# Placing Racial Fluidity in Context

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## Abstract

As mounting evidence demonstrates that an individual's race is subject to change, the question increasingly becomes: under what circumstances is racial fluidity more or less likely? We draw on a geocoded nationally representative longitudinal survey that allows us to link individuals to the U.S. counties in which they live. Our analysis explores whether racial fluidity is more common in some places rather than others, and whether contextual characteristics help to predict the specific racial classification of individuals either in addition to, or instead of, their personal characteristics. The results demonstrate contextual variation in the social construction of race, and underscore the important role that place plays in 'making race' in the United States.

One of the key tenets of the constructionist perspective on race and racialization emphasizes how the same person could be categorized differently in different places. For example, anthropologist Duana Fullwiley has noted how in the space of a day, as she flies from the U.S. to France to Senegal, she changes from African American to "mixed" to white/European ("Race in a Genetic World" 2008). These changes have little to do with Fullwiley herself, and everything to do with changes in the meaning of race and what constitutes membership in a particular race category (Hacking 1999). Such differences in racial conceptualization from one place to another affect how many racial categories are recognized and by what names they are designated. But the re-drawing of racial boundaries across geographic boundaries is not the only way that a place might cause changes in a person's race.

Previous research has uncovered significant fluidity in both racial self-identification (Liebler et al. 2014) and racial classification, or how people are perceived or classified by others (Saperstein and Penner 2012). Other studies have shown how contextual characteristics, such as the local racial composition, affect the racial identities people choose for themselves (e.g., Harris and Sim 2002), and that parents choose for their children (e.g., Xie and Goyette 1997). This study unites these two perspectives on racial formation by exploring both the individual and contextual correlates of racial classification in the U.S. in a longitudinal framework. We incorporate information about the places in which people live to explore whether racial fluidity is more likely to occur for particular types of people, in particular types of places, or whether people experience changes in classification when their contextual surroundings change.

**Data.** For this paper, we utilize the restricted-access geocoded National Longitudinal Survey of Youth, 1979 cohort data. This survey is a representative sample of 12,686 men and women in the

United States who were aged 14-22 in 1979. The data includes racial classifications as recorded by interviewers each survey year between 1979 through 1998, which become the dependent variables for our analyses. The racial categories available to interviewers were: “Black,” “White” and “Other.” The geocoded nature of the dataset allows us to incorporate contextual data for the counties in which respondents live. We obtained estimates of county level crime rates from the FBI’s uniform crime reporting program[1], estimates of the county level unemployment rate from the Bureau of Labor Statistics, and estimates of the severity of county level poverty from the Bureau of Economic Analysis’ Regional Economic Accounts. The county level crime rate included several large outliers, so we fit loess curves to within county crime rates over time to create a smoothed crime measure, and used the fitted values for further analysis. County level poverty was calculated by dividing the poverty rate for 2 adults and 1 child in each year by the county’s average income. Thus, scores of 1 imply the county’s aggregate income is at poverty level and values greater than one indicate greater poverty, on average, in the county. We also included estimates of county population size, percent black, percent Hispanic, and percent foreign born by county obtained from decennial census data. We create annual estimates of these quantities through linear interpolation between censuses.

From these data we also constructed estimates of the Simpson Diversity Index, where each county’s diversity is measured as$\sum_i p_i(1 - p_i)$, where $p_i$ is the proportion of the population in racial-ethnic group, i (Reardon and Firebaugh 2002). In our case, we use four racial-ethnic groups, Hispanic, Non-Hispanic White, Non-Hispanic Black, and Non-Hispanic Other. This gives our index a theoretical range of 0 to 0.75, zero when everyone in a county is of the same racial-ethnic group, and 0.75 when everyone in a county is evenly distributed across all four

[1] Our estimate of the crime rate is the number of index one crimes per capita.

groups. In our analysis we multiply by 100 to rescale this index to 0 through 75. County level summary statistics for all of our contextual characteristics can be found in Table 1.

**Methods.** We are interested both in whether racial fluidity is more common in some places – or types of places – rather than others, and in which characteristics are most associated with particular racial classifications for a given individual. To get at the latter question we used a set of linear probability models with individual fixed effects to estimate the change in probabilities of racial classification within individuals as they experience changes in their social status and context. We model the probability of being classified as white, black, or other separately. Each model includes contextual variables such as the unemployment rate, the crime rate, aggregate levels of poverty, the population size, percent Hispanic, Black, or foreign born, and the Simpson Diversity Index by county. To tease apart the effects of contexts changing around individuals and individuals moving to new contexts, we included an interaction term between whether the individual moved to a different county between survey years and all contextual variables mentioned. The individual status characteristics included whether the individual had ever been unemployed, ever experienced poverty, or had ever been incarcerated. Additional individual controls include age and age squared. Interviewer controls include the interviewer's age, race, education and gender. In addition to the respondent fixed effects mentioned above, we also controlled for year fixed effects to account for year-to-year changes in survey design and other temporal changes in how people came to be assigned to particular racial categories.

We also estimated geographically weighted versions of our main regressions because it is plausible that racial categories will be interpreted and applied differently in different regions within the United States. For this method we iterated through each state, running the three regressions mentioned above but using only data for that state and any neighboring states within

500 miles.[2] The result of this process creates a regression coefficient for each of our variables in each of our regressions for each state. Comparing regression coefficients across states allows us to identify variation in the direction, magnitude or significance of specific contextual or individual correlates of racial fluidity (Brunsdon et al 1998, Fotheringham 1997, Matthews and Yang 2012). This method involves running many regression tests on different, overlapping, subsets of data, and thus should not be understood as rigorous hypothesis testing, but instead an exploratory analysis of spatial variation in effects.

**Results.** A descriptive map of where racial fluidity is more likely to occur is shown in Figure 1. The color ramp refers to the proportion of person-years within each state where a change in race occurs. Darker red states have a higher proportion of person-years where respondents experience changes in their racial category, while states with less racial fluidity are colored with lighter reds. The map suggests that racial fluidity is more common in both the Southwest (California, Arizona and New Mexico), and in "rust belt" areas of the northern Midwest (Michigan and Ohio). Interestingly, many of the states with high levels of racial fluidity in the NLSY in the 1980s and 1990s also appear among the top states in terms of multiple race reporting, based on 2010 census data (Jones and Bullock 2012).

To explore what factors may have contributed to these patterns in racial fluidity, we estimated three otherwise identical regressions predicting classification as white, other or black. We do not estimate a single model predicting the overall level of racial fluidity because previous research suggests the direction of effects for different racial classifications are likely to offset (see Saperstein and Penner 2012). Table 2a presents the main effects from our three separate

[2] As we do not robustly select bandwidths through cross-validation procedures, nor do we explicitly test for statistically significant spatial variation in estimates, these results should be considered preliminary.

regressions. Table 2b presents only the interaction effects between the contextual variables and moving between counties from those same models. The contextual results from Table 2a should thus be read as the effects of context for those who do not move between counties. It is also important to note that these models estimates average effects across the U.S., so while they are suggestive of key characteristics related to racial classification, the national averages also might hide significant variation at regional or more local levels – a point to which we will return below.

*Characteristics of places.* The results in Table 2a suggest that contextual characteristics play a role in predicting the probability that an individual is racially classified as white or other. As expected, the estimates are offsetting; for example, the unemployment rate increases the probability of being classified as other while reducing the probability of being classified as white. The same is true for aggregate poverty, the percent foreign born in the county, and the level of racial-ethnic diversity (as measured through the Simpson index). The percent of the population that was recorded as Hispanic in the census, on the other hand, increases the probability of individuals in that county being classified as white and decreases their probability of being classified as other.[3]

It is important to note that although these coefficients reach statistical significance, they are substantively very small. For example, the estimate for the unemployment rate decreases the probability of being classified as white by 0.2 percentage points for a one percent increase in unemployment in the county. We interpret the results to suggest that higher unemployment,

[3] This effect is consistent with a pre-1980 emphasis on classifying most people with Hispanic origins as white (Rodriguez 2000), and with the conflation of whiteness and American-ness in many Latino communities (e.g., Dowling 2014). It is also consistent with the racial classification instructions to NLSY interviewers conducting the initial 1978 household enumeration screener for the survey. However, we do not include the 1978 classification in our analysis because its coding is inconsistent with later years. In particular, instructions about how to classify people "of Latin-American descent" were not repeated subsequently when annual racial classifications were recorded as part of the interviewer's remarks.

aggregate poverty, percent foreign born and diversity represent stereotypes about the kinds of people interviewers expect to find in particular places, which then colors their perceptions of the people whom they interview in those places. But we do not want to overstate the importance of these factors in explaining the process of racial classification in general.

Indeed, our contextual variables do little to explain when individuals are classified into or out of the category of black. The only estimate to reach significance in our fixed effects model predicting black classification is the crime rate, suggesting that as crime rises in a county, the probability that local residents will be classified as black drops very slightly.[4] The lack of contextual correlates in this model could be due to the relative stability of the black racial category – evidenced, in part, by the amount of variance explained by individual fixed effects (see Table 2a). The higher proportion explained in the model predicting classification as black, as compared to models for white and other, might also indicate that stable individual characteristics play a larger role in who is classified as black in the United States. Although many such racialized markers are not captured in the NLSY, they could include factors such as racially marked names (see e.g., Bertrand and Mullainathan 2004), relatively stable aspects of physical appearance, such as facial features or eye color, and family background.

*Effects of moving.* Perhaps most surprising, the effects of moving, both in terms of the main effect (see Table 2a) as well as the interactions with context (see Table 2b), are a very small portion of the story of racial classification. The main effect of having moved between counties in the past survey year fails to reach statistical significance in any of the regressions, suggesting

[4] We would expect the relationship between crime and classification as black to be positive instead of negative (see, e.g., Eberhardt et al. 2004; Saperstein and Penner 2012). We should note that the raw crime rate data from the Uniform Crime Reports are noisy and not directly comparable between years due to changes in local precincts reporting within counties over time. Though we have tried to correct these data statistically, it is possible that the unexpected results result from an unreliable measure of the crime rate.

that a traditional account of "passing" – where individuals move and sever ties to be classified differently – cannot explain the racial change that we observe in this sample. In addition, the effects of moving into particular contexts, as measured through contextual interaction terms shown in Table 2b, are generally small and statistically insignificant. The only interaction effect that does reach the $p<0.05$ threshold is that of population size, suggesting that individuals who move to counties with larger populations are less likely to be classified as white and more likely to be classified as other.[5] Again, although this effect reaches statistical significance, it is substantively small in magnitude.

Descriptive statistics for "movers" and "stayers" support the plausibility of these generally null multivariate results. Racial fluidity is not significantly more likely among people who move to new counties; rather, respondents who do *not* move experience slightly higher rates of racial fluidity (5.9% of person years in which a respondent does not move involve a change in racial classification, compared to 5.7% of person years in which a respondent moved between counties). Table 3 shows that contexts are similar on average between person years with and without a between-county move. Further, the mean changes in context experienced within respondents are roughly similar between moving and staying person years (see Table 3). All of this evidence suggests that individuals are likely to experience similar changes in context whether moving or staying. Thus, the racial fluidity we observe in the NLSY is not driven by people who move from place to place but by specific characteristics of individuals and places.

*Residuals by Geography***.** We plotted the mean residual by state for each of our three regression models (see Figures 2 through 4), in order to assess whether or not our models were still missing

[5] This result also runs counter to historical expectation from the passing literature, in which people moved to cities where interactions were more anonymous and people's family backgrounds were less salient in order to pass as white. Rather the direction of this effect suggests cities are (now) perceived as less white places on average.

some meaningful variation across geographic space – even with our controls for a number of key contextual characteristics. Higher average residuals are plotted in red (dark red are values above the median positive residual, light values are between 0 and the median positive residual), and lower average residuals are plotted in blue (dark blue are values below the median negative residual, and light values are between 0 and the median negative residual). These maps indicate significant clustering of residuals in both the white and other models, suggesting our models overestimate the white population in some places, and underestimate it in others. In particular, residuals for classification as white are higher than expected in the southwest, while lower than expected in the northwest, and the opposite is true for classification as other. Statistical tests of spatial autocorrelation were also run on the residuals. Moran's I statistic, using spatial weights of either a fixed radius of 500 miles, or by using the 10 nearest neighbors for each state, suggest that the spatial correlation of residuals are statistically significant in all three models (tests not shown). The spatial clustering of residuals suggests that there is something particular to geographic space in the classification of race for which our models are failing to account.

