The Effects of Descriptive Representation in American Legislatures: Evidence from Committee Hearings and Legislative Effectiveness

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Introduction

One of the most significant shifts in Congress over the past 30 years is the growing diversity of its members. In 1980, fewer than 20 nonwhite legislators served in the House and Senate; today, that number exceeds 130. Women's representation has followed a similar trajectory, rising from just over 20 in the 1980s to more than 150 today. LGBTQ+ lawmakers, who until 2011 never exceeded three seats per term, now hold 13 seats. And while working-class candidates are rarely elected to Congress, they do occupy nearly 6% of state legislative seats.

Importantly, these descriptive representatives are not just rank-and-file members—they occupy the most consequential leadership positions in Congress. Nancy Pelosi (D-CA) became the first woman Speaker of the House in 2007 and served four nonconsecutive terms, making her one of the longest-serving Speakers in history. Under her leadership, Congress passed landmark legislation, including the Affordable Care Act, Dodd-Frank Wall Street Reform, the American Rescue Plan, and the Bipartisan Infrastructure Law. Women and nonwhite legislators have also taken on key committee leadership roles. In the 117th Congress, they chaired 12 of the 20 standing House committees, including two of the most powerful economic committees—Appropriations, led by Rosa DeLauro (D-CT), and Financial Services, led by Maxine Waters (D-CA). These shifts signify more than just increasing diversity in Congress; they show that descriptive representatives now play a central role in shaping policy and wielding institutional power.

How, then, have descriptive representatives—and their positions in leadership—shaped policymaking in American legislatures? Most broadly, they prioritize policies affecting their identity groups. Women legislators are more likely than men to focus on "women's issues" (Bratton 2005; Gerrity, Osborn and Mendez 2007; Lawless 2015). They also sponsor and cosponsor more gender-related bills (Rosenthal 2002; Swers 2005) and vote for gender-focused policies at higher rates (Jenkins 2006). Similarly, nonwhite lawmakers are more likely than their white colleagues to sponsor racially salient legislation (Bratton and Haynie 1999; Pinney and Serra 2002; Sinclair-Chapman 2002; Wilson 2010, 2017) and, under certain conditions, to support race-related bills and earmarked spending benefiting nonwhite constituencies (Kerr and Miller 1997; Canon 1999; Whitby 2000; Tate 2004; Grose, Mangum and Martin 2007; Grose 2011).[1] Likewise, working-

[1]Some scholars argue that party identification and the racial composition of a district better predict lawmakers' support for racially salient legislation than their own race (Swain 1995; Hero and Tolbert 1995; Knoll 2009; Grose

class legislators are more likely than white-collar lawmakers to sponsor and cosponsor economic legislation (Carnes 2013), while LGBTQ state legislators are more effective at advancing and passing legislation than non-LGBTQ legislators, regardless of policy topic (Lollis and Dobson 2025).

While existing research provides strong evidence that descriptive representatives advance policies relevant to their identity groups, it largely relies on data from highly observable stages of the lawmaking process, such as bill sponsorship, cosponsorship, and final passage votes. Although informative, these measures often reduce legislative behavior to binary indicators. Committees, in contrast, offer a broader and more nuanced window into the relationship between legislators' identities and their behavior. As the epicenter of policymaking (Fenno 1966), committees serve as forums for substantive, speech-based discussions (Hall 1998). They also allow legislators to develop policy expertise (Krehbiel 1992; Battaglini, Lai, Lim and Wang 2019; Curry 2019), which enables scholars to assess not only which issues and identity groups legislators reference but also how they integrate expertise into legislative discourse. A renewed focus on legislative committees can thus provide deeper insight into the relationship between legislators' identities, their speech, and policymaking.

Another limitation of the current literature is its primary focus on women and nonwhite legislators. This emphasis is well justified, as women and nonwhite lawmakers have experienced the most significant increases in numeric representation over the past thirty years. However, as a result, we know far less about the legislative behavior of working-class lawmakers and how class-based identities differ from gender- and race-based identities.

In this dissertation, I address both of these voids by focusing on the effects of nonwhite and working-class representation in the U.S. Congress and state legislatures. In doing so, I extend the descriptive representation literature with three key contributions: two theoretical and one methodological. First, I extend intergroup contact theory from social and political psychology to legislatures (Allport, Clark and Pettigrew 1954; Pettigrew 1998; Lollis 2024*a*). Given that the institutional design of legislative committees is well-suited to facilitate contact effects, I argue that sustained cross-group interaction between white and nonwhite legislators influences how white lawmakers discuss race in hearings. Specifically, white legislators in racially diverse committees not only mention race more often but also incorporate more evidence into their race-based discussions.

2011).

Second, I expand Anzia and Berry's (2011) theoretical framework on electoral bias and legislative effectiveness to an understudied minority group: working-class state legislators. Because fundraising and party recruitment biases discourage working-class candidates from running, those who do win tend to be exceptionally qualified and politically skilled. As a result, despite structural disadvantages rooted in class bias, working-class state legislators are just as effective as their white-collar peers at advancing and passing legislation.

Alongside these theoretical contributions, I address a methodological limitation in the study of descriptive representation. Most research in this area relies on sponsorship, cosponsorship, and roll-call vote data. Committee hearings, in contrast, are speech-based and substantively rich. However, they have largely been inaccessible to scholars due to the sheer volume of hearings and the challenges associated with operationalizing measures from text. To fill this gap, I analyze 1.4 million committee hearing statements spanning 25 years and develop a systematic method—a bigram dictionary classification approach—to identify references to race. Unlike prior studies that focused on select committees within a single term (Gamble 2007, 2011), this method allows for the creation of systematic, highly accurate measures of identity references in legislative speech. While this dissertation applies it to race, the methodological approach can also be extended to study discussions of gender, sexual orientation, and class.

Chapter Overviews

In the first essay, I examine whether—and by whom—race is discussed in congressional committees. I theorize that while nonwhite lawmakers discuss race most frequently, white lawmakers will reference race more often in racially diverse committees. Extending intergroup contact theory to legislatures, I argue that repeated and sustained interactions between white and nonwhite legislators in diverse committees prompt white lawmakers to engage more frequently in race-based discussions.

To test this argument, I develop four original measures to capture the prevalence of race-based discussions in legislative and oversight committee hearings. Using a training set of 5,000 randomly selected and hand-coded statements, I apply a bigram dictionary classification method to predict whether race is mentioned in 1.4 million statements from the 105th to the 117th Congresses. My findings show that, on average, nonwhite lawmakers discuss race more often than their white colleagues. However, results from a within-legislator model indicate that white lawmakers are more likely to mention race in racially diverse committees. Finally, using a novel measure of race-issue bills, I demonstrate that discussions of race in hearings are linked to policy representation. This essay highlights how the racial composition of committees shapes both the frequency of race-based discussions and policymaking more broadly.

In the second essay, I extend my argument from the first essay to examine not only *who* discusses race in committee hearings but also *how* they do so. I argue that, due to contact effects, white legislators on racially diverse committees are more likely to incorporate evidence into their race-based statements. To link this finding to intergroup contact theory, I assess who is most influenced by cross-group contact and how it shapes their evidence usage. If contact effects drive these patterns, white Democrats—who share a party affiliation with most nonwhite lawmakers and thus align best with the conditions for contact effects—should cite evidence most often. Similarly, white lawmakers on diverse committees should not only reference evidence more frequently when discussing race but also cite the same sources as nonwhite lawmakers.

To evaluate these expectations, I conduct a detailed and systematic content analysis of race-based committee hearing statements, identifying references to evidence. Findings from a within-legislator model indicate that white Democrats are the most likely to use evidence, and white lawmakers on diverse committees often cite the same sources as nonwhite legislators on the same committee. I further show that citing evidence in race discussions is linked to substantive representation, as legislators who use more evidence are more likely to advance and pass race-related bills. These findings suggest that racial diversity within and across committees—not just in Congress as a whole—shapes how legislators engage with evidence which influences the substantive representation of nonwhite Americans.

Finally, in the third essay, I broaden my focus beyond the study of race in Congress to examine the legislative behavior of working-class state legislators. I argue that working-class candidates face significant class-based electoral biases, particularly in fundraising and party recruitment (Carnes 2018), making them less likely to emerge and win elective office. As a result, working-class candidates who do win are highly qualified and politically skilled. Building on Anzia and Berry's (2011) argument, I posit that these electoral selection effects will lead working-class legislators to be at least as effective as their white-collar counterparts.

To test this expectation, I construct a dataset combining the occupational backgrounds of more than 14,000 state legislators (Makse 2019) with their State Legislative Effectiveness Scores (SLES) (Bucchianeri, Volden and Wiseman 2025), resulting in over 50,000 legislator-term observations. Consistent with my expectations, I find that working-class state legislators are equally as effective as their white-collar colleagues. Further, I conduct a negligibility test to demonstrate that, across various models and specifications, the gap between working-class and white-collar legislators' effectiveness is negligible. These findings challenge classist assumptions that working-class individuals are unfit for governance and suggest that, if more working-class Americans run and win office, they have the capacity to advance and pass pro-worker policies.

Race, Contact Effects, and Effective Lawmaking in Congressional Committee Hearings

Essay 1

In June 2021, the House Committee on Education and Labor met to discuss the Department of Education's policy priorities. The primary witness was recently confirmed Secretary of Education, Dr. Miguel Cardona. Committee members considered a variety of topics, including COVID-19 recovery in public schools, student loan forgiveness, and investing in trade schools and community colleges. In discussing policy issues, some committee members contextualized their comments in terms of race, while others did not.

Frederica Wilson, a Black Democrat from Florida and former high school principal, pressed Secretary Cardona on ways to increase access to higher education for Black students. "Supporting Black men and boys in their path of higher education has been my life's work," she said. "And I need to find out from you...how to increase higher education access for black men and boys, which research has shown there is a disproportionate burden on them".[2] Following Representative Wilson's questions, Representative Suzanne Bonamici, a white Democrat from Oregon, also asked Secretary Cardona a series of race-related questions. She linked her question back to Congresswoman Wilson's statement and, while referencing the need for grant programs for racial minority students, stated that "the pandemic exacerbated existing inequities... and widened the achievement gap, especially for Black, indigenous and Latinx students."[3]

Representatives Wilson and Bonamici were not the only lawmakers on the committee who expressed concerns about educational access for nonwhite Americans. Throughout the remainder of the hearing, members referenced race 28 times. Though the bulk of race statements in the hearing were raised by nonwhite lawmakers (70%), white lawmakers also discussed race (30%). And these references were not merely symbolic. In August 2021, Representative Bonamici introduced the "Community Services Block Grant Modernization Act of 2022", cosponsored by Representative Wilson. The bill reauthorized the use of federal funds

[2]GovInfo. June 2021. "Examining the Policies and Priorities of the U.S. Department of Education." U.S. House Committee on Education and Labor

[3]GovInfo. June 2021. "Examining the Policies and Priorities of the U.S. Department of Education." U.S. House Committee on Education and Labor

to address community-based poverty. One specific provision in the bill, which permits funds from the block grant to be distributed to specific institutions of higher education such as Historically Black Colleges and Universities (HBCUs), Tribal colleges and universities, and minority-serving institutions, directly relates to the race-based discussion in the hearing with Secretary Cardona. The bill passed the House in May of 2022.

Representatives Wilson and Bonamici's questions in committee and eventual bill sponsorship and cosponsorship activity highlight a systematic pattern of race-based representation in Congress. Consistent with theories of descriptive and substantive representation, I argue that nonwhite legislators are often the primary conduits for racial representation during committee hearings.[4] I expect, however, that contact between white and nonwhite lawmakers in racially diverse committee hearings leads white lawmakers to discuss race more frequently.

To test my argument, I develop four original measures to capture the prevalence of race-based discussions in legislative, oversight, and investigative committee hearings. With a training set of 5,000 randomly selected and hand-coded statements, I employ a bigram dictionary classification method to predict whether race is mentioned in 1.4 million statements from the 105th to the 117th Congresses. While most existing evidence examining racial representation uses data from highly observable stages of the lawmaking process, like bill sponsorship, cosponsorship, and final passage votes, this paper is the first to systematically consider race-based content in lawmakers' committee hearing statements.[5] This is particularly important given that committees are where the bulk of policy development occurs (Fenno 1973), and hearings are a rare opportunity for lawmakers to reveal preferences by speaking at length about various policy issues (Hall 1998). I find that nonwhite lawmakers mention race more frequently than white lawmakers in hearings, although white lawmakers are notably more likely to discuss race when they sit on racially diverse committees and in racially diverse hearings. I also demonstrate that legislators who frequently mention race in hearings are more effective at passing race-issue bills, while they are no more effective at advancing bills unrelated to

[4]The Government Publishing Office, which is the source used to collect the committee hearing transcripts used in this analysis, defines hearings as "a meeting or session of a Senate, House, joint, or special committee of Congress, usually open to the public, to obtain information and opinions on proposed legislation, conduct an investigation, or evaluate/oversee the activities of a government department or the implementation of a Federal law. In addition, hearings may also be purely exploratory in nature, providing testimony and data about topics of current interest" (*GovInfo—About Congressional Hearings* N.d.).

[5]Though some studies do examine racial representation in committees, their analysis is either limited to one racial identity group (Gamble 2007, 2011; Peay 2021; Rouse 2023) or to a few committees in one congressional term (Gamble 2007; Minta 2009; Gamble 2011). While informative, the generalizability of existing findings is limited to a specific time or racial identity group.

race issues. These findings are important not only because they suggest that increased racial diversity in legislative committees leads to more discussions about race, but also because race-based speech in hearings is linked to policy representation.

Race in Committees, Contact Effects, and Policy Representation

Existing scholarship finds that lawmakers' racial identity meaningfully shapes their legislative behavior in some stages of the lawmaking process. Black and Latino lawmakers are more likely than white lawmakers to introduce racially salient legislation (Bratton and Haynie 1999; Sinclair-Chapman 2002; Wilson 2010; Wallace 2014; Wilson 2017), as are members of the Congressional Black Caucus (Pinney and Serra 2002). Black lawmakers frequently make symbolic references to civil rights issues in their floor speeches (Dietrich and Hayes 2023), while Latino lawmakers often frame their floor speeches around Latino perspectives and issues (Wilson 2017). In terms of substantive representation, Black lawmakers secure earmarked spending and provide enhanced constituency services to Black constituents (Grose, Mangum and Martin 2007; Grose 2011; Broockman 2013). Furthermore, nonwhite lawmakers advocate for nonwhite Americans through interbranch contact with regulatory agencies during policy implementation (Lowande, Ritchie and Lauterbach 2019). And some scholars have found that lawmakers' voting patterns vary by race, though these findings are often conditional on the content of the legislation (Kerr and Miller 1997; Whitby 2000; Tate 2004) or whether the lawmaker was elected from a majority-minority district (Canon 1999).[6]

Yet there is remarkably little systematic evidence explaining the relationship between lawmakers' racial identities and their committee behavior.[7] Scholars have found that racially diverse committees hold more hearings related to race (Ellis and Wilson 2013; Nestor 2023). And when committees hold racially salient hearings, Latino and Black lawmakers participate at higher rates than white lawmakers (Gamble 2007; Minta 2009; Rouse 2023). Though these findings are congruent with the idea that lawmakers' racial identity shapes their actions in committees, they do not consider whether lawmakers' racial identities shape the *content* of their statements in hearings. Gamble (2011) analyzes committee hearing transcripts linked to five bills in three committees in the 107th Congress and finds that there are content-based racial differences

[6]Not all studies uncover these effects. Some scholars find that party identification and the percentage of Black and Latino constituents in a district better predict whether lawmakers support racially salient legislation than does a legislator's race (Swain 1995; Hero and Tolbert 1995; Knoll 2009; Grose 2011).

[7]In the gender and politics literature, scholars find that women lawmakers better represent the interest of women and other marginalized groups during floor debate (Walsh 2002).

in hearing statements. Black lawmakers are more likely than white lawmakers to use liberal policy frames when discussing racially salient legislation. However, her data suggest that Black lawmakers are no more likely than white lawmakers to mention Black citizens or other marginalized groups in their comments during committee hearings.

While informative, data used in existing studies is often constrained to hearing transcripts from a few committees in one congressional term. As a result, the generalizability of existing work remains unclear. This omission is significant because committees serve two essential functions in the lawmaking process. First, supply-side theories argue that committees gather information by inviting experts to learn about issues related to policies within their jurisdiction (Krehbiel 1992; Battaglini et al. 2019). Hearings can range from exploratory investigations into a new policy topic to oversight of the executive branch (Lewallen 2020). Second, demand-side theories highlight that policy development occurs in committees as legislation is drafted and amended (Fenno 1973; Hall 1998). Notably, gathering information in hearings and using it to develop policy requires legislators to speak at length about policy topics. Given that lawmakers reveal their policy and issue preferences in their hearing statements, analyzing the content of such statements offers a good test of whether lawmakers' racial identities shape the way they think and speak about race.

I argue that nonwhite legislators are more likely than white lawmakers to engage in race-based representation in their committee hearing statements. I define race-based representation as whether a lawmaker mentions race in their committee hearing statements. While race-based representation can also occur in other stages of the lawmaking process—such as introducing, cosponsoring, debating, and passing race-related bills—in this paper, I am specifically referencing the content of lawmakers' committee statements when discussing race-based representation.[8]

There are two primary reasons we might expect nonwhite lawmakers to be more likely than white lawmakers to mention race in committee hearings. First, nonwhite lawmakers share lived experiences as members of their racial identity group, and those experiences differ from white lawmakers' (Mansbridge 1999; Burden 2007; Gamble 2011). As a result, nonwhite lawmakers' personal roots will likely inform the questions and comments they offer during hearings. A clear example of this is Representative Frederica

[8] Importantly, my argument and empirical tests do not imply that race-based representation in committee hearings is mutually exclusive from or correlated with race-based representation in other stages of the lawmaking process, apart from passing race-issue bills. I show that lawmakers who mention race in committee hearings are more likely to pass race-issue bills. While race-based representation in committee hearings may be correlated with similar actions during sponsorship, cosponsorship, and floor debates, this paper does not make claims about those relationships.

Wilson's comments during the House Education and Labor Committee hearing described above. She could have questioned Secretary Cardona on any number of education-related topics; however, Congresswoman Wilson chose to cite her experience as a Black high school principal when making the argument that Black students need increased access to higher education.

Second, theories of linked fate suggest that nonwhite lawmakers may feel that their political interests are tied to those of their racial group (Dawson 1995). As a result, nonwhite lawmakers may speak for their racial identity group or nonwhite Americans more generally during committee hearings (Gamble 2011). If nonwhite lawmakers feel as though they are a conduit for the political interests of their racial group, they may be intrinsically motivated to reference race during hearings (Broockman 2013). These expectations can also be applied to lawmakers' specific racial identity groups. I anticipate that Black lawmakers will be more likely than other lawmakers to mention race statements explicitly referencing Black issues, while Latino lawmakers will be more likely to reference Latino-specific racial issues.

> ***H1 (Race References in Committee Hearings)***: Nonwhite lawmakers are more likely to discuss race in committee hearings than white lawmakers. Nonwhite lawmakers are also more likely to reference their specific racial identity group (Black, Latino, or Asian) in their race statements during hearings.

Additionally, race-based representation by nonwhite lawmakers should affect the content of White lawmakers' statements. Intergroup contact theory, born out of social psychology, argues that direct contact between majority and minority groups can improve majority group attitudes toward the minority group (Allport, Clark and Pettigrew 1954; Pettigrew 1998; Enos 2014; Dyck and Pearson-Merkowitz 2014).[9] Though I do not claim that racial diversity in committees produces *attitudinal* change among white lawmakers, it is not unreasonable to expect that contact effects may occur within political institutions. Contact effects, after all, are most likely to occur in environments where individuals cooperate, share common goals, have equal group status, and are guided by rules or norms (Pettigrew 1998, p. 66). The institutional design of legislative committees aligns with most of these features, suggesting that they may facilitate contact effects.

Committee contact effects could prompt race-related statements from white lawmakers in several ways.

[9] The majority of work testing this theory in political science has used surveys to measure citizens' attitudes (Enos 2014; Dyck and Pearson-Merkowitz 2014) For example, Dyck and Pearson-Merkowitz (2014) find that having frequent contact with an LGBT family member reduces individuals' support for a constitutional ban on same-sex marriage.

First, if a diverse committee is more inclined to link policy discussions to race, white lawmakers may actively consider the racial implications of a policy, leading to more frequent racial references. Second, if white lawmakers are unaware of the racial implications of a particular issue, contact between white and nonwhite lawmakers may produce learning effects (Pettigrew 1998). White lawmakers may gain an understanding of how race relates to particular policies and, as a result, mention race more frequently. Finally, positive affective ties may be generated from intergroup contact (Pettigrew 1998). Cross-group interactions may result in white lawmakers feeling positive emotions or empathy toward their nonwhite colleagues. This could lead white lawmakers to advocate for the political interests of nonwhite Americans. If intergroup contact produces any of these three effects, white lawmakers may discuss race more often in racially diverse committees and hearings (Reich and Purbhoo 1975; Batson, Polycarpou, Harmon-Jones, Imhoff, Mitchener, Bednar, Klein and Highberger 1997).

> ***H2 (Committee Contact Effects)***: The likelihood that white lawmakers engage in race-based representation is positively associated with the proportion of nonwhite lawmakers on a committee and in a hearing.

Finally, I assess whether legislators' race-based committee hearing statements are related to the passage of race-issue bills (Volden and Wiseman 2014). If there is not a meaningful relationship between legislators' race statements and the likelihood that their race-issue bills advance beyond committee, then race-based discussion in hearings may not be associated with substantive representation. On the other hand, if legislators who frequently mention race in hearings are more likely to see their sponsored race-issue bills receive floor consideration or pass the House, then race-based statements in hearings may result in substantive representation. Examining the relationship between race-based discussions in hearings and the passage of race-issue bills clarifies whether race-based representation in committees results in policy representation.

Measuring Race Statements in Committee Hearings

To test my expectations, I analyze transcripts from 16,173 legislative and oversight committee hearings in the U.S. House of Representatives from the 105th – 117th Congresses.[10] The data include 1,410,292

[10] I used parsed and cleaned committee hearing transcripts for the 105th – 114th Congress from Park (2021). Julia Park and I then manually cleaned transcripts from the 115th – 117th Congresses. Committee hearing transcripts are publicly available through the Government Publishing Office.

statements by 1,164 unique members from 24 committees.[11] On average, legislators made 11 statements per hearing with a length of 96 words.[12] To measure whether lawmakers discuss race in hearings, I create a "race statement" indicator variable. This measure captures any mention of race, even if the statement does not explicitly mention a racial group (e.g., "people of color" and "minority racial interests"). Next, I created three racial group binary variables measuring whether race statements explicitly reference (1) Blacks or African-Americans; (2) Latinos or Hispanics; or (3) Asians or Pacific Islanders. For example, the Latino statement variable is coded one if the statement mentions "Latino constituents," and the Black statement variable is coded one if the statement references the "Congressional Black Caucus." Statements can be coded one for multiple race categories. Table 1 describes the coding decisions associated with three race statements.

Table 1: Coding Race Statements

Coding Decision	Statement
Race Statement	"So what are some of the challenges associated with building a cohort that is **racially and ethnically diverse**" (Tony Cárdenas, Ways and Means, 115th Congress)?
Race Statement & Black Statement	"You are right the market is 48% of **African Americans** own their own homes compared to 67% of the rest of the population" (Bill Clay, Financial Services, 108th Congress).
Race Statement & Latino Statement & Asian Statement	"Does your involvement also include different languages or postings so that people from different communities might be—we have a large **Asian population** and also **Hispanic population**, so the materials would be made so that folks could come to town hall meetings or meetings that you would conduct" (Hilda Solis, Natural Resources, 107th Congress)?

Note: Examples of race statements and their coding.

To create each race measure, I estimated 154 supervised machine learning and dictionary-based models (Grimmer, Roberts and Stewart 2022). Ultimately, a bigram dictionary classification method performed the best when comparing the predicted values to hand-coded observations in the validation set (AUC = 0.90, κ = 0.87).[13] As a result, the bigram dictionary classification method was used to predict the values of all four

[11] All committees included in the data are listed in Table 2.

[12] A statement is the text associated with each unique time a lawmaker speaks during a hearing. In a typical hearing, the committee chair (or ranking member) recognizes a member for a set amount of time (often five minutes) to question witnesses. The 1.4 million statements used in this analysis are about half of the total statements made in committee hearings during my time series. Two types of statements were excluded. First, witness statements that do not correspond with a legislator's GovTrack identification number were omitted. Given that I am interested in how legislators' racial identities affect the types of statements they make, witness statements are unnecessary. Second, I omit exclusively procedural remarks that occur at the beginning and end of hearings.

[13] A bigram is two consecutive words (or tokens). Area Under the Curve (AUC) is a composite measure of the

race measures. A detailed explanation of each machine learning and dictionary model is included in section A.5 of the appendix. Table 2 summarizes the five steps in the text-to-measure pipeline used to create the four dependent variables (Park and Montgomery 2023).

Table 2: Text-to-Measure Pipeline

Steps	Description
Step 1: Create Training Set (n = 5,000)	• 70% of training set observations (n = 3,500) randomly selected from corpus. • 30% of training set (n = 1,500) observations selected using stratified random sampling from the corpus to ensure race statements would be present in the training set (see A2.1). • 1,000 statements from training set held back for downstream validation.
Step 2: Label Training Set	• 8 undergraduate research assistants were trained to identify and code the four race measures (race statements, Black statements, Latino statements, and Asian statements). • Intercoder agreement was greater than 96% (see A2.3).
Step 3: Preprocess Text	• Lowercased all characters and removed punctuation, numeric values, and stopwords. I then stemmed each token. • Created bigrams from tokens.
Step 4: Predict	• Using a bigram dictionary classification method, I identified race bigrams, Black bigrams, Latino bigrams, and Asian bigrams from race statements in the training set (see A.4). • Used four sets of bigrams to label values for each of the four race variables in the corpus (See A4.2).
Step 5: Validate (n = 1,000)	• Correlation between the predicted race statement variable and the hand-coded race statement variable in the validation set is 0.87. Full performance metrics are included in A4.2.

Note: Table summarizes the process of creating and validating the Race Statement, Black Statement, Latino Statement, and Asian Statement variables.

First, I created a training data set of 5,000 statements from the corpus. Seventy percent of statements were randomly selected from the corpus, while the remaining 30% of statements were selected using stratified random sampling based on whether the statement included race keywords.[14] Given that race is men-

specificity and sensitivity rate when comparing predicted values to hand-coded values. The Kappa correlation coefficient measures the level of agreement between predicted and hand-coded labels. Each of these measures are described in more detail in the method section of the paper.

[14]Race keywords included terms like “people of color”, “black americans”, and “racial”. The full list of race keywords is listed in Table 2.1 in the appendix.

tioned infrequently in committee hearings, it was necessary to ensure that there were race statements present in the training set. Otherwise, learning and dictionary models would be unable to distinguish between race and non-race statements. The race keywords used for stratified random sampling are listed in A2.1.[15]

Second, I hired and trained eight undergraduate research assistants to hand-code each statement in the training set.[16] After correctly coding every observation in a practice set, research assistants were given access to the training data set (n = 5,000). After three research assistants coded each statement, I compiled the final training data set. I only labeled an observation as a race statement if all three research assistants agreed on the coding decision. The average intercoder agreement among the three research assistants on all four variables is greater than 96%.[17] Third, I preprocessed each statement by lowercasing all characters and removing punctuation, numeric values, and stopwords.[18] I then stemmed and tokenized each word and created bigrams from each token. I split the training set to hold back 1,000 statements for downstream validation.

Fourth, I extracted racial bigrams from the training set (now n = 4,000), which were used to predict values in the corpus. I first subsetted statements from the training set that included race statements (n = 429). I then extracted all bigrams from these statements (n = 12,953). I read each bigram and removed all non-racial bigrams. I used the training set protocol to determine whether bigrams included race.[19] After

[15]One concern with using stratified random sampling may be that the training set, or the 30% of observations in the training set selected using stratified random sampling, are not representative of the corpus. Table 2.1 in A.4 displays the percentage of statements in the corpus and the percentage of statements in the training set that include each race keyword. The percentage of statements in the corpus and training set for each race keyword are highly correlated. For example, 7.5% of statements in the training set include the word ”race,” while 7.8% of the keywords in the corpus include the word ”race.” This suggests that the training set, particularly the 30% of observations selected using stratified random sampling, is representative of the overall corpus.

[16]I trained research assistants to read committee hearing statements and distinguish between race and non-race statements. They were then required to code a practice data set, which included a small subset of committee hearing statements. I reviewed their practice data set and provided feedback on their coding decisions. The training protocol can be found in section 2.2 of the appendix.

[17]See A2.3 for Intercoder Agreement for all variables.

[18]Given that preprocessing steps can substantively impact the predicted values produced from learning models, I tried a variety of preprocessing steps that I detail in section A.5 of the appendix (Denny and Spirling 2018). Stopwords are common words in the English language that do not hold functional meaning (e.g., I, me, my, we, our). I used the Quanteda package in R to remove common English language stopwords.

[19]The training set protocol is explained in Section A4.1 in the appendix. Non-racial bigrams were deleted because they were not the portion of the statement that led research assistants to code the speech as a race statement. For example, the following statement includes five bigrams: “important for,” “for black,” “black americans,” “americans improved,” and “improved healthcare.” Even though “improved healthcare” is certainly racialized in this context, it was not included in the list of racial bigrams used for prediction. This is because the statement was coded as a race statement by the research assistants because the “black americans” bigram is included (not because “improved healthcare” was in the sentence). Dropping non-racial bigrams ensures that (1) false positives are not produced during predictions because only racial bigrams are included and (2) false negatives are not produced because the racial bigram

dropping the non-racial bigrams, 536 race bigrams were used for prediction.[20] I then iterated over each statement in the corpus and coded it as a race statement if it included a bigram that matched one of the 536 racial bigrams from the training set. I followed the same procedure to construct the Black statement, Latino statement, and Asian statement measures.[21]

I then validated the final measures. To do so, I compared the agreement between predicted values and hand-coded values for each of the race measures in the validation set (n = 1,000). The validation set was subsetted from the training set, so it includes hand-coded values for all four measures but was not used during model training. The statements are out-of-sample data and, as a result, is an independent test of how well the racial bigrams predict unseen data. Based on the hand-coded race statement variable, 9.8% of statements in the validation set reference race. For all four dependent variables, the specificity is 1.0, indicating that the model never incorrectly codes a non-race statement as a race statement. The sensitivity is 0.79, which suggests that the model identified 79% of race statements in the validation set (the other 21% of statements were false negatives). It is unsurprising that the specificity is higher than the sensitivity, given that the model can only recognize race statements that include the racial bigrams present in the training set. The upside, however, is that while the model may overlook some race statements, it will rarely, if ever, misclassify a non-race statement as a race statement. As a result, my measures are conservative estimates of race-based statements in committee hearings. The Area Under the Curve (AUC), which is a composite measure of sensitivity and specificity, is 0.90. This suggests that the model is very effective at correctly distinguishing between race and non-race statements.[22] The Kappa correlation coefficient is 0.87, indicating a high level of agreement between the hand-coded measure and the predicted measure. [23]

To assess the face validity of the race statement measure, I examine the top 50 bigrams present in statements in the corpus coded as race statements and non-race statements. The complete list of the 50 top bigrams is included in section A4.3 of the appendix. Some of the top bigrams from race statements in the corpus referenced “african americans”, “native american,” “vote rights,” “civil rights’, “people color,” and

that led a statement to be coded as race is still present.

[20]The 100 most frequent race bigrams are presented in section A2.2 of the appendix.

[21]In total, 267 bigrams were used to predict the Black statement variable. 157 bigrams were used to predict the Latino statement variable. And 52 bigrams were used to predict the Asian statement variable. The 25 most frequent Black, Latino, and Asian bigrams are included in Table A4.2 in the appendix.

[22]An AUC of 0.50 suggests random classification of race and non-race statements. An AUC of 1.0 would imply that the model correctly classifies all race and non-race statements.

[23]Full performance metrics for race statements, Black statements, Latino statements, and Asian statements are presented in section Table 4.3 of the appendix.

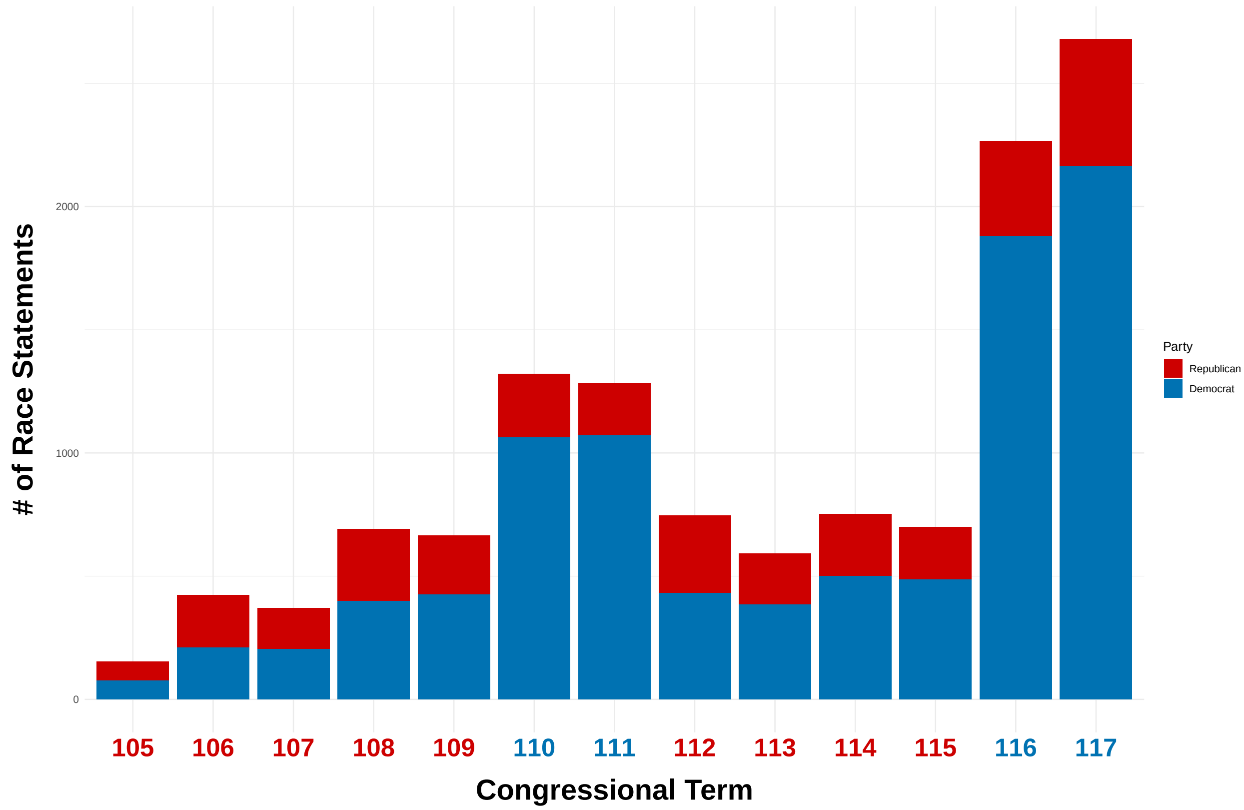
"community color." While the top 50 non-race bigrams from the corpus included procedural remarks, references to small businesses, and concerns about fiscal years, as expected, there are no racial bigrams. I also include 20 randomly selected non-race statements, race statements, Black statements, Latino statements, and Asian statements from the corpus in section A4.2 in the appendix. There are no race references in the 20 randomly selected non-race statements and the racial reference is present (and bolded) in each randomly selected statement for all four race variables.

Results

Out of 1,410,292 statements, 12,646 (approximately 0.9%) mention race. There are 4,726 Black statements (0.3%), 1,785 Latino statements (0.1%), and 478 Asian statements (.03%). The remaining 5,657 statements mention race, but do not reference a specific racial group. This indicates that lawmakers rarely reference race during committee hearings.[24] The data indicate, however, that the frequency of race statements varies by congressional term (see Figure 1). The bars are shaded by the percentage of race statements in that term offered by Republicans (red) and Democrats (blue). Race is more likely to be discussed in committees when Democrats are the majority party. Approximately 60% of all race statements were mentioned when Democrats controlled the House. Further, Republican and Democratic lawmakers reference race at different rates depending on which party is in the majority. Approximately three-quarters of race statements were made by Democrats whe Democrats controlled the House. However, Democrats and Republicans mention race at nearly an equal rate when Republicans are the majority party. Partisan differences in the frequency of lawmakers' race statements are likely due to the types of hearings held and the witnesses called by each party.

[24]It is unsurprising that race references occur infrequently given the numerical underrepresentation of nonwhite lawmakers in the U.S. Congress, especially during earlier points in my time series. In my data, only 16% of lawmakers are nonwhite. If race statements are mentioned primarily by nonwhite lawmakers, we should expect race statements to be relatively infrequent given race-based imbalances in the composition of the House of Representatives.

Figure 1: Race Statements by Term and Majority Party



Note: The bars represent the total number of race statements per term, with shading indicating the percentage of statements from Republicans (in red) and Democrats (in blue). The x-axis labels include the majority party, with terms where Democrats held the majority in the House highlighted in blue.

Though there is significant variation in the rate at which race is discussed across committees, race is mentioned frequently in prestigious and powerful committees. Table 3 presents the average number of race statements per committee across all terms, along with the respective maximum and minimum occurrences of race statements within each committee and the corresponding terms. Race is mentioned most often in the Judiciary Committee, with an average of 220 race statements per term. Race is rarely mentioned in select and procedural committees (e.g., Climate Crisis, Rules, Modernization of Congress). The top five committees where race is mentioned—Judiciary, Financial Services, Oversight, Appropriations, and Energy and Commerce—are among the most desirable assignments due to their consequential policy jurisdictions (Fenno 1973; Deering and Smith 1997; Groseclose and Stewart III 1998).

Table 3: Race Statements by Committee

Committee	Mean Race Statements	Minimum Race Statements (Term)	Maximum Race Statements (Term)
Judiciary	220	**1** (105th)	**578** (109th)
Financial	216	**28** (112th)	**522** (117th)
Oversight	174	**40** (112th)	**617** (110th)
Appropriations	118	**1** (105th)	**203** (111th)
Energy and Commerce	96	**17** (115th)	**382** (110th)
Natural Resources	89	**33** (113th)	**172** (109th)
Education	83	**17** (113th)	**188** (116th)
Foreign Affairs	59	**3** (105th)	**90** (111th)
Small Business	40	**5** (110th)	**80** (117th)
Homeland Security	40	**1** (107th)	**119** (117th)
House Administration	36	**5** (113th)	**90** (110th)
Transportation and Infrastructure	34	**5**(113th)	**97** (117th)
Ways and Means	33	**5** (112th)	**62** (116th)
Agriculture	28	**4** (113th)	**115** (117th)
Science, Space, and Technology	26	**1** (106th)	**78** (117th)
Veterans Affairs	25	**1** (109th)	**81** (117th)
Armed Services	19	**2** (114th)	**58** (117th)
Climate Crisis (select)	19	**18** (116th)	**20** (117th)
Budget	13	**1** (114th)	**65** (116th)
Intelligence (select)	11	**10** (112th)	**11** (116th)
Modernization of Congress (select)	9	**9** (117th)	**9** (117th)
Energy Independence and Global Warming (select)	7	**7** (111th)	**7** (111th)
Rules	5	**1** (108th)	**12** (117th)
Events Surrounding the 2012 Terrorist Attack on Benghazi (select)	0	0	0

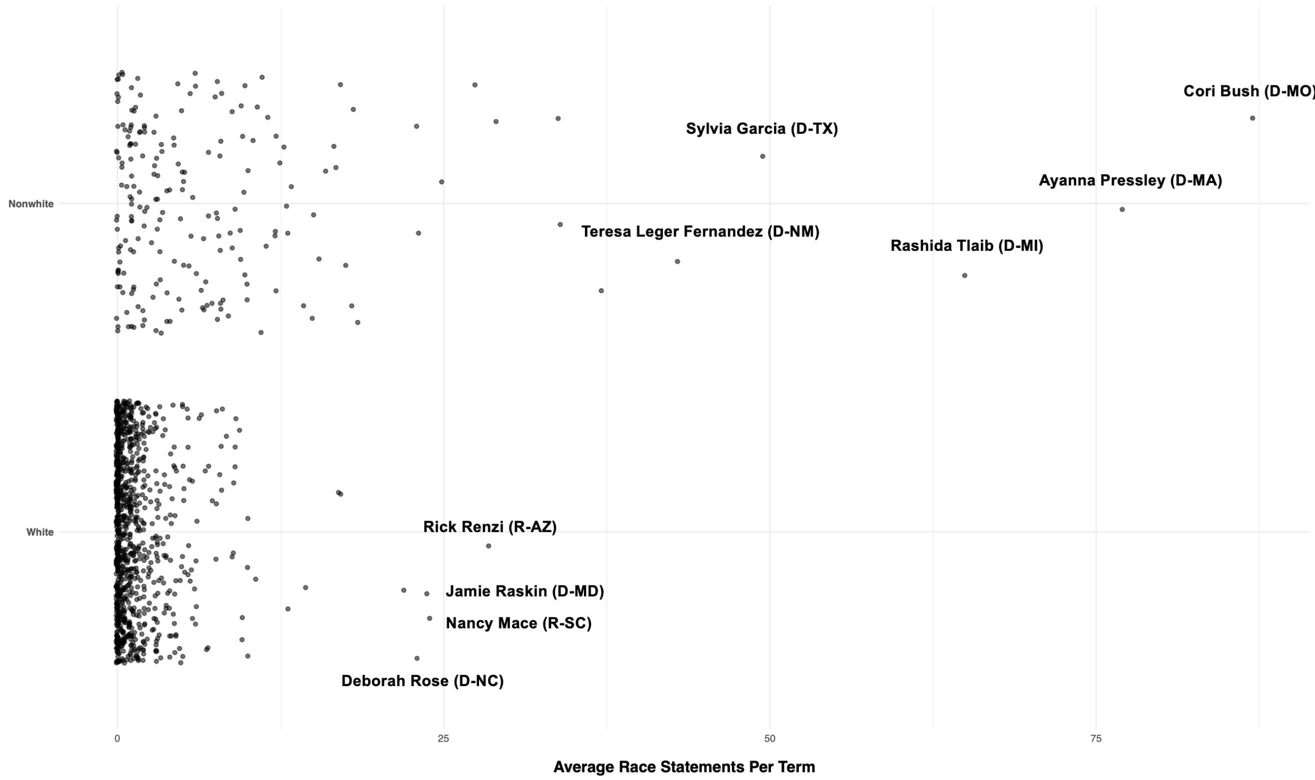
Note: The Judiciary, Financial Services, Oversight, Appropriations, and Energy and Committee committees saw the highest number of race statements across all terms. Table includes the mean number of race statements across all terms and the maximum and minimum value of race statements in a given term. Committees are listed in descending order by the mean number of race statements.

