Neighborhood characteristics and individual perception of social inequity

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Abstract

The neighborhoods that people live in contain a variety of features that color their everyday psychological experience. Whether they feel welcomed by their neighbors, the type of schools they can send their children to, and whether they can find a local job that pays them enough to afford a safe, comfortable home are all examples of ever-present factors that can influence people's perception of the world and their place in it. Previous work has explored the degree to which individual characteristics, such as personal beliefs and social networks, are associated with judgments about whether society is fair and just. Here, we build upon this work by investigating if these judgments are also associated with the features of the neighborhoods that people live in. Specifically, we hypothesize that neighborhood diversity and socioeconomic indicators will relate to individual beliefs about fairness and social order. We test this hypothesis using two large, open datasets – the Attitudes, Identities, and Individual Differences study data, and the Opportunity Insights Neighborhood Characteristics by County data – and through multi-method modeling techniques. Our work can inform theories of individual perception of, and response to, societal inequity, as well as models of public opinion of social welfare policy.

Keywords: neighborhoods, inequality, socioeconomic status, diversity, just world, social dominance

Zoë is six years old and attending 1st grade at a neighborhood public school in an American city. Her Thursdays consist of classes at that neighborhood school, followed by a couple of hours at an after school program, before being picked up by one of her parents to walk a couple of city blocks north to the ballet studio for dance lessons. All told, Zoë will spend the majority of her week, Monday through Friday, within roughly two square miles. Zoë's experience of the American city she lives in is fundamentally shaped by this environment. The people she meets and interacts with at her school nearly all come from her neighborhood—a wealthy suburb adjacent to a private East Coast University—and without intervention, her beliefs about society will naturally develop informed by the people and attitudes that prevail there. How Zoë reasons about inequality in society and whether it is fair may also depend on features of this environment – whether it reveals the magnitude of inequality within the city she resides, and if she comes into regular contact with people who come from different circumstances than she does. In this research project, our aim is to better understand the associations between neighborhood demographic characteristics of the sort that Zoë experiences daily on her trips to and from school, and their relationship to perceptions of societal inequity.

Evidence supports the conclusion that the U.S. is indeed an unequal society (e.g. in concentration of annual income, Fontenot, Semega, & Kollar, 2017; and personal wealth, Zucman, 2019), and further patterns of inequality in attainment of wealth, power, and prestige have been observed across demographics (e.g. education by race, Bohrnstedt, Kitmitto, Ogut, Sherman, & Chan, 2015; earnings by gender, Fontenot, Semega, & Kollar, 2017; intergenerational income mobility by race, ethnicity, and parental socioeconomic status, Chetty, Hendren, Jones, & Porter, 2018). But individual perception of *inequity* – whether this observed distribution is morally fair or just – can drive efforts to reduce it on a national scale. Indeed,

converging evidence from across the social sciences suggests that the degree to which one is dissatisfied with inequality correlates positively with support for government interventions to reduce it (e.g. via welfare programs, Bullock, Williams, & Limbert, 2003; income redistribution, McCall & Kentworthy, 2009; establishing minimum living standards and jobs, Shelton & Wilson, 2009).

Understanding what factors contribute to people's perceptions of inequity is fundamentally a question for psychology that has potential important implications for predicting public support for government intervention. The present research would contribute to such understanding by assessing whether local social context is a factor that shapes equity-based beliefs. Specifically, we will investigate whether economic and racial diversity characteristics of the neighborhood that a person currently lives in relates to their general perceptions of fairness, justice, and social order. We intend to leverage two large, open datasets with national representation to do so: the Attitudes, Identities, and Individual Differences (AIID) Study data (Hussey, Hughes, & Nosek, 2018), and the Neighborhood Characteristics by County dataset produced by Opportunity Insights (Chetty et al., 2010).

Individual outcomes related to neighborhood inequality

We focus on neighborhoods due to the abundance of literature linking individual psychology to inequality at this level. To understand why these are related, it helps to illustrate the experience of individuals living in relatively deprived neighborhoods. Those who live in a low-income area are likely to reside in noisy, crowded, deteriorating buildings (Lott, 2012), be exposed to greater amounts of pollutants (Brulle, & Pellow, 2006) and crime (Brooks-Gunn, Duncan, & Aber, 1997), and have restricted access to grocery stores (Powell, Slater, Mirtcheva,

Bao, & Chaloupka, 2007), greenspaces, transportation, and childcare (see Evans, & Kantrowitz, 2002 for a review).