*Geographically Weighted Regression*. Standard model diagnostic techniques to account for spatial variation in the residuals would be to include geographic – state or county – fixed effects or a spatial autoregressive term (Bivand et al 2008). These methods would correct for the spatial dependence present in the data, and give corrected national estimates. Rather than correct our national estimates for local dependence, we use geographically weighted regression to generate local estimates that allow for variation in effects across space. For example, unemployment or aggregate poverty might differently influence racial classification across the United States, relating to some underlying variation in the cultural significance of these covariates.

Geographically weighted regression creates local regression estimates for each covariate for each state, allowing us to identify when local estimates vary from the national estimates. As it would be impractical to report all the estimates for each covariate in each state we will focus on the six contextual characteristics identified as significant in our prior analysis, namely the unemployment rate, levels of aggregate poverty, the percent foreign born, the percent Hispanic, the Simpson diversity index, and log population size. We first estimate models analogous to those in Table 2 that include all individual and contextual characteristics. Then, for each covariate of interest, we map the resulting regression estimates, with red color scales indicating increased probabilities of being classified as that model's category (light red corresponds to values between 0 and ½ the maximum value, with dark red for ½ the maximum value through the maximum value), and blue color scales indicating decreased probabilities (light blue correspond to values between 0 and ½ the minimum value, with dark blue for ½ the minimum value through the minimum value). So as to not over represent the amount of variation in the regression coefficients, states where the coefficient failed to reach statistical significance at $p<0.05$ have been set to gray. Figures 5 through 19 present our preliminary results, beginning with aggregate poverty (Fig. 5), percent Hispanic (Fig. 6), and Simpson Diversity (Fig. 7) for classification as black. Maps for the effects of the unemployment rate, percent foreign born, and log population on classification as black are not presented as they would be almost entirely gray. Spatial variation in estimates for the unemployment rate, aggregate poverty, percent foreign born, percent Hispanic, Simpson Diversity, and log population are mapped in figures 8 through 13, respectively, for classification as white, and 14 through 19 for classification as other.

The preliminary GWR results for models predicting classification as black are consistent with our previous national estimates. Contextual covariates generally fail to reach statistical significance in these models. From this, we conclude that the null main results presented in Table 2a are not the result of averaging out positive and negative effects distributed across the U.S., but instead reflect a true lack of significant contextual predictors. This also suggests that the determinants of being classified as black varied little across the U.S. during the 1980s and 1990s.

For classification as white, the coefficient estimates for the unemployment rate, percent foreign born, and log population are statistically significant in many states, and the patterning appears meaningfully distributed across space. For example, higher unemployment rates are associated with decreases in the probability of being classified as white in the northeastern United States – consistent with the national average estimate – but associated with contrasting increases in the probability of being classified as white in the western United States (see Fig. 8). A greater share of foreign-born residents decreases the probability of being seen as white in the southwest but increases the probability in the north and east (see Fig. 10). Population size (Fig. 13) is cleanly split east (decreasing the probability of white classification) and west (increasing the probability). This suggests both the possibility of meaningful cultural variation in the classification of race across the U.S., as well as the possibility that regression coefficients in Table 2a are small in some part due to the averaging of competing positive and negative effects. The results for aggregate poverty are less clearly divided by region (see Fig. 9). Instead, only Kansas, Oklahoma, and New Mexico have relatively large and statistically significant estimates that run counter to the national trend, with aggregate poverty increasing the probability that residents will be classified as white in those states. Finally, we find two contextual characteristics with relatively consistent effects across the country in terms of both direction and magnitude: just as we saw in Table 2a, the proportion of the population recorded as Hispanic in the census generally increases the probability that residents will be classified as white (see Fig. 11), while greater racial-ethnic diversity in the population overall decreases that probability (see Fig. 12).

The effects for classification as other again mirror those of classification as white. Aggregate poverty fails to reach significance in the majority of states, leading us to be hesitant to interpret the spatial patterning (see Fig. 15). Racial-ethnic diversity generally has a positive association with classification as “other,” while the association with the percent of the population recorded as Hispanic is mostly negative (see Figs. 17 and 18). Higher unemployment rates increase the probability of being classified as white in the northeast, while decreasing that probability in the west, a similar pattern is found in the percent foreign born (see Figs. 14 and 16). Lastly, population size has positive effects on the probability of being classified as other in the east, and negative effects in the west (see Fig. 19).

Taken together, these maps suggest that there is a relatively consistent east/west divide in in terms of the characteristics associated with whiteness (and non-whiteness). Further, estimates for characteristics that exhibit a strong east/west divide, such as the unemployment rate, percent foreign born, and population size, may be misleadingly small in the national analysis in Table 2a due to averaging positive and negative effects. The fact that coefficients without pronounced regional patterns, such as diversity and percent Hispanic, tend to have larger national estimates also supports this interpretation. Thus, rather than a homogenous national narrative that links center cities and high rates of unemployment with non-whiteness, our results suggest that pattern of associations may be unique to the northeastern U.S., while a high (and increasing) share of foreign born residents serves as the clearest contextual signal of non-whiteness is the southwest.

*Individual Status.* Individual status characteristics, including whether the respondent has ever been unemployed, incarcerated, or in poverty, fail to reach statistical significance in our main regression models. A relative lack of patterning for these variables in the preliminary GWR (not shown) suggest that these null findings are unlikely to be the result of otherwise significant but opposite effects averaging out. However, the estimates for individual status factors in Table 2a are similar in both magnitude and direction to previous estimates from fixed effects models that do not account for the effects of context (see Saperstein and Penner 2012, Table A3). Thus, the lack of statistical significance here might also indicate that we are pushing the limits of our data in trying to identify the effects of both individual status and context simultaneously. If so, then a more nuanced understanding of the relationship between individual and contextual level considerations in predicting racial classification will likely require additional data with more cases and better geographic density, or perhaps additional theorizing that identifies more specific hypotheses about the expected effects of interest.

**Discussion and conclusion.** We find substantial variation in racial fluidity across place in the United States, and the contextual factors we identify do play some role in influencing the probability of particular racial classifications above and beyond the individual characteristics identified in previous research. Further, these contextual effects vary spatially across the United States. One plausible account for this spatial variation in the effect of social context is that the cultural underpinnings of the construction of race vary (cf. Hacking 1999), leading to differential construction of race, or differential application of racial categories, in different areas. Survey interviewers may be influenced by stereotypical expectations and classify individuals into different racial categories depending on a combination of the characteristics of those individuals, and the contexts in which they live. Some of these associations appear to have a national character, as with the lower probabilities that an interviewer will classify any individual as white in places with greater racial-ethnic diversity. Some of these characteristics may fit into broader cultural regimes that vary regionally, such as unemployment, population size, and percent foreign born; others may have a particularly local character, as with associations between aggregate poverty and whiteness in the former Dust Bowl states. This suggests that further studies of the social construction of race will need to be more explicit about the assumed matrix of associations related to racial classification in particular places in order to unpack the sub-national cultural variation that leads to differential racial fluidity.

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**Table 1. County Summary Statistics**

| | Mean | Minimum | Maximum |
|---|---|---|---|
| Unemployment Rate | 7.3% | 0.2% | 28.9% |
| Aggregate Poverty | 0.737 | 0.165 | 2.837 |
| Crime Rate per 100 people (smoothed) | 6.5 | 0 | 33.2 |
| | | | |
| Population Size | 840,153 | 593 | 8,863,164 |
| Percent Black | 13.9% | 0% | 85.6% |
| Percent Hispanic | 8.3% | 0% | 97.9% |
| Percent Foreign Born | 2.5% | 0% | 50.9% |
| Simpson Diversity Index | 3.4 | 0 | 25.4 |

Source: Unemployment - Bureau of Labor Statistics, Poverty - Bureau of Economic Analysis Regional Economic Accounts, Crime Rate - Federal Bureau of Investigation Uniform Crime Reports, Others - US Decennial Census.

Note: Aggregate Poverty is given by the poverty line divided by aggregate family income

**Table 2a: Regression Main Effects**

| | White | Other | Black |
|---|---|---|---|
| **Context Among Non-Movers** | | | |
| Unemployment Rate | -0.002*** | 0.002*** | 0 |
| | (0.00) | (0.00) | (0.00) |
| Crime Rate | 0 | 0 | -0.001* |
| | (0.00) | (0.00) | (0.00) |
| Aggregate Poverty | -0.026* | 0.024* | 0.003 |
| | (0.01) | (0.01) | (0.01) |
| South | 0.003 | -0.004 | 0.001 |
| | (0.01) | (0.01) | (0.00) |
| Log Population Size | -0.002 | 0.001 | 0.001 |
| | (0.00) | (0.00) | (0.00) |
| Percent Black | 0 | 0 | 0 |
| | (0.00) | (0.00) | (0.00) |
| Percent Hispanic | 0.004*** | -0.004*** | 0 |
| | (0.00) | (0.00) | (0.00) |
| Percent Foreign Born | -0.001* | 0.001* | 0 |
| | (0.00) | (0.00) | (0.00) |
| Simpson Diversity | -0.003*** | 0.003*** | 0 |
| | (0.00) | (0.00) | (0.00) |
| | | | |
| **Individual Status** | | | |
| Ever Unemployed | -0.003 | 0.002 | 0.001 |
| | (0.00) | (0.00) | (0.00) |
| Ever Poverty | 0.001 | -0.002 | 0 |
| | (0.00) | (0.00) | (0.00) |
| Ever Incarcerated | -0.008 | 0.004 | 0.004 |
| | (0.01) | (0.01) | (0.00) |
| Moved | 0.002 | -0.001 | -0.001 |
| | (0.00) | (0.00) | (0.00) |
| | | | |
| Interviewer Controls | X | X | X |
| Individual Controls and Fixed Effects | X | X | X |
| Year Fixed Effects | X | X | X |
| | | | |
| Variance Explained by Fixed Effects | 85.4% | 48% | 97.6% |
| | | | |
| N | 119352 | 119352 | 119352 |

Note: P-value <0.05 *, <0.01 **, <0.001***, Standard Errors are reported in parentheses.

**Table 2b: Regression Moving Interactions**

| | White | Other | Black |
|---|---|---|---|
| **Interactions Among Movers** | | | |
| Moved X Unemployment | 0.001+ | -0.001 | 0 |
| | (0.00) | (0.00) | (0.00) |
| Moved X Crime | 0 | 0 | 0 |
| | (0.00) | (0.00) | (0.00) |
| Moved X Poverty | -0.016 | 0.022 | -0.006 |
| | (0.02) | (0.02) | (0.01) |
| Moved X South | 0 | 0.001 | -0.001 |
| | (0.00) | (0.00) | (0.00) |
| Moved X Log Population | -0.005* | 0.006** | -0.001 |
| | (0.00) | (0.00) | (0.00) |
| Moved X Percent Black | 0 | 0 | 0 |
| | (0.00) | (0.00) | (0.00) |
| Moved X Percent Hispanic | 0 | 0 | 0 |
| | (0.00) | (0.00) | (0.00) |
| Moved X Percent Foreign Born | 0.001 | -0.001 | 0 |
| | (0.00) | (0.00) | (0.00) |
| Moved X Simpson Diversity | 0.001 | -0.001 | 0 |
| | (0.00) | (0.00) | (0.00) |

**Table 3: Context Descriptive Statistics for Moving and Staying Person Years**

| | Descriptive Statistics | | Differences (Current - Prior Person Year) | |
|---|---|---|---|---|
| | Movers | Stayers | Mover Difference | Non-Mover Difference |
| | mean | mean | mean | mean |
| Unemployment Rate | 7.2% | 7.6% | -0.06% | -0.06% |
| Aggregate Poverty | 0.61 | 0.61 | -0.02 | -0.01 |
| Crime Rate per 100 Population | 5.55 | 5.64 | -0.04 | -0.08 |
| Percent Black | 14.2% | 15.1% | 0.94% | 0.06% |
| Percent Hispanic | 9.8% | 10.8% | 1.55% | 0.34% |
| Percent Other | 0.03% | 0.03% | 0% | 0% |
| Percent Foreign Born | 7.7% | 8.2% | 0.09% | 0.26% |
| Simpson Diversity Index | 6.55 | 7.26 | 0.12 | 0.18 |
| Log Population | 12.82 | 12.75 | 0.11 | 0.01 |

Note: Aggregate Poverty is given by the poverty line divided by aggregate family income.

