaches that address the complex processes through which social categories shape and, in effect, determine political outcomes." This is a necessary and largely underserved part of the discipline. Research like this is particularly important for scholars of American politics who are interrogating U.S. democracy for those that the democratic promise is unrealized.

It is important to acknowledge who this method is most salient for, which is the scholars who are incorporating intersectionality into their work quantitatively with often unsatisfactory results. These scholars are doing work vital to Political Science at a sociopolitical moment of heightened unrest in the United States, so they deserve methods tantamount to their task. This model is not meant to be a final solution or silver bullet (as Hancock (2007*b*) would say), but a step towards better methods for an important charge of the discipline.

In this piece I have argued for Bayesian Multilevel Models to account for the hetero-

[23] The results were compared to the conventional tactic via Leave One Out (LOO) cross validation. Results are shown in the Appendix on A-4.

geneities produced by race and gender intersections. In replicating Klar's "When Common Identities Decrease Trust: An Experimental Study of Partisan Women", and Sirin, Valentino, and Villalobos's ""Group Empathy Theory: The Effect of Group Empathy on US Intergroup Attitudes and Behavior in the Context of Immigration Threats", the method was able to show the form of intersectionality's effects more accurately than current methods. This method is better than indicator variables, interaction terms, no pooling methods, and ANCOVA in capturing intersectionality because of its accuracy, performance with small sample sizes, ability to incorporate priors based on lived experience, and variation terms based on the multidimensional grouping variable. This piece provided substantive advances to the literature showing women of color have different baseline levels of trust for a candidate than White women Klar (2018), and bolstered the approach of Sirin, Valentino and Villalobos (2016) showing that GEI's effect on immigration attitudes is robust across People of Color when gender is substantively reckoned with.

To be sure, for both cases of intersectionality and multidimensionality, if the dataset has large sample sizes for each subgroup the gained precision from the Bayesian Multilevel Model is no better than the interaction term in conventional regression. However, the multilevel model will still estimate helpful terms such as the ICC, and give more nuanced understandings of group-based variation. Further, intersectional quantitative scholars face data limitations so consistently, that these large datasets where the method does not perform well are sparse.

In sum, the goal of this article is to show this tool has utility to the study of political behavior and attitudes in the U.S., as intersectionality and multidimensional identities undergird the lived experience that shapes these areas of study. It is a methodologically rigorous, and theoretically sound modeling tactic which builds intersectional and multidimensional context into research practices.

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A

Appendix - A

Klar Replication and Revision with Interaction

Table .1: Klar Replication and Revision with Interaction

	Trust in Orignal Model			Trust in Replication with Black and Latina Indicators		
Predictors	*Estimates*	*std. Error*	*p*	*Estimates*	*std. Error*	*p*
Intercept	4.00	0.11	**<0.001**	3.81	0.11	**<0.001**
Woman Candidate	0.12	0.16	0.461	0.16	0.16	0.315
Different Party	-0.52	0.16	**0.001**	-0.52	0.16	**0.001**
Women's Issue	0.56	0.22	**0.011**	0.55	0.21	**0.009**
Woman Candidate * Different Party	-0.17	0.23	0.473	-0.16	0.23	0.483
Different Party * Women's Issue	0.91	0.34	**0.007**	0.88	0.33	**0.007**
Woman Candidate * Women's Issue	0.45	0.32	0.165	0.45	0.31	0.150
Woman Candidate * Different Party * Woman's Issue	-1.16	0.49	**0.018**	-1.05	0.48	**0.027**
Black				0.82	0.15	**<0.001**
Latina				0.88	0.18	**<0.001**
Observations	1088			1096		
R^2 / R^2 adjusted	0.083 / 0.077			0.121 / 0.114		

The original model is featured on the left, and the imputed and respecified model is featured on the right. Note the significant effects for race featured in the revised model. Both models only feature women.