Nonwhite Lawmakers Mention Race More Frequently Than White Lawmakers

To test my first hypothesis, Figure 2 displays the average number of race statements mentioned by legislators per term categorized by race. Nonwhite lawmakers reference race much more frequently than white lawmakers. On average, white lawmakers mention race only once per term. Thirty percent of white lawmakers never mention race in a committee hearing, while 85% of white lawmakers mentioned race fewer than three times per term. In contrast, nonwhite lawmakers, on average, make seven race statements per term. Only 10% of nonwhite lawmakers have never mentioned race in a committee hearing statement. Several nonwhite lawmakers mention race much more frequently than their colleagues. Cori Bush (D-MO) and Ayanna Pressley (D-MA) make 10 times more race statements per term than the average nonwhite lawmaker.

While the distribution is much narrower for white lawmakers, Rick Renzi (R-AZ), Jamie Raskin (D-MD), and Deborah Ross (D-NC) mentioned race most frequently.[25] These descriptive findings are consistent with the expectation that nonwhite lawmakers will discuss race more frequently than white lawmakers.

Figure 2: Nonwhite Lawmakers Mention Race More Frequently Than White Lawmakers



Note: Nonwhite lawmakers mention race more often per term than white lawmakers. Dots on the jitter plot indicate the average number of race statements made by a lawmaker per term. The top half of the plot represents nonwhite lawmakers, while the bottom half represents white lawmakers.

To model the relationship between lawmakers' racial identity and the likelihood that they make a race statement during committee hearings, I estimate four logistic regression models at the statement level. In the first, race statement is the dependent variable. In the other three, Black statement, Latino statement, and Asian statement serve as dependent variables.[26] In each equation, the independent variable of interest is

[25] Interestingly, Rick Renzi represented a highly diverse district in Arizona in which 40% of his constituents were nonwhite. Forty percent of Jamie Raskin's constituents are nonwhite, and Deborah Ross represents a district in which 30% of her constituents are nonwhite. Raskin is the ranking member on the Oversight Committee, which averaged 174 race-related statements per term, and Ross serves on the Judiciary Committee, which averaged 220 race-related statements per term. Oversight and Judiciary were among the most racially diverse committees in the 117th Congress.

[26] Member-level analyses are included in section eight of the appendix. The results are consistent regardless of whether the unit of analysis is the statement or Member.

whether the lawmaker shares the racial identity of the reference group in the statement. In other words, in the first equation, I include a binary variable for nonwhite lawmakers. In the other three equations, I include a binary variable for Black lawmaker (equation 2), Latino lawmaker (equation 3), and Asian lawmaker (equation 4). Given that the number of race statements varies by committee and term, I also include committee and term fixed effects with standard errors clustered by legislator. In an effort to isolate the independent effect of lawmakers' racial identity on the likelihood that they mention race during committee hearings, I include individual, statement, district, and chamber-level controls.[27]

First, I control for several individual-level variables, including party, ideology, gender, sexuality, vote share, and seniority. I also include binary covariates measuring whether the legislator is a committee chair, nonwhite committee chair, or on a committee with a nonwhite chair. Second, I control for the word count of each statement, whether the hearing was legislative or oversight, and whether the topic of the hearing was related to race. Third, given that scholars have demonstrated that the racial makeup of lawmakers' districts affects whether they engage in race-based representation (Lublin 1997; Grose 2011), I include district-level racial demographic controls.[28] I use four covariates that measure the percentage of a lawmaker's district that is nonwhite, Black, Latino, and Asian. Finally, I control for whether a lawmaker is in the majority party and if the hearing occurs within a subcommittee. The fully specified model is reported in Table 6.1 in the appendix.

Figure 3 plots the predicted probabilities from the four separate models that estimate the relationship between lawmakers' racial identity and their likelihood of mentioning race. The panel titled "Race Statements" plots the predicted probability of making a race statement given whether the lawmaker is nonwhite or White. The panel titled "Black Statements" displays the predicted probability of making a race statement that includes an explicit Black or African American reference, given whether the lawmaker is Black or not. The same pattern follows for the "Latino Statements" and "Asian Statements" panels.

The results are consistent with the expectation laid out in my first hypothesis.[29] That is, nonwhite

[27]All models are reported in section six of the appendix with (1) the primary independent variable and committee-term fixed effects and (2) the primary independent variable, full controls, and committee-term fixed effects.

[28]District demographics were collected from the American Community Survey (ACS) administered by the U.S. Census Bureau. The ACS only has racial demographics by congressional district for eight out of the 13 terms included in my analysis (excluded terms are 105-108 and 112). As a result, models that include district demographic variables will have fewer observations than models that do not.

[29]Another significant predictor of whether a lawmaker mentions race is the racial composition of lawmakers' districts. This is unsurprising given that existing work finds that lawmakers from racially diverse districts, regardless of their racial identity, engage in race-based representation (Lublin 1997; Grose 2011). In the context of this paper, I

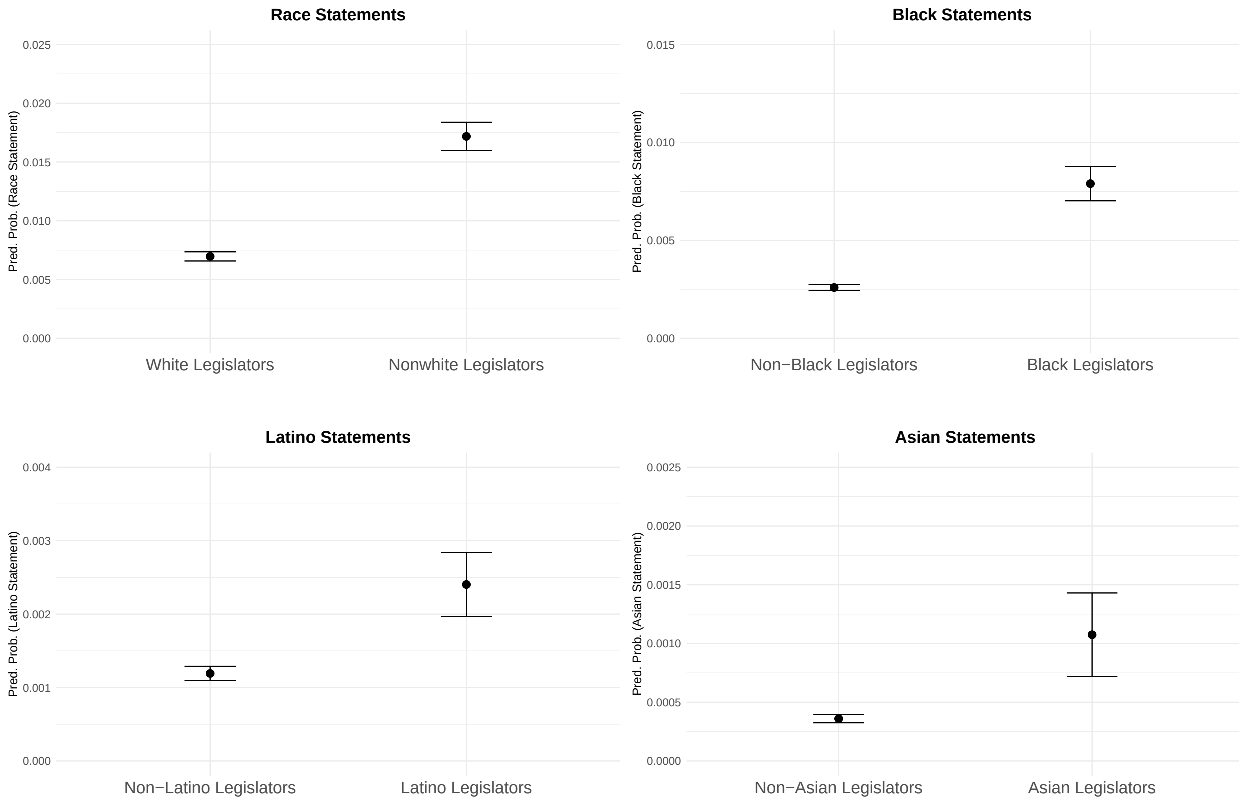
lawmakers are 2.4 times more likely to mention race than white lawmakers, irrespective of their party, the percentage of nonwhite constituents in their district, the committee they serve on, and the congressional term. Likewise, Black lawmakers are 2.9 times more likely to mention Black racial references than White, Latino, and Asian lawmakers, with the same controls. Latino lawmakers are 1.9 times more likely to discuss race-related Latino issues than White, Asian, and Black lawmakers. And Asian lawmakers are 3 times more likely to mention Asian racial references than White, Black, and Latino lawmakers.[30] Each of these coefficients is statistically significant. It is also notable that the party coefficient is null in every model, suggesting that lawmakers' racial identities shape their decision to mention race in hearings more than their partisanship. Collectively, these findings indicate not only that nonwhite lawmakers mention race more frequently than white lawmakers but also that nonwhite lawmakers are more likely to reference their racial identity group in their race statements.[31]

control for the racial composition of districts because I am interested in the independent effect of lawmakers' racial identity on their propensity to mention race in hearings.

[30]I conduct two additional tests that are reported in the appendix. First, I construct four measures counting the number of race references, Black references, Latino references, and Asian references in a statement. I use OLS regression models to estimate whether nonwhite lawmakers make more racially dense statements than white lawmakers. Indeed, nonwhite lawmakers' race statements include four times more racial references than white lawmakers race statements. These models are presented in Table 6.2 in the appendix. Second, I also estimate whether Black, Latino, and Asian lawmakers are more likely to reference other racial groups in their hearing statements. The results are reported in Table 7.3 in the appendix. While Black lawmakers are more likely to reference Latinos in their race statements and Latinos are more likely to reference Black issues in their statements, Asian lawmakers are no more or less likely to reference Latino or Black issues in their race statements than white lawmakers. Black and Latino lawmakers are no more or less likely to make Asian statements.

[31]It is plausible that variation exists in the tone of race statements. For example, while nonwhite lawmakers may mention race as a means of representation, other lawmakers could mention race in explicitly negative and racist ways. To address this possibility, I asked research assistants to identify whether each race statement was positive, neutral, or negative when coding the training set. Statements were coded as positive if the legislator referenced the racial group in explicitly positive ways or negative if the speaker spoke about the racial group in explicitly negative ways. 98% of all race statements were coded as neutral, meaning that the overwhelming majority of race statements were not explicitly negative. As a result, I do not incorporate tone as an independent variable in this analysis. The substantive implication of this finding is that hostile and explicitly racist statements occur only rarely in committee hearings.

Figure 3: Nonwhite Lawmakers Mention Race More than White Lawmakers



Note: Dots indicate the predicted probability of making a race statement, a Black statement, a Latino statement, and an Asian statement. The bands represent 95% confidence intervals. The models were estimated with individual and chamber level controls, committee and term fixed effects, and standard errors clustered by Member. The full model is reported in Table 6.1 in the appendix. Predicted probabilities are calculated from columns 2, 4, 6, and 8 in Table 6.1.

White Lawmakers Mention Race More In Racially Diverse Hearings

Though the results in Figure 3 suggest that nonwhite lawmakers are the primary conduits for race representation, white lawmakers also mention race in hearings. I argue that one explanation for this is that white lawmakers are more likely to mention race when serving on a racially diverse committee (Hypothesis 2). As a result, I expect that white lawmakers should be more likely to mention race as the percentage of nonwhite lawmakers on a committee and in a hearing increases. To test this expectation, I estimate four logistic regression models at the statement level (full results presented in Table 6.3 of the appendix).

This second, more granular measure, most accurately captures racial diversity in committees for three reasons. First, committee hearing attendance is variable (Hall 1998). Legislators may only attend some hearings sponsored by committees to which they are assigned (which may only sometimes be a stochastic choice). Lawmakers may also vacate their seats during a term. In both cases, the racial composition of a committee could change within a term. Second, lawmakers can choose to attend a hearing but not speak. Though these lawmakers would technically be counted as present, they are not shaping the conversation and, as a result, are not likely to contribute to or benefit from contact effects. Third, subcommittees are made up of a small sample of legislators from the parent committee. As a result, the percentage of nonwhite lawmakers on a subcommittee can be much greater (or much smaller) than the percentage of nonwhite lawmakers on the parent committee. A dynamic measure that identifies the percentage of nonwhite lawmakers in each hearing better captures who is actually in the room creating the conversation.

To put this into perspective, despite the presence of 20 nonwhite members on the Armed Services Committee in the 117th Congress, there were zero nonwhite legislators at an Armed Services committee meeting on the 'State of the Surface Navy.' The hearing only included statements from 15 members, which is one-fourth of the total committee membership, and all speaking members were White. We should not expect contact effects to occur in that committee hearing, given that there were no nonwhite lawmakers in the room. As a result, the hearing variable is a better test of whether contact effects may occur in committee hearings. Each model is estimated with the same controls as Figure 3 and with committee and term fixed effects.

Figure 4 presents the marginal effect of white lawmakers mentioning race (relative to nonwhite lawmakers) given the percentage of nonwhite lawmakers in a hearing.[32] The percentage of nonwhite lawmakers in a hearing variable ranges from zero to 95. The average number of nonwhite lawmakers in a hearing is 20%. Zero on the y-axis (dashed line) in Figure 4 represents an equal probability of white and nonwhite lawmakers mentioning race in a hearing. As evident from the curvilinear line in Figure 4, white lawmakers are less likely to mention race than nonwhite when the percentage of nonwhite lawmakers in a hearing ranges from zero to 30. However, when more than 30% of legislators in a hearing are nonwhite, white lawmakers gradually become more likely to mention race. When 70% of lawmakers in a hearing are nonwhite, white lawmakers are equally as likely to mention race as nonwhite lawmakers. White lawmakers speaking in a hearing in which 80% of legislators are nonwhite are approximately three times more likely to mention race than white lawmakers speaking in a hearing where only 20% of lawmakers are nonwhite.[33] These find-

[32] Results using the "% Nonwhite Lawmaker On Committee" variable are presented in Table 6.3 of the appendix. The interaction is directionally the same and significant across both measures.

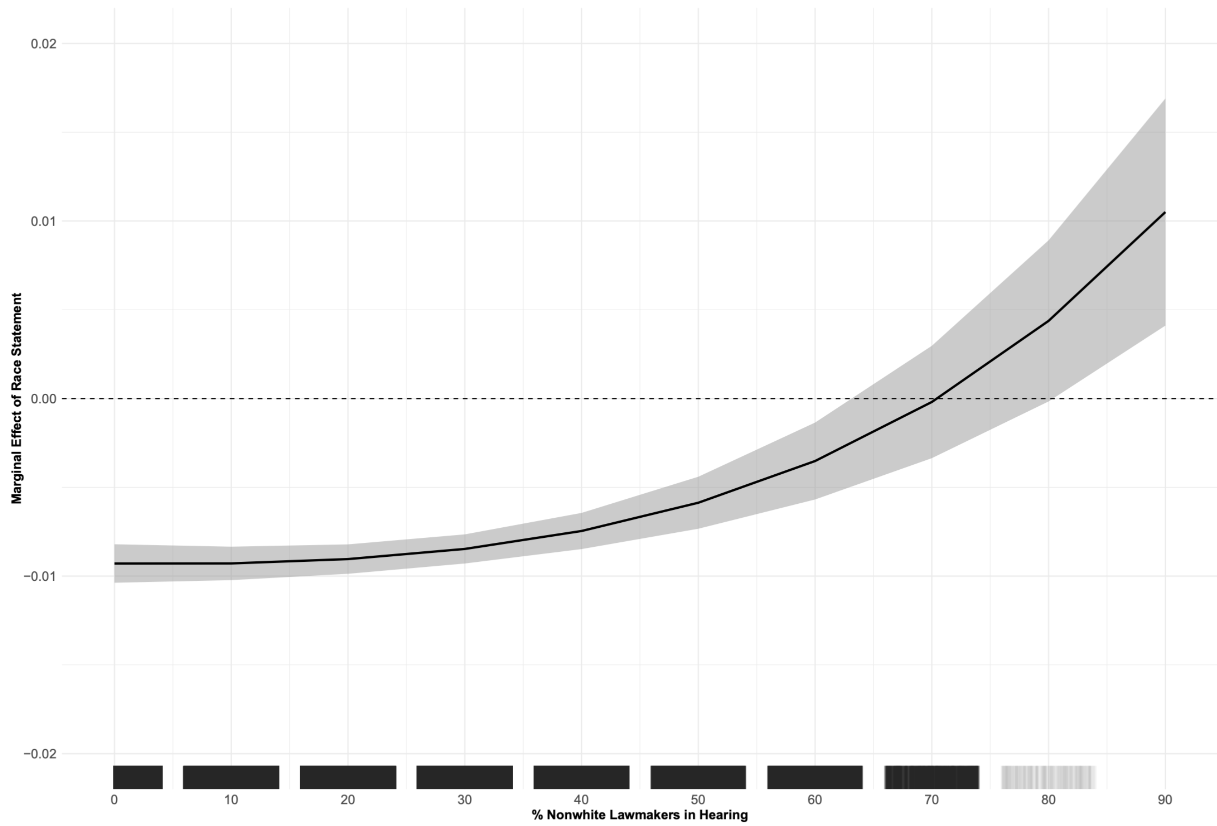
[33] The distribution of the "% Nonwhite Lawmakers in Hearing" variable is left-skewed, meaning that there are more hearing observations with fewer than 50% of nonwhite lawmakers than there are with greater than 50% of nonwhite lawmakers. This is unsurprising given the numeric underrepresentation of nonwhite lawmakers in the U.S. House of

ings suggest that white lawmakers, regardless of their partisan identity or whether they represent a racially diverse district, mention race more frequently when participating in racially diverse committee hearings.[34]

Representatives, particularly at earlier time points in my data. I reestimate the findings in Figure 4 in Table 7.1 in the appendix, omitting all hearing observations with greater than 50% nonwhite lawmakers. Even after omitting half of the distribution, contact effects persist, suggesting that the finding is robust and not dependent on outliers.

[34]One potential concern is that white lawmakers who are predisposed to discuss race more frequently may request to serve on diverse committees. While newly elected lawmakers do submit a letter to party leaders indicating their preferred committee assignment (Miler 2017), ultimately the party's Steering Committee recommends committee assignments. These recommendations must be approved by the party caucus and by the chamber. (CRS 2022). As a result, committee assignments are a combination of legislators' preferences and the strategic interests of their party. Even if lawmakers' committee assignment preferences do influence the committees to which they are assigned, contact effects likely still explain why white lawmakers mention race more in diverse hearings. First, if committee selection effects explain why white lawmakers mention race more frequently, the racial diversity of a *hearing* should not influence the frequency of white lawmakers' race statements. White lawmakers on diverse committees would frequently mention race, and white lawmakers on less diverse committees would not mention race; however, the changing percentage of nonwhite lawmakers within a given committee in a hearing would not shift the number of race statements issued by white lawmakers. Second, existing literature argues that lawmakers' committee assignment preferences are primarily driven by their electoral considerations (Miler 2017). To account for this, I control for the racial composition of a lawmaker's district, the share of the vote they won in their most recent election, and individual and chamber-level variables. Third, while I cannot randomize committee assignments, I can control for factors that may be associated with white lawmakers selecting onto racially diverse committees. If white lawmakers are predisposed to mention race frequently, they should attend more hearings and mention race more often in a given committee and term. I create two variables that measure lawmakers' total committee hearing attendance in a given committee and term and lawmakers' total race statements in a given committee and term. I present the results of all four contact effect models with these two variables as controls in Table 7.2 in the appendix. As expected, the results do not change after adding these two control variables.

Figure 4: White Lawmakers Mention Race More in Racially Diverse Hearings



Note: The black line indicates the marginal effect of white lawmakers making a race statement (relative to Nonwhite lawmakers) given the percentage of nonwhite lawmakers in a given hearing. The gray band represents 95% confidence intervals. The models were estimated using individual and chamber-level controls and committee and term fixed effects. Rug plot displays the distribution of the % Nonwhite Lawmakers in Hearing variable. Full model reported in Table 6.3 in the appendix.

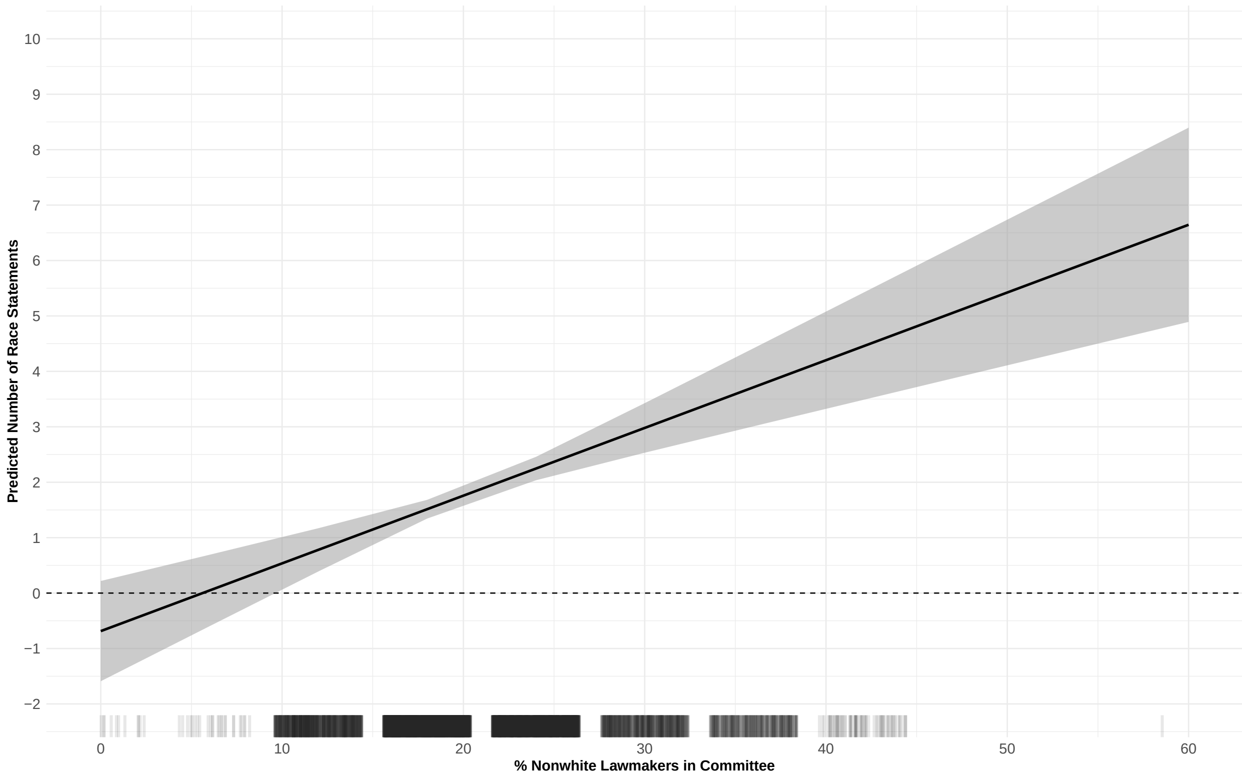
Figure 4 suggests that, holding committee assignment and legislative term constant, white lawmakers are more likely to mention race in racially diverse hearings. Including term fixed effects in the model establishes that the observed effects are independent of time-varying factors like majority party status, the overall diversity of the House, and the unique political context of each legislative term. Another way to model the relationship between racial diversity within committees and lawmakers' race statements is to leverage over-time variation. The racial diversity of the House of Representatives, and legislative committees as a result, has increased dramatically during my time series. While nonwhite lawmakers comprised only 13% of seats in the 105th Congress, they held nearly 30% of seats in the 117th Congress. I conduct a within-legislator analysis that leverages over-time variation in the racial diversity of committees to estimate whether white lawmakers are more likely to mention race as their committee becomes more diverse. The primary advantage of a within-legislator design is that it allows me to control for all time-invariant factors that differ between legislators such as their racial attitudes, the racial diversity of their staff, and their overall involvement in committee proceedings.

I estimate an OLS regression model where the unit of analysis is a legislator-term, the dependent variable is the total number of race statements, and the independent variable is the percentage of nonwhite lawmakers on a committee. I include committee and legislator fixed effects. While I do not include term fixed effects (because time is the variation I am interested in leveraging), I do control for time-varying confounders such as majority party status, the percent of nonwhite lawmakers in the House, the racial composition of lawmakers' districts, ideology, the total number of bills sponsored, and vote share in the previous election.[35]

Figure 5 presents the results from the within-legislator model, which suggests that a white lawmaker discusses race more frequently when a committee is racially diverse. When 40% of members on a committee are nonwhite, a white lawmaker mentions approximately 4 race statements per term. In contrast, when only 15% of seats on a committee are held by nonwhite lawmakers, a white legislator mentions race only once per term. Put differently, the same white lawmaker makes five more race statements when half of the lawmakers on their committee are nonwhite than when their committee includes no nonwhite lawmakers. The results from Figure 4 and Figure 5 indicate that white lawmakers, regardless of their individual traits, committee assignments, or legislative term, discuss race more frequently when committees are racially diverse.

[35]It is necessary to control for the racial diversity of the House in each term because increased nonwhite representation in the legislature is not synonymous with increased nonwhite representation on all committees. Without this control, the effects observed in my model could be a function of increased racial diversity generally, rather than increased racial diversity within a specific committee. For example, white lawmakers may mention race more frequently as chamber diversity increases rather than committee diversity. Including this control suggests that the observed effects are specific to a lawmaker's committee.

Figure 5: White Lawmakers Mention Race More in Racially Diverse Committees (Within-Legislator Design)



Note: The black line indicates the predicted number of race statements per term given the percentage of nonwhite lawmakers on a committee. The gray band represents 95% confidence intervals. The models were estimated using committee and legislator fixed effects and time-varying controls. Full model reported in Table 6.4 in the appendix.

Lawmakers Who Mention Race in Hearings Are More Effective At Legislating Race-Issue Bills

Findings from Figures 3, 4, and 5 suggest that nonwhite lawmakers are most likely to discuss race, though White lawmakers mention race more frequently when serving on diverse committees and in diverse hearings. Whether legislation associated with these racial references dies in committee or advances to the floor, however, speaks to whether race statements result in substantive representation. If race statements are substantive, then lawmakers who frequently discuss race in hearings should be more effective at passing race-issue bills.

To test whether race-based hearing statements are substantive, I create a novel measure that identifies race-issue bills introduced in the 105th – 117th Congresses. Rather than subjectively define legislation ex-ante as “race bills,” I use 22 predefined policy areas from the Policy Agendas Project and the Congressional Bills Project to identify the top three policy issue areas in which nonwhite lawmakers introduce significantly more legislation than White lawmakers (Baumgartner and Jones 2002).[36] Education, housing, and law and crime comprise the race issue policy areas.[37]

Table 4 presents estimates from OLS regression models with four with dependent variables measuring legislative effectiveness (Volden and Wiseman 2014). The unit of analysis is a legislator-term. The first dependent variable (ABC) measures the frequency of a lawmaker’s sponsored bills that received Action Beyond the Committee stage of the lawmaking process. The second and third dependent variables (“PASS” and “LAW”) capture the frequency of a lawmaker’s sponsored legislation that passed the House, and the frequency of a lawmaker’s sponsored bills that are signed into law. The final dependent variable (LES) gauges the lawmaker’s Legislative Effectiveness Score. The first four columns in Table 4 include these four dependent variables subset to race-issue bills (education, housing, and law and crime) and the last four columns in the table use the same four dependent variables subset to non-race-issue bills (all other policy areas). The model includes standard controls used in the legislative effectiveness literature with standard errors clustered by member and term fixed effects.

Across all the race bill models (columns 1-4), the race statement coefficient is significant and positive for all dependent variables except for “LAW”. This suggests that lawmakers who frequently mention race in committee hearings are more likely to see their sponsored race-issue bills passed out of committee and by the House. Lawmakers who discuss race often in hearings also have a higher legislative effectiveness score on race-issue bills than lawmakers who discuss race less frequently in hearings. To clarify the magnitude of the coefficients, making 10 additional race statements in hearings is equivalent to the advantage associated with being in the majority party for the action beyond committee stage of the lawmaking process. Referencing race in 26 additional statements in hearings is associated with having an equivalent legislative effectiveness

[36]My approach to measuring race-issue bills is similar to the approach used by Volden, Wiseman and Wittmer (2018) to measure gender issue bills. The 22 policy areas are: Agriculture, Civil Rights, Commerce, Defense, Education, Energy, Environment, Government Operations, Health, Housing, Immigration, International Affairs, Labor, Law and Crime, Macroeconomics, Miscellaneous, Native Americans, Public Lands, Technology, Trade, Transportation, and Welfare.

[37]52% of nonwhite lawmakers introduce education bills compared to 36% of white lawmakers (16% difference). 29% of nonwhite lawmakers introduce housing legislation, versus 16% of white lawmakers (13% difference). And 52% of nonwhite lawmakers introduce law and crime bills, compared with 44% of white lawmakers (8% difference). More information about the race-issue bill measure can be found in section 9 in the appendix. Table 9.1 in the appendix reports the percentage of nonwhite and White lawmakers that introduce bills in each of the 22 policy areas.

score of a committee chair. These findings suggest that lawmakers who offer race statements in hearings are meaningfully more effective at successfully legislating race-issue bills than lawmakers who rarely, if ever, offer race statements in hearings.

Columns 5-8 of Table 4 estimate the relationship between the frequency of race statements offered during hearings and lawmakers' effectiveness on non-race-issue bills. All four coefficients across each of the dependent variables are null, suggesting that lawmakers who frequently discuss race in hearings are no more (or less) effective at navigating their non-race legislation through the final stages of the lawmaking process than lawmakers who never mention race in hearings. This comparison is important because it demonstrates that the effectiveness boost associated with mentioning race in hearings is unique to race-issue bills. The coefficients associated with two control variables are worth highlighting. First, the nonwhite coefficient is null in every model, indicating that lawmakers who mention race in hearings are more effective at legislating race-issue bills regardless of their racial identity. Second, I include a covariate measuring the total number of bills introduced by a lawmaker in a term. This indicates that the positive and significant relationship between offering race statements in hearings and successfully legislating race-issue bills is independent of the total volume of legislation a lawmaker introduces in a term. [38]

[38]There are two important caveats to this finding. First, I identify race-issue bills not whether an individual bill mentions race. My measure captures the top three *policy areas* in which nonwhite lawmakers are significantly more active than White lawmakers. Other scholars interested in measuring race-based legislation have also identified racialized legislation using policy areas (Bratton and Haynie 1999; Grose 2011). Second, the dependent variables do not link a given hearing to its reported bill. An ideal test of this expectation would identify whether a bill is linked to a specific hearing. And then test whether significant discussions of race were more likely to produce legislation that included race-related policies. Then, it will also test whether these bills were more likely to be passed by the chamber and into law. Given the large number of committee hearings included in my data set, and the fact that not all hearings are related to a specific bill, it is extremely difficult to conduct such an analysis. Despite this limitation, my findings go beyond existing literature by demonstrating that race-based statements in hearings are not symbolic, but are instead associated with substantive representation through race-based bill issue passage.

Table 4: Legislators Who Make Race Statements In Hearings Are More Effective At Legislating Race Issue Bills

	1	2	3	4	5	6	7	8
	ABC (Race Issue Bills)	**PASS (Race Issue Bills)**	**LAW (Race Issue Bills)**	**LES (Race Issue Bills)**	ABC (Non-Race Issue Bills)	PASS (Non-Race Issue Bills)	LAW (Non-Race Issue Bills)	LES (Non-Race Issue Bills)
Race Statements in Hearings	**0.0195*****	**0.0142*****	0.00160	**0.0759*****	0.00901	-0.00489	-0.000983	0.00434
	(0.00481)	(0.00430)	(0.00105)	(0.0148)	(0.0107)	(0.00526)	(0.00295)	(0.00565)
Nonwhite	-0.0449	-0.0362	-0.00898	-0.333	0.0292	0.0300	0.0673	0.0766
	(0.0384)	(0.0297)	(0.0103)	(0.173)	(0.159)	(0.120)	(0.0691)	(0.0904)
Democrat	-0.0756	-0.0706	0.0377	-0.0747	-1.319**	-1.378***	-0.250	-0.702**
	(0.101)	(0.0821)	(0.0268)	(0.442)	(0.436)	(0.380)	(0.150)	(0.240)
% Nonwhite in District	-0.0652	-0.00694	-0.00654	-0.260	0.295	0.554	0.126	-0.399
	(0.0897)	(0.0728)	(0.0275)	(0.431)	(0.484)	(0.365)	(0.170)	(0.254)
Intercept	-0.0752	0.0310	0.00896	0.594	1.896***	1.799***	0.637***	0.709*
	(0.127)	(0.111)	(0.0466)	(0.873)	(0.507)	(0.430)	(0.162)	(0.317)
Full Controls	✓	✓	✓	✓	✓	✓	✓	✓
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2587	2587	2587	2587	2065	2065	2065	2065

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Lawmakers who make race statements in hearings are more effective at legislating race-issue bills and no more (or less) effective at legislating non-race issue bills. Standard errors (in parentheses) are clustered by legislator. ABC = bill received action beyond committee, PASS = bill passed the House, LAW = bill was signed into law, LES = legislative effectiveness score. Race-issue bills include education, housing, and law and crime bills. Columns 1-4 are subset to include only race-issue bills. Columns 5-8 are subset to include only non-race issue bills. Full model with all controls reported in Table 6.5 in the appendix.

Conclusion

Much of the representation literature, particularly within legislative studies, has been interested in uncovering the unique benefits associated with electing descriptive representatives (Tate 2004; Carnes 2013; Lawless 2015). By examining lawmakers' statements in committee hearings, I demonstrate that race-based discussions in legislative committees are contingent on the representation of nonwhite lawmakers. In line with existing theoretical accounts of race-based representation in Congress, my findings suggest that nonwhite lawmakers are more likely to discuss race in hearings than white lawmakers. Within-legislator models indicate that white lawmakers discuss race more frequently in racially diverse hearings, suggesting that a racially diverse Congress may produce racial representation from an amalgamation of nonwhite and white lawmakers. Finally, I go beyond existing literature by connecting hearing statements to policy representation. I show that lawmakers who frequently discuss race in hearings are more effective at passing race-issue bills.

Collectively, these findings underscore the importance of electing a racially diverse Congress. When legislatures are racially diverse, committees are more likely to be racially diverse. And in racially diverse committees, all legislators are more likely to engage in race-based representation. The coalition of white and nonwhite lawmakers referencing race in highly diverse committees may be one reason why lawmakers who mention race in hearings are more likely to see their race-issue bills survive the lawmaking process. These findings highlight that the substantive representation of nonwhite Americans is linked to discussions of race in congressional committee hearings.

I use a methodological framework that allows me to *systematically* measure race-based representation in legislative speech. Existing scholarship often relies on hand-coded data from hearing transcripts in one legislative term. As a result, our current understanding of how lawmakers' racial identities shape their committee behavior is either committee-specific or time-bound. I systematically measure race-based representation in committee hearings by using a variety of text-as-data methods, including supervised machine learning, and find that a bigram dictionary classification approach best predicts race language in legislative speech.

The theoretical and methodological frameworks introduced in this paper can be broadly applied to study the effects of descriptive representation in political institutions. First, scholars can build on this work by exploring whether women and LGBTQ lawmakers discuss gender and sexuality more often than their male and non-LGBTQ colleagues and whether these statements are linked to policy representation (Ban, Grimmer, Kaslovsky, West et al. 2022; Miller and Sutherland 2023). Second, given that many political institutions at various levels of government are similar to legislative committees both in structure and function—for example, advisory committees in executive branch agencies (Potter 2019), city councils (Pelissero and Krebs 1997), and school boards (Collins 2021)—contact effects associated with racial diversity may extend beyond legislative committees. Future work might investigate whether racial diversity produces contact effects in other political institutions. Finally, future research should continue to explore the conditions under which descriptive characteristics, committee hearing statements, and policy representation converge.

Race-Based Contact Effects and Evidence Usage in Congressional Committee Hearings

Essay 2

Findings from decades of research show that increased racial diversity in the U.S. Congress has led to more race-based policymaking. Nonwhite lawmakers are more likely than their white colleagues to sponsor racially salient legislation (Bratton and Haynie 1999; Pinney and Serra 2002; Sinclair-Chapman 2002; Wilson 2010, 2017), highlight race-based issues in committee hearings and floor speeches (Wilson 2017; Dietrich and Hayes 2023; Lollis 2024*b*), and, under certain conditions, vote for race-related bills and earmarked spending directed to nonwhite constituencies (Kerr and Miller 1997; Canon 1999; Whitby 2000; Tate 2004; Grose, Mangum and Martin 2007; Grose 2011).[39] Nonwhite lawmakers also advocate for nonwhite Americans through interbranch contact with executive agencies (Lowande, Ritchie and Lauterbach 2019) and constituency services (Broockman 2013). Together, these findings suggest that increased nonwhite representation in Congress has expanded attention to race-based policymaking.

Although the consequences of Congress becoming more racially diverse are well understood, little research explores how the racial composition of committees shapes legislative behavior and race-based policymaking. Like the House of Representatives writ large, committees in the chamber have become more diverse over time. Nonwhite lawmakers' committee representation, however, varies widely. In the 117th Congress, for example, nearly 40% of Judiciary Committee members were nonwhite, compared to just 15% of Rules Committee members. Given that committees play a central role in policy development (Fenno 1973; Woon and Anderson 2012) and bill advancement (Cox and McCubbins 2007), a complete understanding of race-based policymaking in Congress requires examining how variation in racial diversity across committees affects committee behavior and substantive representation more broadly.

In this paper, I examine how the racial diversity of committees in the U.S. House of Representatives shapes legislators' discussions of race in hearings and affects the advancement and passage of race-related bills. Building on intergroup contact theory, I argue that racially diverse committees foster more interactions

[39] Some scholars argue that party identification and the percentage of Black and Latino constituents in a district better predict lawmakers' support for racially salient legislation than their race (Swain 1995; Hero and Tolbert 1995; Knoll 2009; Grose 2011).

between white and nonwhite legislators, which, in turn, influence how white lawmakers engage in race-based discussions. I test this expectation by analyzing how legislators use evidence to discuss race. Examining evidence usage in committee hearings offers a rigorous and theoretically relevant test of whether cross-group contact shapes how white lawmakers discuss race. Combining a detailed and systematic content analysis of race-based committee hearing statements and a within-legislator identification strategy, I find that white legislators on racially diverse committees are more likely to cite evidence when discussing race.

After empirically demonstrating that white legislators cite more evidence when discussing race on diverse committees, I conduct two mechanism tests to link this finding to intergroup contact theory. To do so, I examine *who* is most likely to be influenced by cross-group contact and *how* it alters their discussions of race. If contact effects explain my findings, white Democrats—who share a party affiliation with most nonwhite lawmakers and thus best align with the conditions for contact effects—should cite evidence most often. Likewise, white lawmakers should not only cite evidence more frequently when discussing race on diverse committees but also cite the same sources of evidence as nonwhite lawmakers. I find that white Democrats are most likely to use evidence, and white lawmakers are more likely to cite the same sources as nonwhite lawmakers when serving on racially diverse committees. I show that citing evidence in race discussions is linked to substantive representation, as legislators who use more evidence are more likely to advance and pass race-related bills.

Understanding how intergroup contact between nonwhite and white legislators in congressional committees shapes legislative behavior is essential. Since nonwhite lawmakers remain underrepresented in most American legislatures, it is important to identify institutional conditions that foster discussions of race—particularly those grounded in evidence—among both white and nonwhite legislators. I show that committee diversity is one such condition: racially diverse committees encourage more evidence-based discussions of race, especially among white Democrats. More broadly, these findings suggest that racial diversity within and across committees—not just in Congress as a whole—shapes legislators' engagement with race-based issues and influences the substantive representation of nonwhite Americans.

Race-Based Contact Effects and Evidence Usage

Existing research has examined how lawmakers' racial identities influence their committee actions. Studies show that racially diverse committees hold more hearings on race (Ellis and Wilson 2013; Nestor 2023), and in racially salient hearings, Black and Latino legislators participate more than their white colleagues (Gamble 2007; Minta 2009; Rouse 2023). Nonwhite legislators are also more likely to discuss race in committee hearings, regardless of the hearing topic (Lollis 2024*b*). These findings collectively show that legislators' racial identity shapes both participation and speech in hearings.

While these findings connect race to committee behavior, less is known about how a committee's racial diversity—and the interactions between white and nonwhite lawmakers in these settings—shape legislators' discussions of race. House committees, however, meet frequently, creating sustained opportunities for legislators to interact. For example, in the 117th Congress, the Judiciary Committee held more than 70 hearings—an average of two to three per week while in session—along with additional bill markups and meetings.[40] Committee members spend significant time together, which allows them to build networks, form friendships, and learn from each other. On racially diverse committees, white and nonwhite lawmakers regularly interact with one another, whereas cross-group interactions are more limited on predominantly white committees. This variation in contact may influence how white lawmakers discuss race.

Indeed, intergroup contact theory posits that, under a well-established set of conditions, contact between majority and minority groups can improve majority group attitudes and behaviors toward the minority group (Allport, Clark and Pettigrew 1954; Pettigrew 1998; Enos 2014; Dyck and Pearson-Merkowitz 2014). These effects are most likely to occur when individuals share similar goals, have incentives to cooperate, maintain equal group status, engage in repeated interactions, and operate within an environment where rules and norms structure interactions (Pettigrew 1998, p. 66). Lollis (2024*b*) extends this framework from social and political psychology to legislatures, arguing that these conditions align closely with the institutional design of congressional committees. He finds that white lawmakers, in fact, discuss race more frequently on racially diverse committees.[41]

[40]The Judiciary Committee calendar from the 117th Congress is available here: https://judiciary.house.gov/schedule

[41]Importantly, I do not claim that cross-group interactions between white and nonwhite legislators in committees alter legislators' *attitudes*. Rather, I argue that a committee's racial composition influences legislators' behavior in observable and testable ways—specifically, whether they cite evidence when discussing race.

I theorize that contact between white and nonwhite lawmakers on diverse committees may increase white lawmakers' use of evidence in race-based discussions for two central reasons. First, white lawmakers who are already informed about certain race-based topics may become more likely to cite evidence in diverse committees—either because race-based issues are discussed more frequently or because they observe nonwhite lawmakers supporting their statements with evidence and follow suit. Second, white lawmakers may be less informed about race-based issues and learn from their nonwhite colleagues by observing how they discuss race and use evidence. If intergroup contact produces either of these effects, white lawmakers should cite evidence more often when discussing race in racially diverse committees.

Contact effects, however, should not influence all white lawmakers equally. Cross-group contact is most likely to change behavior when individuals share equal status and work toward common goals (Pettigrew 1998). Because most nonwhite legislators are Democrats (Griffin 2014) and congressional parties are increasingly homogeneous (Lee 2016), white Democrats are not only more likely than white Republicans to share a partisan affiliation with their nonwhite colleagues, but also to align on policy objectives. As a result, white Democrats are best positioned to experience contact effects and should be more likely than white Republicans to reference evidence when discussing race.

> ***H1 (Contact Effects)***: The likelihood that a white lawmaker makes evidence-based race statements is positively associated with the racial diversity of a committee.