Figure 1: Racial Fluidity by State

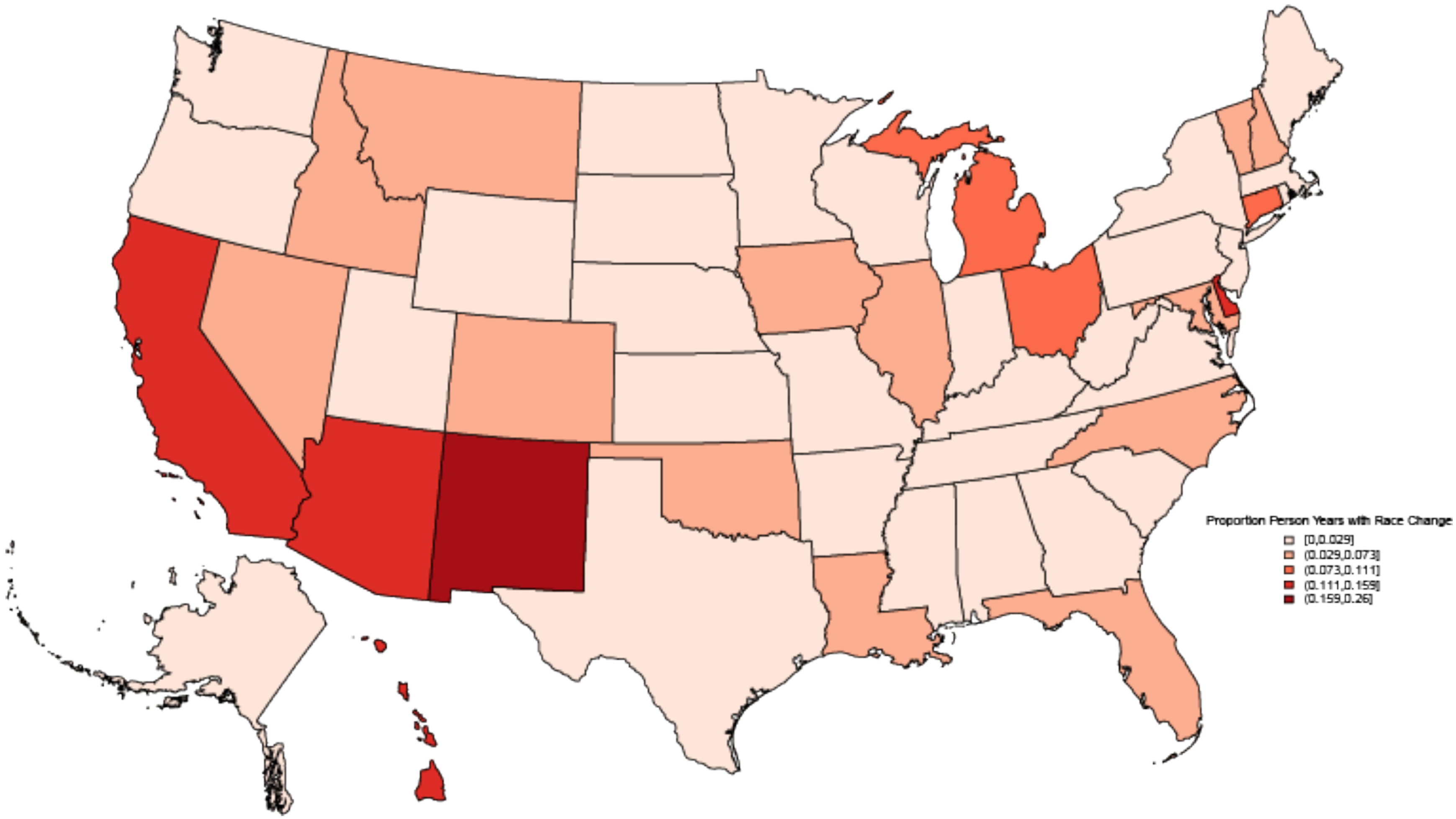

Figure 2: Residuals by State for Classification as Black

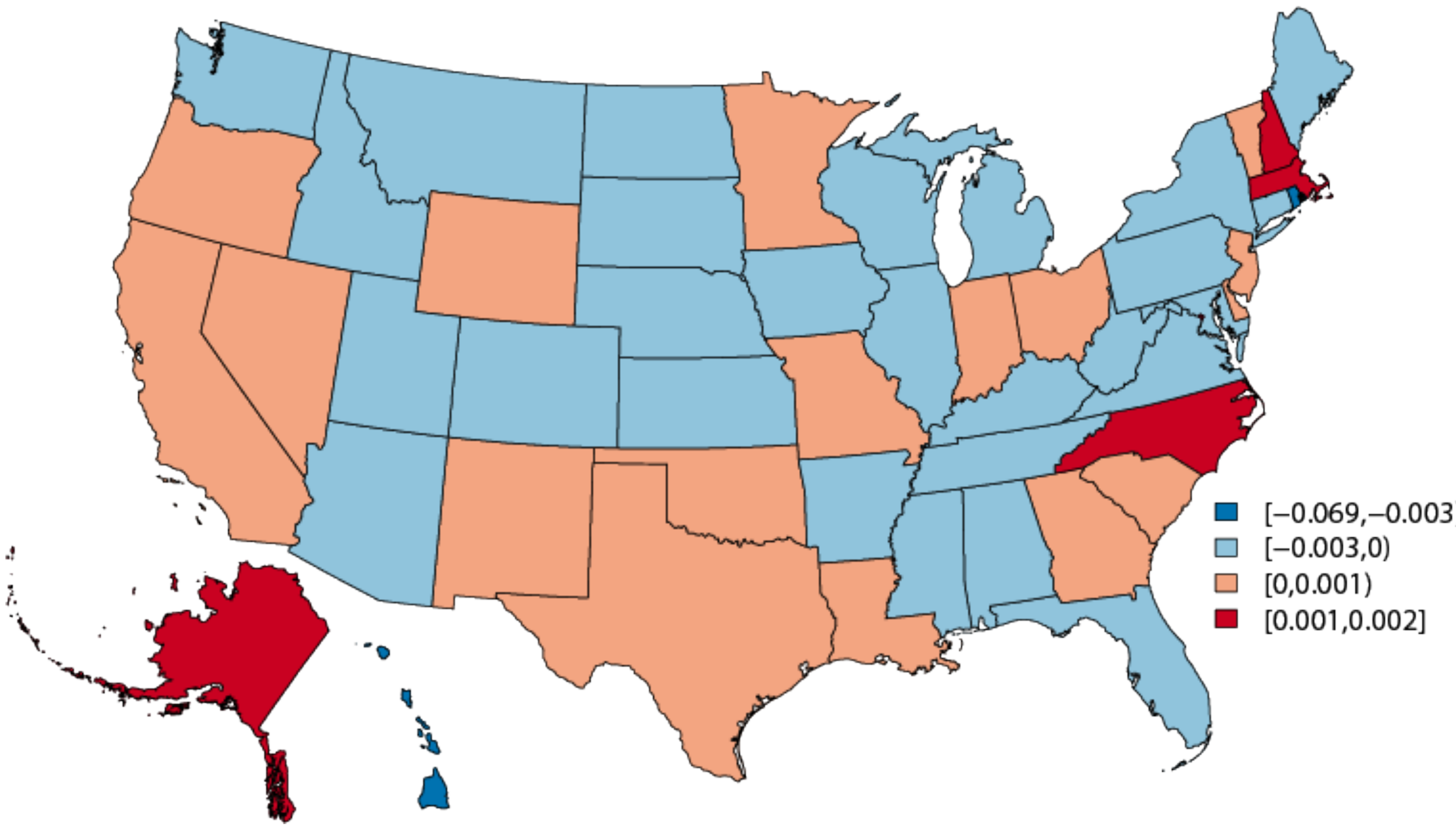

Figure 3: Residuals by State for Classification as White

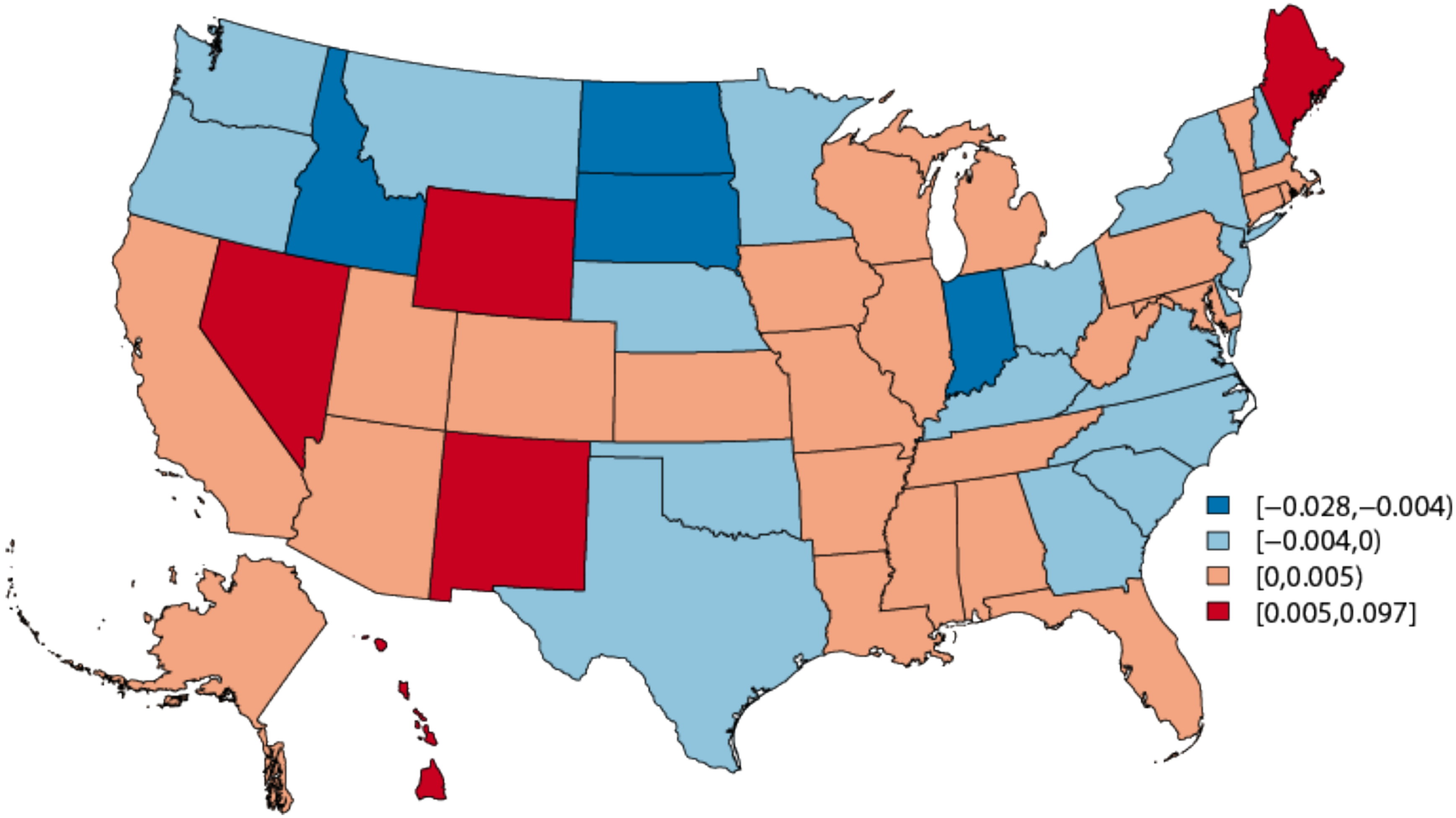

Figure 4: Residuals by State for Classification as Other

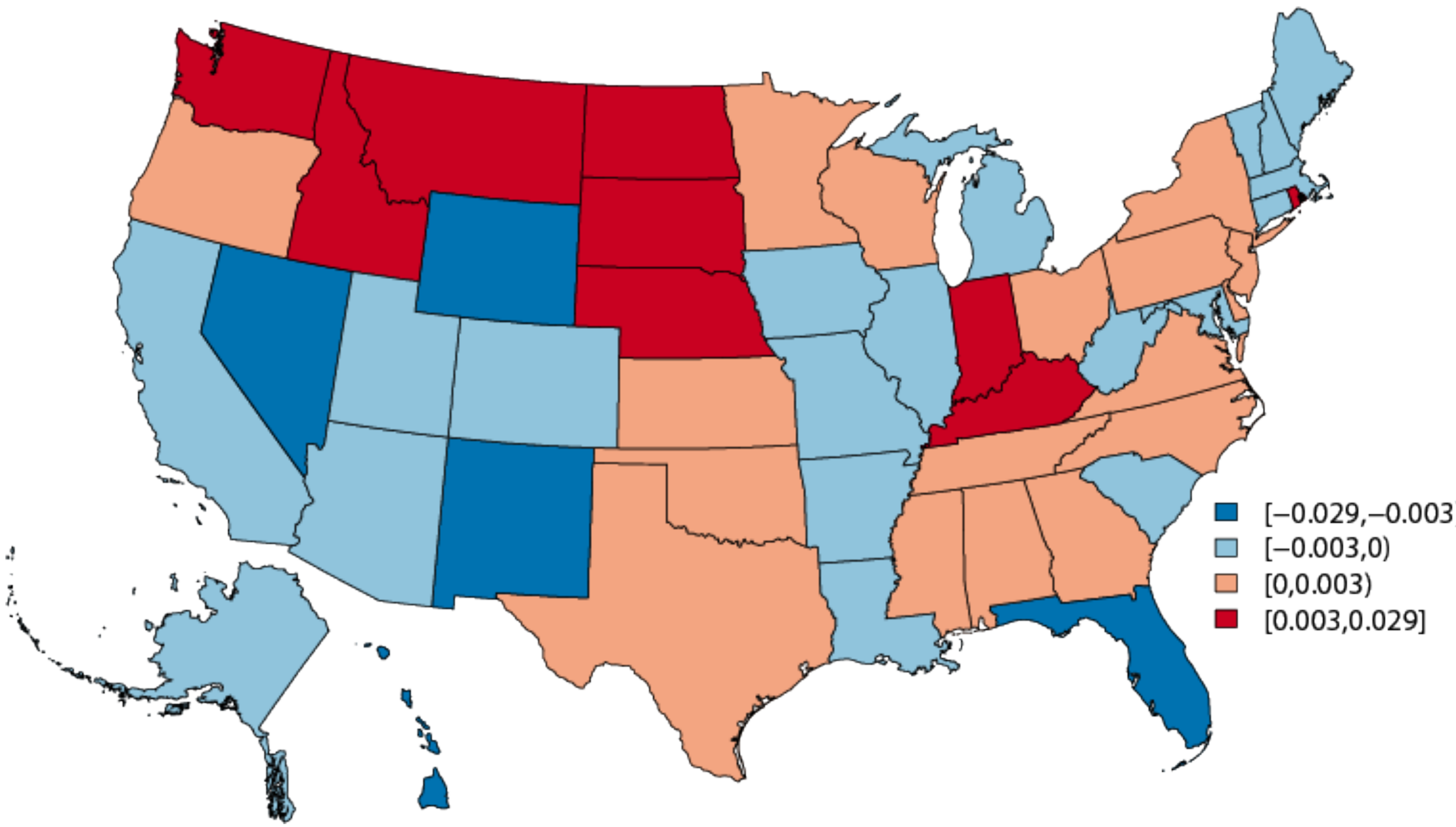

