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Examining relationships among regional economic conditions, cognitive control, and intergroup bias in the implicit association test: A regional modeling approach

Kayla Chaplin [a], Liz Wilson [a,1], Ruben Laukenmann [a,b,c,#], Jimmy Calanchini [a,*]

[a] Department of Psychology, University of California, Riverside, United States
[b] School of Social Science, University of Mannheim, Germany
[c] Institute of Behavioral Science and Technology, University of St. Gallen, Switzerland

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ABSTRACT

Individuals experiencing economic stress demonstrate lower cognitive control and higher intergroup bias. The present research extends beyond individuals to investigate relationships among regional economic conditions, regional cognitive control, and intergroup bias. We aggregated 2.9 million US-based participants' geolocated responses on the Black/White Implicit Association Test, then applied the Process Dissociation Procedure to estimate state-level cognitive control and racial evaluations across the years 2005 to 2019. Black populations' cognitive control was weaker in states where Black residents faced more adverse economic conditions, but stronger in states where White residents faced more adverse economic conditions. White populations' cognitive control was weaker in states where more Black residents faced unemployment. Black populations' outgroup biases were more negative in states where more White residents lived in poverty, and White populations' ingroup biases were more positive in states where more White residents were unemployed. By understanding how economic conditions relate to regional cognition, this research can inform policies to better support economically-vulnerable populations.

As the saying goes, "Money can't buy happiness". Nevertheless, economic stress can negatively impact cognition. For example, when individuals experience economic stress, they demonstrate lower levels of cognitive control (Mani et al., 2013) and higher levels of intergroup bias (Krosch et al., 2017). Psychologists have extensively studied relationships among stressors (economic or otherwise), cognitive control, and intergroup bias within individuals (e.g., Jachimowicz et al., 2022; Kakkar and Sivinathan, 2017; Mani et al., 2013). Other disciplines that traditionally adopt structural perspectives – such as sociology, economics, and political science – have taken a complementary approach, investigating relationships among regional economic conditions and proxies for cognitive control and intergroup bias (e.g., Kelley and Evans, 2015; Kouba, 2016). The present research aims to bridge these two research traditions by examining covariation between regional economic conditions and regional aggregates of psychological measures of cognitive control and intergroup bias using a novel approach: process modeling at the region level.

1. Economic conditions

Economic stress is psychological strain or pressure that people experience when their finances seem unpredictable or when the difference between their assets and needs becomes too wide (Hagquist, 1998). In previous research at the individual level, researchers have either assessed participants' experienced economic stress through self-report measures (e.g., Shek, 2003) or manipulated economic stress through experiments (e.g., Sánchez-Rodríguez et al. 2019) to demonstrate relationships among economic stress, cognitive control, and intergroup bias. However, measuring or manipulating economic stress at region levels is often implausible or unfeasible. Consequently, researchers must identify regional economic conditions that they assume to induce economic stress among populations. One such proxy for economic stress is *economic inequality*, which reflects an unequal distribution of economic rewards like income and wealth within a society (Bradbury and Triest, 2016). In the present study, we operationalize economic inequality in

* Corresponding author.
E-mail address: jimmy.calanchini@ucr.edu (J. Calanchini).
# These authors contributed equally to the preparation of this manuscript.

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two ways: *relative inequality* and *objective disadvantage*. Relative inequality captures the unequal distribution of resources within a population by measuring the disparity between those with more and those with less (Catalano et al., 2009), whereas objective disadvantage reflects absolute material conditions such as rates of poverty or unemployment (Uwayo et al., 2009). From a practical standpoint, objective disadvantage might be more closely linked to economic stress than relative perceptions. As the poets RZA and colleagues put it: "cash rules everything around me" (Wu-Tang Clan, 1994). However, relative operationalizations of economic conditions are often more strongly related to disparate outcomes than are comparable objective measures (e.g., Kahn and Pearlin, 2006; Senn et al., 2014). Consequently, we examine both relative and objective economic conditions as they relate to regional cognitive control and intergroup bias.