Table .2: Original ANCOVA in Sirin

Table 1. Racial/Ethnic Differences in Group Empathy, Perceived Threat, Political Trust, and Economic Competition

	Anglos	African Americans	Latinos
General group empathy	.553	.603*	.588*
	(.008)	(.009)	(.009)
Group empathy for undocumented immigrants	.353	.496*	.500*
	(.012)	(.012)	(.013)
Group empathy for Anglos	.430	.428	.421
	(.011)	(.012)	(.012)
Group empathy for Arabs	.348	.496*	.401*
	(.011)	(.011)	(.012)
Group empathy for African Americans	.432	.795*	.508*
	(.010)	(.011)	(.011)
Group empathy for Latinos	.419	.616*	.663*
	(.011)	(.011)	(.012)
Perceived national threat of immigration	.488	.425*	.396*
	(.013)	(.013)	(.014)
Perceived personal threat of immigration	.342	.319	.305
	(.012)	(.013)	(.014)
Political trust	.282	.381*	.316*
	(.010)	(.010)	(.011)
Perceived economic competition	.434	.484*	.382*
	(.013)	(.013)	(.014)
N per racial/ethnic group	633	614	552
Total *N*	1,799		

This is original ANCOVA table from (**?**).

Table .3: Replication ANCOVA

Table 4: Racial/Ethnic & Gender Differences in Group Empathy, Perceived Threat, Political Trust, and Economic Competition

	Anglo Woman	Anglo Man	Black Woman	Black Man	Latina	Latino
General Group Empathy	.582 (0.011)	**.525 (0.011)**	**.621 (0.012)**	**.586 (0.012)**	**.609 (0.014)**	**.568 (0.012)**
Group empathy for undocumented immigrants	.375 (0.016)	.331 (0.017)	***.493 (0.017)***	***.501 (0.017)***	***.517 (0.019)***	***.485 (0.017)***
Group empathy for Anglos	.447 (0.015)	.412 (0.016)	*.430 (0.016)*	*.427 (0.016)*	.428 (0.018)	.414 (0.016)
Group empathy for Arabs	.381 (0.015)	.315 (0.015)	***.497 (0.015)***	***.496 (0.015)***	***.421 (0.018)***	.382 (0.015)
Group empathy for African Americans	.465 (0.014)	.400 (0.014)	***.812 (0.015)***	***.780 (0.014)***	**.520 (0.017)**	**.494 (0.014)**
Group empathy for Latinos	.441 (0.015)	.397 (0.015)	***.614 (0.016)***	***.618 (0.015)***	***.650 (0.018)***	***.672 (0.018)***
Percieved national threat for immigration	.511 (0.017)	.465 (0.018)	.429 (0.018)	.421 (0.018)	*.377 (0.021)*	*.409 (0.018)*
Perceived personal threat for immigration	.342 (0.017)	.344 (0.017)	.322 (0.018)	.315 (0.018)	.283 (0.02)	.322 (0.017)
Political trust	.294 (0.013)	.269 (0.014)	***.387 (0.014)***	***.376 (0.014)***	**.351 (0.016)**	.286 (0.014)
Perceived economic competition	.403 (0.017)	.462 (0.018)	.449 (0.018)	*.519 (0.018)*	.363 (0.021)	.402 (0.018)
N Per Race, Ethnic Group	322	305	301	296	239	307
N Total	1,770					

Covariates appearing in the model are evaluated at the following values: age = .39906855918, education = .6886136630, ideo = .5014124232, income = .54149403865, metropol = .89, catholic2 = .25.; Mean (Std. Error)

significantly different from white men; **significantly different from white women**; ***significantly different between both Anglo Groups***

This is revised ANCOVA based off of the analysis from (**?**), but taking into account multi-dimensional identities.

Table .4: Leave One Out Cross Validation

Replications:	Klar		Sirin, Valentino, and Villalobos	
	ELPD Difference	SE Difference	ELPD Difference	SE Difference
Conventional Model	-17.3	6.4	-42.8	9.8
Multilevel Model	0.0	0.0	0.0	0.0

This compares the Bayesian MLM to the respective conventional regression tactic.