Figure 5: Spatial Variation in the effect of Aggregate Poverty on Racial Classification as Black

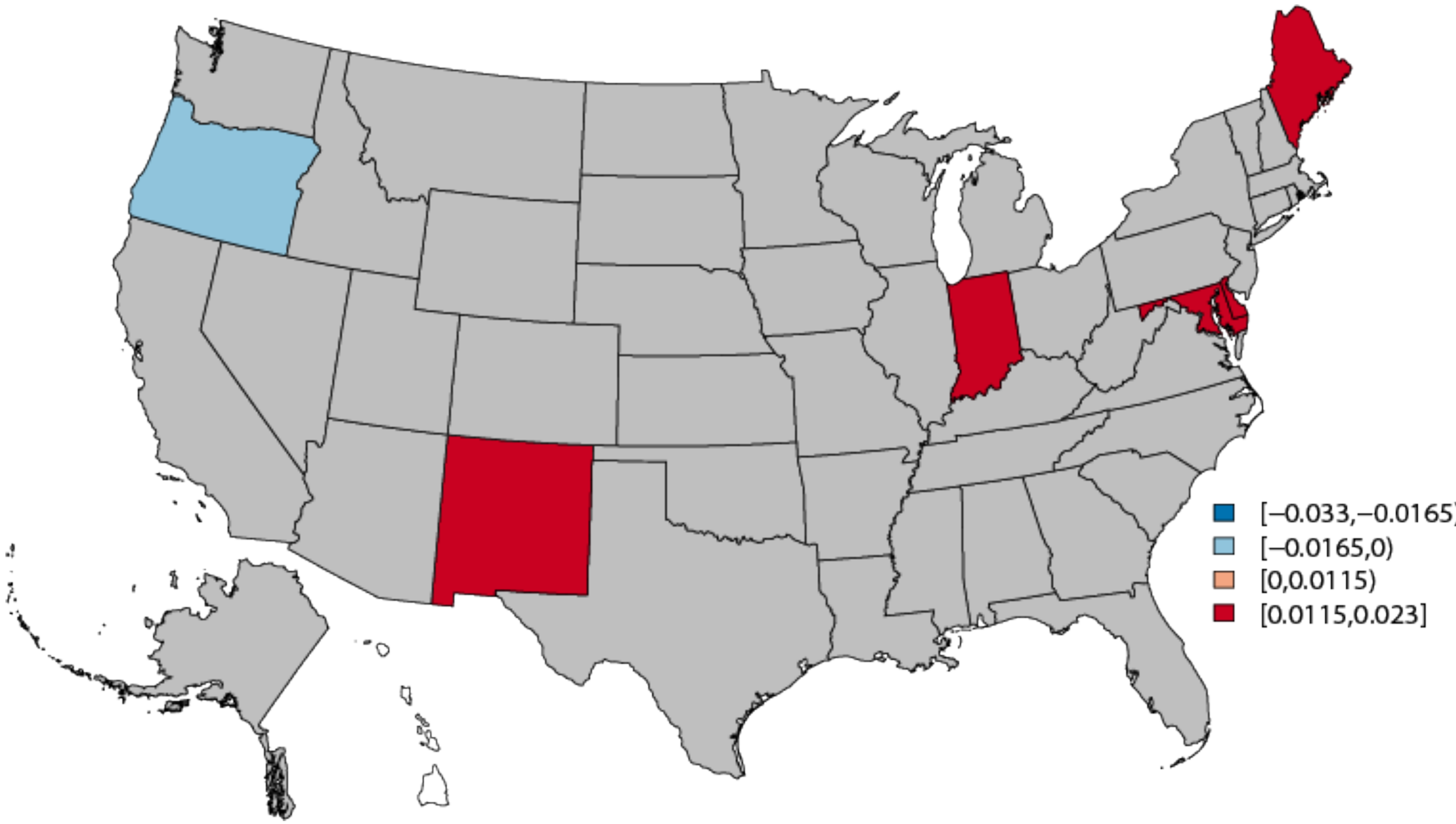

Figure 6: Spatial Variation in the effect of Percent Hispanic on Racial Classification as Black

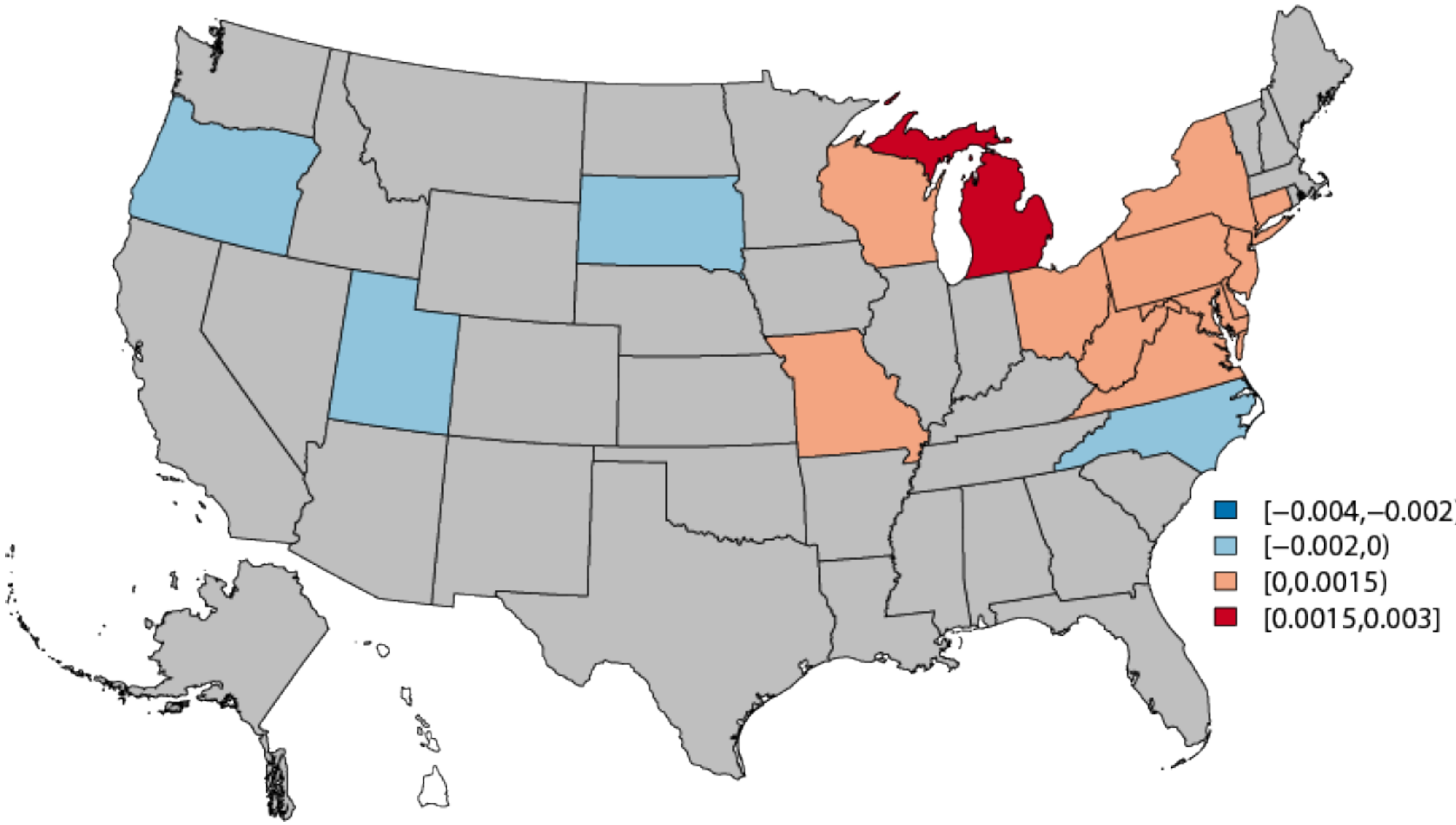

Figure 7: Spatial Variation in the effect of Diversity on Racial Classification as Black