If contact between white and nonwhite lawmakers on racially diverse committees influences how white lawmakers—particularly white Democrats—talk about race, cross-group interactions may shape not only the *frequency* of their evidence-based race statements but also their *content*. I expect that white lawmakers on racially diverse committees will cite the same sources of evidence as nonwhite lawmakers to support their evidence-based race statements. The most straightforward explanation for why white lawmakers may cite the same sources as nonwhite lawmakers on diverse committees is that white legislators learn from their nonwhite colleagues' use of evidence. Drawing on their lived experiences and identity-based expertise (Mansbridge 1999), nonwhite lawmakers likely cite sources that best support their race-based claims. White lawmakers have different lived experiences and, as a result, may rely on different forms of evidence. Exposure to nonwhite lawmakers' citations on diverse committees, however, introduces white legislators to new sources, leading them to adopt evidence more commonly used by their nonwhite colleagues.[42]

> ***H2 (Matching Source Citations)***: The likelihood that white lawmakers cite the same sources as nonwhite lawmakers in their evidence-based race statements is positively associated with the racial diversity of a committee.

Citing evidence in race-based committee discussions stems not only from contact effects but also from legislators' commitment to effective policy representation. Legislators who cite evidence in race-related hearings demonstrate greater knowledge of race-based issues, which may enhance their legislative effectiveness on race-issue bills (Volden and Wiseman 2014). After all, lawmakers who use evidence when discussing race have the expertise to craft high-quality, evidence-based legislation capable of advancing through the legislative process. Further, because legislators often lack information about most policies under consideration in Congress (Curry 2015), they may rely on race-based issue experts as a heuristic when deciding whether to support a bill, increasing the likelihood that a bill sponsored by a race-based issue expert advances through the legislative process. Finally, legislators who specialize in specific policy areas, rather than maintaining a broad legislative agenda, tend to be more effective lawmakers, particularly in the House (Volden and Wiseman 2020). For these reasons, legislators who cite evidence in race-related discussions should be more effective at advancing and passing race-related bills.

> ***H3 (Evidence Usage and Effective Lawmaking)***: Citing evidence when discussing race is positively associated with effective lawmaking on race-issue bills.

Measuring Evidence in Committee Hearing Statements

While legislators may acquire and use evidence in many settings, I focus on measuring evidence usage in committee hearings. Unlike other stages of the lawmaking process—such as floor debates or speeches—committees are where legislators develop policy expertise (Kiewiet 1991; Krehbiel 1992; Battaglini et al.

[42] Of course, we cannot know what evidence white lawmakers were aware of before joining a diverse committee. White legislators may be already aware of the sources nonwhite lawmakers cite but choose to reference them more frequently in diverse settings because they perceive them as stronger or more credible. Either way, this finding would be significant, as it suggests that committee diversity encourages white lawmakers to adopt evidence from identity-based issue experts.

2019). Legislators gain information from witness testimony (Ban, Park and You 2024), committee staff (Ommundsen 2023; Fong, Lowande and Rauh 2025), lobbyists (Ban, Park and You 2023), and experienced colleagues (Curry 2019). Committee hearings, in turn, provide lawmakers with opportunities to apply this knowledge by citing evidence—an act that, unlike merely mentioning a group or topic, signals expertise and substantive engagement with an issue.

Although evidence is central to how committees function, legislators may not always prioritize acquiring or citing it. To be sure, lawmakers rely on information to determine how to vote, when to collaborate, and whether to compromise (Krehbiel 1992; Curry 2015). But gathering relevant information requires significant time and resources—both of which are scarce in an overburdened Congress (LaPira, Drutman and Kosar 2020). And it's unclear whether the costs are always worth bearing. After all, in a polarized environment, grandstanding in hearings may be more strategically advantageous than citing evidence (Park 2021), particularly since voters often reward such behavior (Park 2023). Given that citing evidence in committee hearings may be uncommon, understanding the conditions that encourage evidence-based policymaking—especially on issues like race—becomes even more critical.

Despite the importance of understanding legislators' use of evidence in committee hearings, the endeavor poses serious measurement challenges. Given the length and volume of committee hearing transcripts, existing research analyzing committee statements typically follows one of two methodological approaches: (1) content analysis on a limited number of hearings within a few committees in a single congressional term (Gamble 2007, 2011), or (2) automated coding using classification and machine learning methods (Park 2021; 2023; Lewallen, Park, and Theriault 2024; Ban, Park, and You 2024; Lollis 2024). Content analyses of this type allow scholars to create detailed, highly accurate measures, but they tend to be so time intensive that the findings are often limited to a specific committee or term, which is often a non-random sample of the corpus. Classification and machine learning methods address this limitation by coding a larger volume of statements, but they can struggle to identify complex and multidimensional latent concepts, and thus often produce less accurate measures than hand coding.

To test my expectations, I use a measurement strategy that overcomes the limitations of previous work. Since my theory focuses on how legislators use evidence when discussing race, my analysis is restricted to committee hearing statements that explicitly refer to race (Lollis 2024*b*). Statements are coded as mentioning race if they reference race broadly (e.g., "people of color," "minority racial interests") or specify a racial identity group (e.g., Black, Latino, Asian, Native American).[43] The dataset includes 11,686 race statements from 941 unique legislators across 24 House committees from the 105th to 117th Congress. On average, legislators make 14 race statements per term, with an average length of 300 words.[44]

To identify evidence usage, I conducted a detailed and systematic content analysis of all 11,686 race statements to determine whether they mention evidence and, if so, the specific source cited. I define evidence usage as a legislator citing a source to substantiate a claim.[45] Legislators frequently cite existing laws, current legislation, executive agency and interest group reports, news articles, and witness testimonies when referencing evidence. Statements that met these criteria were coded as evidence statements, while those that relied on unsupported claims or did not make claims were coded as non-evidence statements. Since I code all race statements mentioned in congressional committee hearings over a span of 25 years for evidence usage, I eliminate concerns about non-random sampling and term-or committee-specific findings (Lollis 2024). Moreover, because I manually coded each statement, I produce precise and valid measures that capture not only whether a statement cites evidence but also the specific source referenced.

Table 1 illustrates the coding decisions associated with three variations of the same race statement. The first statement was coded as evidence-based because it cites a source, the Census Bureau, to support a claim (i.e., African Americans were undercounted in the Census). The second statement was not coded as evidence-based because it lacked a citation. The third neither cited a source nor made a claim. While validity is less of a concern since I manually labeled each statement rather than relying on automated coding, Section 2 of the appendix presents 20 randomly selected evidence and non-evidence statements. As expected, all

[43]Using a bigram dictionary classification method, Lollis (2024*b*) identified race-based statements from more than 16,000 legislative and oversight committee hearings in the U.S. House of Representatives during the 105th–117th Congresses. Out of 1,410,292 statements by 1,164 unique members across 24 committees, 11,686 referenced race. Lollis (2024*b*) validated this measure by comparing predicted values to hand-coded values in a validation set held back before model training. The Area Under the Curve (AUC), a composite measure of specificity (false positives) and sensitivity (false negatives), is 0.90—indicating strong classification accuracy. The Kappa correlation coefficient is 0.87, demonstrating high agreement between hand-coded and predicted values. For a detailed description of the creation of the race statement measure, see sections two, three, and four of the appendix in Lollis (2024*b*).

[44]One concern is that legislators may mention race not only as a form of representation but also in explicitly negative or racist ways. Lollis (2024*b*) addresses this possibility by coding for negative and neutral race statements in a training set of 5,000 randomly sampled race statements. Statements were coded as negative if the legislator spoke about nonwhite individuals in negative or racist ways, and neutral otherwise. 98% of all race statements were coded as neutral, meaning that the overwhelming majority of race statements were not explicitly negative. As a result, I do not incorporate tone as an independent variable in this analysis.

[45]Importantly, my definition of evidence differs from work measuring information in congressional committee hearings (Ban, Park and You 2024). Legislators *cite* evidence to make and defend arguments, while they *acquire* information through witness testimony, experts, staff, etc.

20 evidence statements include a source substantiating a claim (bolded), while none of the non-evidence statements do. This face validity check confirms that the measure accurately captures evidence usage.

Table 1: Coding Evidence-Based Race Statements

Coding Decision	Source	Race Statement
Evidence Statement	Census Bureau	"During the last census count in 2010, the **Census Bureau** found that *African Americans were under-counted by over 800,000*."
Non-Evidence Statement	—	"During the last census count in 2010, *African Americans were under-counted by over 800,000*."
Non-Evidence Statement	—	"I'm deeply concerned that African Americans are being undercounted in the Census. Does the Bureau have a goal or plan to improve the Black undercount and increase participation?"

Note: Examples are based on a statement made by Representative Steven Horsford in an Oversight Committee hearing in the 116th Congress.

After determining whether each race statement cited evidence, I created two dependent variables. The first, "Evidence," is a continuous variable that measures the total number of evidence-based race statements a legislator makes per term.[46] It ranges from 0 to 23, with a mean of 1.38. The second variable, "Matching Nonwhite-White Source Mentions," is a continuous variable that measures the number of sources cited by a white lawmaker that also appear in nonwhite lawmakers' statements within the same committee-term. For example, if both a white and a nonwhite legislator cited *Shelby County v. Holder*, the Voting Rights Advancement Act, and the Census Bureau in the Judiciary Committee during the 117th Congress—without citing any other matching sources—each would receive a value of three for this variable. This variable ranges from zero to five, with a mean of one.

[46] I do not construct this variable at the statement or member-committee-term level for two reasons. First, legislators' statements within a hearing are not independent. Lawmakers often engage in dialogue with witnesses throughout their allotted speaking time, meaning multiple statements from the same legislator may be connected (Eldes, Fong and Lowande 2024). Second, because evidence is cited infrequently, estimating models at the member-committee-term level lacks sufficient statistical power. Therefore, calculating this variable at the member-term level (1) best aligns with my theoretical expectations about *legislators'* behavior, (2) reflects the structure of committee hearing discussions, and (3) provides enough statistical power to detect whether a relationship exists.

Results

Evidence Usage is Infrequent

Out of 11,686 race statements, 3,225 (27%) mention evidence. Though these statements are somewhat more common during Democratic majorities (110th, 111th, 116th, and 117th Congresses), variation across terms is minimal. Indeed, Table 2 shows that legislators make an average of one to two evidence-based race statements per term. While the total number of evidence-based race statements per term is relatively low, more than half of the legislators in the dataset make at least one per term (see Table 4, column 2). In the 110th Congress, for example, 71% of legislators made an evidence-based race statement. This suggests that evidence usage is not concentrated among a small set of lawmakers.

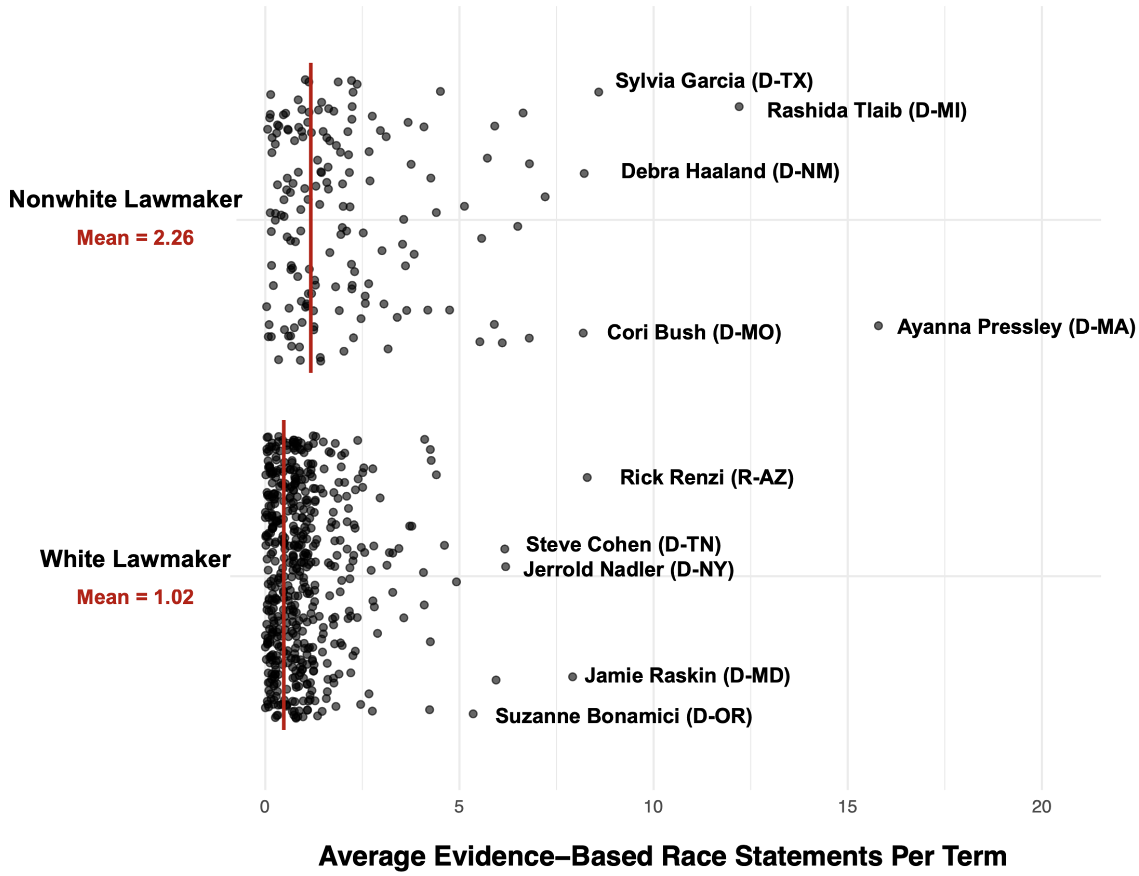
Table 2: Average Number of Evidence-Based Race Statements Per Term

Term	Party in Majority	Mean Evidence-Based Race Statements Per Legislator	% of Legislators Making At Least One Evidence-Based Race Statement	Min	Max
105 (1997)	R	0.714	48.5%	0	3
106 (1999)	R	0.908	54.3%	0	15
107 (2001)	R	1.24	62.6%	0	11
108 (2003)	R	1.58	63.0%	0	11
109 (2005)	R	1.80	62.0%	0	14
110 (2007)	D	2.06	71.8%	0	23
111 (2009)	D	1.58	63.8%	0	21
112 (2011)	R	1.35	62.2%	0	11
113 (2013)	R	0.970	49.1%	0	7
114 (2015)	R	1.13	57.8%	0	10
115 (2017)	R	0.736	56.6%	0	6
116 (2019)	D	1.57	57.8%	0	19
117 (2021)	D	1.44	55.4%	0	21

Note: Evidence-based race statements are infrequent, though a majority of legislators make at least one per term. Table includes the mean number of evidence-based race statements made by each legislator across all terms and the average maximum and minimum value per term. Column 4 displays the percentage of legislators making at least one evidence-based race statement per term.

Although variation across term is minimal, nonwhite lawmakers do make more evidence-based race statements than white lawmakers. Figure 1 plots the average number of evidence-based race statements per term, distinguishing between nonwhite and white lawmakers. Each dot represents a unique lawmaker. On average, nonwhite legislators make 2.26 evidence-based race statements per term, compared to one per term for white legislators. While this difference may seem small, it is substantively large given that the overall average is one evidence-based race statement per term. Notably, the nonwhite lawmakers most likely to integrate evidence into their race statements are all women of color, a pattern consistent with research showing that Black women work together to elevate race-based issues, particularly when they intersect with gender issues (Brown 2014). Ayanna Pressley and Rashida Tlaib made more than 10 evidence-based race statements per term, while Sylvia Garcia, Debra Haaland, and Cori Bush incorporated evidence in more than five. Among white lawmakers, Democrats representing diverse districts most frequently referenced evidence—except for Rick Renzi, a Republican who represented Arizona's first congressional district, home to the Navajo Nation and Hopi Reservation.

Figure 1: Evidence-Base Race Statements for Nonwhite and White Legislators



Note: Dots on jitter plot indicate the average number of evidence-based race statements made by a lawmaker per term. Nonwhite legislators make one additional evidence-based race statement per term compared to white lawmakers.

White Lawmakers, particuarly Democrats, Cite More Evidence On Diverse Committees

To model the relationship between white lawmakers' evidence-based race statements and the percentage of nonwhite lawmakers on committees, I use a within-legislator identification strategy. Within-legislator designs are powerful causal inference tools for observational data because they allow scholars to control for unobserved, time-invariant factors that vary between legislators. In this case, the within-legislator design accounts for confounders that are difficult to measure, such as legislators' racial attitudes, the racial diversity of their staff, and race-based expertise. To address unobserved time-variant confounders, I include term fixed effects. As a result, the findings can be interpreted as independent of all differences between white legislators and any changes over time.

To test my first hypothesis, I estimate an OLS regression model with legislator fixed effects, both with and without term fixed effects.[47] The dependent variable, "Evidence," measures the total number of evidence-based race statements made by white legislators per term. The key independent variable is the average number of nonwhite lawmakers on a legislator's assigned committees. Figure 2 plots the predicted number of evidence-based race statements made by a white lawmaker per term.[48] A rug plot overlays the x-axis to illustrate the distribution of nonwhite representation on committees.

Figure 2 demonstrates that white lawmakers make more evidence-based race statements as the percentage of nonwhite lawmakers on their committees increases. A white legislator serving on an all-white committee makes zero evidence-based race statements per term. In contrast, the same white legislator makes two to three evidence-based race statements per term when serving on the most racially diverse committees in the House. Put differently, a white legislator makes approximately three more evidence-based race statements per term when serving on racially diverse committees, controlling for all factors that vary between legislators and over time.[49] This finding remains robust when excluding legislator fixed effects, using count models instead of OLS, and calculating the dependent variable as the proportion of evidence-based race statements to total race statements.[50]

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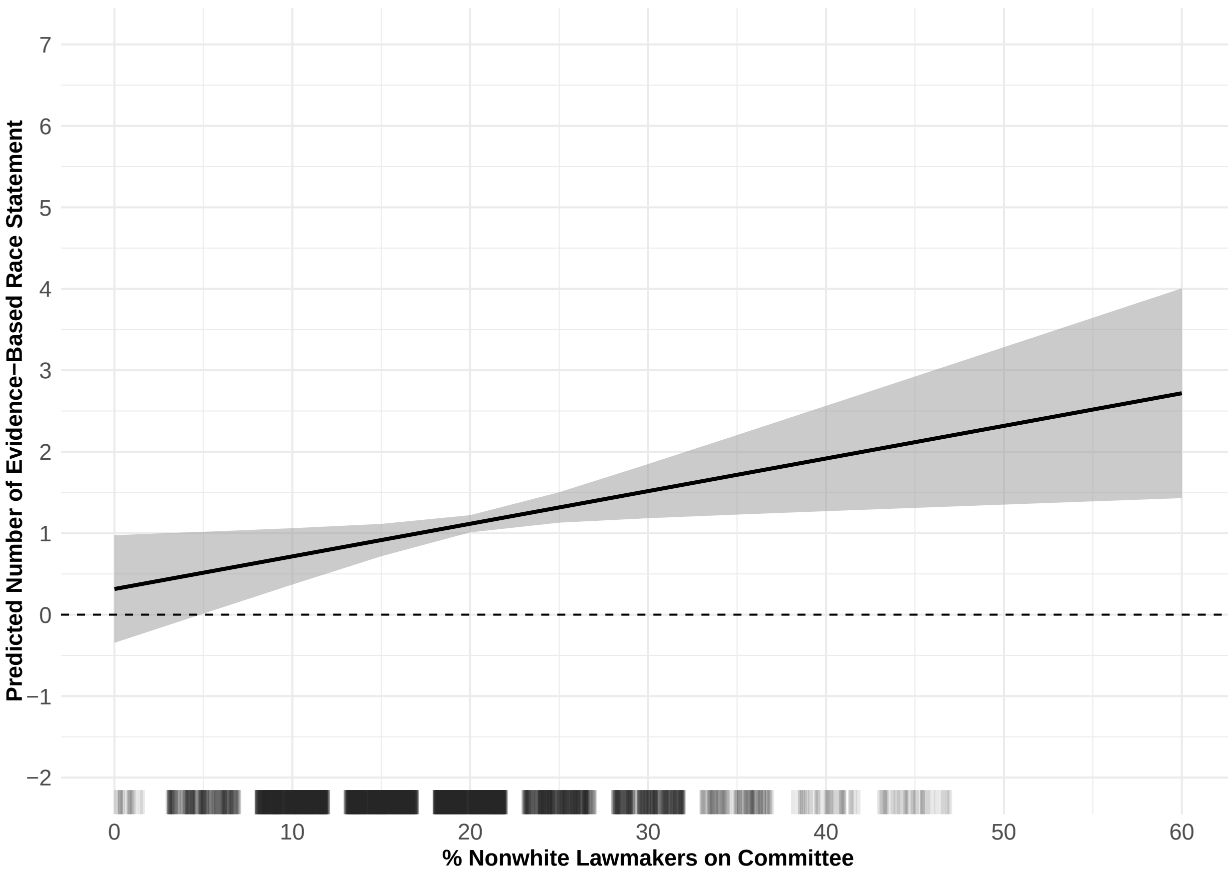
[47]Two-way fixed effects rely on the assumption of linear additive effects (Imai and Kim 2021), which is often violated when using unit- and time-specific fixed effects. To address this, I estimate the same model without term fixed effects, instead controlling for specific time-variant confounders (Table 3.1 in the appendix). The results remain largely consistent.

[48]The full model is reported in Appendix Table 3.1.

[49]One potential concern is that legislators with greater race-based expertise may be more likely to seek assignment on racially diverse committees. Since committee assignment is, to some degree, non-random, the effects reported here could reflect white legislators' committee preferences rather than the influence of committee diversity itself. However, the within-legislator identification strategy rules out this explanation. The findings show that all white lawmakers—regardless of their committee preferences or prior expertise on race-related issues—discuss race more frequently on racially diverse committees.

[50]In Section Four of the appendix, I demonstrate that this result is robust across three alternative model specifications. First, in Appendix Table 4.1, I estimate the model without legislator fixed effects, instead interacting whether a lawmaker is white with the percentage of nonwhite lawmakers on the committee. Second, in Appendix Table 4.2, I replace OLS with two count models, estimating the relationship using Poisson and Negative Binomial regressions. Third, in Appendix Table 4.3, I use a dependent variable measuring the proportion of evidence statements to total race statements. Across all three specifications, the results remain largely consistent with the main findings presented in-text.

Figure 2: White Legislators Make More Evidence-Based Race Statements on Racially Diverse Committees



Note: The black line indicates the predicted number of evidence-based race statements a white lawmaker makes given the percentage of nonwhite lawmakers represented on their assigned committees. The gray band represents 95% confidence intervals. The models were estimated using legislator fixed effects both with and without term fixed effects. The unit of analysis is a member-term. The rug plot displays the distribution nonwhite lawmakers on committees. The full model is reported in Appendix Table 3.1.

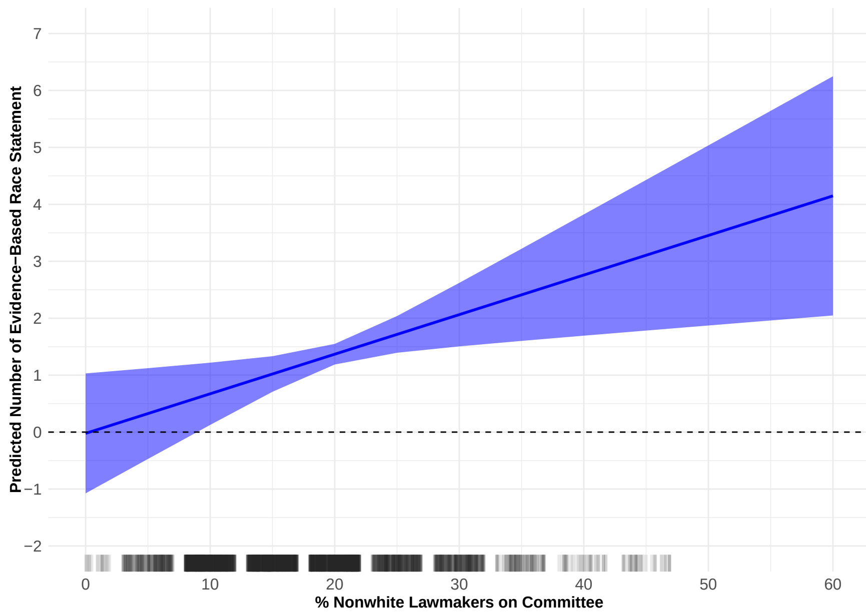
White lawmakers overall are more likely to cite evidence when discussing race as committee diversity increases, but I expect this effect to be strongest for white Democrats, as they are most likely to meet the conditions necessary for contact effects. Figure 3 presents results from the same within-legislator model, but subset to include only white Democrats (Panel 1) or white Republicans (Panel 2).[51] The slope of the blue line (white Democrats) is steeper than that of the red line (white Republicans), suggesting that the relationship between evidence-based race statements and committee diversity is strongest for white Democrats. A white Democrat makes zero race-based statements per term when serving on an all-white committee but

[51]White Democrats mention an average of 1.23 evidence-based race statements per term, compared to 0.86 for white Republicans.

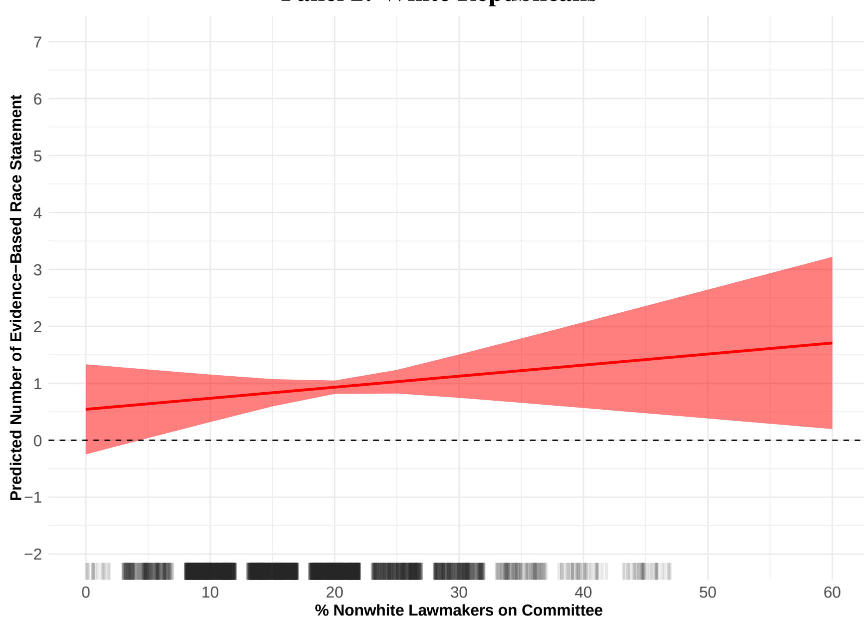
cites evidence in race discussions three to four times per term when serving on the most racially diverse committees. In contrast, white Republicans make zero evidence-based race statements per term on all-white committees and, at most, one additional statement when serving on the most diverse committees. The effect of committee diversity on evidence usage is statistically significant for white Democrats (coefficient = 0.07, $p = 0.01$) but not for white Republicans (coefficient = 0.01, $p = 0.18$).

Figure 3: White Democrats Make More Evidence-Based Race Statements on Racially Diverse Committees

Panel 1: White Democrats



Panel 2: White Republicans



Note: The blue line plots the predicted number of evidence-based race statements a white Democrat makes given the percentage of nonwhite lawmakers on their assigned committees. The red line indicates the predicted number of evidence-based race statements a white Republican makes given the percentage of nonwhite lawmakers on their assigned committees. The gray band represents 95% confidence intervals. The models were estimated using legislator fixed effects with and without term fixed effects. The rug plot displays the distribution of nonwhite lawmakers on committees. The full model is reported in Table 3.1 in the appendix.

Legislators Cite Similar Sources of Evidence on Diverse Committees

In my second hypothesis, I argue that contact effects should also prompt white lawmakers on diverse committees to reference the same sources as their nonwhite colleagues. To test this expectation, I pair descriptive evidence from two committees in the 116th Congress with estimates from a within-legislator OLS regression model. I descriptively analyze the sources cited in the Education and Labor and Judiciary committees for two reasons. First, these committees vary in racial composition: about one-fourth of Education and Labor members are nonwhite—roughly the House average—while nearly 40% of Judiciary Committee members are nonwhite. Second, both committees play a significant role in policymaking and frequently engage in discussions about race. If white and nonwhite lawmakers cite overlapping sources in race-related discussions—and if this pattern is linked to committee diversity—we should observe different citation patterns across these two committees.

Table 3 presents the most frequently cited sources by white and nonwhite legislators in these two committees in the 116th Congress. Consistent with my expectation, white and nonwhite legislators frequently cited the same sources on the Judiciary Committee, but not on the Education and Labor Committee. *Brown v. Board of Education* was the only overlapping source cited by both white and nonwhite members on the Education and Labor Committee throughout the term. In contrast, white and nonwhite lawmakers in the Judiciary Committee referenced four of the same sources: the Department of Justice, the Equality Act, *Shelby County v. Holder*, and the FBI.

This pattern, however, does not suggest that lawmakers on less diverse committees cite irrelevant or unimportant sources. Both white and nonwhite legislators in the Education and Labor Committee frequently referenced significant and timely evidence, including the Civil Rights Act, the Affordable Care Act, and the Bureau of Labor Statistics. However, white and nonwhite lawmakers in the Judiciary Committee showed much greater overlap in the sources they cited. This finding suggests that if these two committees reflect broader patterns, racial diversity within a committee influences the type of evidence white lawmakers cite.

Table 3: Similar Source Citations on Committee with Average and High % of Nonwhite Lawmakers

Education and Labor (116th Congress) *24% Nonwhite Legislators on Committee (Average)*		Judiciary (116th Congress) *39% Nonwhite Legislators on Committee (High)*	
Top Sources Nonwhite Lawmakers	**Top Sources White Lawmakers**	**Top Sources Nonwhite Lawmakers**	**Top Sources White Lawmakers**
Brown v. Board	**Brown v. Board**	**DOJ**	**DOJ**
Paycheck Fairness Act	Civil Rights Act	**Equality Act**	**Equality Act**
DOL	Equal Pay Act	**Shelby County v. Holder**	**Shelby County v. Holder**
Brookings	Government Accountability Office	**FBI**	**FBI**
Commonwealth Fund	Affordable Care Act	Pew	Voting Rights Act
Fair Labor Standards Act	AFL-CIO	Commission to Study Reparations	SUCCESS Act
Federal Reserve	America's College Promise Act	Local Law Enforcement Hate Crimes Prevention Act	Bend the Arc
Maternal CARE Act	Bridge Magazine	National Institute of Standards and Technology	Census Bureau
Religious Freedom Restoration Act	Bureau of Labor Statistics	Social Security Act	Center for Police Equity

Note: White and nonwhite lawmakers cite more of the same sources on the Judiciary committee (39% nonwhite lawmakers) than the Education and Labor committee (24% nonwhite lawmakers). The table reports the nine sources most frequently cited by white and nonwhite lawmakers on two committees in the 116th Congress.

To test my hypothesis more systematically, I model the relationship between the percentage of nonwhite lawmakers on a committee and the number of shared nonwhite-white source citations within a given committee and term. As in Figures 2 and 3, I use a within-legislator identification strategy. The dependent variable, "Matching Nonwhite-White Source Mentions," measures the number of sources a white lawmaker cites that are also referenced by nonwhite lawmakers in the same committee-term. The key independent variable is the percentage of nonwhite lawmakers on the committee. I estimate three OLS regression models, each incorporating legislator fixed effects and varying specifications of committee and term fixed effects. Additionally, I control for the total number of evidence statements and unique sources a lawmaker cites in a committee-term.

Table 4 presents the results, which are consistent across all three model specifications: white lawmakers are more likely to cite the same evidence as nonwhite lawmakers when serving on racially diverse committees. On committees with few nonwhite members, white lawmakers cite no overlapping sources, whereas, on the most diverse committees, they cite nearly two. This effect is substantively meaningful given the variable's range. The maximum number of matching white-nonwhite source citations within a committee-term is five. This relationship occurs for all white legislators, within all committees, across all terms.

Importantly, this result holds even when controlling for the total number of unique sources a legislator cites per term. This suggests that white lawmakers are not simply adding sources cited by their nonwhite colleagues to their existing pool of information; rather, they are replacing previously cited evidence with sources referenced by nonwhite lawmakers. This finding is significant because it indicates that in diverse committees, white lawmakers not only cite evidence more frequently in race-related discussions but also adapt their statements to incorporate sources used by nonwhite lawmakers, who have lived experiences and identity-based expertise in race-related issues.

Table 4: Nonwhite and White Legislators Cite Similar Sources on Diverse Committees

DV: Matching Nonwhite-White Source Mentions (White Lawmakers)			
% Nonwhite on Committee	0.008**	0.009***	0.009***
	(0.003)	(0.002)	(0.002)
Total Race Statements	0.091**	0.091**	0.139***
	(0.032)	(0.032)	(0.031)
Total Sources	0.223***	0.227***	0.159***
	(0.036)	(0.036)	(0.036)
Total Unique Sources	0.000	0.000	0.000
	(.)	(.)	(.)
In Majority Party			-0.110
			(0.123)
DW-Nominate			-0.437
			(0.295)
Vote Share			-0.002
			(0.001)
Intercept	0.442***	0.350***	0.763***
	(0.117)	(0.085)	(0.211)
Legislator Fixed Effects	✓	✓	✓
Committee Fixed Effects	✓		
Term Fixed Effects	✓	✓	
Observations	1958	1958	1923

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White lawmakers cite the same sources of evidence as nonwhite lawmakers on racially diverse committees. The dependent variables measures the total number of sources cited by white lawmakers that were also cited by nonwhite lawmakers in a committee-term. Column one includes legislator, committee, and term fixed effects, while the other two columns drop the committee and term fixed effects. The results are consistent across all model specifications.

Evidence Usage Affects Substantive Representation

Finally, I expect that evidence usage in race-based discussions is linked to substantive representation on race-issue bills. I expect legislators who use evidence more frequently when discussing race to be more effective at advancing and passing their sponsored race issue bills. Conversely, I expect this relationship to be null on bills unrelated to race. To test this expectation, I use Lollis's (2024*b*) measure of race-issue bills. Lollis identified three policy areas—education, housing, and law and crime—where nonwhite lawmakers introduce more legislation than white lawmakers.[52] I code bills associated with these three topics as race-issue bills and all other bills as non-race bills.

Table 5 presents estimates from eight OLS regression models.[53] The dependent variables in the first four columns represent the total number of race-issue bills sponsored by a legislator per term that advanced beyond committee (ABC), passed the House (PASS), became law (LAW), and their average legislative effectiveness score on race-issue bills (LES). Columns five through eight use the same four dependent variables, but instead measure the total number of bills unrelated to race that advanced through each stage of the lawmaking process. The primary independent variable is the total number of evidence-based race statements a lawmaker makes per term. Each model includes standard legislative effectiveness controls and term fixed effects.

The estimates in Table 5 largely support my expectations. As indicated by the positive and significant coefficient for total evidence statements in columns one, two, and four, legislators who frequently cite evidence when discussing race are more likely to advance their sponsored race-related legislation beyond committee, pass the House, and achieve a higher legislative effectiveness score. As expected, these lawmakers are no more effective at legislating bills unrelated to race. The coefficients for total evidence statements in each model of bills unrelated to race fail to reach conventional levels of statistical significance.[54] These

[52]To do so, he used the 22 predefined policy areas from the Policy Agendas Project and the Congressional Bills Project (Baumgartner and Jones 2002). This approach is similar to Volden, Wiseman and Wittmer (2018), who measured gender-issue bills using predefined policy areas. The 22 policy areas are: Agriculture, Civil Rights, Commerce, Defense, Education, Energy, Environment, Government Operations, Health, Housing, Immigration, International Affairs, Labor, Law and Crime, Macroeconomics, Miscellaneous, Native Americans, Public Lands, Technology, Trade, Transportation, and Welfare. For more details on this measure, see Appendix Section 9 in Lollis (2024*b*).

[53]For ease of visualization, Table 5 provides an abbreviated version of the model, while the full model with all controls is reported in Table 3.2 in the appendix.

[54]It is important to note a limitation of Lollis's (2024*b*) measure of race-issue bills. This measure identifies race-issue bills based on policy areas rather than whether an individual bill explicitly mentions race. A more precise measure would assess whether each bill directly references race. However, I choose to identify race bills by policy area because it allows me to create a systematic measure that identifies race-based policies over my time series.

findings suggest that expertise in a particular issue area—in this case, race—provides a unique policymaking advantage on race-issue bills.

Table 5: Legislators Who Make More Evidence-Based Race Statements Are More Effective At Legislating Race Issue Bills

	1	2	3	4	5	6	7	8
	ABC (Race Bills)	**PASS (Race Bills)**	**LAW (Race Bills)**	**LES (Race Bills)**	**ABC (Not Race Bills)**	**PASS (Not Race Bills)**	**LAW (Not Race Bills)**	**LES (Not Race Bills)**
Total Evidence Statements	0.0772**	0.0547**	0.00816	0.264***	0.0110	-0.0304	-0.00609	0.0461
	(0.0237)	(0.0186)	(0.00486)	(0.0671)	(0.0427)	(0.0240)	(0.0121)	(0.0382)
Nonwhite	-0.0304	-0.0214	-0.0180	-0.274	0.0247	-0.0461	0.0260	-0.00504
	(0.0498)	(0.0412)	(0.0126)	(0.253)	(0.206)	(0.149)	(0.0781)	(0.117)
Democrat	-0.201	-0.172	0.0135	-0.459	-2.054***	-1.972***	-0.459*	-1.061**
	(0.140)	(0.123)	(0.0309)	(0.617)	(0.610)	(0.554)	(0.213)	(0.327)
% Nonwhite in District	0.0433	0.0796	0.0424	0.167	0.585	0.865	0.272	-0.442
	(0.117)	(0.0989)	(0.0356)	(0.592)	(0.635)	(0.476)	(0.217)	(0.334)
Intercept	-0.0761	0.0426	-0.0514	0.398	3.062***	2.647***	1.039***	1.292**
	(0.227)	(0.210)	(0.0466)	(1.348)	(0.789)	(0.687)	(0.263)	(0.405)
Full Controls	✓	✓	✓	✓	✓	✓	✓	✓
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1347	1347	1347	1347	1100	1100	1100	1100

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Lawmakers who make more evidence-based race statements are more effective at legislating race-issue bills and no more (or less) effective at legislating non-race issue bills. Standard errors (in parentheses) are clustered by legislator. ABC = bill received action beyond committee, PASS = bill passed the House, LAW = bill was signed into law, LES = legislative effectiveness score. Race-issue bills include education, housing, and law and crime bills. Columns 1-4 are subset to include only race-issue bills. Columns 5-8 are subset to include only non-race issue bills. Full model reported in Table 3.2 in the appendix.

Conclusion

Despite extensive research on how the increasing number of nonwhite lawmakers in Congress has shaped policymaking, variation in nonwhite representation across legislative committees—and its consequences—remains largely overlooked. This paper highlights a key reason why committee racial diversity matters: contact effects. Using a systematic content analysis of over 11,000 race-based committee hearing statements and a within-legislator identification strategy, I demonstrate that cross-group interactions between white and nonwhite lawmakers on racially diverse committees lead white lawmakers to incorporate evidence into their discussions of race.

Moreover, determining race bills based on policy area is a well-established practice by other scholars (Bratton and Haynie 1999; Grose 2011).

These findings offer important insights into how race shapes legislative institutions and policymaking. First, they suggest that committee-level racial diversity—not just the overall diversity of Congress—shapes both legislative discourse and policy outcomes. This distinction is critical because nonwhite lawmakers are not equally represented across committees. I show that evidence is frequently cited by both nonwhite and white lawmakers on diverse committees like Judiciary and Financial Services, whereas race discussions in less diverse committees, such as Rules, Agriculture, and Veterans Affairs, rarely incorporate evidence. This disparity matters not only because race discussions in less diverse committees may lack empirical grounding, but also because legislators who cite more evidence are more likely to advance and pass race-related bills. As a result, race-based policies are more likely to advance in racially diverse committees, making committee composition a key predictor of whether race bills succeed. If parties or caucuses—such as the Congressional Black Caucus (Tate 2020)—seek to expand the legislative focus on race, they must prioritize not only increasing congressional diversity but also ensuring that nonwhite lawmakers serve on a broad range of committees. Otherwise, given that committees are structured around policy jurisdictions, race-related policymaking risks becoming siloed within a narrow set of issue areas.

Beyond highlighting the importance of racial diversity on committees, this paper also examines how legislators engage with evidence in legislative speech. My findings indicate that while evidence usage in race-related discussions is rare, it has remained consistent over time. Over the past thirty years, Congress has grown more polarized (Lee 2016) and increasingly overburdened and under-resourced (LaPira, Drutman and Kosar 2020). Despite these challenges—which could limit legislators' ability to acquire and use evidence—lawmakers today cite evidence in race discussions at similar rates as they did three decades ago. The focus, then, should not be on whether evidence usage has declined over time, but rather on how to increase expertise and encourage greater engagement with evidence in race-related discussions.

These findings also raise several additional questions about the relationships among race, committee diversity, evidence usage, and substantive representation. First, scholars may explore additional pathways to increasing race-based expertise in Congress. I demonstrate that contact between white and nonwhite lawmakers in racially diverse committees increases race-based evidence usage, but prior lived experiences, occupational backgrounds, or constituency demographics may also shape legislators' engagement with evidence. Second, since my focus is on lawmakers' evidence usage, witnesses who testify in hearings are absent from this analysis. Future research could examine how witness expertise influences legislators' engagement with race-related evidence. More broadly, scholars could examine whether and how contact effects extend to other underrepresented groups in legislatures, such as women and LGBTQ+ lawmakers, and how these effects shape gender- and LGBTQ-focused policymaking.

Are Workers Effective Lawmakers?

Essay 3

Approximately half of U.S. citizens are employed in manual labor or service-based jobs, yet only 6% of state legislators and 2% of U.S. representatives have previously been employed in a working-class occupation (Carnes 2013). The effects of America's white-collar government are clear—wealth inequality has dramatically increased in the last half-century with the top 1% of Americans becoming increasingly wealthy while workers' wage earnings have stagnated. Scholars find that U.S. policy advantages the rich while ignoring the interests of working-class and poor Americans (Gilens 2012; Bartels 2016; Miler 2018; Persson and Sundell 2023).[55] One potential reason that policy reflects the interests of the rich is the drastic overrepresentation of wealthy Americans serving in political office (Carnes 2013).

The primary explanation for why workers are underrepresented in American legislatures is that structural biases exist in American elections that prevent working-class candidates from emerging and successfully running for elected office (Carnes 2018). And while a growing literature examines how and why American elections disproportionately disadvantage candidates from a working-class background (Carnes 2018; Treul and Hansen 2023), it is also necessary to consider how class-based electoral bias is related to workers' ability to effectively govern. The current literature suggests that if workers' numerical representation in legislatures increases, better policy representation for working-class Americans will likely follow (Mansbridge 1999; Carnes 2013, 2018). And based on the policy priorities of working-class lawmakers this appears to be true—working-class legislators are more likely than white-collar legislators to introduce and vote for pro-worker policies (Carnes 2013). This logic, however, is contingent on the assumption that workers perform equally or better than white-collar lawmakers once elected to legislative office. If workers are ineffective lawmakers, their policy preferences are unlikely to be successfully legislated into law. In this article, I examine whether a class-based effectiveness gap exists in American legislatures.