The accumulation of these features of low-income neighborhoods can have psychological impacts on the residents. Lack of proper nutrition and sleep that is insufficient in both duration and quality is associated with decreased executive functioning (Bickel, Moody, Quisenberry, Ramey, & Sheffer, 2014; Cunha & Heckman, 2009; Schilbach, Schofield, & Mullainathan 2016). The increased number of daily hassles that people experience while living in these neighborhoods increases their overall stress (Diemer, Mistry, Wadsworth, López, & Reimers, 2013) and this stress is linked with impaired functioning in cognitive control areas of the brain (Duncan, Magnuson, & Votruba-Drzal, 2017). These stressors also likely contribute to the observed trend that individuals in deprived neighborhoods experience mood disorders like depression and anxiety more frequently, regardless of physical health (Muramatsu, 2003). However, other studies have found that the psychological experience of belongingness and cohesion in a neighborhood may attenuate this trend (Franzini, Caughy, Spears, & Esquer, 2005; at the state level, Kawachi, Kennedy, Lochner, & Prothrow-Stith, 1997), particularly for members of marginalized ethnic and racial groups (Hutchinson et al., 2009; Rios, Aiken, & Zautra, 2011).

The epidemiological evidence therefore supports the expected conclusion that neighborhoods are rich with features which influence individual mental health and functioning. Our intention is to build upon this work by investigating whether these features also color individuals' perception of broader society, specifically the degree to which it is equitable or not.

Social Cognitive Predictors of Inequality Beliefs

There are currently many psychological theories attempting to explain variation in individuals' judgment of the level of societal inequality, and their opinions of it; we briefly address a couple here, but see Kay and Brandt (2016) for a more thorough review. One class of theories concerns our general tendency to want to live moral, good, and just lives in societies that possess similar sentiments. These 'just world' belief systems arise from basic needs to predict and control the world, and such justice beliefs serve to bring some measure of stability and explanation to the outcomes that befall us and our kin throughout the lifecourse (Kay & Jost, 2006; Lerner, 1980). Empirical evidence suggests that this belief manifests in the attributions that individuals make about others' socioeconomic position. Individuals who attribute low socioeconomic to personal characteristics, such as laziness, instead of external factors outside of individual control, such as job availability, have been shown to endorse this belief (Cozzarelli, Tagler, & Wilkinson, 2002; Varnum, 2013). Relatedly, research studying perception of economic mobility suggests that avoiding external attributions in service of maintaining belief in controllable outcomes may in turn lead to underestimations of the level of societal inequality (Davidai, 2018; Kraus & Tan, 2015; Kraus, Rucker, & Richeson, 2017). According to this theory, self-protective tendencies may therefore distort judgment of inequity.

An alternative but overlapping theory instead affords status-based threats to the social order in people's perceptions of inequality. Social dominance theory proposes that individuals develop beliefs about inequality that support societies current status hierarchy (Sidanius & Pratto, 1991). Under this theory, high status groups in society are perceived as having greater merit, ability, and general supremacy because such beliefs justify and maintain the current social order. Social dominance orientation (SDO) is a construct of this theory observed at the individual level, and describes a preference for such group-based domination (Pratto, Sidanius, Stallworth,

& Malle, 1994). SDO has been found to cross-nationally positively relate to support for inequality (Pratto et al., 2000). Further, recent evidence suggests that this acceptance of inequality leads to greater satisfaction with, and trust in, a government at the head of an unequal society (Brandt & Reyna, 2017). A social dominance orientation may thus color influence opinions of national inequity via general support for hierarchical systems.

Finally, another class of theories addresses contextual influence on individual perceptions. Social contact theory proposes that intergroup prejudice can be reduced through cross-group exposure within favorable circumstances, generally through the processes of increased individuation of and identification with outgroup members (Miller, 2002). With regards to individual perception of inequality, increased social contact with members of disadvantaged groups may reduce attributing socioeconomic class to personal characteristics, and general support for a hierarchical society. Prior work linking social contact to judgments of equality has found that the racial diversity of an individual's social network is negatively correlated with underestimation of the wealth divide between Black and White Americans (Kraus, Rucker, & Richeson, 2017), that positive interaction with a dominant outgroup can increase support for meritocracy and decrease support for equity policy (Sengupta, & Sibley, 2013), and that greater county-level inequality is associated with differential endorsement of meritocratic beliefs among low- and high-income people in line with their own personal experiences (Newman, Johnston, & Lown, 2015). Social contact may therefore influence perception of societal inequality in line with an outgroup following positive interaction, while lack of this interaction instead may encourage individuals to focus only on their experiences when making such judgments.