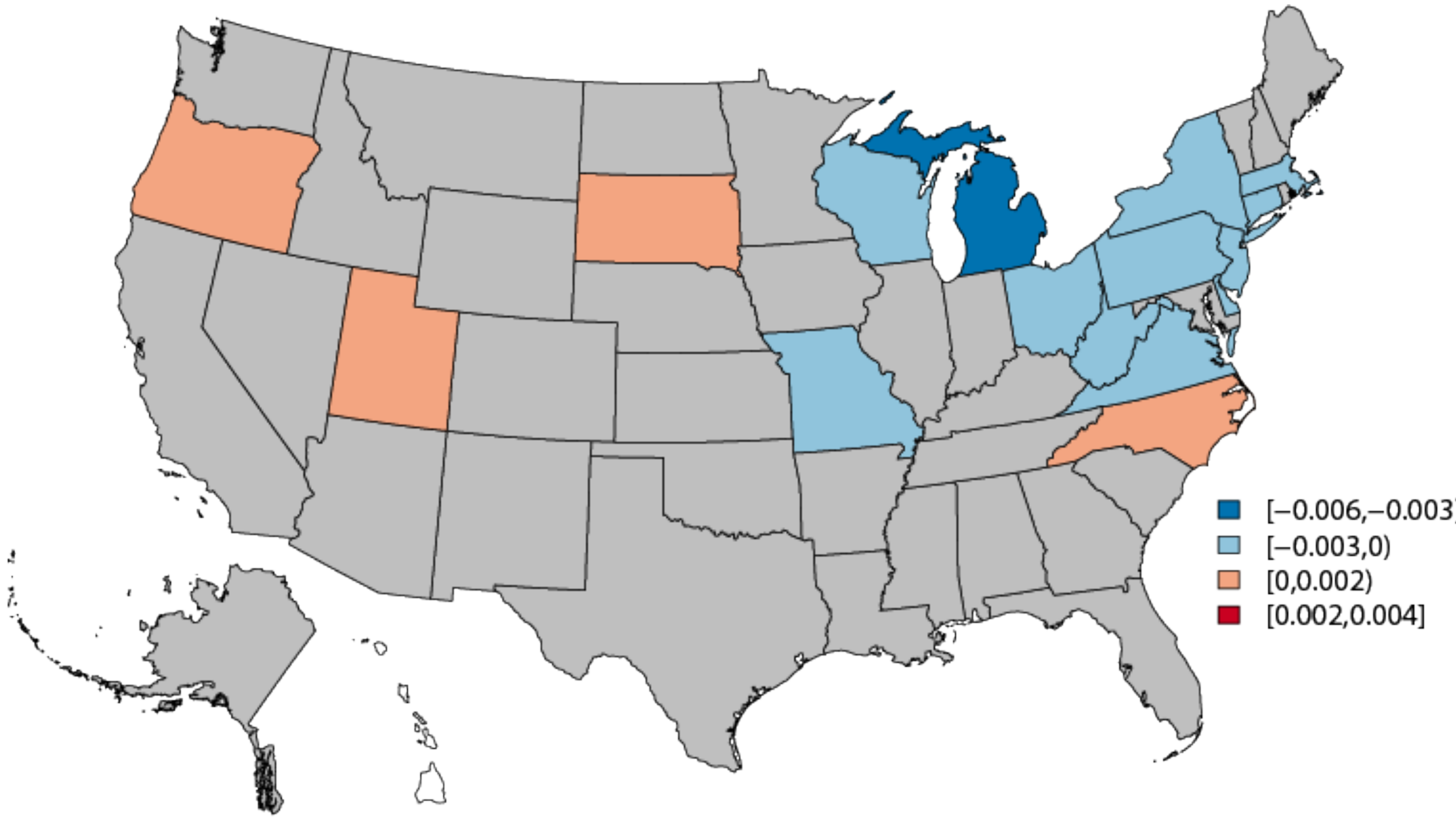

Figure 8: Spatial Variation in the effect of the Unemployment Rate on Racial Classification as White

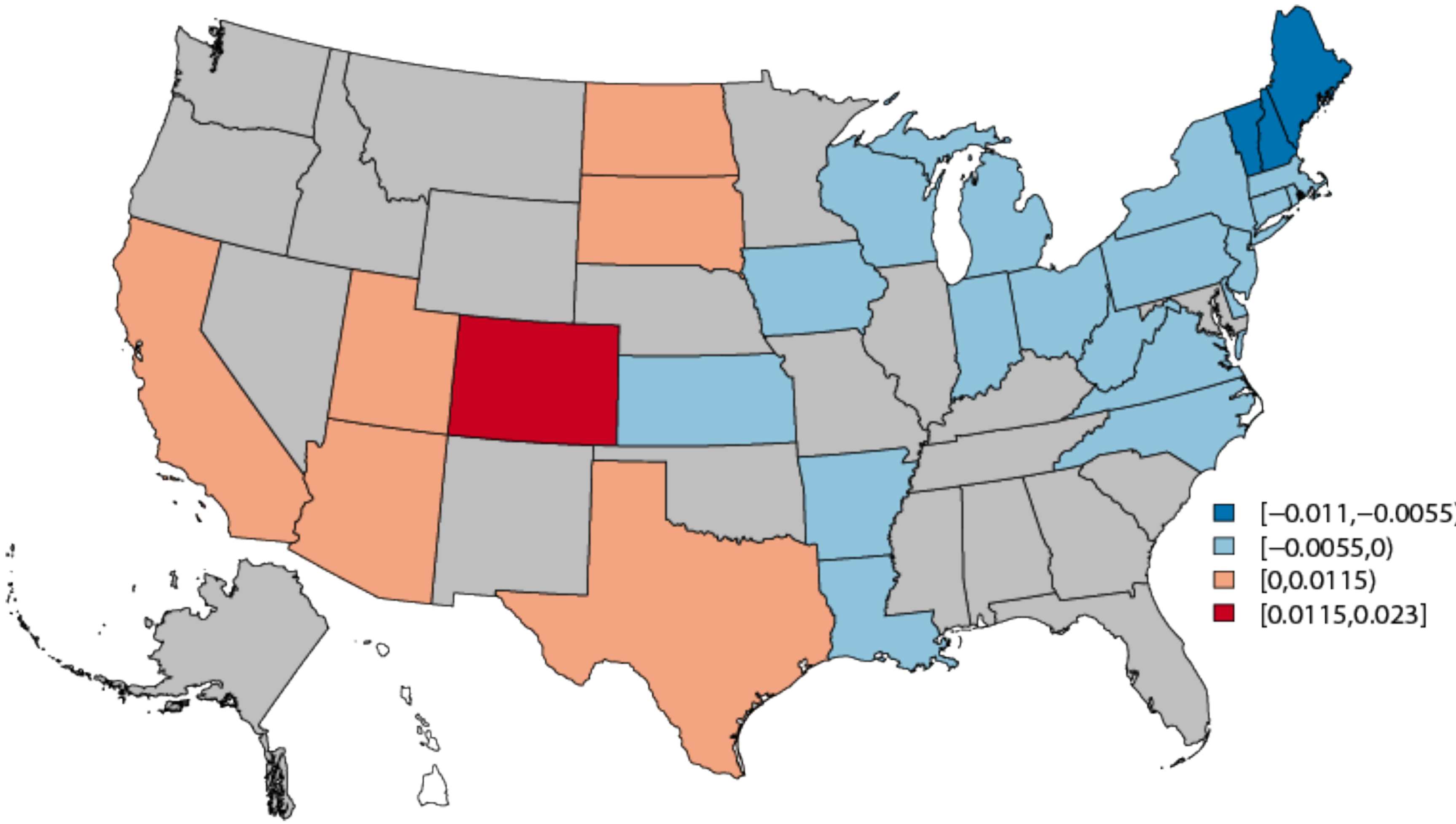

Figure 9: Spatial Variation in the effect of Aggregate Poverty on Racial Classification as White

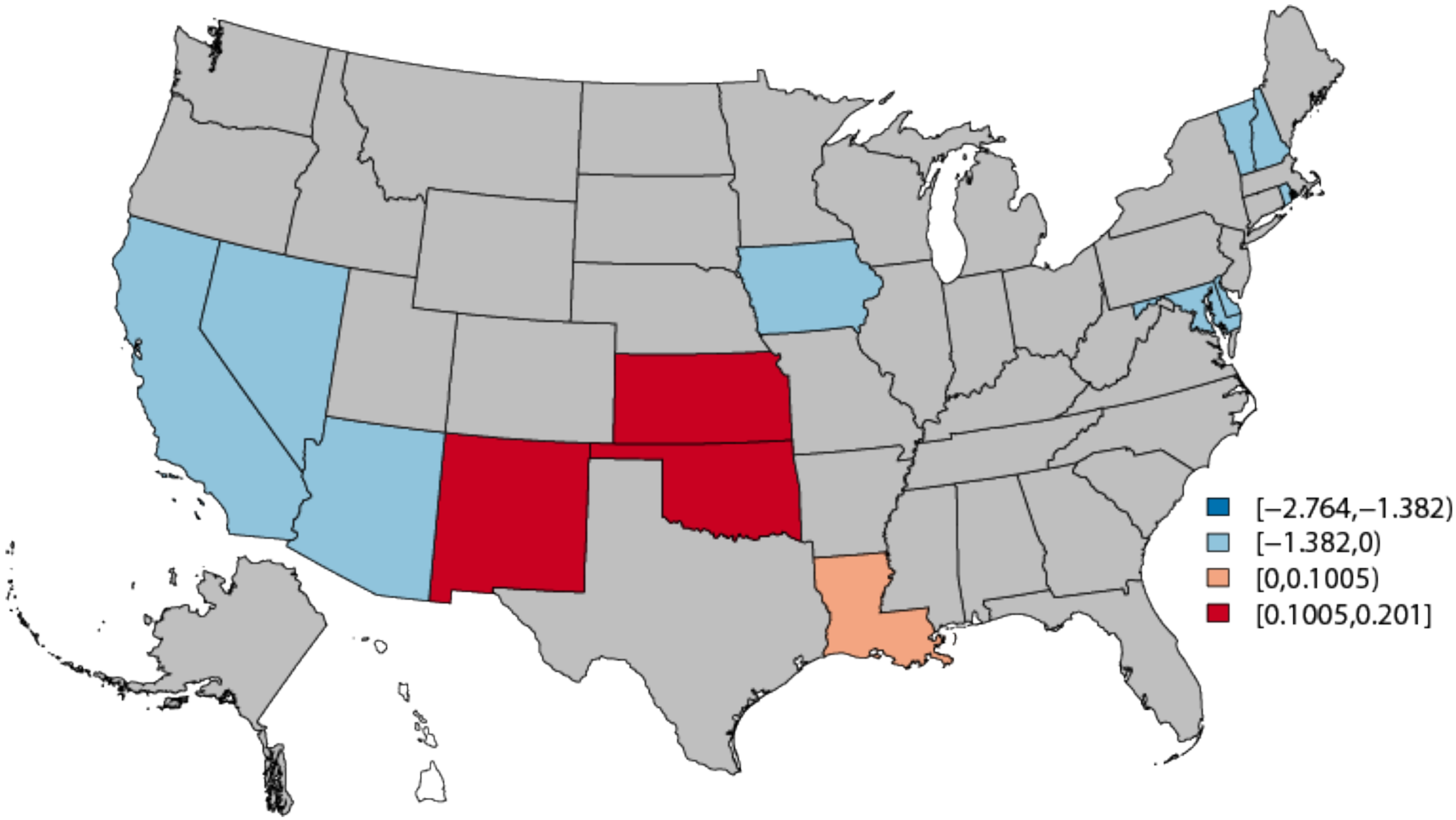

Figure 10: Spatial Variation in the effect of Percent Foreign Born on Racial Classification as White