Throughout America's history, some political leaders have advanced arguments suggesting that, if elected, working-class lawmakers would be ineffective at carrying out the duties and responsibilities of a legislator. Alexander Hamilton, writing in the Federalist Papers, suggests that workers are less politi-

[55] A debate exists among scholars as to whether affluent and poor Americans' policy preferences differ and whether poor Americans lack political representation. See Gilens (2009) for a review.

cally skilled than individuals working in white-collar jobs and are, therefore, less suitable for political office (Hamilton et al. 1788). More recently, President Trump publicly stated in reference to his selection of cabinet secretaries that he preferred to appoint rich cabinet secretaries because he "just didn't want a poor person" in the position (Calfas 2017). If these arguments are correct and white-collar lawmakers are better suited to govern, we may expect working-class legislators to be less effective lawmakers than their white-collar colleagues. To date, however, there is no empirical evidence suggesting that working-class legislators are less effective lawmakers than white-collar legislators.

I argue, in contrast, that working-class legislators should perform equally or better than white-collar lawmakers. I develop a theory of class-based electoral selection that links class-based discrimination in elections to legislators' performance in office (Anzia and Berry 2011). Working-class candidates face class-based biases in elections that make it more difficult to emerge and successfully win elective office (Carnes 2018). Given that white-collar candidates do not face similar biases in elections, working-class candidates must work harder and develop skills to overcome these barriers. As a result, the workers who do win elected office are qualified, hard-working candidates capable of effective lawmaking.

My data set pairs pre-legislature occupational data for over 14,000 unique state legislators (Makse 2019) with Bucchianeri, Volden, and Wiseman's (2025) state legislative effectiveness scores (SLES). The data set in total includes over 50,000 legislator-term specific observations from 49 states over thirty years (1988-2017). Of these 50,000 legislator-term specific observations, approximately 3,500 are working-class legislators. A simple comparison of means shows that, on average, white-collar legislators are marginally more effective than working-class legislators. However, in a regression model with controls, this relationship disappears, suggesting that working-class and white-collar legislators are equally effective lawmakers.

Studying legislators' performance in office, particularly for underrepresented groups, is necessary for several reasons. First, empirically evaluating the legislative effectiveness of underrepresented groups empowers scholars to address discriminatory arguments that these groups are in some way less capable than majority groups. My analysis provides some evidence against these discriminatory arguments; I find no evidence that white-collar legislators are more effective lawmakers than workers. Indeed, my findings stand in contrast to arguments that suggest workers are less suitable for political office because of their occupational background (Hamilton et al. 1788; Calfas 2017). Second, examining the effectiveness of working-class lawmakers may have implications for the substantive representation of working-class Americans. Though I do not directly test whether working-class lawmakers are more likely to pass legislation that would benefit working-class constituents, the fact that workers are equally as effective as white-collar lawmakers certainly suggests that workers have the lawmaking skills necessary to substantively represent working-class Americans.

The Legislative Effectiveness of Underrepresented Groups

There is an extensive literature that seeks to conceptualize, measure, and analyze legislative effectiveness in the U.S. Congress and U.S. state legislatures (Matthews 1959; Weissert 1991; Volden and Wiseman 2014; Volden, Wiseman and Wittmer 2013; Hitt, Volden and Wiseman 2017; Volden, Wiseman and Wittmer 2018; Bucchianeri, Volden and Wiseman 2025). Volden and Wiseman define legislative effectiveness as "the proven ability to advance a member's agenda items through the legislative process and into law" (2014, 18). Bucchianeri, Volden, and Wiseman's (2025) state legislative effectiveness scores (SLES) measure legislative action throughout the lawmaking process (sponsorship, action in committee, action beyond committee, a bill passing one chamber, and a bill becoming law). This measure comprehensively describes legislators' lawmaking efforts at each stage of the lawmaking process. Legislative effectiveness scores are used to analyze institutional and individual-level factors, and how the intersection of both, shapes legislators' effectiveness. Scholars have primarily analyzed the legislative effectiveness of two underrepresented groups—women and Black legislators—in the U.S. Congress (Volden, Wiseman and Wittmer 2013; Volden and Wiseman 2014).

Volden and Wiseman (2013) find that women legislators, when in the minority party, are more effective than male legislators. In the majority party, however, women are equally effective as male legislators. Women legislators are particularly effective at the consensus-building portions of the lawmaking process, like committee and floor action (2013). Volden et al. (2013) attribute women's increased effectiveness at consensus-building stages of the legislative process to behavioral differences between genders—women are more collaborative than their male colleagues.[56]

Black legislators are less effective than White legislators when Democrats are in the majority party. However, they are equally as effective as White legislators when Democrats are in the minority party (Volden and Wiseman 2014). Volden & Wiseman (2014) theorize that this is a result of Black legislators developing a more specialized legislative agenda. Existing scholarship on the legislative effectiveness of women

[56] In contrast, Lawless et al. (2018) argue that female legislators are more likely than male legislators to engage in activities that foster collegiality and collaboration. However, their behavior within the legislative process is not distinct from that of male legislators.

and Black legislators suggests that underrepresented groups are not uniformly less effective than majority groups. Instead, their effectiveness is uniquely shaped by the interaction between legislative institutions and their descriptive identities. Therefore, while considering the legislative effectiveness of women and Black legislators may be theoretically useful, workers' effectiveness will likely be, in part, unique.

There is limited scholarship directly analyzing the relationship between legislators' social class backgrounds and their performance in legislatures. While no existing work uses legislative effectiveness scores to analyze how legislators' social class backgrounds are related to their legislative effectiveness, scholars have used other measures of legislative productivity. The findings are mixed among the existing literature but broadly suggest that working-class legislators are not uniformly less effective than white-collar legislators. Carnes, in his book *White-Collar Government* (2013), examines the legislative entrepreneurship of workers in the U.S. Congress in the context of economic policy. He finds that workers sponsor and cosponsor more economic legislation than white-collar legislators, and pass economic policy at equal rates as their white-collar colleagues.[57] Likewise, Carnes and Lupu (2016b) examine the relationship between legislators' educational backgrounds and their performance in office and find that legislators pass the same number of bills regardless of their educational background. Finally, in an examination of underrepresented groups in state legislative leadership positions, Clark and Hansen (2020) find that workers are equally as likely to be represented in state leadership positions as white-collar legislators. While state legislative leadership positions are not a direct test of legislators' effectiveness, existing work suggests that legislative leaders are among the most effective lawmakers (Volden and Wiseman 2014).

I provide a more robust analysis of class-based legislative effectiveness in two ways. First, using SLES allows me to define legislative effectiveness as a lawmaker's effectiveness at all stages of the legislative process rather than only sponsorship, cosponsorship, or final passage votes. Importantly, this allows me to observe workers' actions at less visible stages of the lawmaking process, like committee hearings and floor proceedings. Second, I analyze state legislators rather than U.S. representatives, where only 2% of representatives have previously been employed in working-class occupations (Carnes 2013). I conduct my analyses at the state legislature level because the percentage of working-class representation is higher than in the U.S. Congress (6% rather than 2%). Additionally, given that there are far more state legislators than U.S.

[57] In contrast, Stacy (2020) examines the relationship between legislators' personal wealth and their effectiveness and finds that the most wealthy legislators have a higher legislative effectiveness score than the least wealthy legislators.

representatives, the raw number of working-class representatives is much higher, offering more variation in levels of representation across time to examine.

Class-Based Electoral Bias & Legislative Effectiveness

I argue that working-class lawmakers are equally or more effective than white-collar lawmakers due to class-based electoral selection effects. Building on existing work, I develop a theory of class-based electoral selection that links class-based discrimination in elections to legislators' performance in office (Anzia and Berry 2011). This theory suggests that because workers face prejudice and discrimination during legislative elections as a result of their class identity, they are forced to work harder and develop the necessary skills to win elections. As a result, the working-class candidates who win elections become effective lawmakers.[58]

Electoral selection effects occur when political candidates face biases in elections as a result of their identity (Anzia and Berry 2011; Ashworth, Berry and Bueno de Mesquita 2023). Existing research suggests that women, non-white, working-class, and LGBTQ+ candidates disproportionately face electoral obstacles that increase the difficulty of winning elections (Piston 2010; Anzia and Berry 2011; Carnes 2018; Wagner 2019; Magni and Reynolds 2021). As a result, candidates from underrepresented groups must work harder than majority groups to win elections. There are at least three causes of electoral selection effects (Anzia and Berry 2011). First, voters may be biased towards a given social group, requiring that candidates who identify with these groups be exceptionally qualified to secure electoral support. Second, candidates may perceive that voters are biased against them, even if they are not. If this is the case, only the most ambitious and qualified candidates will emerge and enter the electoral arena. Third, political elites and gatekeepers may be biased against certain social groups, forcing candidates who identify with these groups to work harder to gain elite support during their campaigns.

Existing scholarship suggests that the type of selection effects candidates face varies across identity groups.[59] Prejudice and discrimination from political elites and gatekeepers—rather than voter bias or

[58]My theoretical argument is not suggesting that positive selection effects in elections do not occur. Rather, I build on existing literature suggesting that working-class candidates face electoral discrimination (Carnes 2018) and argue that both positive selection effects and electoral discrimination are occurring in elections. As a result, when positive selection effects are mixed with electoral discrimination, workers not only have to be equally as good as white-collar candidates to win elections (positive selection argument), they have to be better (positive selection effects and electoral discrimination) (Anzia and Berry 2011).

[59]For example, Anzia and Berry (2011) argue that women candidates perceive and experience sexism within congressional elections and, as a result, perform better than their male colleagues to overcome this discrimination. More

perceived bias—is likely the primary obstacle preventing working-class candidates from winning elections (Carnes 2016, 2018; Griffin, Newman and Buhr 2020; Hoyt and DeShields 2021; Treul and Hansen 2023). Evidence from survey experiments suggests that voters are not biased against working-class candidates relative to white-collar candidates. Carnes and Lupu find that respondents in the United States, Britain, and Argentina viewed hypothetical working-class candidates as "equally qualified, more relatable, and just as likely to get their votes" (2016, 832). Other work suggests that voters rate workers as more "warm" relative to white-collar candidates (Hoyt and DeShields 2021). On the other hand, voters rate white-collar candidates as less honest and less caring than working-class candidates (Griffin, Newman and Buhr 2020). Likewise, working-class candidates do not see themselves as unqualified for elected office. When asked whether they had ever thought about running for elected office, working-class respondents reported a similar level of political ambition as white-collar respondents (Carnes 2018). Similarly, working-class Americans are equally as likely to feel qualified to run for office as white-collar Americans (Carnes 2018).

Workers do experience discrimination during campaigns from political elites and electoral gatekeepers. Party leaders view the working class as less viable political candidates, often citing their difficulty to fundraise and win elections (Carnes 2018, 110). As a result, party leaders are less likely to recruit and support working-class candidates in legislative races. Relatedly, without the financial support of party leaders, working-class candidates struggle to fundraise in elections.[60] This dual resource and recruitment burden makes it extremely difficult for workers to enter the electoral arena, and even more difficult to win the race.

As a result of class-based discrimination, working-class candidates and white-collar candidates experience a very different electoral environment (Carnes 2018). Working-class candidates must work harder than white-collar candidates to receive the same electoral outcome. In doing so, I argue that workers develop and refine skills that promote effective lawmaking once in office (Anzia and Berry 2011). To date, there is little work directly testing mechanisms that may explain why electoral selection effects produce effective lawmakers. I suggest two plausible mechanisms that may explain why class-based electoral selection produces effective working-class lawmakers.

First, one way class-based electoral selection may produce effective lawmakers is that less qualified

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recent work also suggests that sex-based selection leads to women lawmakers being more effective than their male counterparts (Ashworth, Berry and Bueno de Mesquita 2023).

[60]For example, Carnes finds that workers are less likely to win electoral office in districts that run more expensive electoral races (Carnes 2018, 135).

working-class candidates will lose elections. Working-class lawmakers who do not overcome class-based electoral barriers—whether it be because they were not qualified candidates or because the electoral barriers were insurmountable—will lose their election. Given that white-collar candidates face fewer electoral obstacles than working-class candidates, they may be more likely to win elections even if they are less qualified than working-class candidates. Workers' performance in primary versus general elections lend some evidence in support of this expectation. Treul and Hansen (2023) find that workers underperform white-collar candidates in primary elections; however, workers are equally as likely as white-collar candidates to win general elections (Carnes 2018). One explanation for this seemingly inconsistent trend may be that less qualified working-class candidates are weeded out during primary elections, while qualified workers perform equally as well as their white-collar opponents in general elections. This selection process results in only the most effective working-class candidates winning elections and gaining representation in legislatures.

Second, in addition to hollowing out the working-class candidate pool, I expect class-based biases in elections to meaningfully influence the working-class candidates who do win elections. The working-class candidates who do successfully win elections have experienced the effects of class bias in elections, and are aware of the effort that is required to outperform their white-collar colleagues. There is reason to expect that workers will carry this over-performance mindset with them as they begin working in legislatures. Put differently, class-based biases exist within American political institutions, and so similar to the electoral stage of the political process, workers must work harder than their white-collar colleagues in legislatures to accomplish their goals (Carnes 2013, 2018).

Working-class candidates face electoral biases that white-collar candidates do not face. The result of this electoral selection effect is that only the most qualified and capable workers win elected office and gain representation in legislatures. As a result, I hypothesize that working-class lawmakers should be equally or more qualified than their white-collar colleagues.

H1 (Class-Based Legislative Effectiveness): Workers are equally or more effective lawmakers than white-collar legislators.

Data & Measurement

To test this hypothesis, I pair pre-legislature occupational data for over 14,000 unique state legislators (Makse 2019) with Bucchianeri, Volden, and Wiseman's (Bucchianeri, Volden and Wiseman 2025) state legislative effectiveness scores (SLES). The data set includes SLES for 51,929 legislator-term-specific observations for 49 states from 1987-2017.[61] Of these observations, 3,572 (or 6.8% of my sample) were previously employed in a working-class occupation.[62]

SLES are constructed similarly to legislative effective scores (LES) used to measure effectiveness in the U.S. Congress (Volden and Wiseman 2014). SLES, like LES, captures the weighted average of a legislator's actions throughout five stages of the lawmaking process: bill introduction, action in committee (AIC), action beyond committee (ABC), passing one chamber (PASS), and becoming law (LAW) (Bucchianeri, Volden and Wiseman 2025). Therefore, these scores evaluate effectiveness throughout the entirety of the legislative process rather than simply analyzing roll-call votes. Additionally, SLES are weighted to reflect the substance and significance of legislation. Commemorative and symbolic legislation influences a legislator's effectiveness score less than substantive and significant legislation. Bucchinaeri, Volden, & Wiseman (2025) calculated SLES by scraping the legislative history of every bill available on state legislative websites. Bill data are available for some states (Maine, South Carolina, New Hampshire, Texas, and Pennsylvania) dating back to the 1980s. The legislative history of every bill for every state (except Kansas) is included in the data set after 2003.[63]

To operationalize social class, I use pre-legislature occupational data (Makse 2019). I consider legislators to be working-class if their most recent pre-legislature occupation was in construction, office or clerical work, public safety, retail and service, a skilled trade, or as semi-skilled or unskilled laborers. My definition of workers most closely resembles Makse's (2019) definition; however, unlike Makse, I do not consider "transportation professions" which include pilots, railroad engineers, and air traffic controllers to be working-class. My definition of working class differs from Carnes' (2013) definition in that I consider contractors engaged in blue-collar work and public safety professionals to be working-class. I use the occu-

[61] SLES for four states appear in the data set post-2003: Massachusetts (2009), Nebraska (2007), Oregon (2007), and Rhode Island (2007). SLES do not exist for Kansas due to insufficient data.

[62] See Figure 4.1 in Appendix A.4.

[63] See the appendix (A.2) and Bucchinaeri et al. (2020) for a more detailed explanation of how SLES scores are calculated.

pational backgrounds of legislators to operationalize social class because it is arguably the best predictor of individuals' income and social status (Matthews 1954; Hout 2008; Carnes 2012), and it has become convention in the study of social class (Carnes 2013; Makse 2019; Barnes, Beall and Holman 2021; Nickelson and Jansa 2023). A complete list of working-class and white-collar occupations can be found in the appendix (A.1).

One downside of Makse's (2019) occupational data is that lawmakers' occupational histories are limited to their most recent pre-legislature occupation. If a lawmaker's most recent occupation before being elected is in real estate, they are coded as white-collar. Conversely, if a lawmaker's most recent occupation prior to being elected is a retail worker, they are coded as working-class. This data cannot distinguish legislators who worked in a working-class occupation prior to working in a white-collar occupation. For example, a legislator who worked as a retail worker for five years before transitioning into a job in real estate is coded as white-collar. Ideally, I would have complete occupational histories for every state legislator. I would then be able to analyze how legislators' occupational histories influenced their effectiveness within legislatures. Perhaps legislators who entered the workforce as working-class but transitioned into a white-collar job have a higher or lower effectiveness score than legislators who entered the workforce in a working-class job and remained in a working-class job until their election.

Unfortunately, a data set including the occupational histories of state legislators from all state legislatures across the time series of my data does not exist.[64] While this is a limitation within my data, I argue that defining a legislators' social class by their most recent pre-legislature occupation is a reasonable test for my theory. I argue that working-class lawmakers should be equally or more effective than white-collar lawmakers because of class-based biases in elections. These biases will likely be most pronounced for working-class lawmakers currently employed in a working-class occupation during their campaign (rather than a formerly working-class candidate employed in a white-collar occupation during their campaign). For example, given that party leaders discriminate against the working class when recruiting potential candidates, this discrimination will be most pronounced for working-class candidates who are currently employed in a working-class occupation rather than candidates who were previously employed in a working-class occupation. Thus, if class-based electoral selection effects influence working-class and white-collar legislators'

[64]Hansen and Clark's (2020) data set includes the occupational histories of state legislators, but for only thirty state legislatures across twelve years. The time series of the Makse (2019) data set better approximated the time series of the SLES.

effectiveness differently, this effect will be most pronounced for candidates whose most recent occupation was a working-class job. Therefore, while operationalizing legislators' social class as their most recent pre-legislature occupation does not comprehensively describe their occupational history, it is a reasonable test for my theory.

I condition on several covariates that likely influence legislators' effectiveness. First, I control for the percentage of working-class legislators within a legislature-term to ensure that the estimated relationship is not dependent on the proportion of workers represented within a legislature. Second, given that legislators hold multiple social group identities that could confound the relationship between social class and legislative effectiveness, I control for demographic covariates like race, gender, and party identification.[65] Third, I include chamber-specific covariates that differ between legislators, like seniority, vote share, majority party status, governor's party, leadership positions, and polarization. Fourth, I control for covariates that differ across state legislatures like professional and term limits. Finally, I include state and term fixed effects to control for variation specific to each state legislature and term.[66]

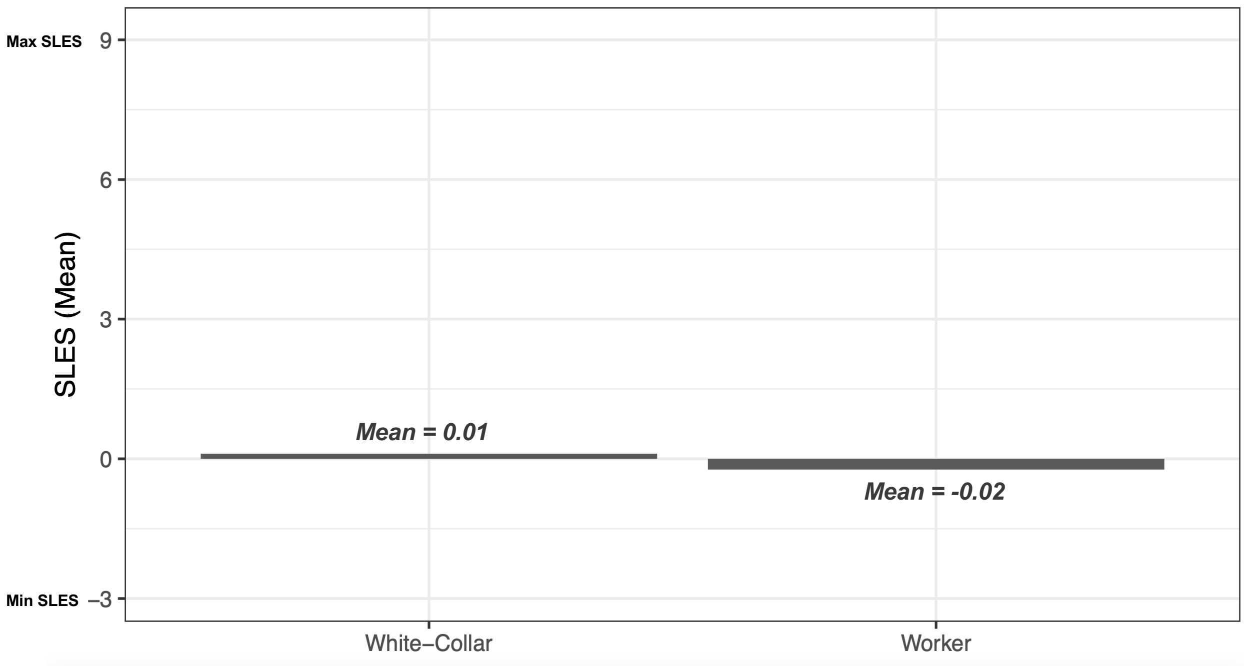
Are Workers Effective Lawmakers?

I first analyze the mean effectiveness score of white-collar and working-class state legislators. Figure 1 plots the mean SLES for both white-collar and working-class legislators. White-collar legislators, on average, have a mean SLES of .01. Working-class legislators, on average, have a mean SLES of -.02. After plotting the average effectiveness score for both white-collar and working-class legislators against the entire range of the dependent variable (-3 to 9), it becomes clear that a class-based effectiveness gap of 0.03 in the raw data is substantively small.

[65]Barnes et al. (2021) have argued that pink-collar workers—female workers— are theoretically and empirically distinct from blue-collar workers. I investigate whether gender moderates workers' effectiveness and find that the interaction term is statistically indistinguishable from zero, suggesting that a worker's gender does not influence their legislative effectiveness (see Appendix A.4).

[66]Descriptive statistics for the variables of interest are presented in Appendix A.3

Figure 1: Average SLES of Working-Class and White-Collar Legislators



The substantively small difference in means between working-class and white-collar legislators' effectiveness entirely disappears in a regression model. I estimate on OLS regression model with "Worker" as the independent variable and "SLES" as the dependent variable. As Column 6 in Table 1 shows, all else equal, workers are, on average, 0.028 times less effective than white-collar legislators. However, the magnitude of the relationship is small and not statistically significant.[67] The dependent variable ranges from -2.9 to 9.9, indicating that an effectiveness gap of 0.028 is substantively small. Put differently, the difference in

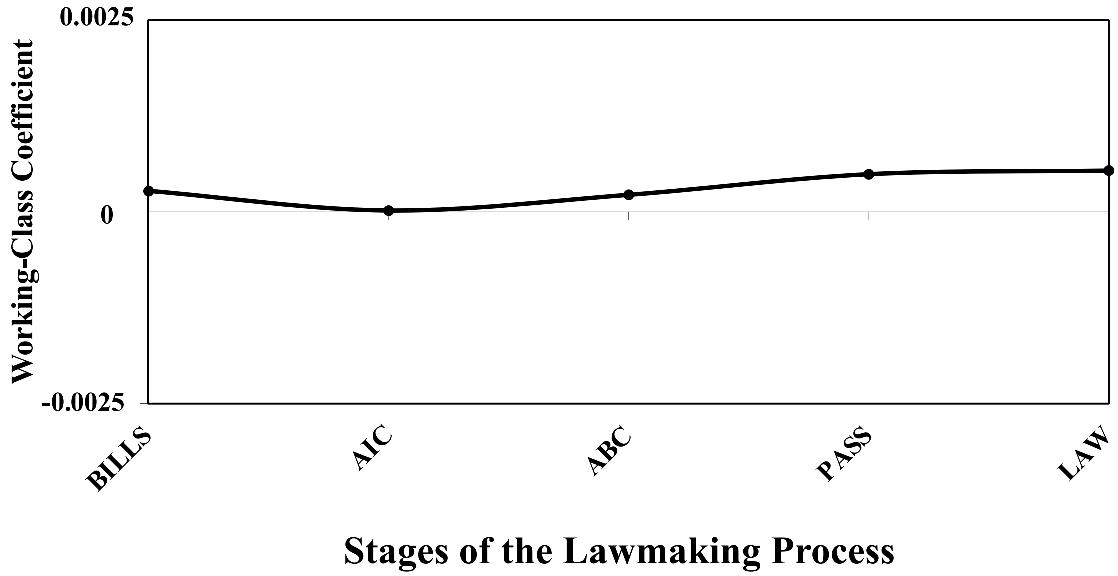
[67]One concern regarding the model estimated in Table 1 may be that the data are structured in a way that creates a two-level model—the data set includes multiple observations for each legislator (given that the unit of analysis is legislator-term observations), and while the occupational background of the legislator is static for each observation, legislators' effectiveness scores are dynamic. To address this, I estimate a model including only observations from a legislator's first term in office. Given that legislators will only have one occupational observation in this model, the two-level data structure becomes a one-level data structure. The results are presented in A.5 (Table 5.2). The results are similar to the results presented in Table 1. Working-class lawmakers are no less effective than white-collar lawmakers, and the error estimates are precisely estimated. The results in Table 5.2, however, may not be generalizable to all legislators if white-collar or working-class legislators disproportionately become more (or less) effective throughout their legislative careers. To test whether this is the case, I interact the dichotomous worker variable with a seniority variable, which measures the number of terms legislators have served in a given chamber. The results from Table 5.3 (in A.5) suggest that while legislators do become slightly more effective throughout their legislative career, working-class and white-collar lawmakers experience this effectiveness boost equally. Collectively, the results from Tables 5.2 and 5.3 suggest that the multi-level structure of the data is not meaningfully changing the observed results.

working-class and white-collar lawmakers' effectiveness is approximately 2.8% of a standard deviation.

I also estimate workers' effectiveness at each stage of the lawmaking process. Table 1 (columns 1-5) shows that the worker coefficient is positive, though small in magnitude and not statistically significant at each of the five stages of the lawmaking process. Figure 2 displays the effectiveness gap between working-class and white-collar legislators at each stage of the lawmaking process—bill introduction, action in committee (AIC), action beyond committee (ABC), passing chamber (PASS), and becoming law (LAW). A point estimate greater than zero indicates that workers are more effective than white-collar legislators. Likewise, a point estimate below zero indicates that white-collar lawmakers are more effective than working-class legislators. To observe any variation away from zero, the Y-axis must be set to a substantively small range (0.0025 to -0.0025) of the dependent variable, suggesting no meaningful difference between working-class and white-collar legislators' effectiveness. Importantly, the absence of a class-based effectiveness gap is independent of workers' numerical representation in the legislature. Working-class lawmakers are equally as effective as white-collar lawmakers regardless of the percentage of workers represented in the legislature. This relationship also holds in various state legislative institutional arrangements.[68] The evidence from Figure 2 and Table 1 is consistent with my expectation that workers are no less effective than white-collar lawmakers.

[68] See Table 5.1 in Appendix A.5 that displays the moderating effect of state legislative institutions and the percentage of workers in the legislature on class-based legislative effectiveness. The professionalization of the legislature does not meaningfully moderate the relationship between social class and legislative effectiveness. Similarly, workers are equally as effective as white-collar legislators in states with and without term limits. Finally, the percentage of workers in a legislature does not meaningfully moderate class-based legislative effectiveness.

Figure 2: Working-Class and White-Collar Legislators Are Equally Effective Lawmakers



Note: This figure plots the Worker coefficient estimated in Table 1 across each stage of the lawmaking process. If workers are more effective lawmakers than white-collar legislators, the coefficient would be positive. Conversely, if white-collar legislators are more effective lawmakers than workers, the coefficient would be negative. The Worker coefficient throughout each stage of the lawmaking process is effectively zero, given the range of the Y-axis, suggesting the absence of a class-based effectiveness gap. ***Working-class and white-collar legislators are equally effective lawmakers throughout each stage of the legislative process.***

Table 1: Working-Class and White-Collar Legislators Are Equally Effective Lawmakers

	1	2	3	4	5	6
	BILL	**AIC**	**ABC**	**PASS**	**LAW**	**SLES**
Worker	0.000248	0.0000188	0.000223	0.000492	0.000539	-0.0284
	(0.57)	(0.04)	(0.47)	(0.95)	(0.97)	(-1.07)
% Worker	-0.00130***	-0.00113**	-0.00105**	-0.00113**	-0.00111*	0.0141
	(-3.53)	(-2.99)	(-2.93)	(-2.87)	(-2.56)	(0.45)
Female	-0.0000376	0.000543	0.000655*	0.000748**	0.000851**	0.0108
	(-0.15)	(1.96)	(2.40)	(2.68)	(2.80)	(0.67)
Black	-0.00275*	-0.00332**	-0.00300*	-0.00279*	-0.00238	0.0551
	(-2.29)	(-2.67)	(-2.37)	(-2.19)	(-1.57)	(0.79)
Hispanic	-0.000689	-0.00127	-0.000825	-0.000743	-0.000489	0.167*
	(-0.63)	(-1.09)	(-0.69)	(-0.61)	(-0.35)	(2.40)
Race (Other)	-0.00162	-0.00157	-0.00141	-0.00552**	-0.00612**	-0.0790
	(-0.65)	(-0.71)	(-0.60)	(-2.78)	(-3.04)	(-0.62)
White	-0.00166	-0.00203	-0.00174	-0.00165	-0.00126	0.144*
	(-1.64)	(-1.89)	(-1.59)	(-1.51)	(-0.98)	(2.52)
Democrat	0.000279	-0.000760***	-0.000807***	-0.000927***	-0.000938***	-0.0237
	(1.28)	(-3.30)	(-3.41)	(-3.82)	(-3.59)	(-1.71)
Seniority	0.0000867	0.0000750	0.0000692	0.0000578	0.0000979	0.0211***
	(1.87)	(1.58)	(1.46)	(1.23)	(1.92)	(6.95)
Committee Chair	0.00561***	0.00746***	0.00844***	0.00885***	0.00883***	0.513***
	(23.98)	(27.77)	(29.50)	(29.59)	(26.68)	(30.38)
In Majority	0.00236***	0.00428***	0.00468***	0.00495***	0.00434***	0.355***
	(9.37)	(14.99)	(16.02)	(18.62)	(15.01)	(20.30)
Governor Same Party	0.000590***	0.000747***	0.000643**	0.000762***	0.00124***	0.0341**
	(3.44)	(4.06)	(3.25)	(3.82)	(5.83)	(3.04)
Majority Leadership	0.00296***	0.00411***	0.00510***	0.00563***	0.00580***	0.179***
	(4.47)	(5.60)	(6.39)	(6.96)	(6.94)	(4.78)
Minority Leadership	0.00251**	0.00211*	0.00172	0.000628	0.000440	0.107**
	(3.21)	(2.17)	(1.72)	(0.97)	(0.63)	(2.92)
Polarization	-0.000213	-0.00131***	-0.00213***	-0.00236***	-0.00270***	-0.175***
	(-0.88)	(-4.74)	(-7.46)	(-10.53)	(-11.32)	(-11.06)
Leader, Speaker, President	0.0000528	0.00101	0.00173	0.00297*	0.00407*	-0.0370
	(0.05)	(0.79)	(1.24)	(1.97)	(2.36)	(-0.55)
Term Limits	0.00148***	0.00162***	0.00180***	0.00179***	0.00194***	0.114***
	(5.57)	(5.99)	(6.20)	(5.87)	(6.00)	(6.75)
Professionalism (Squire)	-0.00815***	-0.00759***	-0.00757***	-0.00761***	-0.00743***	-0.102
	(-11.04)	(-9.89)	(-9.85)	(-9.54)	(-8.42)	(-1.81)
Vote Share	-0.00192***	-0.00192***	-0.00179***	-0.00142**	-0.00146**	0.0382
	(-4.63)	(-3.83)	(-3.39)	(-2.75)	(-2.58)	(1.31)
Senate	0.0142***	0.0135***	0.0131***	0.0132***	0.0131***	-0.164***
	(46.70)	(43.22)	(40.87)	(40.47)	(37.74)	(-10.10)
Intercept	0.00698*	0.00729*	0.00659*	0.00669*	0.00629	-0.331
	(2.30)	(2.33)	(2.17)	(2.08)	(1.77)	(-1.40)
State Fixed Effects	✓	✓	✓	✓	✓	✓
Term Fixed Effects	✓	✓	✓	✓	✓	✓
N	48220	48220	48220	48220	48220	48220
Adjusted-R^2	0.30	0.30	0.30	0.30	0.26	0.18

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A relationship between a set of variables that is not statistically significant, however, is not necessarily a negligible effect (Rainey 2014). A regression coefficient may be statistically indistinguishable from zero for reasons other than the absence of a relationship between a set of variables. For example, a small sample size can result in large error estimates that might make a large coefficient not statistically significant (Rainey 2014). To ensure that the effectiveness gap between working-class and white-collar lawmakers is indeed negligible, I follow the advice of Rainey (2014) and (1) define a contextually specific negligible legislative effectiveness score (-m and m) and (2) use a 90% confidence interval to examine whether the estimated confidence interval falls within the zone of negligibility (-m and m).[69]

I define the zone of negligibility as an effect that ranges between -0.075 and 0.075. It is important to carefully define how I selected this range. Rainey (2014) advises that scholars define negligibility in a way that is contextually specific to their data. This means that scholars are tasked with evaluating their data and determining at what level effects are no longer substantively meaningful (Rainey 2014). The SLES variable ranges from -2.9 to 9.9. Therefore, an effect (and error estimates) that falls within the range of -0.075 and 0.075 is only 15% of a standard deviation. I argue that an effect that falls within this range does not meaningfully explain any variation in legislators' effectiveness. Put differently, if two lawmakers' SLES differ by only 0.075, on average, their actions in all five stages of the lawmaking process look very similar. I plot estimates and their confidence intervals and analyze whether they fall within this zone (-0.075 and 0.075). If the 90% confidence intervals fall within the zone of negligibility, this suggests that the null results indicate a negligible effect (Rainey 2014).

Figures 3.1 and 3.2 plots the estimated relationship between legislators' class backgrounds and their effectiveness using clustered standard errors, bootstrapped standard errors, and median regression.[70] The solid black line labeled "estimate" is the estimated relationship in row one, column six of Table 1. Given that state legislative data is particularly likely to have clustered groups and heavy-tailed distributions, I replicate my results using clustered and bootstrapped standard errors and median regression. I use clustered

[69]It is important to note that a 90% confidence interval is a harder test of whether the difference between working-class and white-collar legislators' effectiveness is indeed negligible than a 95% confidence interval. Given that this approach considers whether any meaningful variation in the dependent variable occurs within the range of the inverted confidence interval, considering a "wider" 90% confidence interval rather than a more "narrow" 95% confidence interval provides a harder test of the negligible result.

[70]Two of the estimated models—the clustered standard error and the bootstrapped standard error—closely approach the negative bound of the negligibility zone. The zone of negligibility was defined prior to plotting the estimates for each of these models. Though the lower bound of the confidence interval for these models approaches the lower bound of the zone of negligibility, the observed relationship still remains within the zone of negligibility.

standard errors and bootstrapped standard errors to ensure that the grouped nature of the data does not produce unmodeled correlations that result in a downward bias in standard error estimates (Harden 2011). Additionally, I replicate the OLS results using median regression to ensure that the heavy-tailed error term does not produce inefficient estimates (Harden and Desmarais 2011).

Figure 3.1 shows that all four estimates and confidence intervals are similar in magnitude and fall within the zone of negligibility. This means that, across four different models, the 90% confidence intervals only include estimates within the zone of negligibility. To better contextualize the negligible relationship between legislators' class background and their effectiveness, Figure 3.2 plots the same data as Figure 3.1 over the entire range of the SLES variable. Figures 3.1 and 3.2 collectively show that the absence of a class-based effectiveness gap is precisely estimated and negligible when considering the range of the dependent variable.

To further clarify the precision of the estimate, the lower bound of the 90% confidence interval for the worker coefficient is less than 1% of the range of the SLES variable. Even more striking, the largest possible value of the worker coefficient is less than one percent of the committee chair coefficient, which is the largest coefficient observed in the model. Therefore, consistent with the findings in Table 1, I conclude that there is no meaningful gap between working-class and white-collar legislators' effectiveness in my sample. These findings support my expectation that workers will be no less effective lawmakers than white-collar legislators.

Figure 3.1: Negligible Class-Based Effectiveness Gap

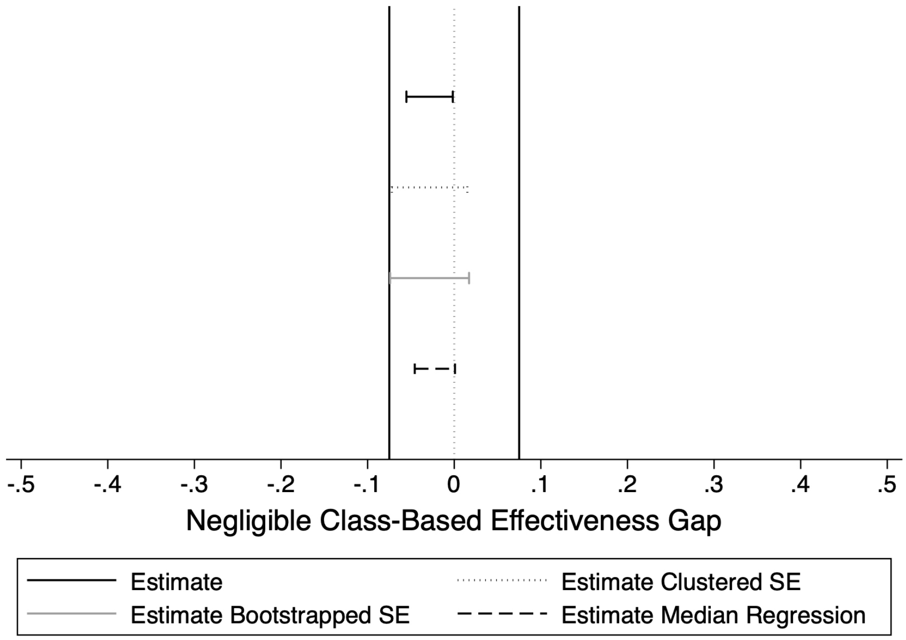
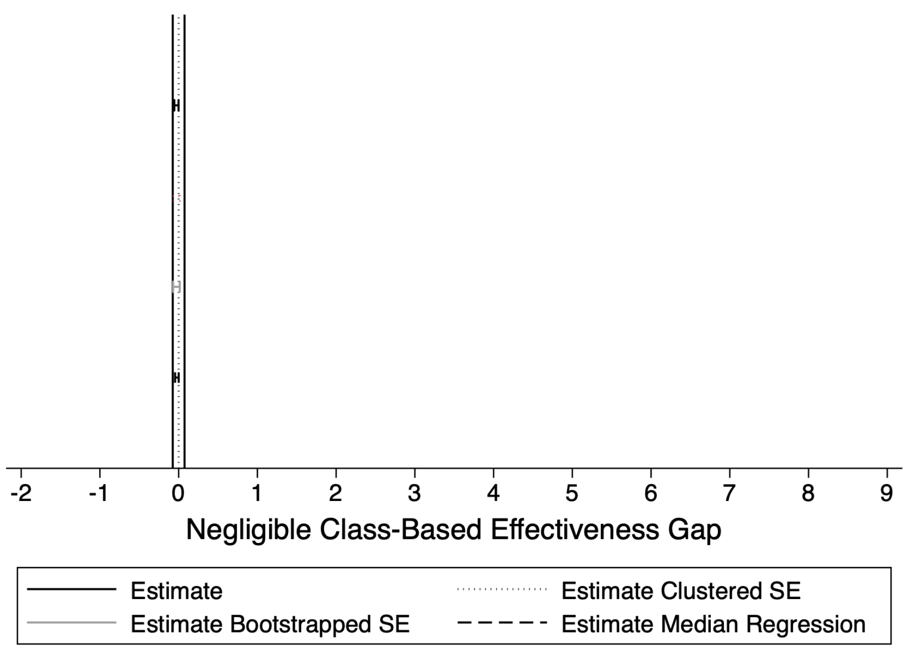


Figure 3.2: Negligible Class-Based Effectiveness Gap Across Entire Range of SLES



Conclusion

Political elites have long argued that, if elected, working-class politicians would be less effective at governing than white-collar politicians (Hamilton et al. 1788; Calfas 2017). I analyze the legislative effectiveness of 14,000 state legislators and find no evidence that working-class legislators are less effective lawmakers than white-collar legislators. Indeed, I provide evidence of a negligible relationship between working-class and white-collar legislators' effectiveness. White-collar and working-class legislators are equally effective throughout each stage of the lawmaking process.

I argue that workers perform equally as well as white-collar legislators once in office because they face class-based discrimination in elections. Class-based electoral biases create incentives for working-class candidates to work harder—both in terms of effort and skill development—than white-collar candidates. As a result, less qualified working-class candidates lose elections and the workers who do win elective office are effective lawmakers.

Future research should continue to explore the legislative behavior of working-class lawmakers. Two future directions are particularly relevant in light of the findings reported in this paper. First, scholars should examine the policy areas in which working-class lawmakers are most effective.[71] If workers prioritize labor and economic policy, we can be more confident that the descriptive representation of working-class lawmakers leads to the substantive representation of workers' policy preferences (Carnes 2013). Second, future work should consider whether workers' effective lawmaking is related to their performance in elections. If effective working-class lawmakers are electorally rewarded for their legislative performance, this may suggest that working-class lawmakers' performance in office is not a primary cause of the numeric underrepresentation of working-class lawmakers.

[71] This analysis is not currently possible given that SLES has not yet been expanded to include policy issue area scores.

Conclusion

In this dissertation, I highlight and address theoretical and methodological limitations in the descriptive representation literature. In doing so, I focus on legislative committees to uncover speech-based differences in how legislators' identities shape policymaking. I also contribute to the growing body of research analyzing the behavior of working-class legislators. The first two essays demonstrate that the racial composition of congressional committees—not just Congress as a whole—shapes whether and how legislators discuss race and advance race-based policies. If the goal is to elevate race-based issues on the legislative agenda, the findings presented in this dissertation suggest that the racial composition of congressional committees should be central to such efforts. The third essay demonstrates that while working-class state legislators are effective lawmakers, their ability to legislate is often connected to and constrained by electoral barriers. Working-class candidates face significant biases in fundraising and recruitment, which limit their numerical representation in state legislatures. However, I find that these challenges do not prevent them from advancing and passing legislation.