The reviewed research demonstrates that individuals' perceptions of the level of inequality in society are associated with personal beliefs, attitudes, and local context. The present research now investigates whether personal beliefs about how fair society *should be* are associated with the characteristics of the neighborhood in which they live.

The present research

This work aims to provide answers to two broad questions by testing several consequential hypotheses. First, our primary question of interest is whether people's judgment of whether society is fair is related to the characteristics of their local context. Based on previous observed trends, we test the following hypotheses:

- 1) Higher status neighborhood socioeconomic characteristics will be positively correlated with endorsement of social inequality, and with belief that the world is fair.
- 2) Greater neighborhood racial diversity will be negatively correlated with endorsement of social inequality, and with belief that the world is fair.

A related, but secondary question that we ask is if individual bias for specific class and/or race groups over others is associated with the features of their everyday environment:

- 3) Higher neighborhood socioeconomic status, and lower neighborhood diversity, will positively correlate with bias towards a dominant group in the social strata.

We intend to contribute answers to these questions via secondary analysis of cross-sectional survey data that have been made openly available for researchers to use. While there are benefits to using these data, doing so also imposes a limitation in that we cannot infer causality among our variables of interest. Our contribution lies in investigating whether there are patterns of association among variables not yet reported in the literature.

Method

Participants and procedure

Participant data were provided by the Attitudes, Identities, and Individual Differences (AIID) Study team. This dataset represents a large ($N = 200,000$), international sample of participants who voluntarily took part in the online ‘virtual laboratory’ Project Implicit (<https://implicit.harvard.edu/implicit/>). Participants were randomly assigned to take one of ninety-five versions of the Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998), a subset of seventy-nine items assessing explicit bias, and a subset of fifteen total individual-differences measures, and completed these in addition to basic demographic information (see original study for details, Hussey, Hughes, & Nosek, 2018). After expressing interest in these data, the authors of this manuscript were provided with an exploratory subset of the data, but neither author has had access to the full dataset prior to submission of this registered report.

Inclusion in our study will be reduced from this original dataset. Specifically, in order to address our primary research aim, participant selection will be restricted to those who reported an accurate U.S. zip code for their current place of residence. Analyses to test our first three hypotheses will be conducted on this reduced dataset. Additional reduction is necessary to answer our secondary research aim; we will further restrict the sample to participants who took the African Americans/European Americans, Asians/Whites, and Poor People/Rich People versions of the IAT, and test our remaining hypotheses on these data. Additionally, due to the small number of individual differences items that we are using, only participants with complete data will be included in both of these data subsets.

Materials

The individual differences measures collected as part of the AIID study that we will use to index personal opinion of social inequality are Belief in a Just World: General Just World (Dalbert, Lipkus, Sallay, & Goch, 2001), Bayesian Racism (Uhlmann, Brescoll, Machery, 2010), Humanitarianism—Egalitarianism (Katz & Hass, 1988), and Social Dominance Orientation (number 4; Pratto, Sidanius, Stallworth, & Malle, 1994). Scale scores will be calculated based on their original instructions. Additionally, we will use the self-reported level of education and annual income bracket demographic items to represent individual socioeconomic status. Education level was collected as a categorical variable, with five options ranging from “not a high school graduate” to “graduate degree or graduate education”; annual income was similarly collected with five categorical levels ranging from “< \$25,000” to “> 150,000”. In some analyses these variables will be re-coded as ordinal (see analysis plan).