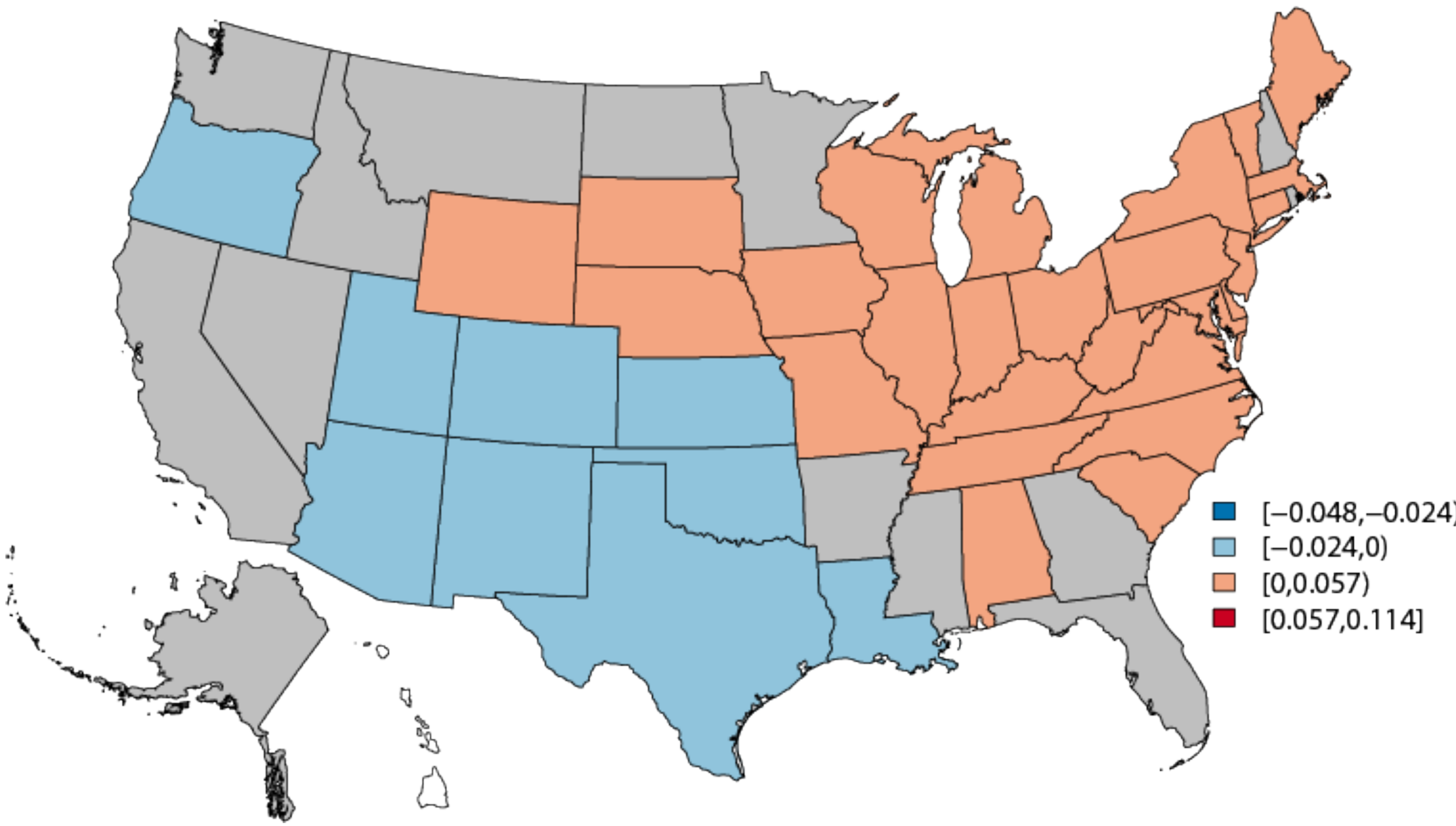

Figure 11: Spatial Variation in the effect of Percent Hispanic on Racial Classification as White

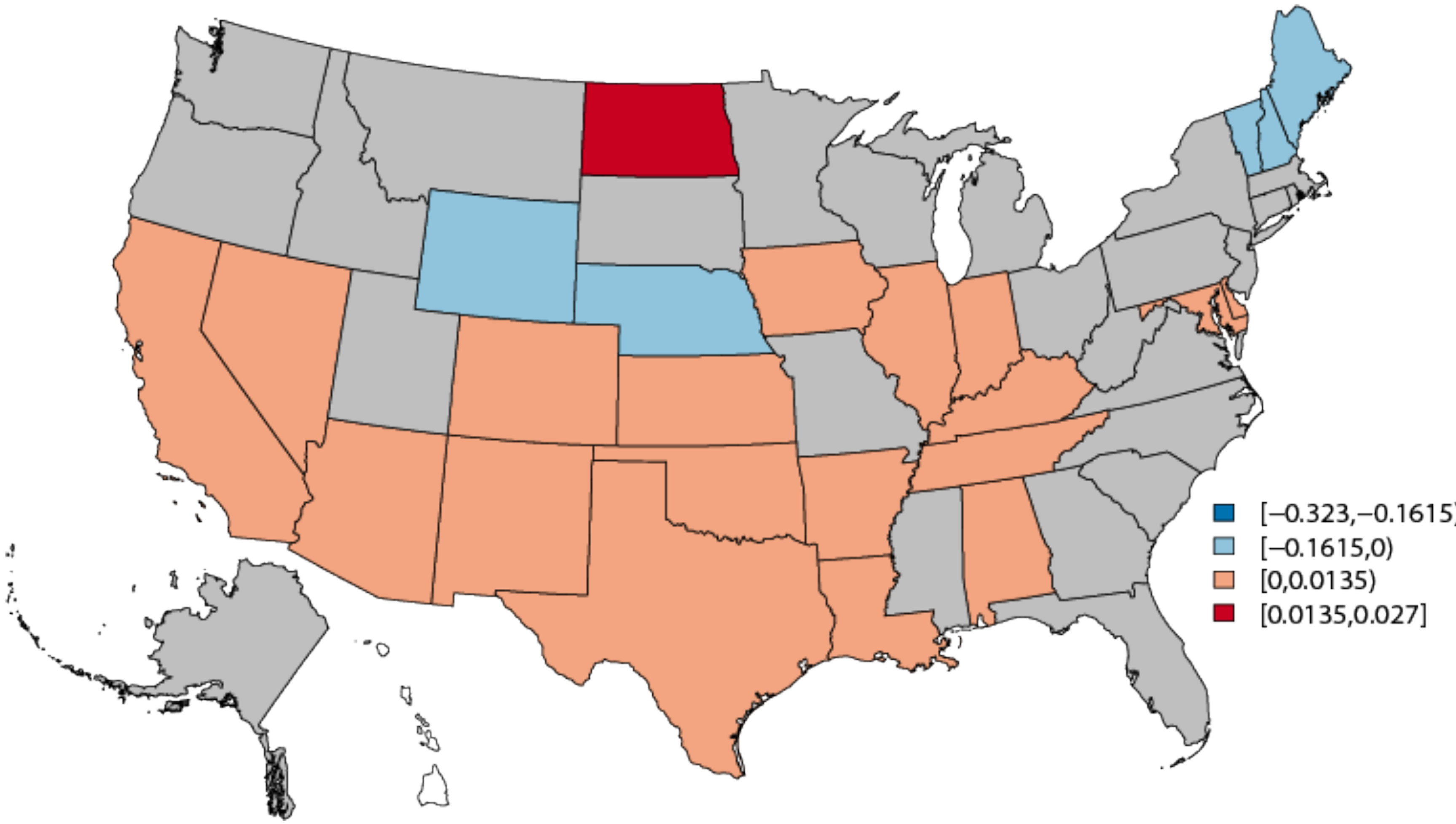

Figure 12: Spatial Variation in the effect of Diversity on Racial Classification as White

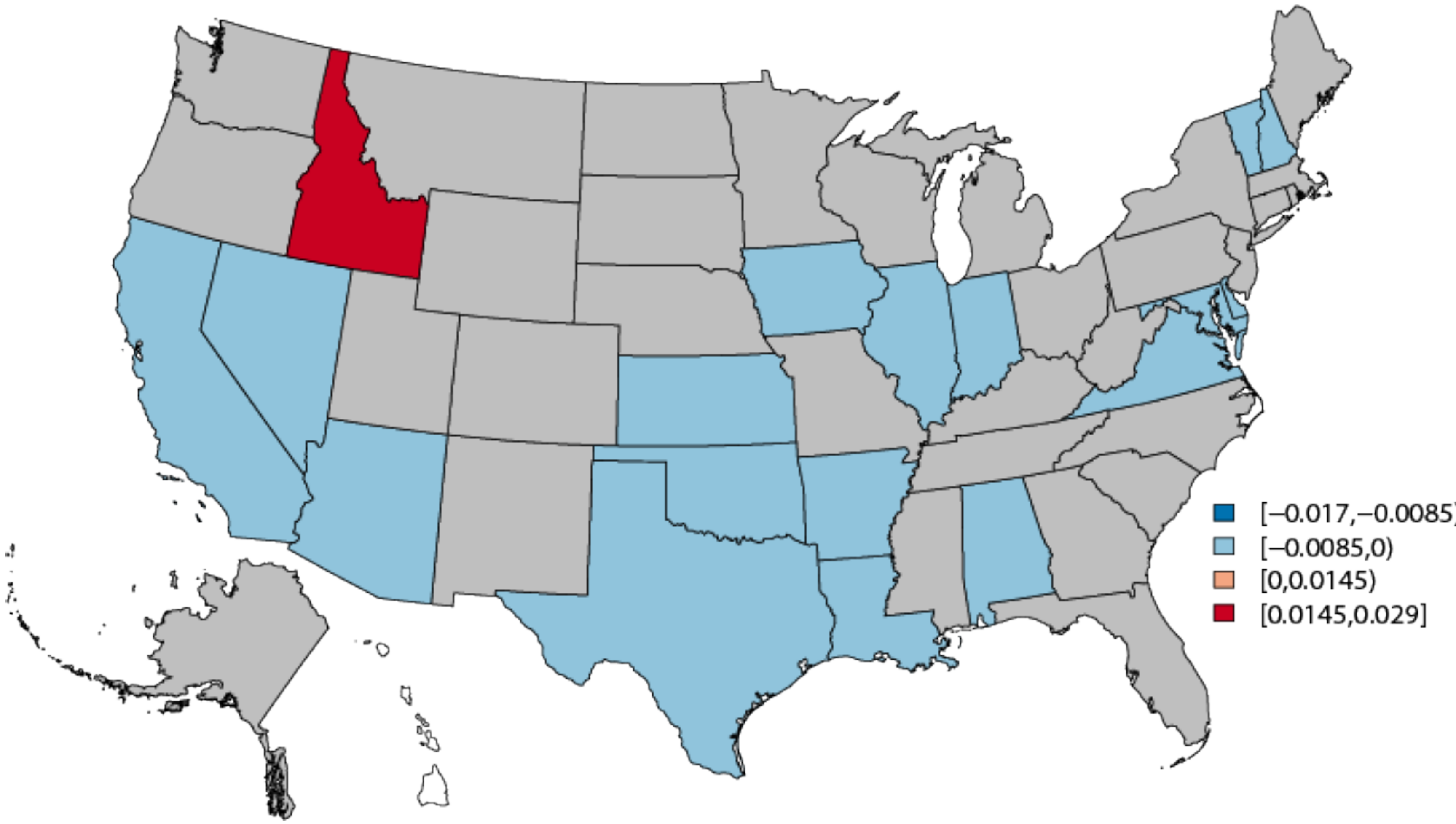

Figure 13: Spatial Variation in the effect of Population Size on Racial Classification as White