Looking ahead, this dissertation raises several questions related to the study of representation. First, if contact effects occur in legislative committees, could similar dynamics also play out in other institutions with comparable structures? School boards and city councils, for example, share similar institutional designs as legislative committees. Building on this, if race-based contact effects are present in committees, it is likely that the gender and LGBTQ+ composition of these bodies also influences discourse and policymaking. Investigating whether contact effects extend to other institutions—and whether the composition of other identity groups produces comparable effects—would deepen our understanding of how intergroup contact theory applies to American political institutions. Relatedly, by showing that working-class legislators are equally as effective as their white-collar counterparts, I raise important questions about whether class-based differences in policymaking exist. Specifically, understanding which policies working-class legislators prioritize and excel at would shed light on whether they substantively represent working-class Americans.

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Appendix—Essay 1

Table of Contents

1 Descriptive Statistics

Variable	Unit of Analysis	Mean	Std. Deviation	Range
Dependent Variables				
Race Statement	Statement	0.0087	0.09	0 – 1
Black Race Statement	Statement	0.0032	0.056	0 – 1
Latino Race Statement	Statement	0.0012	0.035	0 – 1
Asian Race Statement	Statement	0.0003	0.019	0 – 1
(Race Issue Bills) Action Beyond Committee (ABC)	Member-Term	0.20	0.69	0 – 14
(Race Issue Bills) Passed House (PASS)	Member-Term	0.16	0.58	0 – 11
(Race Issue Bills) Signed Into Law (LAW)	Member-Term	0.04	0.26	0 – 6
(Race Issue Bills) Legislative Effectiveness Score (LES)	Member-Term	1.0	3.28	0 – 51
(Non-Race Issue Bills) Action Beyond Committee (ABC)	Member-Term	2.12	2.53	0 – 25
(Non-Race Issue Bills) Passed House (PASS)	Member-Term	1.47	1.81	0 – 14
(Non-Race Issue Bills) Signed Into Law (LAW)	Member-Term	0.46	0.83	0 – 12
(Non-Race Issue Bills) Legislative Effectiveness Score (LES)	Member-Term	1.0	1.49	0 – 14.5
Primary Independent Variables				
Nonwhite Lawmaker	Statement	0.177	0.381	0 – 1
Black Lawmaker	Statement	0.110	0.313	0 – 1
Latino Lawmaker	Statement	0.046	0.208	0 – 1
Asian Lawmaker	Statement	0.018	0.134	0 – 1
White Lawmaker	Statement	0.823	0.381	0 – 1
% Nonwhite in Committee	Statement	19.17	7.32	0 – 61.9
% Nonwhite in Hearing	Statement	19.15	16.0	0 – 95
Control Variables				
Democrat	Statement	.501	0.499	0 – 1
% Nonwhite in District	Statement	0.285	0.190	0.025 – 0.932
% Black in District	Statement	0.131	0.151	0.002 – 0.683
% Latino in District	Statement	0.168	0.174	0.006 – 0.884
% Asian in District	Statement	0.054	0.066	0.002 – 0.577
Committee Chair	Statement	0.080	0.270	0 – 1
Nonwhite Chair	Statement	0.012	0.109	0 – 1
On Committee With Nonwhite Chair	Statement	0.130	0.336	0 – 1
Race Hearing	Statement	.0065796	.097063	0 –1
Legislative Hearing	Statement	.0972418	.2962869	0 – 1
Oversight Hearing	Statement	.0519	.2218251	0 – 1
Female Lawmaker	Statement	0.163	0.369	0 – 1
LGBTQ Lawmaker	Statement	0.010	0.101	0 – 1
DW-Nominate (1st Dimension)	Statement	0.040	0.458	-0.819 – 0.936
DW-Nominate (2nd Dimension)	Statement	-0.0178	0.327	-0.992 – 1
Seniority	Statement	6.11	4.390	1 – 30
Unified	Statement	0.70	0.457	0 – 1
In Majority Party	Statement	0.649	0.477	0 – 1

2 Training Data Set

2.1 Sampling to Construct Training Set

To construct the training set which was used to train the supervised machine learning model, I randomly sampled 5,000 statements from the overall corpus which includes 1,422,460 statements. 70% of the statements in the training set were randomly sampled from the overall corpus with no conditions. 30% of the statements in the training set were selected using stratified random sampling if they included race keywords. I used straified random sampling based off of keywords for a portion of the training set to ensure sufficient representation of race statements to train the learning model.

It is crucial that the training set is representative of the larger corpus to ensure that all types of statements are coded in the training set. For example, if there were no race-related statements in the training set, it would be impossible for the learning model to identify race-based statements in the larger corpus (Park and Montgomery 2023). Therefore, I took a three step approach to ensure that the training set included race-related statements. First, I determined the race keywords inductively from statements within the corpus. I handcoded 600 committee hearing statements from the Education and Labor Committee in the 117th Congress to identify mentions of race. Second, I used a word embedding model to identify word stems that are highly predictive of race references. The word embedding model returned over 30 stems. Finally, I omitted stopwords from the list (e.g. "much", "sure").

In total, the list included 12 keywords. 27,230 statements in the corpus included these keywords. 1,500 statements (or 30% of the training set) were randomly selected from the 27,230 statements that mentioned race. This approach is superior to arbitrarily identifying race-related keywords because it ensures that the keyword list is contextually specific to the corpus. Importantly, using stratified random sampling for 30% of the observations in the training set does not mean that all race statements present in the training set will be identified by these keywords. Given that 70% of the training set is randomly subsetted from the corpus, race statements that were not identified by these keywords should also be present in the training set.

Table 2.1 includes the list of the keywords used to select race statements. The table also displays the number of statements that included these keywords in the overall corpus and in the training set.

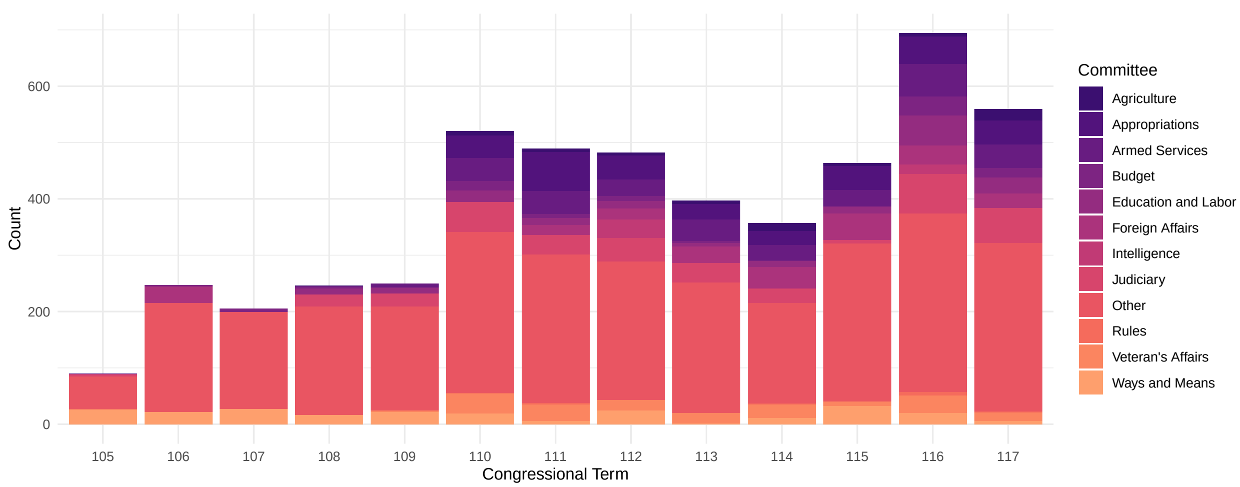
Table 2.1: Keywords Used to Identify Race

	Keywords in Corpus (Frequency)	Keywords in Corpus (%)	Keywords in Training Set (Frequency)	Keywords in Training Set (%)
"people of color"	449	1.6%	19	1.4%
"race"	2133	7.8%	97	7.5%
"black americans"	115	0.4%	9	0.7%
"asian"	1601	5.8%	85	6.8%
"HBCUs"	217	0.8%	15	1.2%
"latino"	732	2.6%	38	3.0%
"hispanic"	1238	4.5%	60	4.6%
"critical race theory"	40	0.1%	3	0.2%
"nonwhite"	8	0.02%	0%	0%
"american indian"	248	0.9%	11	0.9%
"disparities"	1187	4.4%	61	4.7%
"racial"	2111	7.8%	111	8.6%
Total	27,230		1,293	

Note: The data above suggest that the training set is representative of the keywords identified in the corpus. For example, the word "race" is equally likely to appear in the training set (7.5%) as it is in the corpus (7.8%). Though it is not possible to identify how representative the training set is of the entire corpus (given that the corpus is unlabeled), the training set is likely a good reflection of the overall corpus since the keywords were selected inductively and the training set was randomly sampled.

Figure 2.2 displays the total number of statements from each congressional term and committee in the training set. The results indicate that the randomly selected statements in the training set vary by term and committee, which is necessary to successfully train the learning model.

Figure 2.2: Statements in Training Set by Congress and Committee



Note: Figure 2.2 plots the frequency of statements in the training set (n = 5,000) by term and committee. In most terms, particularly after the 108th Congress, all committees are represented in the training set. Major committees are mentioned in the legend. The "other" category includes less prestigious committees like Small Business, Modernization, Natural Resources, Science, Space, and Technology, Transportation and Infrastructure, etc.

2.2 Training Set Coding Protocol

I hired eight undergraduate students at a large public research university to code a training set of speeches that I used to train the supervised machine learning models and bigram dictionary classification model. Research assistants were trained before they were permitted to code the actual training set. First, research assistants read the coding protocol (included below). Then they were asked to code a sample data set with 15 speeches from committee hearings. I then provided comments on each of their sample data sets. Once their sample data set was correctly coded and all comments were resolved, research assistants were given a batch (n = 1,000) of statements to code.

Research assistants were instructed to highlight a row if they were confused about any coding decision. I then provided a comment on the highlighted cell addressing their question.

In the instruction document, research assistants were first provided with a general overview of the task:

- The Excel document that you are assigned to complete will include 9 columns (see full column description below). The main column in the data set is called "speech" and will include 1,000 statements from committee hearing transcripts. You will read each speech and then put a "1" in all of the other 8 columns if the speech included certain information.
- Your task will be to indicate whether each speech references race, the overall tone of the statement (positive, negative, neutral), and, if the document does mention race, the specific racial group it references (Black or African American, Latino or Hispanic, Asian Americans, Other Racial Group).
- Most statements will not mention any identity groups. If this is the case, you can code all columns "0". There is no need, for example, to code tone if the statement doesn't mention a racial group.
- You will only code the racial group columns if the statement mentions race (meaning that you coded the "Nonwhite" column 1). If the statement mentions race but doesn't directly reference a racial group, you can code all racial group columns "0". An example of this may be if a statement says "people of color". You would code the "Nonwhite" column "1", but code all of the specific racial group columns "0".

Research assistants were then provided with information about each variable in the training set:

1. **speech**: this column includes the speech that you will read and base your coding decisions on. Read each speech carefully and in its entirety.

   **Note*: depending on the speech, you may code more than one of these columns "1" for one statement. For example, the statement could mention both race generally, Black Americans, and Latino Americans.

2. **Nonwhite**: Put a "1" in this column if the speech mentions individuals or topics related to race.

**Note*: only code these columns if columns 2 = 1

3. **Positive**: Put a "1" in this column if the overall tone of the statement is positive toward the identity group.
4. **Neutral**: Put a "1" in this column if the overall tone of the statement is not positive or negative in relation to the identity group. Tip: most statements will likely be "neutral". Only code positive or negative if it is a clear case of strong tone (e.g. very happy/excited or very angry/rude/racist/sexist/etc.)
5. **Negative**: Put a "1" in this column if the overall tone of the statement is negative toward the identity group.

Note: only code these columns if Nonwhite = 1 AND a racial group is explicitly mentioned.

6. **Black or African-American**: Put a "1" in this column if the speech directly says "Black" or "African-American".
7. **Latino or Hispanic**: Put a "1" in this column if the speech directly says "Latino" or "Hispanic"
8. **Asian American**: Put a "1" in this column if the speech directly says "Asian" or "Asian American".
9. **Other Racial Group**: Put a "1" in this column if the speech directly references another racial group (Middle Eastern, North African, American Indian, etc.) that is not Black, Latino, or Asian.

A screenshot of the sample set research assistants were required to code before they were permitted to code the training set is included below:

Sample Set RA's Coded Before Coding Training Set

Training Dataset - Master

File Edit View Insert Format Data Tools Extensions Help

	speech	Nonwhite	Female	LGBTQ	Positive	Netural	Negative	Black/AA	Latino or Hispanic	Asian or Asian American	Other Racial Group
2	All right. Thank you very much. Mr. Shorman, in your testimony, you have discussed the lenders' delegated authority. You even state that loans could take weeks or months if they weren't processed with delegated authority. Why do you believe delegated authority is so important as opposed to loans being sent to the SBA?	0	0	0	0	0	0	0	0	0	0
3	There are significant racial disparities in the race by which Americans suffer from chronic diseases like heart disease, diabetes, and asthma. African-American children are 12 percent more likely to suffer from childhood asthma. African-Americans are 30 percent more likely to die of heart disease and twice as likely to have a stroke	1	0	0	0	1	0	1	0	0	0
4	I'm referring to the border, I think she's a little confused. We don't need her to go to Europe's borders, but to go to our border. Do you think it would be helpful for her to come to our border?	0	0	0	0	0	0	0	0	0	0
5	So I'm wondering if you, within the next week--since we have to make decisions on this, could you provide the Committee with updated estimates for the resources that are going to be required from the United States in the next fiscal year to maintain ITER's current schedule and to minimize its total project cost? Is that possible for you to do?	0	0	0	0	0	0	0	0	0	0
6	Thank you. I want to publicly thank you, Attorney General, for your support of Violence Against Women Act. It is long overdue and I do look forward to your support of that law. Also, I look forward to your release of the report next week, for it to be timely, and I look forward to the things that you are saying.	0	1	0	1	0	0	0	0	0	0
7	Apparently, it doesn't include employees at correctional facilities, homeless shelters, meat packing plants or nursing homes, just healthcare. So we'd like to know specifically how we got to where we are, and those documents and questions are proposed in the letter. So whatever you say we still want responses to the letter.	0	0	0	0	0	0	0	0	0	0
8	Nothing is more critical than protecting the hearts and minds of young children who are just now beginning to learn about our great nation. I denounce the efforts of the DOE to keep our children out of classrooms. I denounce the efforts made to indoctrinate them to hate this country using Critical Race Theory, and I stand firmly with the parents of young Americans everywhere	1	0	0	0	0	1	0	0	0	0
9	Thank you very much, Mr. Lamborn. Under Committee Rules, the Chair will now recognize Mr. William Perry Pendley, Deputy Director of Policy and Programs at the Bureau of Land Management. Sir, thank you and welcome, and the floor is yours. Five minutes.	0	0	0	0	0	0	0	0	0	0
10	And what is your opinion with respect to Iranian goals in Iraq, and what are they doing to achieve those objectives?	0	0	0	0	0	0	0	0	0	0
11	So you know, I'm from New Mexico and the Native American populations across this country were among the most academically vulnerable and under-resourced groups before the pandemic. But according to the American Indian Education Foundation, the rate of high school graduation for American Indian students is 46 percent compared to the national average of 89 percent	1	0	0	0	1	0	0	0	0	1
12	So we will come to an agreement, and we will put funding in for those things. But a $100-billion backlog in the Army Corps of Engineers, and $750-billion backlog at the EPA in clean water and sewage systems, and so forth. An $11-billion backlog in our national parks. A huge problem	0	0	0	0	0	0	0	0	0	0
13	So let me understand this. Your biggest concern are the refuelers, and yet we are not making a decision to keep them active enough to take that risk off your plate?	0	0	0	0	0	0	0	0	0	0
14	But my personal opinion is that we obviously have a divided nation. We need to focus on uniting people, not dividing people. I believe Critical Race Theory, I don't believe any part of it, any of the premises. But at the very least I am confident that it divides at a time when we need to unite. So hopefully that position will be taken by the Biden administration and my time is expired	1	0	0	0	0	1	0	0	0	0
15	I've heard that for years, and the bottom line is because of that attitude, 75 percent of the black boys in the State of California are stuck and they do not learn, and they don't have the hopes and dreams that you and I have. I would think, I would hope that if your children were in those schools, that your attitude would be, or the suggestion would be how do we change that?	1	0	0	0	1	0	1	0	0	0

Note: RA's were required to code this sample set before they were allowed to code the training set. I provided feedback on their coding decisions and clarified any mistakes. After all comments were resolved, RA's were given their batch to code from the training set.

2.3 Intercoder Agreement

Table 2.3 displays the intercoder agreement between research assistants for the aggregate training set (n=5,000) and each batch (n=1,000). Research assistants were asked to code one or more batches that included 1,000 statements. Each batch was coded by 3 research assistants. The intercoder agreement score is the number of observations in which all three research assistants coded the statement the same divided by the total number of statements. All aggregate intercode agreement scores for measures used in-text were greater than 96%. Given that 30% of race statements in the training set were selecting using race keywords, the baseline would be an intercoder agreement of 70% if RAs incorrectly labeled all race statements. An intercoder agreement of 96% is a significant improvement over the baseline.

Table 2.3: Intercoder Agreement

	Aggregate	Batch 1	Batch 2	Batch 3	Batch 4	Batch 5
Nonwhite	96.6%	97.5%	96.2%	96.7%	96.6%	96.1%
Black/ African American	99.4%	99.8%	99%	99.6%	99.1%	99.3%
Hispanic/ Latino	99.5%	99.8%	99.8%	98.9%	99.3%	99.5%
Asian/ Asian American	99.6%	99.7%	99.1%	99.5%	99.9%	99.7%
Other Racial Group	99.0%	98.5%	98.9%	99.4%	99.3%	98.8%
Observations	5,000	1,000	1,0000	1,0000	1,0000	1,000

Note: Intercoder agreement greater than 96%. Intercoder agreement measures the total number of statements in which three RAs agreed on the coding decision divided by the total number of statements.

3 Text Pre-Processing Steps

Before predicting values for the four race variables, I pre-processed text using the following steps. First, I lowercased all characters and removed punctuation. Second, I remove numeric values. Third, I removed stopwords (e.g. I, me, my, we, our) which are common words in the English language that don't hold functional meaning.[1] Finally, I stemmed each word so that a word would be coded the same regardless of its tense (e.g. the stemmed version of racial and racially would both be racial).

After pre-processing lawmakers' committee hearing statements, I transformed each statement into bigrams. Bigrams are pairs of consecutive words in a string of tokens. Bigrams are useful because they are more contextually specific than unigrams. For example, it is plausible that legislators reference both a "competitive race" in a congressional district and "Race policies". Using bigrams allows me to distinguish between the context in which race is mention and identify "Race policies" as a race statement and "competitive race" as a non-race statement.

[1] I used the Quanteda package in R to remove common English language stopwords.

4 Bigram Dictionary-Based Classification

4.1 Identifying Bigrams

I use a bigram dictionary-based classification method to predict whether committee hearing statements mention race. I selected this method because it had the highest performance metrics when predicting the validation set. The next section of the appendix describes the supervised machine learning approaches that I tried and their performance metrics. Ultimately, the bigram dictionary-based classifcation performed best, so it is the classification method used to calculate the final measures.

To calculate the race measures I first subset the training set to only race-based statements and extract all the bigrams in these statements. In total, there are 12,953 unique bigrams in race-based statments in the training set. I then read each bigram to determine whether it mentioned race. I used the training set protcol (described in Section 2.2 of the appendix) to determine whether bigrams included race. If bigrams did not include race they were deleted. These bigrams were deleted because they were not the portion of the statement that led research assistants to code the speech as a racial statement. For example, the following statement includes five bigrams: "important for" "for black" "black americans" "americans improved" "improved healthcare". Even though "healthcare" is certainly racialized in this context, it was not included in the race bigrams. This is because the statement was coded as a race-based statement by the research assistants because the "black americans" bigram is included. Said differently, dropping non-racialized bigrams ensures that (1) false positives are not produced during predictions because only racial bigrams are included and (2) false negatives are not produced because the racial bigram that led to the statement being coded as race is still present. I then wrote a loop that iterated over each statement and coded it as a race statement if it included a race bigram.

After dropping the non-racial bigrams, 536 race bigrams were used for prediction. The 100 most frequent race bigrams are included below.

Table 4.1: Top 100 Race Bigrams from Training Set

Race Bigrams				
“african american”	“racial profil”	“asian american”	“peopl color”	“women color”
“nativ american”	“black women”	“racial wealth”	“black american”	“hispan communiti”
“racial ethnic”	“american indian”	“communiti color”	“race ethnic”	“latino communiti”
“base race”	“black communiti”	“black latino”	“american latino”	“ethnic minor”
“hispan worker”	“racial bias”	“racial minor”	“african-american communiti”	“close racial”
“critic race”	“hispan caucus”	“minor communiti”	“race theori”	“racial dispar”
“racial justic”	“affirm action”	“american hispan”	“black brown”	“black caucus”
“color women”	“congression black”	“hispan women”	“impact black”	“impact racial”
“minor women”	“minority-own busi”	“percent african-american”	“percent black”	“percent latino”
“race discrimin”	“racial discrimin”	“racial equiti”	“racial group”	“african-american hispan”
“alleg racial”	“among african”	“among asian”	“among hispan”	“asian communiti”
“believ racial”	“black live”	“black male”	“black matern”	“black mother”
“black white”	“color skin”	“director asian”	“hispan american”	“hispan black”
“hispan latino”	“hispan latinx”	“hispan popul”	“issu racial”	“jim crow”
“latino parent”	“minority- women-own”	“pacif island”	“percent hispan”	“race gender”
“racial divers”	“racial gender”	“racial inequ”	“rate black”	“women african”
“women black”	“aapi communiti”	“abort race”	“advanc racial”	“african-american borrow”
“african-american latino”	“african-american parent”	“african-american women”	“american asian”	“among black”
“among racial”	“anoth hispan”	“asian-american voter”	“associ hispan”	“black student”
“black wealth”	“black woman”	“born hispan”	“brown communiti”	“center racial”
“color disproportion”	“color low-incom”	“communiti asian”	“concentr hispan”	“concern hispan”
“congression hispan”	“end racial”	“environment racism”	“ethnic racial”	“femal african-american”
“first black”	“group hispan”	“hbcus district”	“hispan asian”	“hispan chamber”
“hispan group”	“hispan male”	“impact hispan”	“latino district”	“latino senior”
“latino worker”	“level hispan”	“minority-own firm”	“minority-serv institut”	“multiraci categori”

I followed the same approach to calculate the Black statement, Latino statement, and Asian statement measures. In total, 267 bigrams were used to predict the Black statement variable. 157 bigrams were used to predict the Latino statement variable. And 52 bigrams were used to predict the Asian statement variable. The 25 most frequent Black, Latino, and Asian bigrams are included below in Table 4.2.

Table 4.2: Top 25 Black, Latino, and Asian Bigrams from Training Set

Black Bigrams	Latino Bigrams	Asian Bigrams
'african american'	'hispan communiti'	'aapi communiti'
'black women'	'black hispan'	'aapi staffer'
'black hispan'	'latino communiti'	'advoc aapi'
'black american'	'black latino'	'american asian'
'black communiti'	'american latino'	'american pacif'
'black latino'	'hispan caucus'	'among asian'
'african-american communiti'	'hispan worker'	'apprentic asian-american'
'black caucus'	'american hispan'	'asia-pacif island'
'black live'	'hispan women'	'asian american'
'percent african-american'	'percent latino'	'asian communiti'
'percent black'	'african-american hispan'	'asian cultur'
'african-american hispan'	'among hispan'	'asian group'
'black brown'	'hispan american'	'asian hispan'
'black male'	'hispan latino'	'asian minority-own'
'black white'	'hispan latinx'	'asian policeman'
'hispan black'	'latino parent'	'asian popul'
'women african'	'percent hispan'	'asian provok'
'women black'	'african-american latino'	'asian ses'
'african-american borrow'	'anoth hispan'	'asian societi'
'african-american latino'	'associ hispan'	'asian-american voter'
'african-american parent'	'born hispan'	'asian-american worker'
'african-american women'	'concentr hispan'	'center asian'
'black matern'	'concern hispan'	'citi asian'
'black mother'	'group hispan'	'congression asian'
'black student'	'hispan asian'	'council asian'

4.2 Validating Final Measure

To assess how well the bigram dictionary-based classification performed, I take the 536 racial bigrams from the training set and use them to predict whether statements in the validation set include race. The validation set is subsetted from the training set, meaning that it was hand-coded by research assistants, however, it was not used to determine the racial bigrams. Given that the validation set was not used in the training process, it is an independent test of how well the racial bigrams predict out-of-sample data. The performance metrics are calculated from a confusion matrix that compares the predictive performance between the hand-coded race columns and the predicted race columns in the validation set. Table 4.3 presents the performance metrics for the aggregate race statement variable, as well as the three racial group variables.

The performance metrics suggest that agreement between the predicted values from the bigram dictionary method and the hand-coded values is high. In all four models, when comparing the predictive performance of the binary dictionary method on the validation set, the model never predicts a false positive (i.e. the model never codes a non-race statement as a race statement) and rarely predicts false negatives (i.e. fails to code a race statement as a race statement). Accuracy is a ratio of the number of correctly predicted cases divided by the total number of cases. A higher values suggests the model is correctly predicting more cases. Across all four variables, the accuracy is equal to or greater than 0.98. Specificity measures the percentage of negative cases identified, while sensitivity measures the percentage of positive cases identified. The specificity across all four variables is 1.0, suggesting that the model never codes a non-race statement as a race statement. The sensitivity for the Race Statement variable is 0.79, suggesting that the model identifies 79% of all race statements in the validation set. It is unsurprising that the specificity is higher than the sensitivity, given that the model can only identify race statements that include race bigrams present in the training set. This means that though the model may miss some cases of race when predicting values in the corpus, it is extremely unlikely that it will incorrectly code non-race statements as race statements. As a result, my findings are likely a conservative estimate of the relationship between lawmakers' racial identities and their propensity to mention race. I expect that the positive and significant relationship between Nonwhite lawmakers and race statements may be stronger if the sensitivity of the model were higher given that my measure of race statements may be a conservative estimate of total race statements in the corpus.

The Area Under the Curve (AUC) is a measure of the true positive rate (i.e. Specificity) against the false positive rate (i.e. 1 - Specificity). The AUC is a good overall summary of predictive performance of the model. The AUC ranges from 0.82 - 0.90 across the four variables, with the primary Race Statement variable having an AUC of 0.90. Balanced accuracy is similar to the AUC, however, it considers imbalanced data between classes. Given that race statements occur infrequency (both in the training set and the corpus), it is necessary assess the predictive power of the model given class imbalance. Similar to the AUC values, Balanced Accuracy ranges from 0.82 - 0.90, suggesting that the model performs quite well even when considering the imbalance between race and non-race statements. Finally, the Kappa Correlation Coefficient measures the agreement between the predicted Race Statement variable and the hand-coded Race Statement variable. The Kappa Coefficient is 0.87 for the Race Statement variable, suggesting there is high agreement between the predicted values and the hand-coded values.

Table 4.3: Performance Metrics Comparing Predicted and Hand-Coded Values in Validation Set

	Accuracy	Sensitivity	Specificity	AUC	Balanced Accuracy	Kappa Correlation Coefficient
Race Statement	0.98	0.79	1.00	0.90	0.90	0.87
Black Statement	0.99	0.64	1.00	0.82	0.82	0.77
Latino Statement	0.99	0.74	1.00	0.87	0.87	0.85
Asian Statement	0.99	0.75	1.00	0.88	0.88	0.86

Note: Bigram dictionary classification method performs well across all race measures. The table reports the predictive performance metrics when comparing the hand-coded values in the validation set to the predicted values in the validation set for all four dependent variables. The validation set includes 1,000 statements from the training set that were subsetted out prior to model training. As a result, the performance metrics are based on how well each set of bigrams predict on unseen data.

To substantively validate each race measure, Table 4.4 displays the top 50 bigrams present in race and non-race statements in the corpus. As expected, racial bigrams appear in the list of the 50 most frequent bigrams in speeches coded as race statements, while no racial bigrams appear in the top 50 most frequent bigrams from non-race statements. This suggests that, when applied to the corpus, the bigram dictionary correctly predicts race statements. To further validate the final measures, Tables 4.5 - 4.9 present 20 randomly selected non-race, race, Black, Latino, and Asian statements. The race reference in the latter four tables are bolded.

Table 4.4: Top 50 Bigrams from Race and Non-Race Statements in the Corpus

Bigrams from Race Statements	**Frequency in Corpus**	**Bigrams from Non-Race Statements**	**Frequency in Corpus**
“mr chairman”	5693	“mr chairman”	74940
“african american”	5445	“thank mr”	60791
“thank mr”	3549	“hold hear”	37725
“unit state”	3485	“thank much”	33110
“native american”	3392	“unit state”	24958
“look forward”	3119	“yield back”	19752
“thank much”	2710	“make sure”	19399
“rank member”	2586	“look forward”	19243
“want thank”	2373	“rank member”	16259
“vote right”	1890	“want thank”	15807
“small busi”	1856	“5 minut”	15032
“make sure”	1847	“open statement”	13419
“open statement”	1798	“littl bit”	13317
“civil right”	1675	“feder govern”	12233
“yield back”	1532	“just want”	12000
“right act”	1411	“small busi”	11822
“today hear”	1410	“chairman thank”	11585
“feder govern”	1339	“right now”	11359
“law enforc”	1250	“ask question”	11192
“suprem court”	1136	“let ask”	10223
“new york”	1127	“health care”	9920
“will come”	1049	“one thing”	9664
“thank wit”	1044	“last year”	9533
“5 minut”	1023	“social secur ”	9250
“people color”	1005	“much mr”	9228
“last year”	1001	“thank wit”	8571
“year ago”	1001	“new york”	8558
“health care”	986	“go back”	8259
“forward hear”	964	“now recogn”	8129
“us today”	963	“thank madam”	8126
“minor community”	957	“year ago”	7871
“without object”	936	“without object”	7429
“just want”	915	“want ask”	7391
“hear today”	893	“today hear”	7289
“come order”	849	“let just”	7204
“community color”	838	“madam chair”	7197
“american indian”	827	“want make”	6975
“hold hear”	820	“fiscal year”	6607
“section 5”	804	“give us”	6525
“thank chairman”	801	“tell us”	6402
“chairman thank”	799	“can get”	6368
“member committe”	770	“mr secretary”	6280
“navajo nation”	762	“move forward”	6179
“thank madam”	760	“come back”	6175
“wit today”	743	“thank chairman”	6162
“littl bit”	736	“question mr”	6095
“ask question”	732	“unanim consent”	6058
“much mr”	731	“law enforc”	6040
“across countri”	727	“homeland secur”	5893
“right now”	720	“will come”	5813

Table 4.5: 20 Randomly Selected Non-Race Statements From Corpus

Number	Speech
1	“You just bring a wealth of information and perspective that many of us don’t have since we are brand new to this.”
2	“Thank you very much, Mr. Chairman. I will just ask a few questions. First of all, to Mr. Forrey, the FAA has just completed, I guess, a major redesign of the New York and nearby airspace which they are hoping will, among other things, reduce delays by about 20 percent. Have you or your organization had a chance to look at that? Do you have any opinion on their redesign or whether the prospects are as rosy as they forecast?”
3	“But what’s interesting to me is had she not died, we never would have known that there was in fact anthrax at that facility. We never would have known it, ever. What I’m hearing you say about the validated approach is that we are going to know the strengths for the most part and weaknesses of the process.”
4	“Exactly my point, though. You did access the PFC, you were able to build it, you were able to finance it. You weren’t limited by lack of PFCs. In fact, there is $7 billion in the airline trust fund, right, the airport trust fund now. So you have indicated my exact point, which is–you made a point, Mr. Lopano, you made a good–you made an excellent point earlier, and I agree with you. You make more money–you get more revenue, let me put it that way–from your parking fees than you do from the PFC. I agree wholeheartedly local control. So what do you say we eliminate the PFC, and airports raise the funds they need to raise through whatever mechanisms they have: parking fees, some people have fees on access in the airport, concession fees. If you want local control, why don’t we do that?”
5	“So there is no time frame on this monitoring, but it falls within the same regime protocol system that any other species–if it is seen after a year that the Patagonian toothfish, under this catch document system, their stock is dropping, then other measures can be taken? If it is seen that stock is stable or rising, it will just continue under this catch document system?”
6	“For records. Take ConAgra, the salmonella and peanut, we are still waiting for those records, and you have no subpoena power, FDA has no subpoena power to get those records. Would you support subpoena power to get records of the producers?”
7	“Sure. But you don’t get 10 minutes to answer because that’s all I have to question.”
8	“I thank the gentleman from California. I just have a few questions and then we’ll wrap up. Julia, I really am grateful for the teachings that you share here today. You went to the issue of the tax-exempt status. Congress has set aside legislation, or has created legislation, that exempts the National Health Service Corporation, as well as the Department of Defense, on their scholarship benefits. If we were able to provide a tax-exempt status for IHS scholarships, what kind of figures do you think we’re looking at? How big is the program right now? I guess we could start there.”
9	“The gentleman from Missouri, Mr. Clay, Chair of our Subcommittee on Housing, Community Development and Insurance, is recognized for 5 minutes.”
10	“My time is up. I just want to make one sentence here. From 1999 to 2001, FDA sent 36 warning letters to biologic manufacturers for manufacturing violations. From 2002 through 2004 FDA has sent six. This is a decline of over 80 percent. I think we need to do more, not less. That is why I believe we ran into the problem we did. You may disagree with me, but that is my view.”
11	“Thank you. The chair thanks the Chairman, and would like to thank our witnesses for their testimony today. In consultation with Mr. Goodlatte, we traditionally don’t ask questions of Members so unless anybody has a burning desire to ask any questions, we will thank our panelists for their testimony. Thank you. We now would like to have panel two, Ms. Nivin Elgohary, Acting Assistant Administrator, Rural Utilities Service, United States Department of Agriculture. Ms. Elgohary, when you are ready, you may proceed.”
12	“The blanket approach, this is kind of typical of Washington. We tend to try to look at things in a one-size-fits-all context. But I just think there is so much difference geographically in climate conditions and so on at different times of the year. Further south, it is not uncommon at all for them to get a second crop. A ratoon crop is fairly common in places like Louisiana and east Texas. That is not something that is common in our neck of the woods. Southeast Missouri and northeast Arkansas and further south into Mississippi, that is the exception. The other issue is, what is not included is row rice. And that is another complaint that we get from our rice farmers, across the Belt, is that row rice is not included in crop insurance. Any comment on that?”
13	“Oh.”
14	“Jerome, do you want to put your insight into the same question? ”
15	“I thank you, Mr. Chairman. Mr. Sabin, let me follow up on a matter of previous questioning, and ask you, is there any group that is operating, or allegedly operating, out of Saudi Arabia, that has been designated as a terrorist organization?”
16	“So when Mr. Becker then later on in the process when he is–there are some accounts and some conversations that you had and I think after it was determined he shouldn’t testify because of the conflict, you said, “I believe this, that don’t worry, you will have other opportunities.” You were all kind of making light of the fact that he didn’t get to testify. At that point in time, didn’t it dawn on you then, or when did it dawn on you, I guess is what I am asking? When the newspaper account came out, did it dawn on you then or did it dawn on you before then?”
17	“Yes or no? I mean, if you think no, it is fine, and we can keep rolling here.”
18	“That scares me–scares me as well. So I guess the fundamental question is I think you are all there. There should probably be some kind of–some kind of restriction. Mr. Ferguson, I think you have said we should just ban it, right?”
19	“Thank you, Mr. Chairman. Thank you, Mr. Darling, for the work that you have done and for your testimony today. Given the testimony of both Mr. Walp and Mr. Doran–and I note that Mr. Doran’s son is here. It is your son with him?”
20	“August 19, even though you had had this information for quite some time. Now between April the 1st and August the 19th, the contractors were working out options and the Integrating Program Office was evaluating these options, is that correct? Vice Admiral Lautenbacher. And the tri-agency steering group was meeting as well to evaluate it, so the chain was working on trying to come to grips with the issues that the contractor presented to us during that time.”

Table 4.6: 20 Randomly Selected Race Statements From Corpus

Number	Speech
1	“Let me ask about another category that comes to mind, and that is the church records of birth, marriage, and the county records of death, etc. To what degree does that apply to a lot of the African mission? I think there were churches strictly **African American** after the Civil War was over, and I don’t know if those records have been looked at, but it seems to me that is another valuable record.”
2	“–this shows losses in median household incomes, again disproportionately impacting **black and Hispanic** households. Put up the next slide, please.”
3	“You have reviewed the studies that have been done to date on the health effects of uranium contamination on the **Navajo Nation**, is that correct?”
4	“Thank you, Mr. Chair. Since the beginning of the COVID-19 pandemic, several of my constituents of **Asian** descent have reported **racist incidents**. One Chinese constituent was labeled a communist in a disparaging newspaper article. A college student found her Chinese New Year display in her dorm destroyed. Others have been verbally harassed to the extent that they worry about their safety in public. Unfortunately, this is not the first time in our nation’s history. **Asian Americans** have found themselves subject discrimination, as we have heard today. This stems directly from xenophobic Federal policies. Earlier we heard Representative Matsui testify about the impact of living in an internment camp on her family. I would like to address my first question to Professor Motomura. I know that we have talked about **anti-Asian laws** and how they’ve contributed to our society. Could you give us examples of when **anti-Asian laws** have been repealed and how public sentiment has come to allow for that repeal?”
5	“So your position is that “exceptional cases” refers to cases involving **racial bias**, and there is not some separate class of cases.”
6	“Yes. Dr. Khan, is there anything unique to certain **minority communities**–let’s just take the example of the Muslim American community–that we should be aware of in terms of vaccine confidence or the lack thereof?”
7	“Okay. Thank you. Mr. Manger, again, many congressional hearings and we constantly hear from women, **minority firms**, rural America, the fact that on average, it is very difficult for them to get the lending they need. When we look at the 7(a) program, pre-recession levels was 17*billion*;*todayitis*27 billion. Yet, lending for women, **minority**, and rural America, has seen a decrease compared to pre-recession levels. What are you doing to address that issue?”
8	“Well, thank you. And it is an honor to have someone who has dedicated their life to helping others so much as you have. I was a little concerned when I–in your statement earlier, you said you were concerned about the **children of color** and the mistreatment of **African American** youth. So I was relieved to hear at the end when you said you were concerned about every American youth, **regardless of race**. And we appreciate–obviously your life speaks volumes about what you have done to try to help others. And we may disagree about ways to try to help them. But clearly you have a heart for helping others. And I thank you for being here.”
9	“OK. Let me ask this question. Mr. Gonzalez, I mention in my questioning of the Commissioner the studies. I find the studies to be rather flawed, especially when it comes to the **minority** and women ownership issue. In fact, study one looks at how people receive their news; and its use of data basically excluded **Latinos** in that study. Do you believe the FCC had properly considered **minority media ownership** especially as it relates to Latinos as they have come up with this proposal?”
10	“Okay. Thanks for your answer. Mr. Chairman, just before I yield back, I was talking about a business roundtable that I did in Jacksonville, Florida, and it still is a lot of disconnect, especially in a **minority community** in the U.S., and I can imagine what the disconnect might be from the distance of being in Puerto Rico and that is some gap that we ought to fill. With that, Mr. Chairman, I yield back.”
11	“Dr. Michener, you have spoken so eloquently about **racial inequity**. Tell us how a Medicare for All system would help alleviate those **racial health inequities** that people are facing right now.”
12	“Right. I am running out of time, and I totally agree with you. I just want to make sure that I thank, again, President Begaye and your incredible work. I am very upset that the EPA took even longer to notify the **Navajo Nation**. I appreciate the work by our two Senators to look at notification legislation; and, because I am running out of time, perhaps the best thing is that I intend to support you. I think there will be many Members of Congress, and I hope it is a bipartisan effort, to require the EPA to have much better relationships and a government-to-government, recognizing the sovereignty of the **Navajo Nation**. You should expect from your Federal Government and the state that level of one-to-one collaboration, so that you have your plan, your efforts, and your own independent process; and that should be respected and supported, sir. You are welcome. Thank you, Mr. Chairman.”
13	“Thanks. I hope you’re right for sure. And you know I’m a former union organizer. My first job in that space was helping nursing home workers organize with SCIU I think almost 40 years ago, but we won’t dwell on the passage of time. Making sure the direct care workforce has a safe workplace, a living wage, and great benefits is a cause near and dear to my own heart, and I know it is to yours. And I know from my–first-hand experience that this critical workforce is made up largely of **women of color** and immigrants who are paid on average about $12.00 an hour. So, Mr. Secretary how will HHS partner with the Department of Labor and us to invest in the direct care workforce, and how will you do it in a way that improves worker recruitment, retention, development and make sure that they’re paid well and protected in their workplaces?”
14	“Building off that, then, you know, how can Congress ensure that only small firms owned by individuals with genuine claims of being **Native American** get certified into the program?”
15	“Lee.—-with the sharp disparities that you see in the **African American population**–is that—-”
16	“I’m going to ask the others to respond as well, but before I do, would you please talk a little bit about how we can get more girls, young women and **minorities involved**?”
17	“I appreciate that. Do you in your seminars explore at all the fact that we are having monies rescinded each year out of NAHASDA? Last year, $33 million were rescinded back, unused monies that the Government is actually putting out there for **Native Americans** to achieve homeownership, and yet we are not using it. Any thoughts in both your experiences on how we can buy down, use that money, get it down to zero, and why we are not?”
18	“Thank you, Mr. Chairman. Mr. Foster, let me just again commend you and your company for its strong record of involvement with **minority- and women-owned businesses**. You raised some concerns in relationship to the 5 percent goal. My question is, in your own company, have you found that advocacy and ombudsman type programs like the one that we are really talking about were effective in helping your company move to the point where it developed this strong record? I really do think that you have a strong–one of the strongest that I have actually seen. I have been involved with **minority- and women-owned business** development efforts for many, many years. I think that you have developed one of the more outstanding records in the country. Does this type group that this legislation really creates assist your company in developing its approach to these kinds of business entities?”
19	“The Fiscal Year 2017 budget proposes a modest 3 percent increase to work with the **Navajo Nation**, the **Bureau of Indian Affairs**, and the other Federal departments and agencies to ensure that this program can be brought to a fair end, and to ensure that any responsibilities remaining after the closure will be transferred to the appropriate Federal or **Navajo** entities.”
20	“Do you see the need also for enhancing experts within the **minority communities**, because we are certainly limited in the Ph.D. candidates and Ph.D. graduates from those communities?”