To assess implicit and explicit bias we include items relevant to the IAT category that participants saw. The IAT paradigm purports to measure implicit bias by comparing participants’ response times when matching opposing groups (e.g. cats and dogs) to opposing evaluative terms (e.g. good, friendly and bad, aggressive). The D score indexes this relative difference in response times to pairings (Greenwald, Banaji, & Nosek 2003), and is the measure of implicit bias that we use here. For explicit bias, we include the attitude questions that participants answered with regards to each group presented during the IAT; as a reminder, these categories were African Americans/European Americans, Asians/Whites, and Poor People/Rich People. These included general attitudes about each group (e.g., “which do you prefer, rich people or poor people?”), affective evaluations of each (“how warm or cold do you feel about poor people?”), and perception of the cultural treatment of people belonging to each group (“how much does the culture you live in like or dislike rich people?”). Each explicit bias item was always asked for

each group in the IAT category, although participants completed only a subset of all possible explicit items; see Appendix A for a list. To accommodate for this missingness and increase complete data, composite scores will be created by averaging across like-items, as suggested by the AIID team; for example, the items asking participants to rate positive affect for, warmth towards, and liking of each group will be averaged into a single general positivity item for that group.

Finally, we will include items from the Opportunity Insights neighborhood characteristics data to measure neighborhood socioeconomic and diversity levels. While the AIID data includes individuals' zip codes, the neighborhood characteristics data is instead in terms of county. We will use a crosswalk file provided by the United States Census to translate between the two. As United States counties are larger than zip codes, and may indeed contain multiple zip codes within them, we will map neighborhood county data to the most populous zip code in that area. For some analyses, highly correlated neighborhood socioeconomic or diversity variables will be averaged across and then z-scored to create a composite variable (see analysis plan for more details, and Appendix B for a variable list). Both the Census crosswalk and county neighborhood variables are taken from the year 2010.

Analysis plan

All analyses will be run in R (version 3.6.0; R Core Team, 2018). Prior to tests of our hypotheses we will conduct reliability estimates of all scale measures and constructed composites using McDonald's omega (ω). Poor reliability ($< .70$, per convention) will serve as an indicator to interpret relevant parameters with caution. If composite variables appear non-normally skewed (i.e., with a long right- or left- tail), we will use a Tukey ladder of powers transform (Tukey, 1977) to normalize the variable distribution. The assumption of variable

normality is made by several of our planned inferential tests (Pearson's R , albeit contested- see Nefzger & Drasgow, 1957; maximum likelihood estimation for structural equation models and multi-level models, Klein, 2011) and though violations of this assumption are common when working with social and psychological variables, evidence suggests that violating this assumption may bias results (e.g. for r , Kowalski, 1972; for random forests, Coulston, Blinn, Thomas, & Wynne, 2016). Therefore, we will apply this transformation should visual inspection of a composite variable reveal severe skew.

We will use the following methods to test our hypotheses:

- 1) To test the hypothesis regarding neighborhood socioeconomic characteristics with individual beliefs, we will conduct a series of bivariate correlations and either a random forest regression or multilevel model dependent upon sample size (see below).
- 2) To test the hypothesis that neighborhood racial diversity is associated with individual beliefs, we will also conduct a series of bivariate correlations and either a random forest regression or multilevel model.
- 3) Tests of the hypothesis that neighborhood characteristics are associated with measures of bias will be performed using a structural regression model.

Bivariate Pearson correlations will be run on each individual difference scale with each of the composite neighborhood variables as well as indicators of individual socioeconomic status for a total of sixteen comparisons. Our hypotheses are directional, and we therefore will evaluate tests of bivariate relations as one-tailed and at an alpha level of .05. Bivariate relationships will be interpreted according to their sign and statistical significance.

If sample size is large enough ($N > 700$ observations) we will proceed to run a random forest regression, predicting scale scores from neighborhood characteristics, individual SES, and

political identity. The use of multiple decision trees in random forests makes them well-suited to modeling complex, even non-linear associations among many features to improve predictive accuracy; though this process makes them a “black box” in that the coefficients among these features in the model are difficult to interpret. As our research question is more focused on uncovering whether a relationship exists between neighborhood and individual characteristics at all, not the particulars of those relationships, a random forest model will meet our needs. We will do this using the `randomForest` package in R (Liaw & Wiener, 2002). We will first split the data 7:3 into training and test sets, and perform model tuning on the training set before proceeding with the final test of the model’s performance in the test set. Model performance will be evaluated with regards to the percent variance that it explains in the test data, as the standard outcome metric for this method. We will also inspect the model parameter estimates of node purity, minimal depth, and times a root, and interpret these as revealing the relative importance of a variable in increasing model performance (that is, the variable is contributing meaningfully to explaining variance).