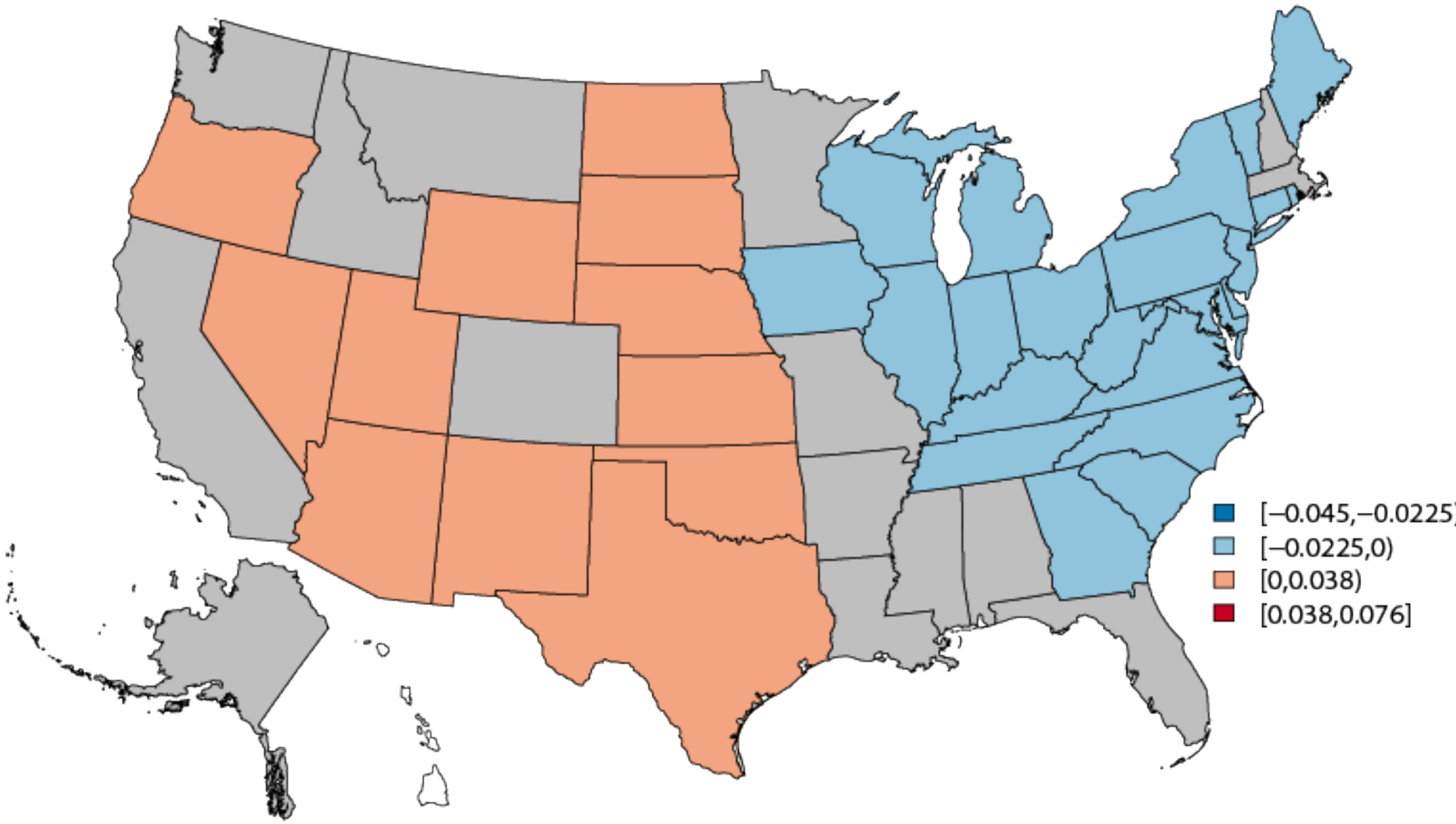

Figure 14: Spatial Variation in the effect of the Unemployment Rate on Racial Classification as Other

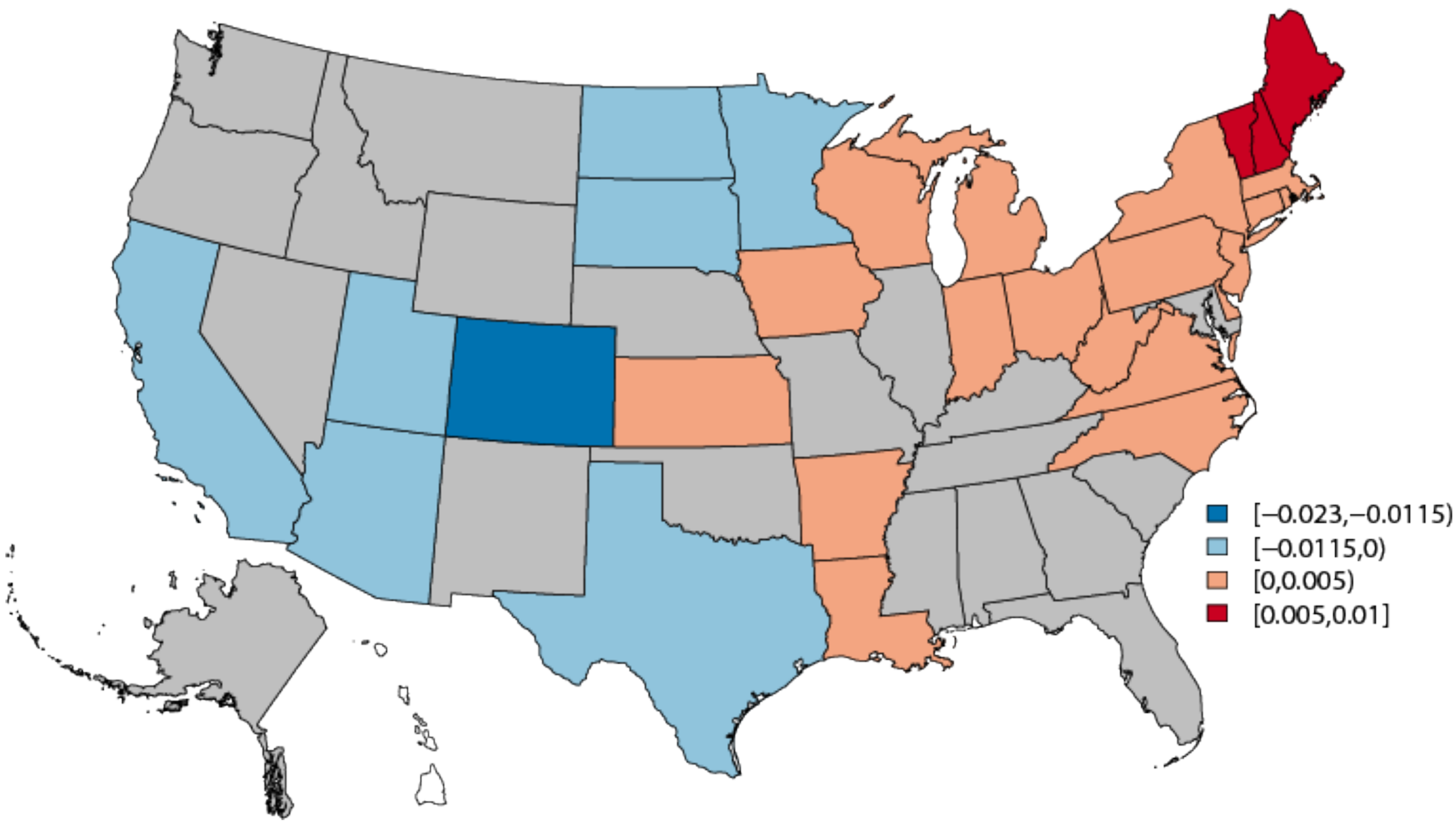

Figure 15: Spatial Variation in the effect of Aggregate Poverty on Racial Classification as Other

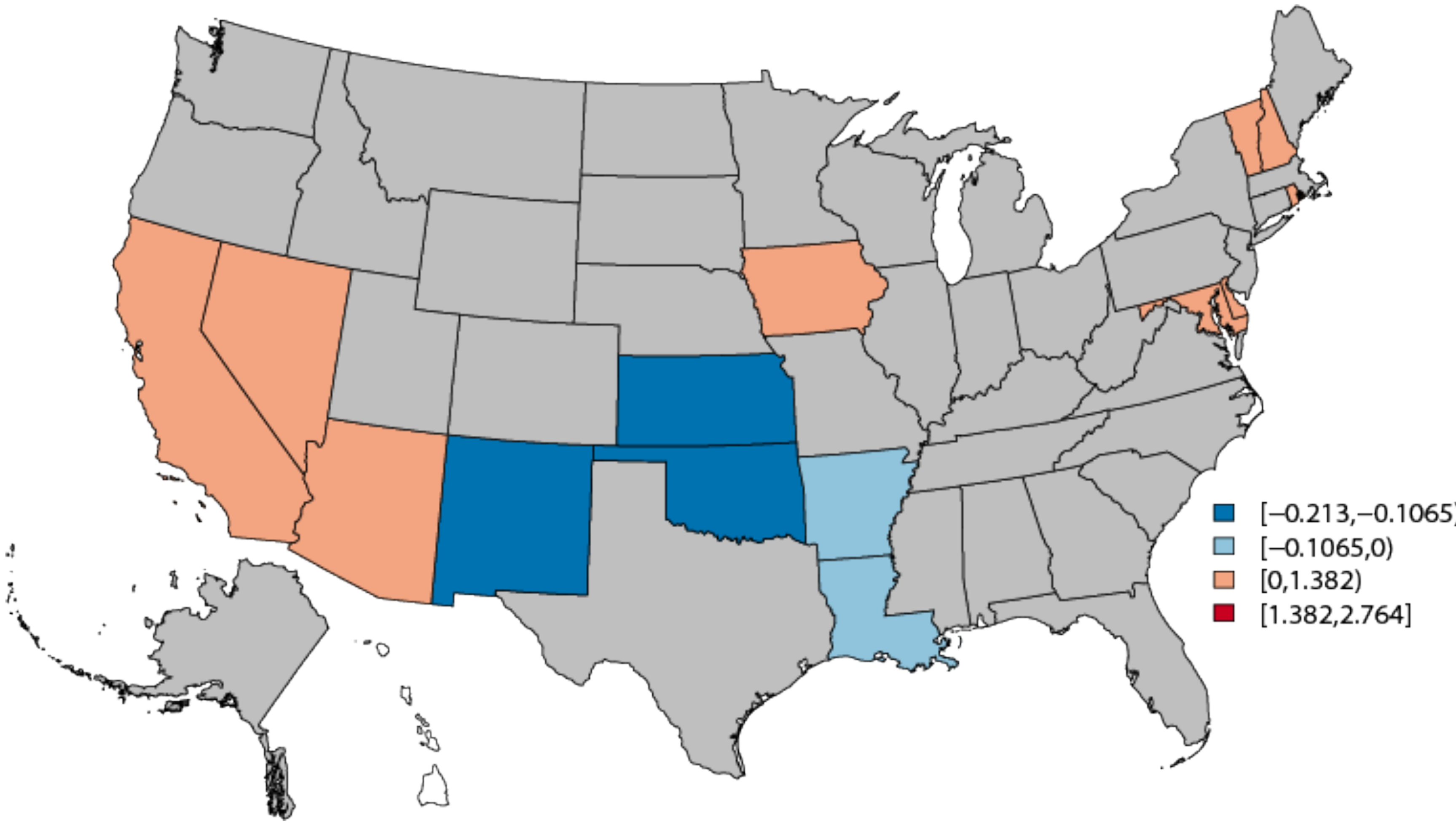

Figure 16: Spatial Variation in the effect of Percent Foreign Born on Racial Classification as Other