Table 4.7: 20 Randomly Selected Black Statements From Corpus

Number	Speech
1	"Sixty-one percent? That is **African-American** and Latino? Okay. Thank you very much. Let me also ask, did you find and are you finding, in terms of the housing stock, that rural America significantly needs more housing stock? Or is it rehabilitation only that is a strategy that makes sense?"
2	"Thank you, Congressman Comer. Mr. Langan, earlier this morning when Congressman Donalds was speaking, you mentioned in the FBI and domestic terrorism, there are these subcategories of domestic terrorism: racial, anti-government, animal, environmental, abortion, and catch-all. I think those are what I heard. Under the anti-government category or subcategory of domestic terrorism, would that include groups like antifa or **Black Lives Matter** folks who commit violence or acts of domestic terrorism?"
3	"My concern is that there is excessive, some would say over-policing in minority communities. I understand why. But it has resulted in **African Americans** being incarcerated at four times the rate of white Americans. **African Americans** are over-represented in mug shots that some facial recognition systems scan for potential matches. Ms. Del Greco, do you agree that both the presence, the overrepresentation of **African Americans** in mug shot photos, the lower accuracy rates that facial recognition systems have when assessing darker-skinned people such as **African Americans**, that it is possible that false convictions could result from the FBI's use of these external systems if they are not audited?"
4	"Okay, thank you very much. I think one of the first steps in addressing White supremacy, though, is really acknowledging the seriousness and the fact that it exists at all. Before our last election, we had four acts of domestic terrorism the week or two before, and they were not called that. From the man who had the bombs that fortunately didn't go off, the individual that was in search of **African Americans** to kill in Kentucky. He tried to enter a church and he couldn't, and so he killed two random **Black folks**. The horrible massacre at the synagogue, and then the shooting several days later at a yoga studio, where someone was looking for specifically women of color. In that, we have the FBI that is very concerned about **Black identity extremists**, and I just wondered, Ms. Clarke, if you could tell me of examples–how many acts of domestic terrorism were carried out by **African Americans** in the last few years?"
5	"But, Mr. Secretary, something went wrong. The previous Administration created more than 23 million new jobs. People were doing very well. Now people are losing their jobs, people are not doing very well. People are owning and buying homes, especially minorities–Spanish, **African Americans**, and others. Something went wrong with this Administration, and with the previous budget and this budget that you're proposing now. Again, I ask you, is this good medicine? Is this a good prescription for our economy?"
6	"What percentage would you say of the people that you serve are **African-American**, Hispanic, other backgrounds?"
7	"Thank you. And I agree, obviously, with everything you have said. It is so frustrating to hear to the contrary. Let's talk about FHA for just a moment, because FHA plays a major role for first-time home buyers. And FHA has helped almost half-a-million people get into homes since 2014, and about one-half of them are brown and **black Americans**. Do you believe that FHA, as we talk about the future, is one of the agencies that absolutely must be preserved so that we can continue to provide this kind of assistance to first-time home buyers as well as others?"
8	"Now, second, we know, Ms. Ahmad, that in the United States our criminal system over targets the poor and over targets people of color, **particularly Black Americans**. Correct?"
9	"Thank you. We must have remedies for things like the persistent racial wealth gap. Along with nearly 200 of my colleagues, I am a co-sponsor of H.R. 40, the Commission to Study and Develop Reparation Proposals for **African Americans** Act. This bill has advanced through a committee markup, and I look forward to its passage. Dr. Berry, when the commission under this bill is established, what approaches or methods could it employ to review and quantify the historical involvement of the financial sector in the institution of slavery? How could the commission guide private-sector actors, like financial institutions, to achieve appropriate atonement for slavery?"
10	"And then, finally, there was an assertion here that **African Americans** are 50 percent less likely. Why is that? What is happening here? Why would that happen? I can't remember who brought that point up in the prior—-"
11	"Thank you. Madam Chair, I realize my time is up. If there is a second round, I certainly do want to talk to the Secretary about some other issues, particularly impacting **African-American** students, **Black students** in particular. Thank you very much. And I yield back. Thank you, Mr. Secretary."
12	"Thank you, Reverend Woodberry. If I could with the last 20 seconds, Mr. Williams, what are your recommendations to the committee to address environmental **inequalities in black and brown and low-income communities**, including opportunities to create these clean jobs?"
13	"Has the advisory committee worked with the Bureau to find or locate qualified **African Americans** and recommended them to it"
14	"Let me ask. Has the **African American** advisory committee recommended that the Bureau formalize and expand the recruitment program with **historically Black colleges and universities**? The Bureau's response was that it is working with **HBCUs** to facilitate enabling Goal 5 of the Bureau's strategic plan to maintaining a highly qualified and motivated work force. However, you believe this goal is not being met because **African Americans** at the Bureau are not motivated. How did you arrive at the conclusion that **African Americans** at the Bureau were not motivated?"
15	"On your testimony I think you indicate that 51 percent of **African-American** home buyers, as well as about 45 percent of Hispanic families, purchase homes through FHA and that you are leading in that area. Do we know the actual numbers, for example, of the ones you mentioned in foreclosure? Do you have those figures?"
16	"The fact is that an African American family, low-income **African American** family could not purchase the disability or survivor benefits with dollars that they receive under Social Security."
17	"Thank you for that response. According to the Bureau's estimates, it undercounted **African Americans** by 628,000, Hispanics by 248,000, Hawaiian or Pacific Islanders by 13,000 and the American Indian and Native Alaskans by 10,000. There are some in the statistical community who believe the actual undercounts are much higher."
18	"I would love to talk about **Black communities** if you would like me to."
19	"Thank you, Ms. Bridges. And to your point about called on to be the future defenders, you know, in communities throughout the country, **Black students** of all ages continue to face white supremacist violence just for trying to access quality education. I mean, recent threats on our **HBCUs** are a stark example of this in fact. So how do you think the removal of books like yours will affect this young generation of students who might not be aware of the struggle to fight segregation in America? How does it affect their sense of purpose, their agency?"
20	"Say that one more time. What has happened to **African-American** unemployment?"

Table 4.8: 20 Randomly Selected Latino Statements From Corpus

Number	Speech
1	"Let me just say that–that the secretary has actually been proactive in asking for meetings, not only with the **Hispanic Caucus**, but other stakeholders, and we will be making those arrangements."
2	"Thank you so much. Thank you. One of the issues that has been discussed in our community a lot is this whole issue of combining race and **Hispanic origin** questions into a single question. Some claim people as prominent as the NALEO, the **National Association of Latino Elected Officials**, claims that it is a–they believe that a "combined question with a detailed checkbox" approach holds great promise as a means for producing less nonresponse, and fewer ambiguous and inaccurate responses. On the other hand, there are some folks who think that it may not help in getting a clear picture across the government in terms of who the people are. So, what made you go in that direction? How long has this been discussed, and secondly, is it a set situation? Is it going to happen? Is it being tested? And are you fearful of some of the things that have been put forward and supportive of some of the things–positive–that have been said."
3	"The economy was good–it was better for African Americans, **Hispanic Americans**. It was better for all Americans, wasn't it, low-earning Americans, high-earning Americans? Wages up, unemployment down. It was better for everyone, wasn't it?"
4	"Thank you for an opportunity to introduce Mr. David Lizarraga. He is founder of the one of the biggest CDCs in the country, TELACU. He now services at the **Hispanic Chamber of Commerce**. He has long been involved in providing housing opportunities for low- and moderate-income people, and I would like to welcome him, and I thank him for coming."
5	"We get all of these reports from the drug czar from everybody. We get report after report telling us teen usage is down. Teen usage is up; we get a whole lot of data. In your 18 years, can you kind of tell us–and this will be my last question–what you have seen? The differences in who you see, what kind of people you see, was there one time, for example, just about the only people you saw were African Americans or **Hispanics**, and now do you see a change? Has it been constant? Was there a point in time when you saw things sort of explode? Can you answer that for us?"
6	"Mr. de Posada, in your testimony you eventually got to the conclusion that we would see a significant increase in Medicaid, pressure for increase in Medicaid spending, which is terribly frustrating to me as a conservative. But it is also frustrating to me because this entire hearing, this entire discussion, is about working Americans. The people that are working, that are employed, and despite the hateful stereotypes that can attach to minority communities, you have been an eloquent voice in this hearing today for the **Hispanic community** and its desire, people's desire to build wealth and be productive parts of the economy and small business sector, in particular. Where do we focus right now that is going to make the biggest difference?"
7	"In 2016, the imprisonment rate of African American women was twice the rate of imprisonment for White women. **Hispanic women** were imprisoned 1.4 times more than White women. Ms. McCurdy, why are women of color more likely to be imprisoned at twice the rate than White women? What solutions do you see in solving this gap?"
8	"One of the concerns I have and something that the **Hispanic community** and the caucus is very concerned about is the increase, actually the upsurge or upping of teenage pregnancies amongst the **Latino population**. It is well above, I would say, in some cases 20 percent. In fact the statistics prove that 51 percent of **Latino** teens get pregnant at least once before the age of 20 and for African American it is 57 percent become pregnant at the age of 20. So obviously the abstinence program is not working well. And one of the concerns we have is that information be provided in a culturally competent, linguistically competent manner. And I have yet to see any evidence that is happening in all the years of funding for these programs. Can you respond to that?"
9	"Well, I am just curious, because they really are not being regulated right now. And so it would seem to me they have enormous flexibility that could be used for something that most people believe to be important. I don't have much time left, so I apologize, but–I wanted to get into that even more with you. But let me move to the–one of the other issues that I am concerned about. And it is unemployment among African-Americans and **Latinos** in this country. Through the Obama Administration, and then the Trump Administration continuing, the unemployment in the country has, blessedly, dropped significantly. All of us should be happy about it. However, the minority communities are still not dropping at the same rate as non-minorities. Is there anything that can be done, in your portfolio, there is this issue of employment that–do you have anything in the toolbox that you think would be of help in trying to reduce minority unemployment?"
10	"Thank you, Mr. Chairman. Mr. Chairman, the only thing I would add, if I get a word beyond the last word, would be that I think the solution we should look for is one that does not give effect to–in the United States–to foreign confiscation. And I second what Mr. Veroneau said about that. How we get about doing that and who wins and who loses in this regard I am not completely clear. But I would like to, in furtherance of what the gentleman from California said, ask that a letter to you, Mr. Chairman, and to Ranking Member Smith, from Jaime Suchlicki, who is a professor at the University of Miami and the director of the Institute for **Cuban American** Studies and offers his opinion on what impact this might have in Cuba, with regard to any retaliation on the part of the Castro regime–I would ask that that be made a part of the record."
11	"Pretty good. Ms. Bennet, you have talked about the concern about low-income folks, the minorities, people that ostensibly don't have as easy access to, you know, internet services, broadband, and that the merger could be very detrimental to a lot of those folks that rely on some of the largesse from both Sprint and T-Mobile at this point in time. The question I have is why are you so concerned about that but the U.S. Hispanic Chamber of Commerce, the Black Chamber of Commerce, the **National Hispanic Caucus of State Legislators**, National Rural Education Association, Puerto Rico Chamber of Commerce all think this is a good thing? Why the disparity?"
12	"Yeah. And I think part of that is–I mean, I was in with General Miller today, and his service stripes, his overseas service stripes were above his elbow which means he has had more time downrange than he has before, okay, and that is our senior leaders. I mean, I was gone for 3 years out of 5 at one point in my kids' life; 3 years out of 5, I was downrange. And so we all face that, but how do we get African American, **Latino**? Is that recruiting HBCU [Historically Black Colleges and Universities] universities and ROTC in greater numbers? How do we get greater numbers at the entry level because until they are at the entry level, we can't get them at the exit level. And then we have to have people, we have got to figure out what it makes–what it does to keep them to stay to be a senior officer. Yes, ma'am."
13	"Thank you, Mr. Chairman. Mr. Secretary, we very much appreciate your being here. In the meantime, in Race to the Top and the additional funding for higher education, my district involves enough territory to put four eastern States in it, including the two major military bases. But probably your department doesn't know that the first funding, the very first funding that ever went in for **HSIs–Hispanic-serving Institutions**–was a proposal of my own. And could you give me an idea of what you are proposing for **Hispanic-serving institutions** last year versus this year versus the coming year?"
14	"Thank you, Madam Chairwoman, for having this continuing timely conversation and this hearing. I am going to direct my comments and question to Ms. Crawford. What we saw during this pandemic was a bigger gap between the haves and the have nots. Plenty of people in my working-class immigrant community lost their jobs. Many had to take on new debts. Businesses closed, but housing prices are through the roof. In 2019, right before the pandemic, **Latino homeowners** had a net worth 40 percent higher than Latino renters. That number is alarming, and it has only increased. Can you talk about the impact of rising house prices for first-time **Latino** and Black homebuyers and what we can do to help them?"
15	"Thank you. And it has also been my understanding that many people who are eligible for government benefits sometimes do not apply because they lack strong English skills. This includes both citizens and legal immigrants. How would you rate the USDA's assistance to limited English proficiency families in respect to the Food Stamp Program? And this is a constant problem and I know that the Under Secretary indicated that they need to do a better job in doing the outreach and reaching out to our communities, because many of the **Hispanic members** within the communities don't even know that they are even eligible to receive assistance."
16	"I thank the gentleman for his participation and know the gentleman from Puerto Rico to be probably the most outspoken and outstanding advocate of issues related to the **Hispanic community** in this country."
17	"And let me go to other members of the panel. Of course, we have data that reveals a disproportionate share of African American assessments, African American and **Latinos** receiving higher-rate home loans, notwithstanding location, income. We see non-disclosure in fair lending exams and lack of transparency, thereby compromising entire communities of their right to participate in public negotiations; and CRA's lack of uniform standards where reasonableness of assessment areas, as well as nature, extent and strength of evidence of discriminatory practices are at the discretion of the examiner. I guess what I'm really trying to arrive at is this business of when is enough or how do you decide? The question then becomes, what level of evidence is sufficient to adversely impact an agency's CRA valuation? Ms. Thompson, perhaps I would—-"
18	"Well, you should, because he is your great- grandfather. He started this war in the 1930s and he was tuned out too, and he did it to get–the American public had problems, and sometimes I think we still have them, with **Hispanics** and Mexicans coming into this Country, and it was a war on Hispanics and African-Americans. And that is when they made marijuana illegal, was in the 1930s, and it was all directed at those people. And **Latinos** are just as much discriminated against as African-Americans in disparate arrests. It still continues to this day. It is 85 years since Anslinger started this. And the fact that we spend so much time arresting people is sinful. You talked about the overall effects of marijuana. Again, you can't name one person who has died from an overdose of marijuana, can you?"
19	"Mr. Alford and Ms. Jackson, can you explain in any more detail what you have done with leaders in the **Hispanic community**, in addition to this legislation, and what–where can it be helpful?"
20	"Thank you. Our next witness is Gary Acosta, President, SDF Realty, San Diego; CEO and Chairman-elect of the **National Association of Hispanic Real Estate Professionals**. Mr. Acosta"

Table 4.9: 20 Randomly Selected Asian Statements From Corpus

Number	Speech
1	“Thank you, Mr. Lieu. Mr. Lieu makes an important point as well, that the President’s language has been incendiary in how he has described this virus. And attacks against **Asian Americans**, as you all probably have seen, have skyrocketed during this pandemic, in no short measure because of how the President has described this virus, and others as well. With that, I am going to go over to Debbie Dingell, but, first, I need to read just a few lines. I ask unanimous consent for Representative Debbie Dingell of Michigan to participate in this hearing and ask questions after all subcommittee and committee members have done so. Hearing no objection, I will go to Debbie Dingell of Michigan.”
2	“Madam Chairperson, thank you. Welcome, Ms. Helm, and Mr. Bunch. Congratulations, Mr. Bunch, on your new book and on your very inspiring and successful service as the Director of the National Museum on African American History and Culture. And my first question is actually about that. It has obviously inspired other efforts, as the Chairperson was saying, to create the museum on the woman, American women, on a Latino museum, an **Asian American museum**. One of the remarkable things about the African American Museum is, first of all, I think it is now the most popular museum destination. Is that right?”
3	“Thank you for that. Ms. Jang, the **Asian** advisory committee has made several recommendations to the Bureau regarding the recruitment and hiring of **Asian American** candidates including collaborating with strategically selected higher education institutions with high **Asian enrollment** to establish a work force diversification pipeline program. This recommendation was made in April 2005. In your opinion, has the Bureau made significant progress in implementing the recommendation?”
4	“I guess, Karen Narasaki, OK. She is the executive director of the **Asian American Justice Center**, testified before the subcommittee last year that the Bureau needed to improve its work on language translations, and she noted that in 2000 the Bureau was late in making critical decisions on translation materials and that there was no centralized clearinghouse of translated materials. I have that problem in my district. To what do you attribute the problems and what has the Bureau done to resolve them on this round?”
5	“Yes, thank you for your testimony. The Witnesses will be reminded that they need to keep to five minutes because we have so many Witnesses and we want to get all of you in. So, thank you so much for that. We will now move to Hammad Alam, a staff attorney and program manager for national security and civil rights at **Asian Americans Advancing Justice**, A**sian Law Caucus**. Mr. Alam’s work at the **Asian Law Caucus** focuses on protecting communities, and, in particular, Arab, Middle Eastern, Muslim, and South Asian communities, from government surveillance and policing in the name of national security and counterterrorism. His work also includes advocating for an end to surveillance and policing programs that disproportionately and unjustly target communities on the basis of their religion, ethnicity, and national origin. Mr. Alam has a law degree from the University of California, Los Angeles, School of Law, and a master’s in theological studies from Harvard Divinity School. Mr. Alam, you are recognized for five minutes.”
6	“Thank you, Madam Chair. Ms. Seecharran, how is the legacy of the 9/11 attack continue to impact **South Asian communities** in New York?”
7	“Leigh A. McGee, Chair of the Census Advisory Committee on the American Indian and Alaska Native Populations, thank you for being here. Dr. Bernie Miller, Chair of the Census Advisory Committee on the African American Population, welcome. Deeana Jang, policy director for the **Asian and Pacific Islander American Health Forum**, thank you for coming today, and Stephen J. Pemberton, chief diversity officer and VP for diversity and inclusion at Monster Worldwide, Inc. I welcome all of you and thank you for being with us today. We will start with Ms. Rosales. You may begin.”
8	“Thank you, Mr. Chair. Judge Donald, I was interested in your written comments. There is this one paragraph that sort of got me thinking about what we are talking about, and it says, you say, I am sad to report today that despite significant recent progress in diversifying the legal profession, the Federal judiciary is not yet visibly open to talented and qualified individuals from every corner of this great Nation. As of exactly 1 year ago in March 2020, women accounted for only one-third, 34 percent of Article III judgeships despite amounting to more than half of the U.S. population. Similarly, African Americans, Latinx Americans, and **Asian Americans** combined accounting for only 26 percent of Federal jurists, while 40 percent of the country identifies as non-White. I guess, Judge Donald, it prompts me to ask. What is the objective? Is it to have a quota so that you are not really or not there until the numbers match the background population?”
9	“Coleman. Thank you, Mr. Johnson. Thank you, Ms. Shaw and Mr. Johnson, to the witnesses in our first panel. Thank you for being here and taking our questions and giving us your testimony. Before adjourning, I would ask for unanimous consent to submit statements to the record from the American Civil Liberties Union, the Detention Watch Network, the American Immigration Council, the National Immigration Justice Center, the Government Accountability Project, the Southern Poverty Law Center, the Transgender Law Center, and the **Asian American Advancing Justice**. Without objection, so admitted.”
10	“So let me move on. Okay. Thank you so much, and I want to get to a couple of other questions. So let me move to another topic. I commend your stated efforts on improving diversity and inclusion at the CFTC, along with your work to create the agency’s first Chief Diversity Officer. The need for a CDO is important. And according to the CFTC, the employee breakdown of management is woefully homogenous with only 14 African Americans, ten **Asian Americans**, five Hispanic Americans at the grade level 15, and only 33 percent of your senior level employees are women. Number one, first of all, I do find that troubling. So what is your strategy to increase racial, ethnic, and gender diversity at the CFTC? And will the Commission plan to include recruitment from historically Black colleges and universities and minority-serving institutions?”
11	“All right. Retired Foreign Service officer, businessman, policy commentator with over 35 years experience in China, Taiwan and Mongolia, he spent 24 years in the Department of State and in diplomatic and counselor offices in Taiwan and China, and was the Chief of China Analysts in the Bureau of Intelligence and Research before he retired in 1994. He joined the Heritage Foundation in 2001 where he was a senior fellow in **Asian studies**. He has edited two books, Reshaping the Taiwan Strait and Rethinking One China. He is fluent in Chinese and has degrees from Harvard and Georgetown Universities. He’s currently president of the China Business Intelligence, and then Sadanand Dhume, got it, is a resident fellow at the American Enterprise Institute. He is also a South Asian columnist for the Wall Street Journal. He has worked as a foreign correspondent for the Far Eastern Economic Review and my friend, Bertil Lintner. Is he still there?”
12	“Let the record reflect that all of the witnesses answered in the affirmative. Our second panel today consists of five distinguished witnesses. We will go in this order, first with the Honorable Robert L. Bowser, mayor of East Orange, NJ, and vice chairman of Urban Policy Committee for the U.S. Conference of Mayors. Second will be Karen Narasaki, president and executive director of **Asian American Justice Center**, on behalf of the Leadership Conference of Civil Rights. Then we will have the Honorable Kenneth Prewitt, professor of Columbia University and former Director of the U.S. Census Bureau from 1998 to 2001. Then we will have Dr. Joseph Salvo, director of the Population Division for New York City Department of City Planning, and Mr. Michael Murray, the vice president of programs, Civil Business Unit, Government Communications Systems Division for Harris Corp. Welcome to all of you. Thank you for coming to day. Mayor Bowser, we will begin with you. Please proceed.”
13	“Yes, ma’am. To that point, I am concerned about how we make the pipeline better. **Asian Americans**, despite having increased their numbers and outscoring other applicants, have been disproportionately denied admission to Ivy League schools, particularly Harvard, and I think that was sustained nonetheless by the First Circuit as an appropriate first–appropriate affirmative action thing to do. The Administration recently dropped its support for **Asian Americans discrimination** contentions against Yale. Is it possible to discriminate against Asian Americans in Ivy League schools, and yet, improve the pipeline for Asian Americans getting access to judicial positions?”
14	“Tell me, in my home State of Texas, Latino, African American, **Asian American**, and Native American students already make up the majority of the students enrolled in many of our colleges and universities. Can you highlight what States are doing to ensure that these students are part of the President’s college completion goal?”
15	“And what does GPO plan to do to increase the representation of **Asian American** officials in the SES ranks?”
16	“The gentleman yields back. The chair now asks for unanimous consent to insert the following statements into the record. We have statements from the **Asian Americans Advancing Justice**, Bethany Christian Services, Church World Service, the Episcopal Church, Franciscan Action Coalition, HIAS, Interfaith Immigration Coalition, the International Refugee Assistance Project, International Rescue Committee, Leadership Conference of Women Religious, Lutheran Immigration and Refugee Service, National Council of Jewish Women, National Immigration Law Center, the Refugee Congress, and also a letter from more than 85 U.S. mayors in support of refugee resettlement. So, without objection, those will be entered into the record.”
17	“Thank you for that. Ms. Jang, the **Asian advisory committee** has made several recommendations to the Bureau regarding the recruitment and hiring of Asian American candidates including collaborating with strategically selected higher education institutions with high **Asian enrollment** to establish a work force diversification pipeline program. This recommendation was made in April 2005. In your opinion, has the Bureau made significant progress in implementing the recommendation?”
18	“I want to thank you, Mr. Chairman. This has been quite a hearing, and I am not surprised. I want to congratulate the Ranking Member for bringing this issue to the floor. But as I sit here and hear some of the questions and some of the commentary, it really, really infuriates me about some of the attitudes and opinions and some of the remarks that I have heard. I am trying to maintain my cool, so to speak. But first of all, Mr. Chairman, there are some letters that I would like to enter into the record, and some of them may be included, but I am told that–in your packet, but I am told that they aren’t included, and we have a statement from the NAACP, the Leadership Council on Civil Rights and Human Rights, the United Church of Christ, the National Organization for Women, the **Asian American Justice Center**, Disability Rights, Education, and Defense Fund, and from the CWL. I would like those included in the record.”
19	“I appreciate it and you are in the midst and you are working toward it. We want to follow up on this and stay closely engaged in the future development. I want to close–maybe get one more member in. Regrettably Ms. Matsui went off to vote. Sacramento, which she represents, is one of the great examples of mobility on the South line, which is creating 2,210 new transit trips weekly. It provides transportation for people who didn’t have transportation before to get them to jobs in the Hispanic, **Asian**, African American section of Sacramento. Enormous success. And now they are building on that success, moving to the next extension. Isn’t that a mobility factor?”
20	“**Asian American**. Okay. All right. Harry’s Law. One minority in a supporting role; is that correct? Audience Member. In the pilot, yes, but we are recasting the show, so we’ll have more of an update—-”

5 Supervised Machine Learning Models

I estimated 154 supervised machine learning models and one model using a dictionary of racial bigrams. The bigram dictionary classification method performed better on all performance metrics than any of the supervised machine learning models. As a result, this method was used to label each of the four race variables in the corpus, which is further explained in the prior section of the appendix. In this section, I detail the process of estimating the learning models.

First, I used the training set to train the learning model (n = 4,000). Initially, I used SentimentIt through Amazon's Mechanical Turk to create race scores for each statement (Carlson and Montgomery 2017); however, MTurk workers were unable to distinguish between race and non-race statements successfully. I then hired undergraduate research assistants to hand-code a training set. Next, I pre-processed statements in the training set, validation set, and corpus. Then, I used three different models to transform committee hearing statements into numeric vectors. First, I use a Word2Vec model varying the token (unigram, bigram), dimensions (300, 400, & 600), window size (5, 7, 10, & 12), and epoch (10, 15, 30, & 45).[2] Second, I used a Paragraph2Vec model varying the same dimensions (minus the parameter arrangements with a dimension of 600). Third, I used a document-term matrix varying only the token (unigram, bigram). In total, these parameter combinations produced 154 supervised machine-learning models.

I used the SuperLearner package in R to estimate each supervised machine learning model (Van der Laan, Polley and Hubbard 2007). SuperLearner is an ensemble-based package that uses cross-folded validation to weight multiple learning algorithms. The model weights were then combined into an ensemble, which was used to predict values. Table 5.1 details the machine learning algorithms used in the learning library. The coefficients in the Word2Vec, Paragraph2Vec, and DTM columns represent the weights applied for the best-performing parameter arrangement for each model. Table 5.2 shows performance statistics calculated from a confusion matrix comparing hand-coded and predicted values in the validation set for the best-performing Word2Vec, Paragraph2Vec, and DTM models. All models perform worse than the bigram dictionary method. The Kappa Correlation coefficient between the hand-coded and predicted values for the race statement variable is less than 0.1 across all models.

Table 5.1: Machine Learning Algorithms

Learning Model	Abbreviated Name	Coefficient (Word2Vec)	Coefficient (Paragraph2Vec)	Coefficient (DTM)
Kernlab's Support Vector Machine	KSVM	0.02	0.64	-
Elastic Net Regression (Lasso)	GLMNET	-	-	0.02
Neural Networks	NNET	-	-	-
Random Forest	randomForest	0.61	-	0.96
Linear Discriminant Analysis	LDA	-	-	0.015
Recursive Partitioning for Classification and Regression Trees	RPART	-	-	-
Lasso and Elastic Net for Big Data	BigLasso	-	-	-
Bayesian Generalized Linear Model	BayesGLM	-	-	-
Extreme Gradient Boosting	XGBoost	-	-	-
Linear Regression Model	LM	-	0.36	-
Fast Implementation Random Forest	Ranger	0.36	-	-

Note: Machine learning algorithms and coefficient weights used for each ensemble. Coefficient weights listed for the best performing Word2Vec, Paragraph2Vec, and DTM models.

[2]These values were based on parameters used in existing work that uses supervised machine learning models to estimate scores from committee hearing text (Park 2023).

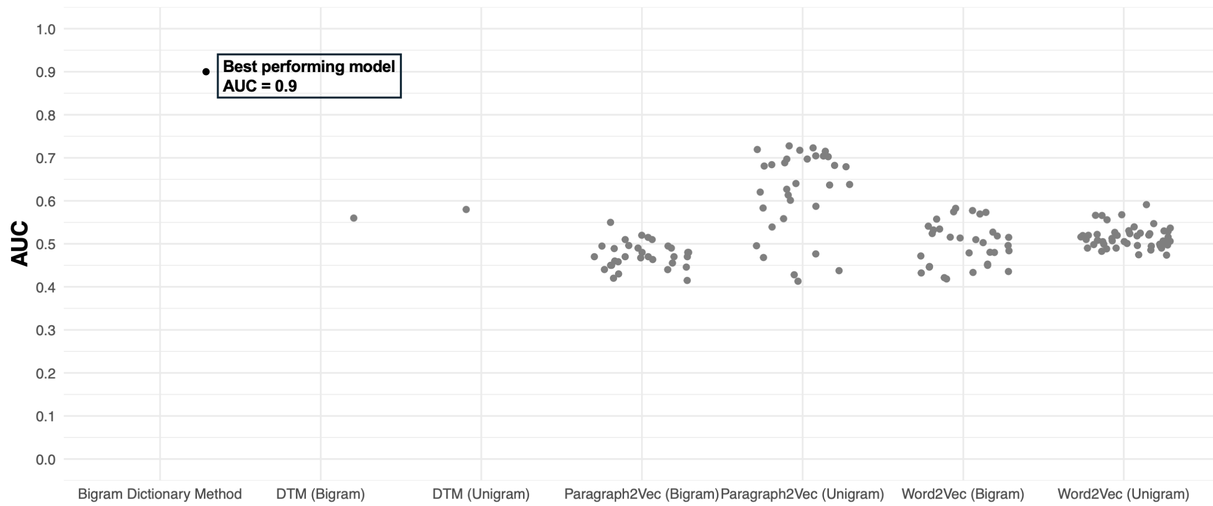
Table 5.2: **Performance Metrics with Supervised Machine Learning Models**

	Algorithm	Class Imbalance Weighting	Oversampling Minority Class	Accuracy	Sensitivity	Specificity	AUC	Balanced Accuracy	Kappa Correlation Coefficient
Word2Vec	Ensemble	(0 = 1, 1 = 1.5)	Yes	0.40	0.92	0.08	0.50	0.51	0.009
Paragraph2Vec	Ensemble	(0 = 1, 1 = 1.7)	Yes	0.73	0.93	0.13	0.56	0.53	0.07
Document-Term Matrix (DTM)	Ensemble	(0 = 0.7, 1 = 1)	Yes	0.10	1.00000	0.08546	0.53	0.54	0.003

Note: Machine learning models performed poorly. Table lists performance statistics for best performing Word2Vec, Paragraph2Vec, and DTM models. Across all three models, the AUC was no greater than 0.56 and the Kappa Correlation Coefficient was less than 0.1.

Figure 5.3 displays the AUC for each machine learning model compared to the bigram dictionary method. Though Paragraph2Vec models outperform the DTM and Word2Vec models, the bigram dictionary model substantially outperforms all models. As a result, the bigram dictionary model was used to predict the final measures for each race variable.

Figure 5.3: Distribution of AUC from Supervised Machine Learning Models



Note: Each dot represent the AUC from a supervised machine learning model. The bigram dictionary method was the best performing model (AUC = 0.9).

6 Models for In-Text Figures

6.1 Table 6.1: Nonwhite Lawmakers Discuss Race More Than White Lawmakers

	Race Statement	Race Statement	Race Statement (Black)	Race Statement (Black)	Race Statement (Latino)	Race Statement (Latino)	Race Statement (Asian)	Race Statement (Asian)
Nonwhite Lawmaker	1.215***	0.992***						
	(0.022)	(0.118)						
% Nonwhite in District		0.751**						
		(0.265)						
Black Lawmaker			1.647***	1.202***				
			(0.036)	(0.154)				
% Black in District				1.847***				
				(0.350)				
Latino Lawmaker					1.794***	0.730**		
					(0.067)	(0.230)		
% Latino in District						1.535***		
						(0.349)		
Asian Lawmaker							2.039***	1.125**
							(0.180)	(0.365)
% Asian in District								1.406
								(1.177)
Democrat		-0.217		-0.623		-0.469		-0.369
		(0.303)		(0.497)		(0.587)		(0.703)
Committee Chair		-0.122		-0.070		-0.515		-0.732
		(0.150)		(0.202)		(0.337)		(0.387)
Nonwhite Committee Chair		-0.828***		-0.775**		-0.414		0.348
		(0.189)		(0.243)		(0.394)		(0.510)
On Committee With Nonwhite Chair		0.146		0.019		0.168		0.002
		(0.082)		(0.116)		(0.119)		(0.225)
Race Hearing		0.823***		0.680***		0.599***		0.663***
		(0.104)		(0.055)		(0.067)		(0.095)
Legislative Hearing		0.105		-0.019		-0.369*		-0.446
		(0.062)		(0.119)		(0.168)		(0.265)
Oversight Hearing		-0.165*		-0.143		-0.484**		-0.534
		(0.071)		(0.103)		(0.172)		(0.275)
Female Lawmaker		0.324***		0.456***		0.223		0.376
		(0.078)		(0.099)		(0.127)		(0.208)
LGBTQ Lawmaker		-0.587*		-1.167***		-1.066*		-0.013
		(0.238)		(0.333)		(0.542)		(0.555)
DW-Nominate (1st Dimension)		-0.707*		-1.265*		-1.549*		-1.329
		(0.321)		(0.527)		(0.703)		(0.849)
DW-Nominate (2nd Dimension)		-0.487***		-1.011***		-0.341		-0.321
		(0.142)		(0.206)		(0.263)		(0.376)
Seniority		-0.033***		-0.053***		-0.049***		-0.011
		(0.008)		(0.010)		(0.014)		(0.020)
Word Count		0.004***		0.003***		0.003***		0.002***
		(0.000)		(0.000)		(0.000)		(0.000)
In Majority Party		-0.112		-0.235*		-0.326**		-0.209
		(0.074)		(0.098)		(0.125)		(0.224)
Subcommittee Hearing		0.004		-0.072		-0.003		0.455*
		(0.074)		(0.107)		(0.145)		(0.214)
Vote Share		0.002		0.003		0.017***		0.009
		(0.003)		(0.004)		(0.004)		(0.008)
Intercept		-6.012***		-6.759***		-8.429***		-8.606***
		(0.502)		(0.545)		(0.731)		(1.075)
Hearing Fixed Effects	✓		✓		✓		✓	
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Committee Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	466382	785565	260264	785565	143644	778004	46567	777563

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Nonwhite, Black, Latino, and Asian lawmakers mention race more frequently (and their respective racial group) than white lawmakers. Standard errors are in parentheses under the coefficient and are clustered by legislator. Models are estimated with hearing fixed effects or committee and term fixed effects.

6.2 Table 6.2: Nonwhite Lawmakers' Statements Are More Racially Dense Statements than White Lawmakers

	Race Statement Density	Race Statement Density	Race Statement Density (Black)	Race Statement Density (Black)	Race Statement Density (Latino)	Race Statement Density (Latino)	Race Statement Density (Asian)	Race Statement Density (Asian)
Nonwhite Lawmaker	0.031^{***}	0.028^{***}						
	(0.001)	(0.005)						
% Nonwhite in District		0.029^{**}						
		(0.009)						
Black Lawmaker			0.020^{***}	0.018^{**}				
			(0.000)	(0.005)				
% Black in District				0.024^{*}				
				(0.010)				
Latino Lawmaker					0.008^{***}	0.004^{**}		
					(0.000)	(0.001)		
% Latino in District						0.004^{***}		
						(0.001)		
Asian Lawmaker							0.004^{***}	0.004^{*}
							(0.000)	(0.001)
% Asian in District								0.002
								(0.002)
Democrat		-0.012		-0.003		-0.002		-0.000
		(0.008)		(0.004)		(0.002)		(0.000)
Committee Chair		0.002		0.001		-0.000		0.000
		(0.003)		(0.001)		(0.000)		(0.000)
Nonwhite Committee Chair		-0.029^{***}		-0.014^{***}		-0.002		-0.000
		(0.007)		(0.004)		(0.001)		(0.001)
On Committee With Nonwhite Chair		0.003		-0.000		0.000		-0.000
		(0.003)		(0.002)		(0.000)		(0.000)
Race Hearing		0.142^{***}		0.051^{***}		0.007^{**}		0.005^{**}
		(0.024)		(0.010)		(0.002)		(0.002)
Legislative Hearing		0.002		0.000		-0.001^{**}		-0.000^{*}
		(0.002)		(0.001)		(0.000)		(0.000)
Oversight Hearing		-0.004^{**}		-0.002^{*}		-0.001^{*}		-0.001^{*}
		(0.001)		(0.001)		(0.000)		(0.000)
Female Lawmaker		0.010^{**}		0.005^{***}		0.000		0.000
		(0.003)		(0.002)		(0.001)		(0.000)
LGBTQ Lawmaker		-0.014^{*}		-0.006^{*}		-0.002^{*}		-0.000
		(0.006)		(0.003)		(0.001)		(0.001)
DW-Nominate (1st Dimension)		-0.014		-0.003		-0.004^{*}		-0.001
		(0.009)		(0.004)		(0.002)		(0.001)
DW-Nominate (2nd Dimension)		-0.019^{**}		-0.011^{**}		-0.001		-0.001
		(0.007)		(0.004)		(0.001)		(0.000)
Seniority		-0.001^{**}		-0.000^{**}		-0.000^{*}		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Word Count		0.000^{***}		0.000^{***}		0.000^{***}		0.000^{***}
		(0.000)		(0.000)		(0.000)		(0.000)
In Majority Party		0.011^{***}		0.004^{***}		0.001^{***}		0.000^{**}
		(0.002)		(0.001)		(0.000)		(0.000)
Subcommittee Hearing		0.001		-0.000		0.000		0.001^{*}
		(0.002)		(0.001)		(0.000)		(0.000)
Vote Share		0.000^{*}		0.000^{*}		0.000^{**}		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Intercept	0.011^{***}	-0.038^{**}	0.003^{***}	-0.012^{*}	0.001^{***}	-0.005^{***}	0.000^{***}	-0.001
	(0.000)	(0.012)	(0.000)	(0.005)	(0.000)	(0.001)	(0.000)	(0.001)
Hearing Fixed Effects	✓		✓		✓		✓	
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Committee Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1422938	786161	1422938	786161	1422938	781801	1422938	786161

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Nonwhite, Black, Latino, and Asian lawmakers make more racially dense statements than White lawmakers. Dependent variables (continous) measure the total number of racial bigrams in a given statement. Models are OLS regressions with standard errors in parentheses under the coefficient (clustered by legislator). Models are estimated with hearing fixed effects or committee and term fixed effects.

6.3 Table 6.3: White Lawmakers Mention Race More on Racially Diverse Committees

	Race Statement	Race Statement	Race Statement	Race Statement	Race Statement	Race Statement
White Lawmaker	-1.756***	-1.603***	-1.689***	-1.341***	-1.690***	-1.339***
	(0.069)	(0.085)	(0.040)	(0.059)	(0.040)	(0.059)
% Nonwhite on Committee	0.000	-0.005			0.002	-0.004
	(.)	(0.003)			(0.002)	(0.003)
White Lawmaker x % Nonwhite on Committee	0.022***	0.025***				
	(0.003)	(0.003)				
% Nonwhite in Hearing			0.007***	0.009***	0.007***	0.009***
			(0.001)	(0.001)	(0.001)	(0.001)
White Lawmaker x % Nonwhite in Hearing			0.018***	0.019***	0.018***	0.019***
			(0.001)	(0.002)	(0.001)	(0.002)
Democrat		-0.154		-0.048		-0.051
		(0.092)		(0.092)		(0.092)
% Nonwhite in District		0.669***		0.697***		0.696***
		(0.083)		(0.084)		(0.084)
Race Hearing		0.829***		0.805***		0.806***
		(0.032)		(0.031)		(0.031)
Legislative Hearing		0.103*		0.120**		0.119**
		(0.046)		(0.046)		(0.046)
Oversight Hearing		-0.165***		-0.152**		-0.152**
		(0.050)		(0.050)		(0.050)
Female Lawmaker		0.350***		0.337***		0.337***
		(0.028)		(0.028)		(0.028)
LGBTQ Lawmaker		-0.568***		-0.568***		-0.567***
		(0.098)		(0.098)		(0.098)
DW-Nominate (1st Dimension)		-0.638***		-0.582***		-0.587***
		(0.098)		(0.099)		(0.099)
DW-Nominate (2nd Dimension)		-0.477***		-0.471***		-0.470***
		(0.040)		(0.040)		(0.040)
Committee Chair		-0.517***		-0.516***		-0.518***
		(0.056)		(0.056)		(0.056)
On Committee With Nonwhite Chair		0.093*		0.065		0.071
		(0.037)		(0.036)		(0.037)
Seniority		-0.035***		-0.034***		-0.034***
		(0.003)		(0.003)		(0.003)
Word Count		0.004***		0.004***		0.004***
		(0.000)		(0.000)		(0.000)
In Majority Party		-0.044		-0.065*		-0.066*
		(0.031)		(0.031)		(0.031)
Subcommittee Hearing		-0.001		-0.025		-0.027
		(0.032)		(0.032)		(0.033)
Vote Share		0.003**		0.003*		0.003*
		(0.001)		(0.001)		(0.001)
Intercept		-4.876***	-4.749***	-5.265***	-4.768***	-5.220***
		(0.185)	(0.111)	(0.179)	(0.113)	(0.183)
Hearing Fixed Effects	✓					
Term Fixed Effects	✓	✓	✓	✓	✓	✓
Committee Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	466382	785565	1418885	784271	1418885	784271

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White lawmakers discuss race more frequently in diverse committees and hearings. Standard errors in parentheses under the coefficient (clustered by legislator). Models are estimated with hearing fixed effects or committee and term fixed effects.

6.4 Table 6.4: White Lawmakers Mention Race More on Racially Diverse Committees (Within-Legislator Design)

	Total Race Statements Per Term (White Lawmakers)
% Nonwhite on Committee	0.122^{***}
	(0.022)
In Majority Party	1.918
	(1.944)
% Nonwhite Lawmakers in House	0.092
	(0.050)
% Nonwhite in District	2.479
	(1.721)
DW-Nominate (1st Dimension)	2.840
	(4.386)
Number of Bills Sponsored	0.046^{***}
	(0.012)
Vote Share	-0.019
	(0.011)
Intercept	-5.080
	(3.056)
Legislator Fixed Effects	✓
Committee Fixed Effects	✓
Observations	2051

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White lawmakers discuss race more frequently in diverse committees and hearings. Standard errors in parentheses under the coefficient. Models are estimated with legislator and committee fixed effects, as well as time-varying controls.