However, as model performance of random forest regression is optimized by some estimates in samples of up to fifty observations per feature (van der Ploeg, Austin, & Steyerberg, 2014), we would not feel confident in interpreting the results from a model with insufficient sample size. Thus, if sufficient sample size is not reached in our data subset we will instead test this hypothesis using a series of multilevel models. Multilevel modeling allows us to extract group-level variance (i.e., neighborhood characteristics) that might otherwise lead to correlated residuals among person-level variables of interest from people in those groups (i.e., individual differences). Using these models we can assess if differences in individuals’ beliefs vary systematically according to the neighborhood they live in, and according to their own SES. We

will test a version of the following model for all individual differences scores, thereby predicting each from participants' individual SES and neighborhood characteristics:

First level equation:

$$Y_{ij} \text{ (Individual belief of person } i \text{ by neighborhood } j) = b_{0j} + b_{1j}\text{Income}_{ij} + b_{2j}\text{Education} + b_{3j}\text{PoliticalID} + \varepsilon_{ij}$$

Second level equations:

$$b_{0j} = g_{00} + g_{01}\text{NeighborhoodSES} + g_{02}\text{NeighborhoodDiversity} + \mu_{0j}$$

$$b_{1j} = g_{10} + \mu_{1j}$$

$$b_{2j} = g_{20} + \mu_{2j}$$

Finally, we will run a structural regression model using the lavaan package (Rosseel, 2012). This technique permits us to model variables of interest that are not directly observed as latent factors; for example, several individual items asked about various was participants felt towards an IAT group that we can then model as mapping to a latent construct of general self-perception of the group. We can then impose a structure on our variables of interest and test for model fit to the observed data. We will model neighborhood characteristics and individual socioeconomic status as formative latent constructs with composite socioeconomic characteristics and composite diversity characteristics, and education and annual income, established respectively as indicators. Each implicit and explicit bias variable will then be regressed on these two latent factors. Where possible, to help with model identification, highly correlated ($r > .4$) explicit bias items will be modeled as reflective indicators of one common latent factor. Should items not correlate well together, they will instead be modeled as single indicators. Figure 1 is a depiction of this planned model, although we note that this figure may require an update based on the correlation of items and model identification needs as previously addressed. Fit of the model will be evaluated according to the fit statistics comparative fit index (CFI), Tucker-Lewis index (TLI), and Root Mean Square Error of Approximation (RMSEA), to assess both “goodness-of” and “badness-of” fit, respectively. If the model fits poorly (CFI and

TLI of $< .60$, RMSEA $< .80$) this will indicate that parameter estimates may not be stable. We will interpret the parameter estimates for the regressions based on their sign and statistical significance at the alpha level of .05, two-tailed.

This primary model will then be compared to one in which neighborhood variables are not included. We will test the performance of this nested model by comparing its Akaike information criterion (AIC), which decreases as the predictive accuracy of a model improves (Aho, Derryberry, & Peterson, 2014), as well as a change in chi-square test. While AIC is a relative statistic, we will interpret one model as performing better than another if chi-square is statistically significantly decreased, as indicated by $p < .05$.

Figure 1. Planned structural equation model of neighborhood characteristics, individual socioeconomic status, and measures of bias. Neighborhood socioeconomic and diversity characteristics, and individual education and income, are treated as formative indicators of latent neighborhood character and individual socioeconomic status, respectively. The structural regressions are of these latent factors on individual's explicit self-reported bias towards X and Y category that they saw during the implicit association test, as well as the implicit bias IAT score, D.

Timeline

The estimated timeline for completion of the final manuscript is four months. The data will first need to be acquired from the AIID study team and then cleaned prior to analysis. While analysis scripts are already written (and will be provided via an open source host), we will need time to acquire and interpret results.

Appendix A – Explicit Bias Questions

Note: Items were collected as part of the Attitudes, Identities, and Individual Differences (AIID) Study (Hussey, Hughes, & Nosek, 2018). Questions refer to the IAT version the participants saw, which included two categories of stimuli (X or Y). Participants randomly received 27-29 of these items to complete.