2. Economic conditions and cognitive control

Cognitive control reflects individuals' ability to intentionally guide thought and behavior, especially in the presence of distraction or competing responses (Botvinick et al., 2001). The negative impact of individuals' experience of economic stress on cognitive control has been demonstrated in a wide variety of internally-valid experimental and ecologically-valid quasi-experimental ways across many cultural contexts. For example, low- but not high-income Americans performed worse on cognitive control tasks after considering a hypothetical, expensive car repair (Mani et al., 2013). Similarly, Indian farmers' cognitive control diminished over the planting cycle, as money became increasingly tight, but rebounded after harvest when the farmers were paid for their crops (Mani et al., 2013). When faced with everyday difficulties, low-income people are less able to rely on financial resources and, thus, report higher levels of distress compared to their higher-income peers (Jachimowicz et al., 2022). Perceived lack of control mediates the relationship between economic stress and cognitive control, which aligns with other work suggesting that financial scarcity tends to decrease feelings of agency (Kraus et al., 2009). People also report a lower sense of control in times of economic insecurity, which are characterized by higher poverty and unemployment rates (Kakkar and Sivanathan, 2017). Furthermore, socioeconomic inequality has been linked to worse executive functioning from a young age, suggesting a link between development and environmental disparities (Noble and Giebler, 2020). Adverse economic conditions may lead people to ruminate, which increases production of the stress hormone cortisol; both rumination and cortisol negatively impact cognitive functioning (Bohnen et al., 1990; De Lissnyder et al., 2012). Taken together, adverse economic conditions can manifest in many ways that reduce cognitive control.

3. Economic conditions and intergroup bias

In addition to negatively impacting control, economic conditions can also influence *intergroup bias*: the systematic tendency to view one's own membership group (i.e., the ingroup) more or less favorably than a group to which one does not belong (i.e., the outgroup). Intergroup bias can manifest in many ways, including discriminatory behavior, prejudiced attitudes, and stereotypical thinking (Hewstone et al., 2002). For example, White people allocate fewer resources to Black people when they believe that the economy is doing poorly (Krosch et al., 2017; see also Brewer and Silver, 1978). Similarly, people experiencing economic stress are more likely to exclude racially ambiguous others from the ingroup (Rodeheffer et al., 2012) and perceive outgroup members more stereotypically (Krosch and Amodio, 2014). In addition, people in more globalized countries report higher levels of intergroup bias when economic inequality is high (Caluori et al., 2021). One potential explanation for the relationship between economic conditions and intergroup bias is that economic scarcity induces zero-sum thinking, thereby leading people to limit access to resources for outgroup members (Brown et al., 2022). Complementing this body of work, economic perspectives suggest that institutional factors that mitigate economic threat (e.g., public services, social safety nets) may foster broader cooperation and trust in others, thereby reducing ingroup favoritism (Hruschka and Henrich, 2013).

4. Distinguishing the contributions of cognitive control and intergroup bias in implicit measures

Though cognitive control and intergroup bias are distinct constructs, their separate assessment is complicated by the fact that cognitive control influences responses on a wide variety of psychological measures, including measures of intergroup bias. Indeed, this issue is at the heart of classical efforts to distinguish variance related to the construct of interest (e.g., intergroup bias) from variance related to the assessment method (e.g., cognitive control; Buckley et al., 1990). The pursuit of a relatively pure assessment of intergroup bias, free of the influence of other processes that would constrain the expression of bias, contributed to the development of implicit[1] measures (e.g., Fazio, 1990; Gawronski et al., 2020).