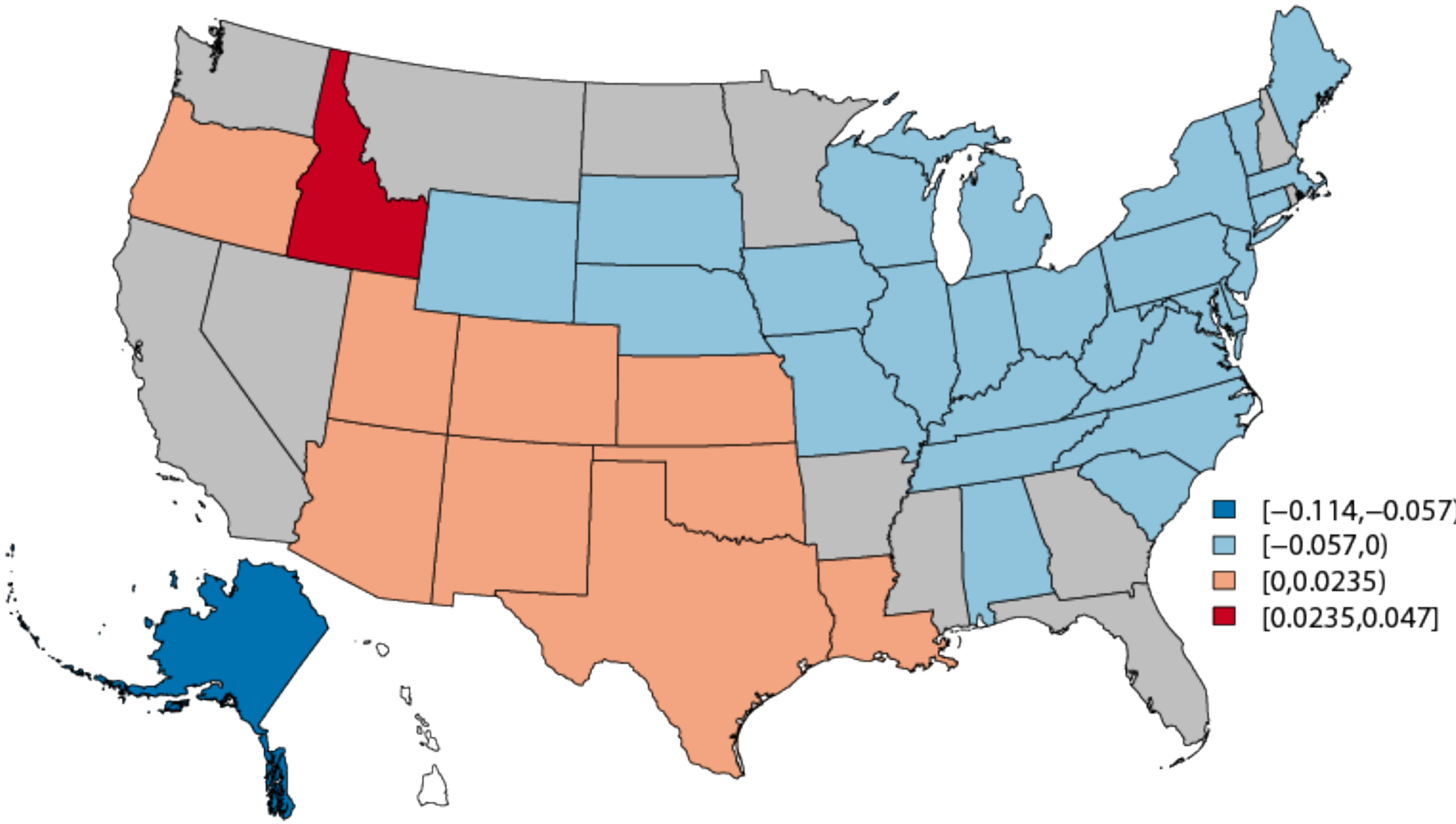

Figure 17: Spatial Variation in the effect of Percent Hispanic on Racial Classification as Other

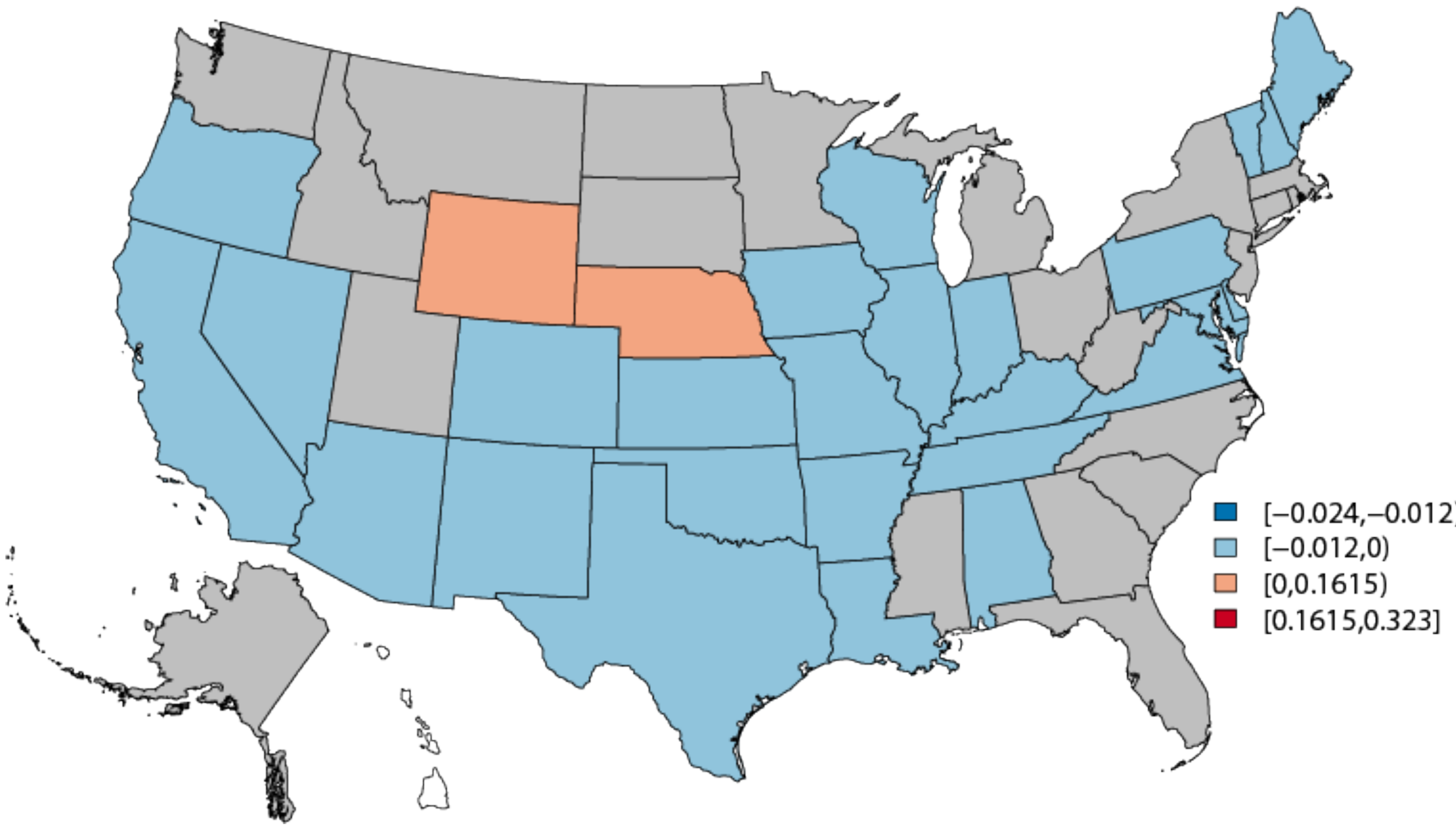

Figure 18: Spatial Variation in the effect of Diversity on Racial Classification as Other

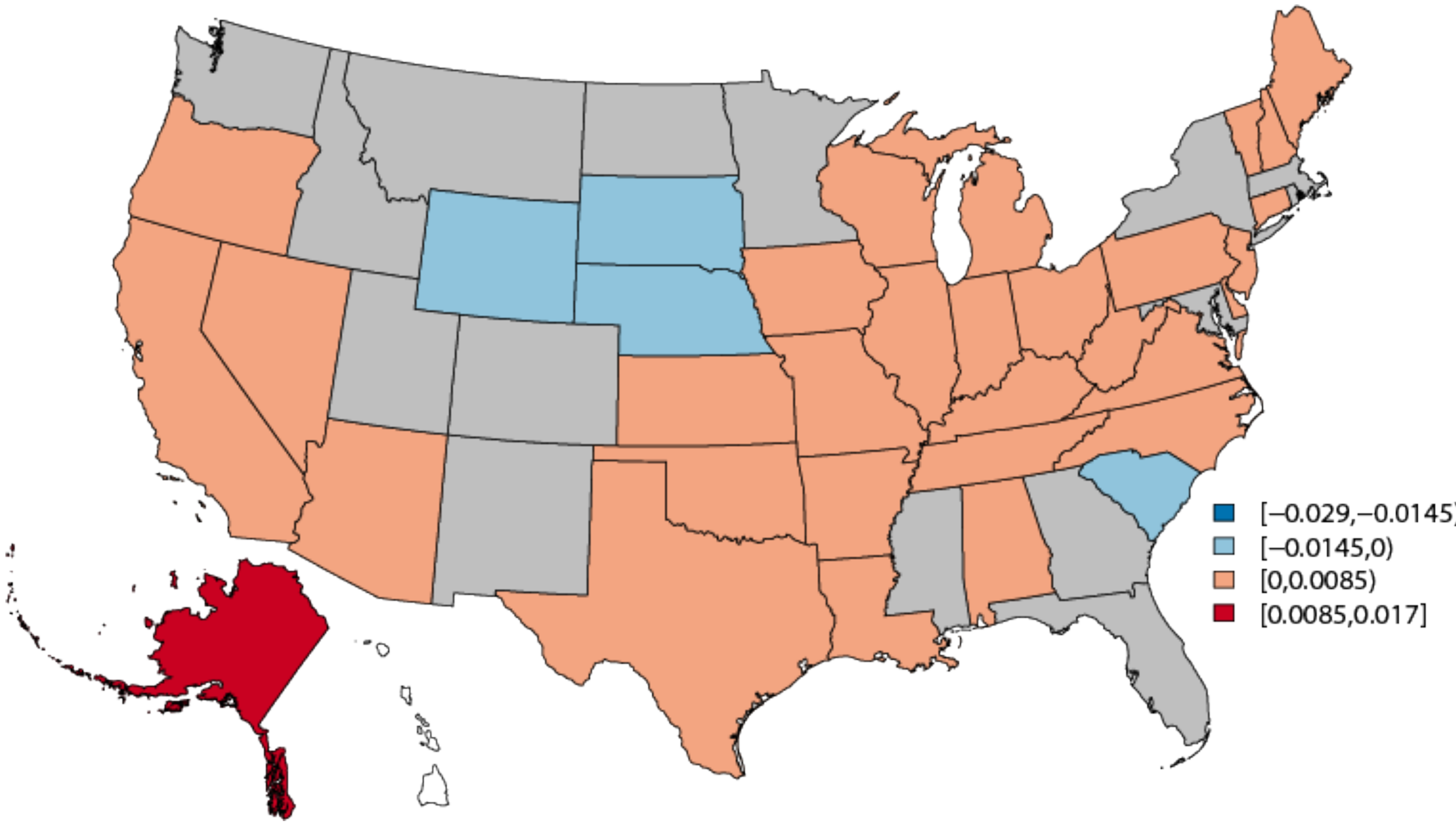

Figure 19: Spatial Variation in the effect of Population Size on Racial Classification as Other