6.5 Table 6.5: Lawmakers Who Make Race Statements In Hearings Are More Effective At Legislating Race Issue Bills

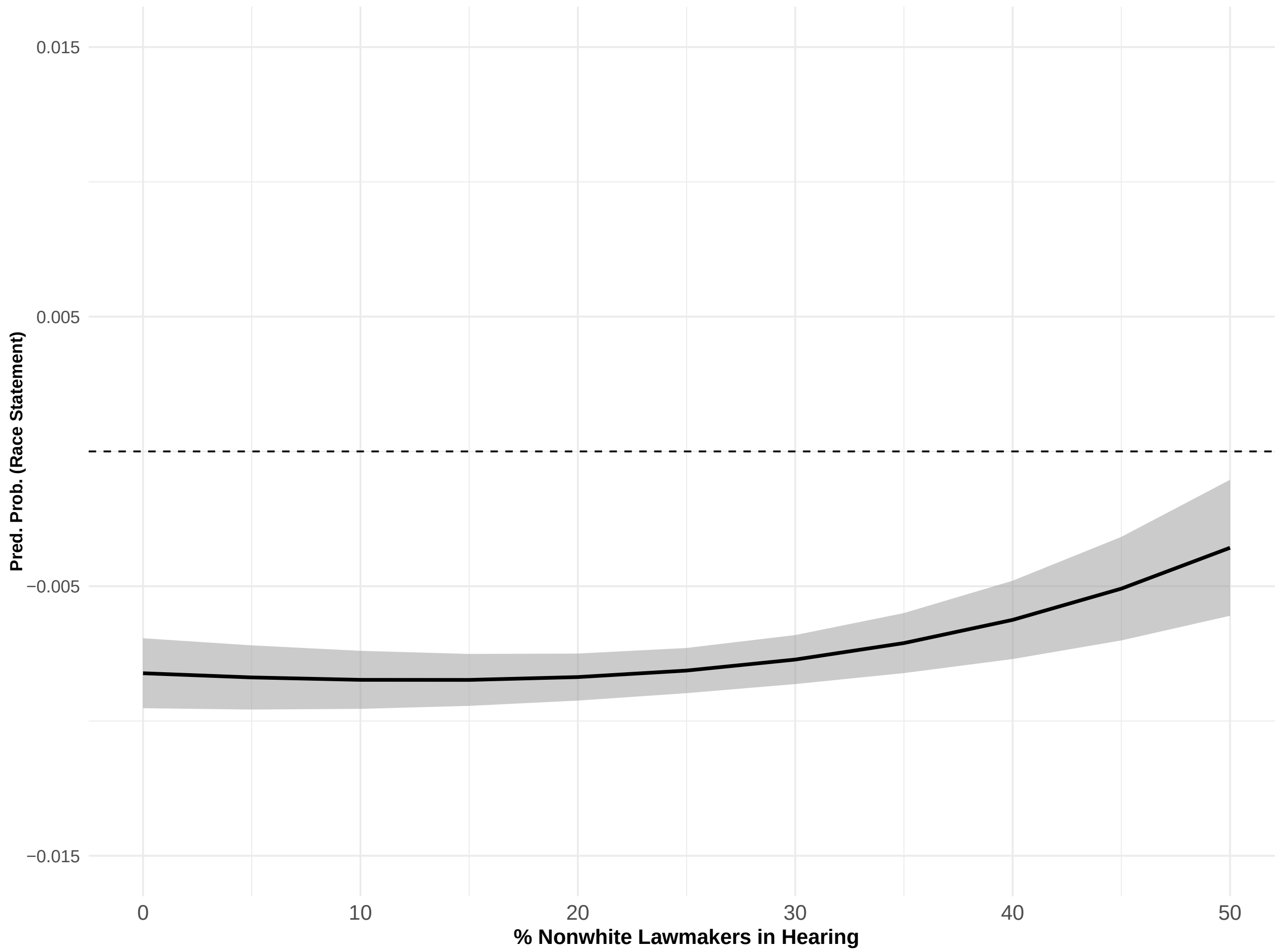
	1 ABC (Race Issue Bills)	2 PASS (Race Issue Bills)	3 LAW (Race Issue Bills)	4 LES (Race Issue Bills)	5 ABC (Non-Race Issue Bills)	6 PASS (Non-Race Issue Bills)	7 LAW (Non-Race Issue Bills)	8 LES (Non-Race Issue Bills)
Race Statements in Hearings	**0.0195*****	**0.0142*****	0.00160	**0.0759*****	0.00901	-0.00489	-0.000983	0.00434
	(0.00481)	(0.00430)	(0.00105)	(0.0148)	(0.0107)	(0.00526)	(0.00295)	(0.00565)
Nonwhite	-0.0449	-0.0362	-0.00898	-0.333	0.0292	0.0300	0.0673	0.0766
	(0.0384)	(0.0297)	(0.0103)	(0.173)	(0.159)	(0.120)	(0.0691)	(0.0904)
Democrat	-0.0756	-0.0706	0.0377	-0.0747	-1.319**	-1.378***	-0.250	-0.702**
	(0.101)	(0.0821)	(0.0268)	(0.442)	(0.436)	(0.380)	(0.150)	(0.240)
% Nonwhite in District	-0.0652	-0.00694	-0.00654	-0.260	0.295	0.554	0.126	-0.399
	(0.0897)	(0.0728)	(0.0275)	(0.431)	(0.484)	(0.365)	(0.170)	(0.254)
Nonwhite Chair	-0.179	-0.303	-0.127	-0.690	0.946	0.183	-0.347	-0.814
	(0.231)	(0.201)	(0.0754)	(1.328)	(1.196)	(0.959)	(0.483)	(0.623)
Committee Chair	0.332*	0.282*	0.144**	1.991*	3.679***	2.537***	0.918***	1.816***
	(0.148)	(0.126)	(0.0464)	(0.812)	(0.583)	(0.414)	(0.190)	(0.302)
In Majority Party Leadership	0.261	0.272*	0.0590	1.639	0.299	0.380	0.0609	0.291
	(0.152)	(0.132)	(0.0456)	(1.109)	(0.372)	(0.277)	(0.155)	(0.307)
In Minority Party Leadership	0.00658	0.0195	-0.0127*	-0.0821	-0.213	-0.0723	0.0475	-0.0149
	(0.0361)	(0.0332)	(0.00611)	(0.132)	(0.288)	(0.231)	(0.101)	(0.190)
Speaker	-0.453**	-0.402**	-0.0934*	-2.151	2.022***	0.447	0.711***	1.513***
	(0.160)	(0.139)	(0.0449)	(1.121)	(0.393)	(0.289)	(0.163)	(0.309)
Subcommittee Chair	0.0372	0.0535	0.0118	0.458*	0.599***	0.337**	0.132*	0.443***
	(0.0397)	(0.0347)	(0.0133)	(0.209)	(0.164)	(0.125)	(0.0578)	(0.104)
Ideological Distance from Floor Median	0.163	-0.0205	-0.0383	0.712	-1.280**	-0.911*	-0.495**	-0.389
	(0.129)	(0.106)	(0.0329)	(0.654)	(0.475)	(0.375)	(0.153)	(0.267)
Served in State Legislature	-0.00129	-0.0110	0.00654	0.166	0.0530	-0.0238	0.0358	0.0564
	(0.0275)	(0.0238)	(0.00782)	(0.149)	(0.115)	(0.0875)	(0.0363)	(0.0639)
Female Lawmaker	-0.00425	-0.00315	0.00553	0.0446	-0.0751	-0.00397	-0.0526	0.0270
	(0.0333)	(0.0286)	(0.0104)	(0.198)	(0.135)	(0.108)	(0.0482)	(0.0793)
LGBTQ Lawmaker	0.0789	0.0521	0.0708	0.760	0.280	0.261	0.0623	0.116
	(0.109)	(0.0698)	(0.0579)	(0.857)	(0.287)	(0.237)	(0.102)	(0.220)
DW-Nominate (1st Dimension)	-0.0232	-0.0124	0.0630	0.0307	-0.732	-1.022*	-0.165	-0.544
	(0.137)	(0.108)	(0.0333)	(0.581)	(0.500)	(0.421)	(0.163)	(0.290)
DW-Nominate (2nd Dimension)	0.103	0.0457	0.00318	0.348	0.662**	0.518**	0.152*	0.119
	(0.0552)	(0.0442)	(0.0134)	(0.230)	(0.204)	(0.161)	(0.0713)	(0.130)
Seniority	0.00166	-0.000174	0.00289	-0.00964	0.00587	-0.00907	-0.000181	0.0329**
	(0.00545)	(0.00407)	(0.00158)	(0.0186)	(0.0168)	(0.0122)	(0.00580)	(0.0120)
In Majority Party	0.212***	0.0815	-0.00285	0.726*	0.449	0.223	-0.150	0.174
	(0.0618)	(0.0501)	(0.0188)	(0.306)	(0.245)	(0.197)	(0.0800)	(0.140)
Vote Share	-0.00145	-0.000301	0.0000326	-0.00605	-0.0114*	-0.00975*	-0.00215	-0.00135
	(0.00121)	(0.00106)	(0.000421)	(0.00688)	(0.00479)	(0.00384)	(0.00169)	(0.00310)
Total Number of Bills Sponsored	0.00680***	0.00504***	0.00130**	0.0376***	0.0869***	0.0554***	0.0165***	0.0410***
	(0.00142)	(0.00114)	(0.000452)	(0.00646)	(0.00936)	(0.00610)	(0.00232)	(0.00427)
Intercept	-0.0752	0.0310	0.00896	0.594	1.896***	1.799***	0.637***	0.709*
	(0.127)	(0.111)	(0.0466)	(0.873)	(0.507)	(0.430)	(0.162)	(0.317)
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2587	2587	2587	2587	2065	2065	2065	2065

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Lawmakers who make race statements in hearings are more effective at legislating race-issue bills and no more (or less) effective at legislating non-race issue bills. Standard errors (in parentheses) are clustered by legislator. ABC = bill received action beyond committee, PASS = bill passed the House, LAW = bill was signed into law, LES = legislative effectiveness score. Race-issue bills include education, housing, and law and crime bills. Columns 1-4 are subset to include only race-issue bills. Columns 5-8 are subset to include only non-race issue bills.

7 Additional Models

Figure 7.1: Committee Hearing Contact Effects Are Not Dependent On Outliers



Note: Line indicates the predicted probability of white lawmakers making a race statement given the percentage of nonwhite lawmakers in a given hearing. Models were re-estimated when the percentage of nonwhite lawmakers in a hearing is fewer than 50%. The bands represent 95% confidence intervals. The models were estimated with individual and chamber level controls and committee and term fixed effects. Full model reported in Table 7.1 in the appendix. Findings suggest that contact effects exist after removing outliers (the limited number of hearings with greater than 50% Nonwhite lawmakers).

7.1 Table 7.1: Contact Effects Are Not Dependent On Outliers

	Race Statement	Race Statement	Race Statement	Race Statement
White Lawmaker	-1.839***	-1.690***	-1.925***	-1.483***
	(0.070)	(0.093)	(0.058)	(0.082)
% Nonwhite on Committee	0.056***	-0.007		
	(0.004)	(0.004)		
White Lawmaker x % Nonwhite on Committee	0.023***	0.028***		
	(0.003)	(0.003)		
% Nonwhite in Hearing			0.011***	0.013***
			(0.002)	(0.002)
White Lawmaker x % Nonwhite in Hearing			0.026***	0.026***
			(0.002)	(0.003)
Democrat		-0.162		0.024
		(0.092)		(0.102)
% Nonwhite in District		0.672***		0.837***
		(0.084)		(0.092)
Race Hearing		0.823***		0.739***
		(0.032)		(0.031)
Legislative Hearing		0.102*		0.110*
		(0.046)		(0.050)
Oversight Hearing		-0.183***		-0.072
		(0.051)		(0.052)
Female Lawmaker		0.359***		0.311***
		(0.028)		(0.030)
LGBTQ Lawmaker		-0.568***		-0.586***
		(0.098)		(0.103)
DW-Nominate (1st Dimension)		-0.649***		-0.531***
		(0.099)		(0.108)
DW-Nominate (2nd Dimension)		-0.485***		-0.479***
		(0.040)		(0.044)
Committee Chair		-0.523***		-0.595***
		(0.056)		(0.061)
On Committee With Nonwhite Chair		0.096*		-0.019
		(0.037)		(0.042)
Seniority		-0.035***		-0.037***
		(0.003)		(0.003)
Word Count		0.004***		0.004***
		(0.000)		(0.000)
In Majority Party		-0.036		-0.023
		(0.031)		(0.034)
Subcommittee Hearing		-0.014		-0.045
		(0.033)		(0.035)
Vote Share		0.003**		0.004**
		(0.001)		(0.001)
Intercept	-6.356***	-4.815***	-4.649***	-5.413***
	(0.089)	(0.190)	(0.123)	(0.204)
Hearing Fixed Effects	✓			
Term Fixed Effects	✓	✓	✓	✓
Committee Fixed Effects	✓	✓	✓	✓
Observations	1419542	782652	1076504	651541

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Contact effects are not dependent on outliers. White lawmakers discuss race more frequently in diverse committees even when the percentage of nonwhite lawmakers on committees and in hearings does not exceed 50%. Standard errors reported in parentheses under the coefficient (clustered by legislator). Models are estimated with hearing fixed effects or committee and term fixed effects.

7.2 Table 7.2: Potential Committee Selection Effects Do Not Drive Contact Effects

	Race Statement	Race Statement	Race Statement	Race Statement
White Lawmaker	-1.756***	-1.843***	-1.689***	-1.363***
	(0.069)	(0.085)	(0.040)	(0.059)
% Nonwhite on Committee	0.000	-0.019***		
	(.)	(0.003)		
White Lawmaker x % Nonwhite on Committee	0.022***	0.037***		
	(0.003)	(0.003)		
% Nonwhite in Hearing			0.007***	0.007***
			(0.001)	(0.001)
White Lawmaker x % Nonwhite in Hearing			0.018***	0.023***
			(0.001)	(0.002)
Democrat		0.028		0.136
		(0.092)		(0.093)
% Nonwhite in District		0.337***		0.389***
		(0.086)		(0.086)
Race Hearing		0.782***		0.761***
		(0.031)		(0.030)
Legislative Hearing		0.100*		0.119**
		(0.046)		(0.046)
Oversight Hearing		-0.160**		-0.149**
		(0.050)		(0.050)
Female Lawmaker		0.210***		0.184***
		(0.029)		(0.029)
LGBTQ Lawmaker		-0.458***		-0.476***
		(0.098)		(0.098)
DW-Nominate (1st Dimension)		-0.496***		-0.448***
		(0.100)		(0.100)
DW-Nominate (2nd Dimension)		-0.390***		-0.400***
		(0.041)		(0.041)
Committee Chair		-0.805***		-0.800***
		(0.058)		(0.058)
On Committee With Nonwhite Chair		0.081*		0.027
		(0.037)		(0.037)
Seniority		-0.056***		-0.054***
		(0.004)		(0.004)
Word Count		0.004***		0.004***
		(0.000)		(0.000)
In Majority Party		-0.139***		-0.173***
		(0.031)		(0.031)
Subcommittee Hearing		0.001		-0.005
		(0.032)		(0.033)
Vote Share		0.003*		0.002
		(0.001)		(0.001)
Race Statement (Total)		0.031***		0.030***
		(0.001)		(0.001)
Hearings Attended (Total)		0.007***		0.006***
		(0.001)		(0.001)
Intercept		-4.396***	-4.749***	-5.005***
		(0.187)	(0.111)	(0.180)
Hearing Fixed Effects	✓			
Term Fixed Effects	✓	✓	✓	✓
Committee Fixed Effects	✓	✓	✓	✓
Observations	466382	785565	1418885	784271

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Committee selection effects do not drive contact effects. White lawmakers discuss race more frequently in diverse committees and hearings after controlling for lawmakers' total race statements and total hearing attendance. This suggests that effects are not driven by lawmakers who may be predisposed to discuss race and attend hearings more frequently. Standard errors reported in parentheses under the coefficient (clustered by legislator). Models are estimated with hearing fixed effects or committee and term fixed effects.

7.3 Table 7.3: Are Nonwhite Lawmakers More Likely To Reference Other Racial Groups?

	Race Statement	Race Statement (Black)	Race Statement (Latino)	Race Statement (Asian)
Black Lawmaker	0.873***	1.204***	0.968***	0.638
	(0.136)	(0.153)	(0.257)	(0.353)
Latino Lawmaker	0.532***	0.449*	1.155***	0.177
	(0.146)	(0.185)	(0.209)	(0.397)
Asian Lawmaker	0.261	-0.280	-0.147	1.317***
	(0.208)	(0.243)	(0.320)	(0.376)
Democrat	-0.320	-0.506	-0.358	-0.281
	(0.287)	(0.456)	(0.549)	(0.668)
% Black in District	1.325***	2.332***	0.663	1.179
	(0.321)	(0.387)	(0.573)	(0.780)
% Latino in District	0.487*	0.554	1.605***	1.310*
	(0.234)	(0.305)	(0.373)	(0.595)
% Asian in District	-0.041	0.674	-0.054	2.407*
	(0.622)	(0.963)	(1.248)	(1.177)
Committee Chair	0.001	0.294	0.079	-0.340
	(0.167)	(0.215)	(0.358)	(0.305)
Nonwhite Chair	-0.752***	-0.775**	-0.956*	
	(0.179)	(0.238)	(0.436)	
On Committee With Nonwhite Chair	0.117	-0.005	0.189	-0.105
	(0.080)	(0.107)	(0.118)	(0.216)
Female Lawmaker	0.421***	0.429***	0.167	0.228
	(0.073)	(0.098)	(0.109)	(0.194)
LGBTQ Lawmaker	-0.679	-1.265**	-1.273	0.025
	(0.360)	(0.462)	(0.757)	(0.474)
DW-Nomiate (1st Dimension)	-0.884**	-0.970*	-1.085	-0.794
	(0.289)	(0.476)	(0.626)	(0.792)
DW-Nominate (2nd Dimension)	-0.609***	-0.932***	-0.429*	-0.472
	(0.123)	(0.166)	(0.202)	(0.350)
Seniority	-0.032***	-0.035**	-0.032**	-0.005
	(0.007)	(0.011)	(0.012)	(0.020)
Statement Frequency	-0.010**	-0.021***	-0.018***	-0.010*
	(0.003)	(0.003)	(0.005)	(0.004)
Word Count	0.004***	0.004***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
In Majority Party	-0.010	-0.083	-0.196	-0.076
	(0.066)	(0.097)	(0.128)	(0.219)
Subcommittee Hearing	0.043	0.024	0.094	0.517*
	(0.069)	(0.093)	(0.137)	(0.207)
Vote Share	-0.002	-0.000	0.003	-0.003
	(0.003)	(0.004)	(0.005)	(0.008)
Intercept	-5.340***	-6.467***	-7.468***	-7.809***
	(0.511)	(0.522)	(0.682)	(0.998)
Term Fixed Effects	✓	✓	✓	✓
Committee Fixed Effects	✓	✓	✓	✓
Observations	781562	781562	778361	773560

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Nonwhite lawmakers are more likely to reference other racial groups in their hearing statements (except for Asian lawmakers and Asian statements). Standard errors reported in parentheses under the coefficient (clustered by legislator). Model estimated with term and committee fixed effects.

7.4 Table 7.4: Lawmakers Who Make Race Statements In Hearings Are More Effective At Legislating Race Issue Bills (Nonwhite Interaction)

	ABC (Race Issue Bill)	PASS (Race Issue Bill)	LAW (Race Issue Bill)	LES (Race Issue Bill)	ABC (Non-Race Issue Bill)	PASS (Non-Race Issue Bill)	LAW (Non-Race Issue Bill)	LES (Non-Race Issue Bill)
Race Statements in Hearings	0.018*	0.015*	0.003	0.059*	0.038	0.007	0.003	0.028
	(0.009)	(0.007)	(0.003)	(0.023)	(0.029)	(0.013)	(0.006)	(0.019)
Nonwhite Lawmaker	-0.052	-0.034	-0.002	-0.419*	0.173	0.090	0.089	0.194*
	(0.040)	(0.033)	(0.010)	(0.162)	(0.166)	(0.128)	(0.075)	(0.089)
Race Statements in Hearings x Nonwhite Lawmaker	0.002	-0.001	-0.002	0.023	-0.038	-0.016	-0.006	-0.031
	(0.010)	(0.009)	(0.003)	(0.029)	(0.030)	(0.014)	(0.006)	(0.020)
Democrat	-0.075	-0.071	0.037	-0.069	-1.332**	-1.384***	-0.252	-0.712**
	(0.101)	(0.082)	(0.027)	(0.443)	(0.433)	(0.380)	(0.149)	(0.239)
% Nonwhite in District	-0.064	-0.007	-0.008	-0.244	0.268	0.542	0.122	-0.421
	(0.090)	(0.074)	(0.028)	(0.429)	(0.488)	(0.366)	(0.170)	(0.258)
Nonwhite Chair	-0.189	-0.300	-0.117	-0.810	1.191	0.285	-0.310	-0.615
	(0.223)	(0.200)	(0.072)	(1.292)	(1.197)	(0.967)	(0.482)	(0.633)
Committee Chair	0.336*	0.280*	0.140**	2.040*	3.590***	2.500***	0.904***	1.743***
	(0.143)	(0.120)	(0.044)	(0.817)	(0.581)	(0.418)	(0.192)	(0.300)
In Majority Party Leadership	0.261	0.272*	0.059	1.637	0.300	0.381	0.061	0.291
	(0.152)	(0.133)	(0.046)	(1.108)	(0.373)	(0.278)	(0.155)	(0.309)
In Minority Party Leadership	0.007	0.020	-0.013*	-0.082	-0.218	-0.074	0.047	-0.019
	(0.036)	(0.033)	(0.006)	(0.132)	(0.284)	(0.229)	(0.100)	(0.186)
Speaker	-0.454**	-0.402**	-0.093*	-2.158	2.032***	0.452	0.713***	1.522***
	(0.160)	(0.139)	(0.045)	(1.120)	(0.396)	(0.290)	(0.164)	(0.311)
Subcommittee Chair	0.038	0.053	0.011	0.472*	0.574***	0.326**	0.128*	0.423***
	(0.041)	(0.035)	(0.014)	(0.211)	(0.165)	(0.126)	(0.058)	(0.102)
Ideological Distance fromn Floor Median	0.166	-0.021	-0.041	0.742	-1.347**	-0.939*	-0.505**	-0.443
	(0.129)	(0.105)	(0.033)	(0.656)	(0.486)	(0.378)	(0.155)	(0.271)
Served in State Legislature	-0.001	-0.011	0.006	0.169	0.044	-0.028	0.034	0.049
	(0.027)	(0.024)	(0.008)	(0.150)	(0.114)	(0.087)	(0.036)	(0.063)
Female Lawmaker	-0.005	-0.003	0.006	0.039	-0.067	-0.001	-0.051	0.033
	(0.033)	(0.028)	(0.010)	(0.199)	(0.134)	(0.108)	(0.048)	(0.080)
LGBTQ Lawmaker	0.078	0.052	0.072	0.751	0.296	0.268	0.065	0.130
	(0.109)	(0.070)	(0.058)	(0.852)	(0.281)	(0.237)	(0.100)	(0.207)
DW-Nominate (1st Dimension)	-0.024	-0.012	0.064	0.023	-0.720	-1.017*	-0.163	-0.534
	(0.136)	(0.107)	(0.033)	(0.583)	(0.499)	(0.421)	(0.163)	(0.290)
DW-Nominate (2nd Dimension)	0.103	0.046	0.003	0.346	0.665***	0.519**	0.152*	0.121
	(0.055)	(0.044)	(0.013)	(0.230)	(0.200)	(0.160)	(0.071)	(0.128)
Seniority	0.002	-0.000	0.003	-0.010	0.006	-0.009	-0.000	0.033**
	(0.005)	(0.004)	(0.002)	(0.019)	(0.017)	(0.012)	(0.006)	(0.012)
In Majority Party	0.212***	0.082	-0.003	0.725*	0.444	0.221	-0.151	0.170
	(0.062)	(0.050)	(0.019)	(0.307)	(0.248)	(0.197)	(0.080)	(0.142)
Vote Share	-0.001	-0.000	0.000	-0.006	-0.011*	-0.009*	-0.002	-0.001
	(0.001)	(0.001)	(0.000)	(0.007)	(0.005)	(0.004)	(0.002)	(0.003)
Total Number of Bills Sponsored	0.007***	0.005***	0.001**	0.038***	0.086***	0.055***	0.016***	0.040***
	(0.001)	(0.001)	(0.000)	(0.006)	(0.009)	(0.006)	(0.002)	(0.004)
Intercept	-0.073	0.030	0.007	0.622	1.866***	1.786***	0.633***	0.684*
	(0.125)	(0.110)	(0.047)	(0.877)	(0.506)	(0.429)	(0.162)	(0.319)
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2587	2587	2587	2587	2065	2065	2065	2065

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Lawmakers who make race statements in hearings are more effective at legislating race-issue bills and no more (or less) effective at legislating non-race issue bills. Nonwhite lawmakers race-based committee hearing statements does not increase their effectiveness on race-issue bills more than white lawmakers. Standard errors (in parentheses) are clustered by legislator. ABC = bill received action beyond committee, PASS = bill passed the House, LAW = bill was signed into law, LES = legislative effectiveness score. Race-issue bills include education, housing, and law and crime bills. Columns 1-4 are subset to include only race-issue bills. Columns 5-8 are subset to include only non-race issue bills.

7.5 Table 7.5: Lawmakers Who Make Race Statements In Legislative Hearings Are More Effective At Legislating Race Issue Bills

	ABC (Race Issue Bill)	PASS (Race Issue Bill)	LAW (Race Issue Bill)	LES (Race Issue Bill)	ABC (Non-Race Issue Bill)	PASS (Non-Race Issue Bill)	LAW (Non-Race Issue Bill)	LES (Non-Race Issue Bill)
Race Statements in Legislative Hearings	0.000449^{+}	0.000358*	0.000008	0.000405	-0.000327	-0.000589**	0.000117	0.000414
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Nonwhite	0.079016	0.052188	0.007967	0.108119	0.093548	0.013072	0.097044	0.190703^{+}
	(0.051)	(0.042)	(0.012)	(0.239)	(0.197)	(0.134)	(0.068)	(0.115)
Democrat	-0.179785	-0.142957	0.013843	-0.495111	-0.984331*	-1.199138**	-0.223757	-0.729246**
	(0.120)	(0.095)	(0.026)	(0.548)	(0.490)	(0.392)	(0.178)	(0.272)
% Nonwhite in District	-0.098263	-0.004542	-0.025355	-0.414824	0.297259	0.775471^{+}	0.282653	-0.340015
	(0.120)	(0.099)	(0.033)	(0.594)	(0.613)	(0.440)	(0.198)	(0.338)
Nonwhite Chair	-0.374377	-0.439993*	-0.165629^{+}	-2.129995	0.148213	-0.383939	-0.220239	-0.775372
	(0.318)	(0.213)	(0.091)	(1.601)	(1.766)	(1.377)	(0.661)	(0.951)
Committee Chair	0.452850*	0.384243*	0.207413**	2.904739*	4.445104***	2.941621***	0.872591***	1.951070***
	(0.206)	(0.174)	(0.063)	(1.136)	(0.749)	(0.514)	(0.226)	(0.336)
In Majority Party Leadership	0.315120	0.310031	0.017553	1.803046	0.597846	0.761043	0.228859	0.554637
	(0.241)	(0.207)	(0.041)	(1.605)	(0.621)	(0.484)	(0.286)	(0.536)
In Minority Party Leadership	-0.032505	-0.013866	-0.014319^{+}	-0.255797^{+}	0.128257	0.232525	0.210565^{+}	0.262144
	(0.036)	(0.032)	(0.008)	(0.154)	(0.290)	(0.239)	(0.126)	(0.367)
Speaker	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Subcommittee Chair	0.049072	0.058068	0.002269	0.632250*	0.314604	0.194683	0.043142	0.309135**
	(0.050)	(0.043)	(0.015)	(0.259)	(0.194)	(0.144)	(0.069)	(0.113)
Ideological Distance from Floor Median	0.235179	0.018683	-0.034780	0.981959	-1.490141*	-1.095582*	-0.723173***	-0.603327^{+}
	(0.171)	(0.130)	(0.037)	(0.882)	(0.610)	(0.444)	(0.191)	(0.342)
Served in State Legislature	0.010834	-0.002109	0.005124	0.257540	0.091224	0.016659	0.059781	0.025620
	(0.035)	(0.031)	(0.010)	(0.197)	(0.144)	(0.104)	(0.046)	(0.078)
Female Lawmaker	0.046752	0.045264	0.007297	0.105544	-0.117840	-0.053037	-0.044125	-0.001401
	(0.046)	(0.041)	(0.014)	(0.232)	(0.173)	(0.128)	(0.058)	(0.105)
LGBTQ Lawmaker	0.106997	0.069726	0.063303	1.094526	0.318279	0.403863	0.220305*	0.288055
	(0.158)	(0.099)	(0.076)	(1.211)	(0.265)	(0.295)	(0.101)	(0.299)
DW-Nominate (1st Dimension)	-0.151886	-0.093781	0.030745	-0.519818	-0.185532	-0.642870	-0.003763	-0.511965
	(0.161)	(0.123)	(0.031)	(0.718)	(0.548)	(0.425)	(0.191)	(0.320)
DW-Nominate (2nd Dimension)	0.068921	0.022685	-0.019181	0.009919	0.594363*	0.640803***	0.164291*	0.132789
	(0.068)	(0.052)	(0.014)	(0.310)	(0.239)	(0.171)	(0.079)	(0.145)
Seniority	0.002025	-0.000171	0.003180^{+}	-0.009769	0.000888	-0.011115	-0.000785	0.034815*
	(0.007)	(0.005)	(0.002)	(0.026)	(0.022)	(0.014)	(0.008)	(0.016)
In Majority Party	0.281694**	0.126359^{+}	0.005701	1.013835*	0.455739	0.168961	-0.239220*	0.098075
	(0.085)	(0.065)	(0.022)	(0.422)	(0.316)	(0.242)	(0.101)	(0.188)
Vote Share	-0.000514	0.000589	0.000034	-0.002465	-0.009961^{+}	-0.010884*	-0.003461^{+}	-0.002489
	(0.001)	(0.001)	(0.001)	(0.009)	(0.006)	(0.004)	(0.002)	(0.004)
Total Number of Sponsored Bills	0.006805***	0.005046**	0.001148^{+}	0.040712***	0.091595***	0.058763***	0.017473***	0.038221***
	(0.002)	(0.002)	(0.001)	(0.009)	(0.013)	(0.008)	(0.003)	(0.005)
Intercept	-0.123486	-0.002884	0.035645	0.980184	1.744839**	1.778096***	0.784839***	0.991279**
	(0.163)	(0.146)	(0.061)	(1.266)	(0.623)	(0.487)	(0.181)	(0.336)
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1791	1791	1791	1791	1369	1369	1369	1369

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Lawmakers who make race statements in legislative hearings are more effective at legislating race-issue bills and no more (or less) effective at legislating non-race issue bills. Standard errors (in parentheses) are clustered by legislator. ABC = bill received action beyond committee, PASS = bill passed the House, LAW = bill was signed into law, LES = legislative effectiveness score. Race-issue bills include education, housing, and law and crime bills. Columns 1-4 are subset to include only race-issue bills. Columns 5-8 are subset to include only non-race issue bills.

8 Member-Level Models

8.1 Table 8.1: Nonwhite Lawmakers Mention Race Statements More than White Lawmakers

	Race Statement	Race Statement	Race Statement (Black)	Race Statement (Black)	Race Statement (Latino)	Race Statement (Latino)	Race Statement (Asian)	Race Statement (Asian)
Nonwhite Lawmaker	1.397***	0.980***						
	(0.133)	(0.190)						
Black Lawmaker			2.228***	1.539***				
			(0.117)	(0.268)				
% Black in District				2.622***				
				(0.619)				
Latino Lawmaker					1.853***	0.942**		
					(0.216)	(0.333)		
% Latino in District						1.413**		
						(0.512)		
Asian Lawmaker							1.986***	1.327***
							(0.401)	(0.349)
% Asian in District								2.421
								(1.475)
Democrat		-0.152		0.269		0.124		0.292
		(0.340)		(0.416)		(0.474)		(0.668)
Nonwhite Chair		0.000		0.000		0.307		1.041
		(.)		(.)		(0.777)		(0.812)
Committee Chair		0.779**		0.863*		0.124		0.266
		(0.293)		(0.360)		(0.443)		(0.400)
On Committee With Nonwhite Chair		0.057		0.343		0.315		-0.036
		(0.203)		(0.194)		(0.206)		(0.267)
Female Lawmaker		0.427**		0.499***		0.449**		0.570*
		(0.151)		(0.139)		(0.160)		(0.226)
LGBTQ Lawmaker		-0.015		-0.136		0.554		0.235
		(0.546)		(0.398)		(0.488)		(0.445)
DW-Nominate (1st Dimension)		-0.857*		-0.090		-0.757		-0.498
		(0.401)		(0.483)		(0.550)		(0.792)
DW-Nominate (2nd Dimension)		-0.672***		-1.078***		-0.639*		-0.584
		(0.200)		(0.225)		(0.252)		(0.379)
Seniority		0.021		0.012		0.034*		0.044*
		(0.016)		(0.019)		(0.017)		(0.021)
In Majority Party		0.192		0.350**		0.056		0.229
		(0.099)		(0.115)		(0.125)		(0.209)
Vote Share		0.005		0.004		0.020***		0.016*
		(0.004)		(0.005)		(0.005)		(0.007)
Intercept	-1.343***	-1.869**	-3.825***	-3.221***	-3.969***	-4.092***	-3.979***	-5.485***
	(0.172)	(0.578)	(0.380)	(0.618)	(0.488)	(0.731)	(0.645)	(1.163)
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Committee Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4920	2569	4930	2569	4917	2572	4878	2569

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Nonwhite, Black, Latino, and Asian lawmakers mention race more frequently (and their respective racial group) than White lawmakers when the unit of analysis is Member-Term. Standard errors are in parentheses under the coefficient and are clustered by legislator. Models are estimated with committee and term fixed effects.

9 Measuring Race Issue Bills

There are a variety of ways to classify race and non-race issue bills. Most existing approaches have used theoretical considerations to identify race-based legislation. For example, Bratton and Haynie (1999) define race bills as any bill that reduces racial discrimination or improves the socioeconomic status of Black Americans. They find that Black lawmakers introduce more bills related to education, welfare, and appropriations. Grose (2011) defines race bills as civil rights legislation. Rather than classifying race bills *ex-ante*, my approach allows nonwhite lawmakers to identify race issue bills. Using bill data from the 105th – 117th Congresses, I calculate the percentage of nonwhite and white lawmakers that introduce bills in 22 different policy areas. Bills are categorized into policy areas by the *Congressional Bills Project* using the pre-defined coding categories developed by the *Policy Agendas Project* (Baumgartner and Jones 2002). I define race issue bills as the top three policy areas in which nonwhite lawmakers introduce significantly more legislation than white lawmakers. Nonwhite lawmakers are more likely to introduce Education, Housing, and Law and Crime legislation than white lawmakers, and so I code race issue bills as any bill that is included in one of these three policy areas. Importantly, this classification method does not include every policy area in which nonwhite lawmakers introduce more legislation than white lawmakers, but rather the three policy areas in which the percentage of bills introduced by nonwhite and white lawmakers is the greatest.

Most existing scholarship that has classified race issue bills has done so for one racial identity group. For example, both Bratton and Haynie (1999) and Grose (2011) were interested in measuring *Black race bills*. Given that my hearing statement measures identify *all* race statements, my approach to classifying race issue bills should be inclusive of all racial groups. This complicates identifying race legislation based on theoretical considerations, given that Black, Latino, and Asian lawmakers may prioritize different types of legislation. As a result, coding racial legislation as the types of bills that all nonwhite lawmakers are more likely to introduce than white lawmakers addresses this concern.

Table 4 on page 27 models the relationship between lawmakers' race statements in hearings and their legislative effectiveness on race issue bills. The Action Beyond Committee (ABC) variable used in Table 4 counts a lawmaker's total number of sponsored **race** issue legislation (education, housing, and law and crime bills) that receives floor consideration in a given term. The PASS variable counts a lawmaker's total number of sponsored race issue legislation that passes the House of Representatives in a given term. The LAW variable counts the number of lawmakers' sponsored race issue bills that are signed into law. The legislative effectiveness score (LES) variable is a lawmaker's average LES score across each of the three race issue policy areas.

Table 9.1: Race-Issue Bill Introductions by Issue Area

Issue Area	% of Nonwhite Lawmakers Introducing Bills	% of White Lawmakers Introducing Bills	% Nonwhite Bill Introduction Distance	Average Number of Introductions (Nonwhite)	Average Number of Introductions (White)	Average Nonwhite Bill Introduction Distance
Agriculture	18%	22%	-4%	0.319	0.36	-0.041
Civil Rights	18	12	6	0.249	0.162	0.085
Commerce	51	47	4	1.39	1.06	0.33
Defense	47	51	-4	1.13	1.22	-0.09
Education	52	36	**16**	1.15	1.069	**0.46**
Energy	20	33	-13	0.31	0.59	-0.28
Environment	28	36	-8	0.49	0.61	-0.12
Government Operations	66	64	2	1.74	1.52	0.22
Health	62	61	1	1.76	1.88	-0.12
Housing	29	16	**13**	0.53	0.23	**0.3**
Immigration	28	25	3	0.7	0.55	0.15
International Affairs	28	25	3	0.7	0.55	0.15
Labor	38	34	4	0.68	0.62	0.06
Law & Crime	52	44	**8**	1.38	0.94	**0.44**
Macroeconomics	41	52	-11	0.9	1.28	-0.38
Miscellaneous	17	10	7	0.27	0.13	0.14
Native Americans	7	4	3	0.31	0.17	0.14
Public Lands	41	45	-4	0.85	1.08	-0.23
Technology	19	22	-3	0.32	0.36	-0.04
Trade	16	24	-8	0.73	0.95	-0.22
Transportation	33	33	0	0.61	0.6	0.01
Welfare	19	19	0	0.29	0.29	0

Note: Nonwhite lawmakers introduce Education, Housing, and Law & Crime legislation more frequently than white lawmakers. Positive values in the distance columns indicate that bills in the policy area are more likely to be introduce by nonwhite lawmakers, while negative values indicate that bills in the policy area are more likely to be introduced by white lawmakers.

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Appendix—Essay 2

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1 Descriptive Statistics

Variable	Unit of Analysis	Mean	Std. Deviation	Range
Dependent Variables				
Evidence Statements	Member-Term	1.38	2.37	0 – 23
Matching Nonwhite-White Source Mentions	Member-Committee-Term	0.990	0.481	0 – 5
(Race Issue Bills) Action Beyond Committee (ABC)	Member-Term	0.25	0.77	0 – 12
(Race Issue Bills) Passed House (PASS)	Member-Term	0.19	0.65	0 – 11
(Race Issue Bills) Signed Into Law (LAW)	Member-Term	0.04	0.27	0 – 6
(Race Issue Bills) Legislative Effectiveness Score (LES)	Member-Term	1.21	3.69	0 – 51
(Non-Race Issue Bills) Action Beyond Committee (ABC)	Member-Term	2.35	2.76	0 – 25
(Non-Race Issue Bills) Passed House (PASS)	Member-Term	1.59	1.90	0 – 13
(Non-Race Issue Bills) Signed Into Law (LAW)	Member-Term	0.50	0.84	0 – 7
(Non-Race Issue Bills) Legislative Effectiveness Score (LES)	Member-Term	1.08	1.51	0 – 13.7
Primary Independent Variables				
Avg % Nonwhite on Committee	Member-Term	20.8	7.67	0 – 61.9
% Nonwhite on Committee	Member-Committee-Term	20.9	7.94	0 – 61.9
White Lawmaker	Member-Term	0.71	0.46	0 – 1
Control Variables				
Democrat	Member-Term	0.58	0.49	0 – 1
Total Race Statements	Member-Term	5.09	7.87	1 – 87
Total Unique Sources	Member-Committee-Term	1.31	0.88	0 – 13
Nonwhite	Member-Term	0.29	0.46	0 – 1
% Nonwhite in House	Member-Term	17.8	4.71	5.75 – 24.1
% Nonwhite in District	Member-Term	0.33	0.20	0.034 – 0.932
Committee Chair	Member-Term	0.04	0.21	0 – 1
Nonwhite Chair	Member-Term	0.008	0.09	0 – 1
On Committee With Nonwhite Chair	Member-Term	0.132	0.336	0 – 1
Female Lawmaker	Member-Term	0.240	0.427	0 – 1
LGBTQ Lawmaker	Member-Term	0.015	0.121	0 – 1
In Majority Party Leadership	Member-Term	0.021	0.14	0 – 1
In Minority Party Leadership	Member-Term	0.018	0.131	0 – 1
Subcommittee Chair	Member-Term	0.25	0.44	0 – 1
Ideological Distance from Chamber Median	Member-Term	0.43	0.00	0 – 1.09
DW-Nominate (1st Dimension)	Member-Term	-0.035	0.456	-0.819 – 0.936
DW-Nominate (2nd Dimension)	Member-Term	-0.037	0.295	-0.992 – 0.995
Seniority	Member-Term	5.62	4.44	1 – 28
In Majority Party	Member-Term	0.541	0.498	0 – 1
Vote Share	Member-Term	68.3	13.1	43 – 100
Total Bills Sponsored	Member-Term	17.9	12.1	0 – 105

2 Validating Evidence Measure

To assess the face validity of my evidence measure, I report 20 randomly selected evidence statements and 20 randomly selected non-evidence statements. If the measure accurately captures evidence usage, references to evidence should be present in all selected evidence statements and absent from all non-evidence statements—exactly as Tables 2.1 and 2.2 confirm. In Table 2.1, I bolded the evidence references in all 20 evidence statements. While validity is less of a concern since I manually labeled the data rather than relying on automated coding, this face validity check reinforces that the measure accurately captures evidence usage.