Implicit measures are generally successful at reducing the influence of the kind of cognitive control that is reflected in responses on traditional explicit measures (e.g., self-presentation motivations), but other forms of cognitive control nevertheless influence responses on implicit measures. For example, performance on the implicit association test (IAT: Greenwald et al., 1998) is typically operationalized in terms of a single summary statistic interpreted as a measure of association strength (i.e., the *D-score*; Greenwald et al., 2003), which corresponds with the initial goal of the IAT to provide pure estimates of intergroup bias. However, this approach overlooks the fact that IAT responses also reflect the influence of control-oriented executive functions like task-set switching and working memory updating (Ito et al., 2015; Klauer et al., 2010). Summary statistics like the D-score are ill-suited to distinguish among multiple cognitive processes when they jointly contribute to responses. Instead, multinomial processing tree (MPT) models (Riefer and Batchelder, 1988) serve as an alternative approach to scoring responses on implicit measures by disentangling and quantifying the contributions of multiple processes to responses on tasks like the IAT.

MPT models belong to a class of formal mathematical models that link latent processes to observable responses. MPT models are tailored to specific experimental paradigms that provide frequency data (e.g., number of correct and incorrect responses), and specify the number, nature, and composition of cognitive processes thought to contribute to responses in the paradigm (Hütter and Klauer, 2016). In creating MPT models, researchers must make theoretically-grounded decisions about the specific manner in which multiple cognitive processes produce responses in each task condition. In this way, MPT models are mathematical instantiations of psychological theory packaged in a well-defined form.

The Process Dissociation Procedure (PDP: Payne, 2001) is an MPT model that has been applied to implicit measures like the IAT (Ito et al., 2015; Laukenmann and Calanchini, in press). The PDP consists of two parameters: one that quantifies the influence of cognitive control in terms of controlled responding, and another that quantifies the influence

[1] In this manuscript, we use the term "implicit" to mean "indirect." Thus, an "implicit measure" assesses mental contents indirectly, in contrast to other forms of explicit measurement that assess mental contents through direct inquiry. Our use of this term contrasts with other definitions that refer to the qualitative nature of the construct (e.g., unconscious), but aligns with the perspective that implicit measures assess evaluations under suboptimal processing conditions (DeHouwer & Boddez, 2022). Here, we specify indirect measurement as the defining procedural feature of the task that is the focus of the present research (i.e., the Implicit Association Test; Greenwald et al., 1998).

of intergroup bias in terms of response bias. Consequently, the PDP is very well-suited to bring a high degree of theoretical precision to our investigation into how economic conditions relate to cognitive control and intergroup bias.[2]

5. Economic conditions, cognitive control, and intergroup bias at regional levels

The evidence reviewed thus far summarizes relationships among economic conditions, cognitive control, and intergroup bias that is largely drawn from psychologically-oriented studies conducted with the individual as the unit of analysis. However, social and economic contexts also play an important role in shaping psychological processes (e.g., Murphy et al., 2018; Payne et al., 2017). For example, individual-level racial bias increases under conditions of higher economic stress, such as during a recession and in states with high unemployment rates (Bianchi et al., 2018). This kind of research dovetails with other disciplines that traditionally adopt a structural rather than individual focus – such as sociology, economics, and political science – that routinely test similar hypotheses with geographic regions as the unit of analysis. Importantly, such regional investigations generally rely on either self-report measures of intergroup bias (e.g., Johnston and Lordon, 2016) which conflate the influences of bias and cognitive control, or on behavioral proxies assumed to correspond with cognitive control such as credit card delinquency rates and alcohol-related driving fatalities (Findley and Brown, 2018).

In the present research, we synthesize structural and psychological perspectives by adopting a geographic psychological approach, aimed to understand how regional variation in psychological phenomena relates to features in the environment (Chen et al., 2020; Rentfrow et al., 2008). Until relatively recently, psychologically-rich data of sufficient size and scope to conduct regional analyses have been scarce. Now, the internet enables psychological scientists to collect massive amounts of data from a variety of populations and locations. In this way, researchers can aggregate the responses of individual participants into regional estimates and, in conjunction with other data sources (e.g., administrative, archival), predict outcomes of consequence (Calanchini et al., 2022). Moreover, regional aggregation reduces measurement error and other unsystematic variance inherent in psychological measures (Rushton et al., 1983) and amplifies the influence of whatever is shared among participants in geographic proximity (Calanchini et al., 2022). Thus, the geographic psychological approach is well positioned to provide ecologically-valid, statistically-powerful, and theoretically-precise insight into relationships among regional economic conditions, cognitive control, and intergroup bias.