- 1.) Which do you prefer, Y or X?
- 2.) People's gut reactions about a topic can be different from their feelings after they have had time to think about it. For example, someone who is trying to quit smoking might have a very positive gut reaction, but negative actual feelings toward smoking. Rate your gut reactions and actual feelings toward the topics below:
 Gut reactions toward X/Y
 Actual feelings toward X/Y
- 3.) How positive or negative do you feel towards X/Y?
- 4.) How warm or cold do you feel towards X/Y?
- 5.) How much do you like or dislike X/Y?
- 6.) Considering only the positive things about X/Y, and ignoring the negative things, how positive are those things?
- 7.) Considering only the negative things about X/Y, and ignoring the negative things, how negative are those things?
- 8.) How personally important are your feelings toward X/Y?
- 9.) How much do you think about your feelings toward X/Y?
- 10.) How certain are you about your feelings toward X/Y?
- 11.) How much do you expect your feelings toward X/Y to change over time?
- 12.) How much is X/Y part of your self-concept?
- 13.) Having positive feelings toward X/Y implies having negative feelings toward Y/X.
- 14.) How warm or cold does the average person feel toward X/Y?
- 15.) How much does the average person like or dislike X/Y?
- 16.) How positive or negative does the average person feel toward X/Y?
- 17.) How warm or cold is society toward X/Y?
- 18.) How much does the culture you live in like or dislike X/Y?
- 19.) How positive or negative is society toward X/Y?
- 20.) How motivated is the average person to conceal negative feelings about X/Y?
- 21.) How motivated is the average person to conceal positive feelings about X/Y?
- 22.) How motivated is the average person to express negative feelings about X/Y?
- 23.) How motivated is the average person to express positive feelings about X/Y?
- 24.) There is cultural pressure to think positive things about X/Y.
- 25.) There is cultural pressure to think negative things about X/Y.
- 26.) No one gets upset if people say bad things about X/Y.
- 27.) No one gets upset if people say good things about X/Y.
- 28.) Does the average person prefer X or Y?
- 29.) Does the culture you live in prefer X or Y?
- 30.) Do most people prefer X or Y?
- 31.) Do your friends tend to prefer X or Y?

- 32.) Do your family members tend to prefer X or Y?
- 33.) Do people you know tend to prefer X or Y?
- 34.) I try to hide unfavorable thoughts about X/Y to avoid negative reactions from others.
- 35.) I attempt to appear accepting of X/Y to gain approval from others.
- 36.) I try to hide favorable thoughts about X/Y to avoid negative reactions from others.
- 37.) I attempt to appear rejecting of X/Y to gain approval from others.
- 38.) I try to express unfavorable thoughts about X/Y to avoid negative reactions from others.
- 39.) I attempt to appear rejecting of X/Y to avoid disapproval from others.
- 40.) I try to express favorable thoughts about X/Y to avoid negative reactions from others.
- 41.) I attempt to appear accepting of X/Y to avoid disapproval from others.
- 42.) Being rejecting of X/Y is inconsistent with my self-concept.
- 43.) Being accepting of X/Y is inconsistent with my self-concept.
- 44.) Being rejecting of X/Y is important to my self-concept.
- 45.) Being accepting of X/Y is important to my self-concept.
- 46.) Because of my personal values, I believe that making negative judgments about X/Y is wrong.
- 47.) Because of my personal values, I believe that making positive judgments about X/Y is wrong.
- 48.) Because of my personal values, I believe that making negative judgments about X/Y is acceptable.
- 49.) Because of my personal values, I believe that making positive judgments about X/Y is acceptable.

Appendix B – Neighborhood characteristic variables

Note: Variables were collected by Opportunity Insights (Chetty et al., 2010) at the county level.

We will include variables representing 2010 characteristics only. More information is available in the data codebook found at <https://opportunityinsights.org/data>.

- 1.) Population density (total county population as reported in the decennial Census divided by the county land area in square miles)
- 2.) Share of non-Hispanic Black residents
- 3.) Share of non-Hispanic Asian residents
- 4.) Share of non-Hispanic White residents
- 5.) Share of Hispanic residents
- 6.) Share of foreign born residents
- 7.) Mean household income
- 8.) Share of residents aged 25 or older who have earned a terminal four-year degree or higher education level.
- 9.) Share of residents living below the federal poverty line
- 10.) Share of single-parent households with children under 18 years of age
- 11.) The unemployment rate.

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