Table 2.1: 20 Randomly Selected Evidence Statements

Number	Speech
1	“Thank you, Madam Chair. It was briefly mentioned before, **a report came out from the ACLU** about new facial recognition technology where t**hey downloaded 25,000 arrest records, used them against pictures of every current Member of Congress in the last term. There are 28 false matches**. People of color made up 20 percent of Congress at that time, more now, by the way. And 40 percent of the false matches were people of color, including legendary civil rights hero John Lewis. Obviously, the software as it stood there would disproportionately target minorities. This is a technology that is being used in my hometown of Orlando, only voluntarily, to track officers to test the technology, but certainly it is something that is concerning for us.”
2	“My bill, H.R. 4604, the **CFPB Data Collection Security Act**, once again tries to stop some of **CFPB’s massive data collection by allowing consumers to opt out of all CFPB data collection**. The provision has been modeled after the successful National Do Not Call Registry.”
3	“This is kind of a long set of data, that I am going to mention, but **according to the central personnel data file**, as of September 2006, **the percentage of women in the career SES Government-wide was 28.4 percent and the percentage of minorities was 15.9 percent. Of these, African Americans constituted 8.6 percent, Hispanics 3.6 percent, Asian American/Pacific Islanders 2.3 percent, and American Indian/Alaska Natives 1.3 percent.**”
4	“Thank you very much. Now let’s go to another college, and that is the Coast Guard Academy. The C**omprehensive Climate and Cultural Optimization Review** effort conducted at the Academy, dated February 2007, found that “**The number of African American high school students who are academically ready for an Academy experience, eligible and interested in military services estimated at only 640 young people per year in the Nation.**” Where does this number come from and what is limiting this number? Is it academic qualification or interest in military service, or both?”
5	“I want to talk collections. **ProPublica**, in 2015, conducted an investigation into collection lawsuits, and it was very troublesome because one of the things they discovered was **that debts in most African-American communities were, on average, 20 to 25 percent smaller than the debts in predominantly non-minority communities.** And you had nothing to do with creating that, but I want to know if there is anything afoot in the CFPB to address that issue and reduce the pain it is causing.”
6	“Thank you. Dr. Goodwin, in **October 2021 GAO reported data on missing and murdered Indigenous women is unknown because Federal data bases do not contain comprehensive national data**. I’m deeply concerned about this as Indigenous populations in Oklahoma are affected by these crimes, including human trafficking. What steps can be taken to improve data collection and analysis to better understand and identify these trends of crimes?”
7	“The original bill, the **Dodd-Frank Act**, **created new data reporting requirements that are aimed at helping regulators understand credit conditions for small, women-owned, and minority-owned businesses.**”
8	“Thank you, Mr. Chairman. Mr. Secretary, when you were in Laredo, as you know, Laredo, percentage-wise, according to the **U.S. Census**, is the **most Hispanic city in the country, 96 percent Hispanic.**”
9	“A **2017 report by the Government Accountability Office** found hat violence from the far right has actually accounted for **73 percent of deadly attacks since 9/11**. Last week, the **FBI** urged that White supremacy is a, quote, **“persistent and pervasive threat,”** unquote. Yet, the Administration’s response has been to rescind grants and ask Congress to eliminate DOJ’s community relations service dedicated toward hate crimes and which is dedicated toward preventing hate crimes and combating racial tensions, and DOJ has prosecuted hate crimes at a 20 percent decrease, despite acknowledging the rise in such crimes. What is your organization doing to ensure that there is an appropriate enforcement against these types of hate crimes?” ”
10	“There is a provision in the **Workforce Investment Act** that **prohibits discrimination based on race, color, creed, national origin or sex**. Is there any reason why we ought to change that? Anyone suggesting that we change that so that people would be able to discriminate? ”
11	“The issues raised here today impact far too many people in this country. According to a study by the **Center for American Progress**, **women are the primary sole, or co-bread winners in 64 percent of families.**”
12	“Although Tribal Labor Relations Ordinances have been adopted by some tribes, these ordinances vary greatly in the levels of workforce protection. I have **Section 3107 of the 2010 Blackfeet Tribal Employment Rights Ordinance and Safety Enforcement Act of 2010**, which I ask to insert in the record. It reads ‘‘**Unions are prohibited in the Blackfeet Indian reservation.”** So, there are tribes that discourage unions in their organizations.”
13	“Thank you, Mr. Chairman. Mr. Chairman, I have intelligence indicating that a **2020 Rand survey commissioned by FEMA** found serious cultural issues at the agency for people of color and minorities. The survey assessed gender bias, sexual harassment, and gender discrimination. **This survey found that 29 percent of the employees expressed the views that their civil rights were being violated. Twenty percent reported having experienced civil rights violations based on sex.** Eighteen percent reported having experienced civil rights violations based on race or ethnicity. So, this begs the question, what is FEMA doing to address these allegations? So, Madam Administrator, thank you for being with us today. Sorry, to rush right into this. I have been busy with some other committee assignments as well and if this has already broached–this issue has been brought to your attention, I beg that you would forgive me for asking it twice. But these are things of concern to me.”
14	“Ms. Patterson, you wrote **in your article “Climate Change and Civil Rights Issues”** that the **Black community tends to have a greater dependence on public transportation, that Black individuals are more likely to live in inner cities, and are disproportionately affected in rises in home energy costs.** I would imagine all of these factors play a role in how COVID-19 is impacting the Black community. Is that true? And if yes, how so?”
15	“Mr. Attorney General, in the 2013 decision, **Shelby County v. Holder**, the Supreme Court gutted section 5 of the Voting Rights Act, rendering its preclearance provision inoperative. As a direct result of this decision, the right to vote has come under a renewed and steady assault and States have spent the past eight years enacting a slew of barriers to voting to target or impact communities of color and other historically disenfranchised groups. ”
16	“As I have explored in previous hearings, there are many racial disparities in the unbanked population, and we need to do everything we can to address the underlying factors that inhibit access to basic financial services so that people of color can save and invest for their future. **According to a 2019 FDIC survey**, **nearly half of the unbanked households didn’t even have enough money to start a bank account. About one-third of unbanked households cited both high bank fees and unpredictable bank fees as barriers to getting banked.** ”
17	“Earlier we hard that the Navajo Nation, **EPA has a list of 80 to 90 homes they suspect may have elevated levels of radon. In other words, they believe these homes may be radioactive.** They aren’t sure how many of these homes are currently occupied. Let me ask you, for the record, the Navajo Nation EPA says that it provided a list of these homes to U.S. EPA in 2001. Is that true, and has U.S. EPA had a list of these homes for the past 6 years?”
18	“**The New York Times**, in June 2021, **reported that White disaster victims received more from FEMA than people of color, even when the amount of damage to their homes and properties is the same.** Could you explain why this occurred?”
19	“Yes. But they looked at **31 million HMDA records in a year-long analysis** and found that **61 municipal areas across the United States had denied people of color, black and brown people, the right to take on a mortgage compared to equally qualified whites.** What is the economic impact of that discrimination, in your view? When people can afford a mortgage and are told you can’t have one, what sort of impacts could we expect to see when that happens on a systematic basis?”
20	“The **National Association of Hispanic Real Estate Professionals** predicted that **foreclosures in the Hispanic community alone are expected to reach nearly $25 billion in 2007, and almost twice that–$52 billion–in 2008**. ”

Table 2.2: 20 Randomly Selected Non-Evidence Statements

Number	Speech
1	"Would you, please? Because that would kind of answer some of the questions I have. And then, how many other agencies are involved, or should be involved, besides Fish and Wildlife and the National Institute of Health for being able to determine the status of the health concerns? CDC? What about BIA, Bureau of Indian Affairs? What role do they play in being able to notify Native American tribes? Are they immediate, do you work with them, or do you get them involved immediately and task them with doing the outreach? "
2	"How do you structure a counseling program to not just reach people who are low income and who recognize that they have problems buying a home? That is an obvious target group for you to reach. I am sure there are fairly easy ways to reach them. How do you take it a step further, though, to proactively reach what may be affluent, but discriminated-against homeowners who may be African American or Latino, Puerto Rican? "
3	"Housing is a fundamental human right, yet across the country and in my district, the Massachusetts 7th, millions of people do not have access to a safe, decent, and affordable place to call home. For decades, Black families have been locked out of homeownership opportunities due to discriminatory lending. And now, private-equity-backed institutional landlords have pushed this dream even further out of reach by gobbling up single-family homes and worsening the housing crisis across this country. "
4	"Dr. Fradkin, my first questions nicely piggyback on Mr. Shimkus's question because one of the big concerns of the Diabetes Caucus for a long time has been the disparities between minority populations like African Americans, Latinos and American Indians and Alaska Natives and Anglos, and we are not really sure why those disparities exist other than a combination of factors of health access, community, environment, genetics, so I am wondering if you can talk a little bit more about any ongoing research by NIH to address the cause of the disparities because until we find out the cause, we can't really address how to deal with it."
5	"Thank you, Mr. Chairman. I thank you for this very important hearing on how COVID-19 has increased racial inequities in the country. The shift to distance learning has exposed the educational inequities many students of color have been facing for decades as States start to open back up and grapple with the depleted budgets. It is the role of the Federal Government historically to ensure equity in every sector. And, recently, many competitive colleges, like the University of California's system, private schools such as Harvard University, have suspended the use of ACT and SAT scores in their admissions process to help level the playing field. Mr. King, from your experience, how much of the college admissions process is reliant on these test scores?"
6	"Wages were up, taxes have been cut, regulations reduced, unemployment at its lowest in 50 years, unemployment for African Americans, Hispanic Americans, stock market up, the best economy we've seen. I have had businessowners in our district say best economy they've seen in their entire 30, 35 years in business, best economy ever. "
7	"Are there any African American executive producers types in the audience? Are there any Latino executive producers in the audience? Do you know of any African American and Latino or Asian executive producers?"
8	"It is part racial discrimination– I am just going to submit this for the record. I am new here and this timing thing, there is nothing that Chairwoman Waters can do, but it really–it is just awful, and I come from the Michigan legislature and we never had this like timing thing. But I want to submit this for the record. But I think it is really important to show that right now black applicants were almost twice as likely to be denied conventional home purchase loans as white applicants in 2016, and Detroit alone ranked 44 out of 48 communities nationally that found blacks were denied loans at a higher rate. "
9	"Mr. Lappin, 50 percent, as Mr. Davis indicated, of felons are African American men. I mean, I understand that there have been court suits and we want to make sure we are not segregating people, but of the values, penology values, the notion that–I suppose I would have to ask you."
10	"Great. So, you know, Chicago residents are–that are most impacted by lead service lines are often in communities of color and more low-income communities. So, Mr. Regan, how does investing in drinking water infrastructure contribute to your environmental justice agenda?"
11	"The Coast Guard invited 50 African Americans to the Academy earlier this year and helped them to complete applications. How many of these individuals were subsequently offered appointments to the Academy?"
12	"Thank you. Ms. Sharp, should this committee make the climate justice investments in every Native American nation in this country, as we do in our bill and as we did for COVID-19 funding?"
13	"What specific recommendations do you propose to members of this committee to enact to ensure economic empowerment to the Hispanic community, and what should be the consequences of hearing focused on and what legislative steps can we take?"
14	"Can you tell us how this collaboration between law enforcement and fossil fuel companies puts indigenous women, in particular, at heightened risk of abduction and murder?"
15	"And building off of that a moment, ma'am, targeting amongst the groups that you indicated, minorities, women, lower income communities, and other populations currently underrepresented in the energy sector, how do we assure that they have access to the training and employment in that offshore–as we try to bring offshore wind to market?"
16	"Mr. Chairman, I just simply want to ask permission that my opening statement be included in the record and point out that I am a lead co-sponsor of the bill to End Racial Profiling Act and am very interested in this hearing. Thank you."
17	"Mr. Watts, that is not a protected right. There are certain protected rights. Racial discrimination is a protected right. Discrimination based upon sex is a protected right. But you can discriminate against people because of their views. That is not a protected right under our system. You can do that."
18	"Hey, Chair Castor, this is Garret. Thank you very much for the opportunity for the certainly appropriate honoring of John Lewis. It has been an incredible experience to be able to serve with someone who has played such an amazing role in the Civil Rights Act. You read about these iconic figures, but to be able to serve alongside of him has just been an awing experience. "
19	"Thank you very much. Even though I had not planned on asking this question, I am very interested in knowing what is happening with the evaluation of homes in the Black community, and what is happening with the way that the discrimination appears to have been taking place for so many years."
20	"The gentleman from North Carolina and Ranking Member of the Subcommittee is also the Chairman of the Congressional Black Caucus and has been extraordinarily busy with the passing of Rosa Parks, and so he has been concerned about his time. I leaned over and asked him if he thought I should tap, and his response was more or less no, this is great because we don't have to read it. And so I suggest that is exactly my view, by the way. And so we are going to be a little bit liberal, in fact, forget the clock. Just be interesting and, if you see one of us nodding off, then you know you have probably gone on too long."

3 Models for In-Text Figures

3.1 Table 3.1: White Legislators Make More Evidence-Based Race Statements on Racially Diverse Committees

	Evidence (White Lawmakers)	Evidence (White Lawmakers)	Evidence (White Democrats)	Evidence (White Democrats)	Evidence (White Republicans)	Evidence (White Republicans)
% Nonwhite on Commmittee	0.040^{*}	0.049^{*}	0.070^{**}	0.028	0.019	0.018
	(0.016)	(0.021)	(0.027)	(0.037)	(0.019)	(0.023)
In Majority Party		1.023		-1.898		1.066
		(2.173)		(6.500)		(1.805)
% Nonwhite in House		-0.068		0.003		-0.184^{**}
		(0.053)		(0.084)		(0.058)
% Nonwhite in District		0.106		-0.873		0.098
		(2.026)		(3.305)		(2.511)
DW-Nominate		0.579		-7.187		3.044
		(4.939)		(14.420)		(4.104)
Vote Share		-0.006		-0.016		0.012
		(0.014)		(0.021)		(0.015)
Intercept	-0.280	0.818	-1.304	5.519	0.333	1.411
	(0.494)	(3.581)	(0.927)	(8.802)	(0.535)	(3.418)
Legislator Fixed Effects	✓	✓	✓	✓	✓	✓
Term Fixed Effects	✓		✓		✓	
Observations	1292	750	567	364	725	386

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.2 Table 3.2: Legislators Who Make Evidence-Based Race Statements In Hearings Are More Effective At Legislating Race Issue Bills

	1	2	3	4	5	6	7	8
	ABC (Race Bills)	**PASS (Race Bills)**	**LAW (Race Bills)**	**LES (Race Bills)**	**ABC (Not Race Bills)**	**PASS (Not Race Bills)**	**LAW (Not Race Bills)**	**LES (Not Race Bills)**
Total Evidence Statements	0.0772**	0.0547**	0.00816	0.264***	0.0110	-0.0304	-0.00609	0.0461
	(0.0237)	(0.0186)	(0.00486)	(0.0671)	(0.0427)	(0.0240)	(0.0121)	(0.0382)
Nonwhite	-0.0304	-0.0214	-0.0180	-0.274	0.0247	-0.0461	0.0260	-0.00504
	(0.0498)	(0.0412)	(0.0126)	(0.253)	(0.206)	(0.149)	(0.0781)	(0.117)
Democrat	-0.201	-0.172	0.0135	-0.459	-2.054***	-1.972***	-0.459*	-1.061**
	(0.140)	(0.123)	(0.0309)	(0.617)	(0.610)	(0.554)	(0.213)	(0.327)
% Nonwhite in District	0.0433	0.0796	0.0424	0.167	0.585	0.865	0.272	-0.442
	(0.117)	(0.0989)	(0.0356)	(0.592)	(0.635)	(0.476)	(0.217)	(0.334)
Nonwhite Chair	-0.389	-0.495*	-0.148	-1.761	0.783	0.0321	-0.370	-0.855
	(0.273)	(0.243)	(0.0887)	(1.605)	(1.339)	(1.052)	(0.491)	(0.631)
Committee Chair	0.467*	0.409*	0.158**	2.790*	3.884***	2.746***	1.069***	1.836***
	(0.209)	(0.184)	(0.0595)	(1.271)	(0.800)	(0.578)	(0.246)	(0.370)
In Majority Leadership	0.304	0.299	0.0489	1.357	0.308	0.355	0.238	0.533
	(0.214)	(0.186)	(0.0461)	(1.396)	(0.606)	(0.464)	(0.254)	(0.481)
In Minority Leadership	-0.0250	0.00500	-0.0196	-0.194	-0.354	-0.117	0.181	-0.0793
	(0.0778)	(0.0718)	(0.0116)	(0.261)	(0.551)	(0.414)	(0.174)	(0.233)
Subcommittee Chair	0.0386	0.0563	0.00520	0.290	0.444	0.224	0.169*	0.426**
	(0.0615)	(0.0546)	(0.0188)	(0.282)	(0.227)	(0.165)	(0.0827)	(0.136)
Ideological Distance from Floor Median	0.319	0.0749	-0.0530	1.130	-2.294***	-1.658**	-0.755***	-0.855*
	(0.182)	(0.148)	(0.0362)	(0.830)	(0.631)	(0.524)	(0.205)	(0.358)
State Legislature	-0.0377	-0.0414	-0.0187	-0.0844	0.0681	-0.0603	0.0216	0.0864
	(0.0420)	(0.0375)	(0.0110)	(0.207)	(0.156)	(0.117)	(0.0508)	(0.0857)
Female	-0.00481	-0.000705	0.00180	0.153	0.0326	0.0903	-0.0205	0.0288
	(0.0519)	(0.0462)	(0.0147)	(0.249)	(0.176)	(0.135)	(0.0638)	(0.101)
LGBTQ	-0.00363	0.00955	-0.0325**	0.105	0.365	0.427	0.217	0.281
	(0.115)	(0.0862)	(0.0110)	(0.626)	(0.315)	(0.258)	(0.124)	(0.336)
DW-Nominate (1st Dimension)	-0.118	-0.0838	0.0348	-0.326	-1.148	-1.404*	-0.316	-0.985**
	(0.174)	(0.151)	(0.0341)	(0.771)	(0.684)	(0.596)	(0.218)	(0.368)
DW-Nominate (2nd Dimension)	0.219**	0.120*	0.00479	0.513	0.648**	0.546**	0.116	0.0656
	(0.0739)	(0.0602)	(0.0126)	(0.314)	(0.250)	(0.196)	(0.0913)	(0.144)
Seniority	-0.00209	-0.00143	0.00110	-0.0183	0.00457	-0.0130	-0.00896	0.0245*
	(0.00581)	(0.00554)	(0.00162)	(0.0255)	(0.0203)	(0.0167)	(0.00740)	(0.0115)
In Majority Party	0.317***	0.147*	-0.00827	1.169**	0.305	-0.00558	-0.292*	-0.00106
	(0.0900)	(0.0718)	(0.0215)	(0.413)	(0.352)	(0.277)	(0.116)	(0.196)
Vote Share	-0.0000766	0.00109	0.000364	-0.00129	-0.00961	-0.00771	-0.00238	-0.00195
	(0.00186)	(0.00165)	(0.000569)	(0.0101)	(0.00674)	(0.00558)	(0.00263)	(0.00427)
Total Bills Introduced	0.00657***	0.00514**	0.00122*	0.0336***	0.0823***	0.0511***	0.0136***	0.0369***
	(0.00191)	(0.00164)	(0.000617)	(0.00768)	(0.0109)	(0.00646)	(0.00249)	(0.00459)
Intercept	-0.0761	0.0426	-0.0514	0.398	3.062***	2.647***	1.039***	1.292**
	(0.227)	(0.210)	(0.0466)	(1.348)	(0.789)	(0.687)	(0.263)	(0.405)
Term Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1347	1347	1347	1347	1100	1100	1100	1100

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Additional Models

4.1 Table 4.1: White Legislators Make More Evidence-Based Race Statements on Racially Diverse Committees (Interaction Model)

	1	2	3
	Evidence	**Evidence (Democrat)**	**Evidence (Republican)**
White Lawmaker	-0.921*	-1.308**	1.547
	(0.392)	(0.490)	(1.200)
% Nonwhite on Committee	-0.0296*	-0.0322*	0.0620
	(0.0148)	(0.0149)	(0.0478)
White Lawmaker * % Nonwhite on Committee	0.0563**	0.0749***	-0.0513
	(0.0172)	(0.0225)	(0.0474)
Democrat	-0.00809	—	—
	(0.321)		
% Nonwhite in District	-0.0729	-0.0307	-0.720
	(0.363)	(0.473)	(0.522)
Committee Chair	0.210	0.336	-0.0291
	(0.361)	(0.601)	(0.246)
Nonwhite Chair	1.076	0.845	—
	(0.561)	(0.745)	
On Committee With Nonwhite Chair	-0.0389	-0.0409	-0.00980
	(0.163)	(0.253)	(0.129)
Total Race Statements	0.229***	0.232***	0.215***
	(0.0147)	(0.0154)	(0.0210)
Female	0.0742	0.0448	0.0759
	(0.120)	(0.139)	(0.160)
LGBTQ	0.219	0.263	—
	(0.225)	(0.252)	
DW-Nominate (1st Dimension)	-0.258	-1.107	0.522
	(0.405)	(0.931)	(0.470)
DW-Nominate (2nd Dimension)	0.0677	0.104	0.357
	(0.176)	(0.293)	(0.207)
Seniority	0.0200	0.0292	0.00767
	(0.0121)	(0.0154)	(0.0155)
In Majority Party	-0.0538	-0.676	2.276
	(0.0667)	(0.586)	(1.409)
Vote Share	-0.00120	-0.00813	0.00368
	(0.00362)	(0.00504)	(0.00527)
Intercept	1.385	0.419	-2.575*
	(0.999)	(0.686)	(1.284)
Term Fixed Effects	✓	✓	✓
Observations	1126	717	409

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Table 4.2: White Legislators Make More Evidence-Based Race Statements on Racially Diverse Committees (Count Models)

	1	2
	Evidence White Lawmaker (Poisson Model)	**Evidence White Lawmaker (Negative Binomial)**
% Nonwhite on Committee	0.0289***	0.0266**
	(0.00765)	(0.00961)
Intercept	—	-0.242
		(0.335)
Legislator Fixed Effects	✓	✓
Term Fixed Effects	✓	✓
Observations	913	913

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3 Table 4.3: White Legislators Make More Evidence-Based Race Statements on Racially Diverse Committees (Proportion Models)

	Evidence (White Lawmakers)	Evidence (White Lawmakers)	Evidence (White Democrats)	Evidence (White Democrats)	Evidence (White Republicans)	Evidence (White Republicans)
% Nonwhite on Committee	0.007*	0.006	0.008*	0.012*	0.005	0.001
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.006)
In Majority Party		-0.276		-0.373		-0.278
		(0.360)		(0.891)		(0.432)
% Nonwhite in House		-0.034***		-0.043***		-0.021
		(0.009)		(0.012)		(0.014)
% Nonwhite in District		0.593		0.688		0.236
		(0.335)		(0.453)		(0.601)
DW-Nominate		-0.488		-0.619		-0.488
		(0.817)		(1.977)		(0.982)
Vote Share		0.003		0.005		0.002
		(0.002)		(0.003)		(0.004)
Intercept	0.152	0.802	0.222	0.835	0.122	0.829
	(0.085)	(0.593)	(0.140)	(1.207)	(0.111)	(0.818)
Legislator Fixed Effects	✓	✓	✓	✓	✓	✓
Term Fixed Effects	✓		✓		✓	
Observations	1292	750	567	364	725	386

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix—Essay 3

Table of Contents

1 Occupational Categories (Makse 2019)

Working-Class Occupations	Blue-collar Contractors & Construction Workers Office & Clerical Workers Public Safety Professions Retail & Service Professions Semi-Skilled Laborer Skilled Trade Unskilled Laborers
White-Collar Occupations	Artist Attorney & Judge Business Executive Business owner Clergy Consultant Conservation Professions Design Professions Doctor Education Administrator Education Staff Educator Engineer Finance & Banking Financial Specialists Government Homemaker Humanities Professions Insurance IT Professions Journalism and Media Management Specialists Medical Professions Military Professions Non-profit Operations Managers Physical Scientist Politics & Advocacy Real Estate Social Scientist Social Worker Sports & Entertainment Technician Transportation

2 Computing State Legislative Effectiveness Scores

State Legislative Effectiveness Scores (SLES) are weighted averages calculated for individual legislators (i) in each legislative term (t) within each legislative chamber. SLES consider the number of bill's a legislator (i) introduced (BILL), received action in committee (AIC), received action beyond committee (ABC), passed their chamber (PASS), and became law (LAW) (Bucchianeri et al. 2020, p.6). Each bill is weighted by its overall significance. Commemorative bills are weighed α=1, substantive bills are weighted β=5, and substantive/significant bills are weighed $\gamma = 10$.

Finally, this equation is normalized (n/5) across N legislators to ensure SLES takes a mean value of 1 for each chamber (Bucchianeri et al. 2020, p. 6). I z-score the SLES variable to produce a normal distribution with a mean of zero.

The equation below explains how SLES scores are calculated. For a more detailed description of how legislative effectiveness scores are calculated see Volden & Wiseman (2014), and for more information on state legislative effectiveness scores see Bucchinaeri et al. (2020).

$$SLES_{it} = \left[\begin{array}{c} \dfrac{\alpha BILL_{it}^{C} + \beta BILL_{it}^{S} + \gamma BILL_{it}^{SS}}{\alpha \sum_{j=1}^{N} BILL_{it}^{C} + \beta \sum_{j=1}^{N} BILL_{it}^{S} + \gamma \sum_{j=1}^{N} BILL_{it}^{SS}} \\ + \dfrac{\alpha AIC_{it}^{C} + \beta AIC_{it}^{S} + \gamma AIC_{it}^{SS}}{\alpha \sum_{j=1}^{N} AIC_{it}^{C} + \beta \sum_{j=1}^{N} AIC_{it}^{S} + \gamma \sum_{j=1}^{N} AIC_{it}^{SS}} \\ + \dfrac{\alpha ABC_{it}^{C} + \beta ABC_{it}^{S} + \gamma ABC_{it}^{SS}}{\alpha \sum_{j=1}^{N} ABC_{it}^{C} + \beta \sum_{j=1}^{N} ABC_{it}^{S} + \gamma \sum_{j=1}^{N} ABC_{it}^{SS}} \\ + \dfrac{\alpha PASS_{it}^{C} + \beta PASS_{it}^{S} + \gamma PASS_{it}^{SS}}{\alpha \sum_{j=1}^{N} PASS_{it}^{C} + \beta \sum_{j=1}^{N} PASS_{it}^{S} + \gamma \sum_{j=1}^{N} PASS_{it}^{SS}} \\ + \dfrac{\alpha LAW_{it}^{C} + \beta LAW_{it}^{S} + \gamma LAW_{it}^{SS}}{\alpha \sum_{j=1}^{N} LAW_{it}^{C} + \beta \sum_{j=1}^{N} LAW_{it}^{S} + \gamma \sum_{j=1}^{N} LAW_{it}^{SS}} \end{array} \right] \left[\frac{N}{5} \right]$$

Note: Equation from Bucchinaeri et al. 2020 (p.6)

3 Descriptive Statistics

Table 1: Descriptions of Key Variables

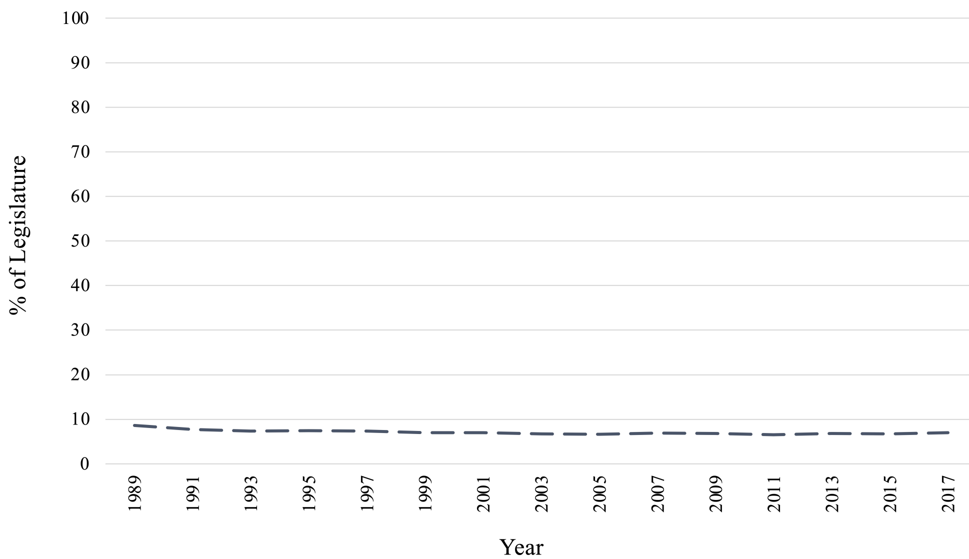
Variables	Min	Max	Mean	Std. Dev.
Dependent Variables				
Legislative Effectiveness Variables				
SLES (SLES_z)	-2.94	9.92	.009	.981
Bill Introduction (BILL)	0	.287	.014	.015
Action in Committee (AIC)	0	.323	.014	.016
Action Beyond Committee (ABC)	0	.367	.014	.017
Pass One Chamber (PASS)	0	.014	.014	.018
Become Law (LAW)	0	.014	.014	.019
Electoral Variables				
Reelected	0	1	.784	.412
Challenged	0	1	.737	.440
Vote Share	0.015	1	.713	.225
Independent Variables				
Worker	0	1	.068	.253
% Worker	1.11	22.97	6.88	.991
Female	0	1	.232	.422
Black	0	1	.023	.149
Hispanic	0	1	.184	.184
Race (other)	0	1	.031	.031
White	0	1	.929	.257
Democrat	0	1	.487	.499
Seniority	1	25	3.894	3.245
Committee Chair	0	1	.279	.449
Majority Party	0	1	.620	.485
Governor Same Party	0	1	.539	.498
Majority Leadership	0	1	.055	.229
Minority Leadership	0	1	.032	.176
Polarization	0	4.999	.674	.602
Leader, Speaker, President	0	1	.028	.165
Term Limits	0	1	.233	.427
Professionalism (Squire)	.027	.629	.216	.124
Vote Share	.015	1	.713	.225
Senate	1	2	1.283	.450
N				48,220

4 Demographics of Working-Class State Legislators

My data set includes 51,929 legislator-term specific observations. Of those legislator-term specific observations, 3,572 are from working-class backgrounds. From this, on average, 6.8% of state legislators are workers. The numerical representation of workers in state legislatures peaked in 1990 at around 10% (though the early data is sparse); however, the percentage of workers serving in state legislatures since 1990 has remained consistent around 6%. Figure A.4.1 shows the numerical representation of workers in state legislatures from 1989-2018.

The figures below present the partisan, race, and gender breakdown of workers across state legislatures. Workers are approximately evenly split between the two parties (Republicans = 47%, Democrats = 52%). Workers are overwhelmingly white (94%) and male (88%). I condition on gender, race, and partisanship to ensure that demographic factors aren't confounding the estimates of workers' effectiveness. I also consider whether demographic factors moderate workers' effectiveness. To do this I interact gender, race, and partisanship with the worker variable. All three of the interactions are not statistically significant, indicating that demographic factors do not moderate workers' effectiveness.

4.1 Figure 4.1: Numerical Representation of Workers in State Legislatures (1989-2018)



4.2 Table 4.2: Class-Based Effectiveness Given Gender, Race, and Party

	1	2	3
	SLES	SLES	SLES
Worker	-0.0163	-0.0360	0.00190
	(-0.56)	(-1.38)	(0.05)
Female	0.0148	0.0108	0.00914
	(0.90)	(0.67)	(0.57)
Worker + Female	-0.101		
	(-1.56)		
Non-White		-0.0525	
		(-1.85)	
Worker + Non-White		0.124	
		(0.81)	
Democrat			0.216**
			(3.02)
Worker + Democrat			-0.0565
			(-1.07)
% Worker	0.0141	0.0142	0.0151
	(0.45)	(0.46)	(0.49)
Black	0.0554		
	(0.79)		
Hispanic	0.167*		
	(2.40)		
Race (other)	-0.0790		
	(-0.62)		
White	0.144*		
	(2.52)		
Democrat	-0.0240	-0.0234	-0.230***
	(-1.72)	(-1.69)	(-3.35)
Seniority	0.0212***	0.0211***	0.0211***
	(6.96)	(6.96)	(6.95)
Committee Chair	0.513***	0.513***	0.512***
	(30.36)	(30.37)	(30.31)
In Majority	0.356***	0.358***	0.362***
	(20.30)	(20.42)	(20.55)
Governor Same Party	0.0339**	0.0336**	0.0382***
	(3.02)	(3.00)	(3.40)
Majority Leadership	0.179***	0.178***	0.180***
	(4.78)	(4.75)	(4.79)
Minority Leadership	0.107**	0.107**	0.113**
	(2.92)	(2.93)	(3.08)
Polarization	-0.175***	-0.172***	-0.170***
	(-11.05)	(-10.89)	(-10.69)
Leader, Speaker, President	-0.0372	-0.0373	-0.0387
	(-0.55)	(-0.55)	(-0.57)
Term Limits Applied	0.114***	0.116***	0.112***
	(6.76)	(6.89)	(6.63)
Professionalism (Squire)	-0.104	-0.0967	-0.100
	(-1.82)	(-1.72)	(-1.79)
Vote Share	0.0384	0.0398	0.0383
	(1.31)	(1.36)	(1.31)
Senate	-0.164***	-0.164***	-0.168***
	(-10.10)	(-10.12)	(-10.26)
Intercept	-0.332	-0.194	-0.00269
	(-1.40)	(-0.85)	(-0.01)
State Fixed Effects	✓	✓	✓
Term Fixed Effects	✓	✓	✓
N	48220	48220	48220
Adjusted-R^2	0.18	0.18	0.18

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Additional Models

5.1 Table 5.1: Class-Based Legislative Effectiveness Given Professionalism, Term Limits, and % Worker

	1 SLES	2 SLES	3 SLES
Worker	-0.0497	-0.0342	-0.330
	(-0.91)	(-1.09)	(-1.34)
Professionalism (Squire)	-0.0649	-0.0596	-0.0599
	(-1.11)	(-1.05)	(-1.06)
Worker + Professionalism (Squire)	0.0804		
	(0.36)		
Term Limits	0.0643***	0.0638***	0.0642***
	(3.91)	(3.77)	(3.91)
Worker + Term Limits		0.00595	
		(0.11)	
% Worker	-0.0116	-0.0116	-0.0152
	(-0.37)	(-0.38)	(-0.49)
Worker + % Worker			0.0429
			(1.22)
Female	0.00326	0.00321	0.00312
	(0.20)	(0.20)	(0.19)
Black	0.0610	0.0615	0.0612
	(0.87)	(0.88)	(0.87)
Hispanic	0.168*	0.169*	0.168*
	(2.38)	(2.39)	(2.38)
Race (other)	-0.0913	-0.0908	-0.0909
	(-0.71)	(-0.70)	(-0.70)
White	0.156**	0.156**	0.156**
	(2.70)	(2.71)	(2.71)
Democrat	-0.00749	-0.00753	-0.00760
	(-0.54)	(-0.54)	(-0.55)
Committee Chair	0.547***	0.547***	0.547***
	(31.53)	(31.54)	(31.54)
In Majority	0.337***	0.337***	0.337***
	(19.53)	(19.52)	(19.54)
Governor Same Party	0.0317**	0.0317**	0.0318**
	(2.81)	(2.81)	(2.82)
Majority Leadership	0.207***	0.207***	0.207***
	(5.58)	(5.58)	(5.58)
Minority Leadership	0.133***	0.133***	0.133***
	(3.60)	(3.60)	(3.61)
Polarization	-0.184***	-0.185***	-0.184***
	(-11.63)	(-11.62)	(-11.61)
Leader, Speaker, President	-0.00954	-0.00957	-0.00942
	(-0.14)	(-0.14)	(-0.14)
Vote Share	0.0927**	0.0928**	0.0933**
	(3.20)	(3.20)	(3.22)
Senate	-0.167***	-0.167***	-0.166***
	(-10.21)	(-10.21)	(-10.20)
Intercept	-0.114	-0.115	-0.0907
	(-0.49)	(-0.49)	(-0.38)
State Fixed Effects	✓	✓	✓
Term Fixed Effects	✓	✓	✓
N	48220	48220	48220
Adjusted-R^2	0.18	0.18	0.18

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Table 5.2: Class-Based Legislative Effectiveness for Legislators' First Term

	1 BILL	2 AIC	3 ABC	4 PASS	5 LAW	6 SLES
Worker	0.000273	0.000143	0.0000824	0.0000857	-0.0000107	-0.0300
	(0.65)	(0.34)	(0.19)	(0.19)	(-0.02)	(-1.29)
% Worker	-0.00224*	-0.00230**	-0.00208**	-0.00231**	-0.00238*	-0.102*
	(-2.52)	(-2.93)	(-2.63)	(-2.70)	(-2.39)	(-2.01)
Female	-0.000427*	-0.00000815	0.000323	0.000515	0.000574	-0.0158
	(-2.04)	(-0.04)	(1.35)	(1.93)	(1.89)	(-1.05)
Black	-0.00148	-0.00174	-0.00103	-0.000358	0.000124	0.0250
	(-1.42)	(-1.36)	(-0.76)	(-0.24)	(0.08)	(0.32)
Hispanic	-0.000473	-0.00122	-0.000995	-0.000649	-0.0000576	-0.0130
	(-0.51)	(-1.03)	(-0.82)	(-0.48)	(-0.04)	(-0.18)
Race (other)	-0.00191	-0.00337	-0.00283	-0.00300	-0.00354	-0.177
	(-1.30)	(-1.86)	(-1.54)	(-1.62)	(-1.85)	(-1.71)
White	-0.000354	-0.000608	-0.000504	-0.000123	0.000664	0.0510
	(-0.41)	(-0.54)	(-0.44)	(-0.10)	(0.47)	(0.80)
Democrat	-0.000541**	-0.00136***	-0.00155***	-0.00163***	-0.00174***	-0.0408**
	(-2.76)	(-6.63)	(-7.36)	(-7.26)	(-6.89)	(-3.02)
Committee Chair	0.00755***	0.00971***	0.0103***	0.0109***	0.0116***	0.417***
	(14.03)	(16.03)	(16.06)	(15.42)	(13.98)	(13.23)
In Majority	0.00212***	0.00363***	0.00409***	0.00422***	0.00354***	0.249***
	(7.33)	(12.28)	(13.43)	(13.17)	(10.03)	(13.36)
Govenor Same Party	0.000727***	0.00104***	0.000923***	0.000916***	0.00123***	0.0371**
	(3.65)	(4.97)	(4.19)	(3.89)	(4.63)	(2.74)
Majority Leadership	0.00282	0.00396*	0.00430*	0.00376	0.00344	0.191*
	(1.72)	(2.15)	(2.10)	(1.80)	(1.43)	(1.99)
Minority Leadership	0.00125	-0.000840	-0.000794	-0.000664	-0.0000659	0.0628
	(0.79)	(-0.63)	(-0.57)	(-0.48)	(-0.04)	(0.81)
Polarization	0.000177	-0.000577**	-0.00124***	-0.00177***	-0.00215***	-0.182***
	(0.82)	(-2.58)	(-5.36)	(-7.30)	(-8.19)	(-12.31)
Leader, Speaker, President	-0.00111	-0.000618	0.0000762	0.000199	0.00106	-0.00824
	(-0.44)	(-0.23)	(0.02)	(0.06)	(0.30)	(-0.05)
Term Limits	0.00157***	0.00170***	0.00118***	0.000769*	0.000837*	0.0582***
	(6.12)	(6.25)	(4.17)	(2.50)	(2.39)	(3.33)
Professionalism (Squire)	-0.0000802	0.000429	0.00151	0.00214*	0.00256*	0.565***
	(-0.11)	(0.54)	(1.85)	(2.43)	(2.55)	(9.09)
Vote Share	-0.00159***	-0.00159***	-0.00178***	-0.00176***	-0.00200***	-0.0932**
	(-3.63)	(-3.41)	(-3.70)	(-3.42)	(-3.38)	(-2.98)
Senate	0.0127***	0.0119***	0.0115***	0.0113***	0.0112***	-0.0530**
	(39.86)	(37.21)	(34.87)	(31.76)	(28.00)	(-3.11)
Intercept	0.0138	0.0155*	0.0147*	0.0167*	0.0171*	0.553
	(1.92)	(2.32)	(2.17)	(2.28)	(2.00)	(1.32)
State Fixed Effects	✓	✓	✓	✓	✓	✓
Term Fixed Effects	✓	✓	✓	✓	✓	✓
N	9927	9927	9927	9927	9927	9927
Adjusted-R^2	0.39	0.40	0.40	0.37	0.32	0.20

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 Table 5.3: Class-Based Legislative Effectiveness Interacted With Seniority

	1 BILL	2 AIC	3 ABC	4 PASS	5 LAW	6 SLES
Worker	0.000281 (0.47)	-0.0000111 (-0.02)	0.000120 (0.19)	0.0000386 (0.05)	-0.000246 (-0.30)	-0.0496 (-1.18)
Seniority	0.0000872 (1.82)	0.0000746 (1.52)	0.0000678 (1.39)	0.0000513 (1.07)	0.0000867 (1.67)	0.0208*** (6.69)
Worker + Seniority	-0.00000868 (-0.06)	0.00000791 (0.05)	0.0000272 (0.16)	0.000120 (0.59)	0.000208 (0.86)	0.00559 (0.46)
% Worker	-0.00130*** (-3.53)	-0.00113** (-2.99)	-0.00105** (-2.93)	-0.00113** (-2.86)	-0.00111* (-2.54)	0.0142 (0.46)
Female	-0.0000374 (-0.15)	0.000543 (1.96)	0.000654* (2.40)	0.000744** (2.67)	0.000845** (2.77)	0.0107 (0.66)
Black	-0.00275* (-2.30)	-0.00332** (-2.67)	-0.00301* (-2.37)	-0.00280* (-2.20)	-0.00240 (-1.59)	0.0546 (0.78)
Hispanic	-0.000688 (-0.62)	-0.00127 (-1.09)	-0.000826 (-0.70)	-0.000751 (-0.62)	-0.000504 (-0.36)	0.167* (2.40)
Race (other)	-0.00162 (-0.65)	-0.00157 (-0.71)	-0.00141 (-0.61)	-0.00552** (-2.78)	-0.00613** (-3.04)	-0.0792 (-0.62)
White	-0.00166 (-1.64)	-0.00203 (-1.89)	-0.00174 (-1.59)	-0.00166 (-1.51)	-0.00126 (-0.99)	0.143* (2.51)
Democrat	0.000279 (1.28)	-0.000760*** (-3.30)	-0.000807*** (-3.41)	-0.000928*** (-3.82)	-0.000939*** (-3.59)	-0.0238 (-1.71)
Committee Chair	0.00561*** (23.98)	0.00746*** (27.77)	0.00844*** (29.50)	0.00885*** (29.59)	0.00883*** (26.68)	0.513*** (30.38)
In Majority	0.00236*** (9.36)	0.00428*** (14.98)	0.00468*** (16.02)	0.00496*** (18.62)	0.00435*** (15.02)	0.355*** (20.29)
Govenor Same Party	0.000590*** (3.44)	0.000747*** (4.06)	0.000642** (3.25)	0.000760*** (3.81)	0.00124*** (5.81)	0.0340** (3.03)
Majority Leadership	0.00297*** (4.47)	0.00411*** (5.60)	0.00510*** (6.39)	0.00563*** (6.96)	0.00580*** (6.94)	0.179*** (4.78)
Minority Leadership	0.00251** (3.21)	0.00211* (2.17)	0.00173 (1.72)	0.000634 (0.97)	0.000449 (0.64)	0.107** (2.93)
Polarization	-0.000213 (-0.88)	-0.00131*** (-4.74)	-0.00213*** (-7.45)	-0.00236*** (-10.52)	-0.00269*** (-11.30)	-0.175*** (-11.05)
Leader, Speaker, President	0.0000530 (0.05)	0.00101 (0.79)	0.00173 (1.24)	0.00296* (1.96)	0.00407* (2.35)	-0.0371 (-0.55)
Term Limits	0.00148*** (5.57)	0.00162*** (5.99)	0.00181*** (6.21)	0.00179*** (5.88)	0.00194*** (6.02)	0.114*** (6.76)
Professionalism (Squire)	-0.00815*** (-11.03)	-0.00759*** (-9.88)	-0.00757*** (-9.85)	-0.00761*** (-9.54)	-0.00743*** (-8.42)	-0.103 (-1.81)
Vote Share	-0.00192*** (-4.63)	-0.00192*** (-3.83)	-0.00179*** (-3.39)	-0.00142** (-2.76)	-0.00147** (-2.60)	0.0380 (1.30)
Senate	0.0142*** (46.71)	0.0135*** (43.22)	0.0131*** (40.86)	0.0132*** (40.47)	0.0132*** (37.73)	-0.164*** (-10.10)
Intercept	0.00698* (2.30)	0.00730* (2.33)	0.00659* (2.17)	0.00671* (2.08)	0.00632 (1.77)	-0.331 (-1.40)
State Fixed Effects	✓	✓	✓	✓	✓	✓
Term Fixed Effects	✓	✓	✓	✓	✓	✓
N	48220	48220	48220	48220	48220	48220
Adjusted-R^2	0.30	0.30	0.30	0.30	0.26	0.18

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$