Importantly, the present research reflects more than the sum of its parts by synthesizing theoretical perspectives from across the social sciences. Specifically, we interpret regional estimates of cognitive control and intergroup bias to reflect shared psychological tendencies shaped by structural and contextual forces, rather than direct proxies of individual traits (Calanchini et al., 2022). For example, regional cognitive control may capture the prevalence of institutions that require strong executive functioning (e.g., educational systems, job markets), whereas regional intergroup bias may reflect local norms, policies, or segregation history. These patterns do not simply reflect the average of individuals; instead, they emerge from the shared social, structural, and institutional factors within a region.

6. The present research

In the present research, we apply the PDP to IAT responses aggregated to the level of the U.S. state to produce regional estimates of cognitive control and intergroup bias. To our knowledge, this effort reflects the first application of MPT modeling to regional psychological data and has several advantages over existing research. Previous inquiries into regional variation in intergroup bias (for a review, see Calanchini et al., 2022) have relied on operationalizations of intergroup bias that are theoretically imprecise (e.g., IAT D-scores; self-report measures) because they also reflect the contributions of cognitive processes unrelated to bias (Calanchini et al., 2014). Moreover, we are unaware of any existing datasets of process-level measures of cognitive control large enough to be aggregated into regional estimates. By applying the PDP to a large set of IAT data, we can simultaneously produce state-level estimates of both intergroup bias and cognitive control from the same participant sample. In doing so, we eliminate the confound of selection effects that would be posed if different participants completed the measures of cognitive control versus intergroup bias. Based on a single sample of participants, we examine here regional variation in both control and bias as a function of regional economic conditions.

By adopting a regional MPT modeling approach, the present research aims to understand relationships among regional economic conditions, cognitive control, and intergroup bias. We focus our investigation within the United States context, with the 50 states plus the District of Columbia as the unit of analysis. We operationalize regional cognitive control and regional intergroup bias in terms of PDP parameters estimated from geolocated aggregates of IAT responses. We assume that the kinds of economic conditions that affect cognition can take different forms, so we operationalize them in two main ways: objective economic disadvantage and relative inequality. In our analyses, we regress state-level cognitive control parameters and, separately, state-level intergroup bias parameters on state-level indices of objective and relative economic conditions and relevant regional characteristics as covariates.

For theoretical precision, we model Black participants' responses separately from those of White participants. Extensive research at the individual level (e.g., Calanchini et al., 2023) indicates that both Black and White people demonstrate robust ingroup favoritism on explicit measures of racial bias. However, on implicit measures, White people typically demonstrate robust favoritism for their racial ingroup, whereas Black people typically demonstrate more attenuated levels of bias, sometimes moderately favoring their racial ingroup and sometimes moderately favoring the higher-status (i.e., White) outgroup (e.g., Jost et al., 2004). However, to assume that an effect that emerges at the individual level necessarily persists at the state level would be to commit the ecological fallacy (Robinson, 1950). Instead, the observed dissociation between explicit and implicit measures of racial bias at the individual level disappears at the state level, such that state-level aggregates of explicit and implicit racial bias correlate very strongly ($r = .87$; Calanchini et al., 2022). Consequently, we expected each group to demonstrate ingroup favoritism, such that White participants' evaluations of White people should be more positive than Black participants evaluations of White people. Conversely, we expected Black participants' evaluations of Black people to be more positive than White participants' evaluations of Black people. Modeling both populations together would obscure these important differences, whereas modeling them separately positions us to gain more nuanced insight into how economic conditions relate to psychological processes within each group.

[2] We considered multiple MPT models for the present research and ultimately selected the PDP because it offers flexibility in how it models intergroup bias. For example, the Quad model (Conrey et al., 2005) has been extensively applied to IAT data at the individual level, and assumes a directionality of bias. Specifically, in the context of a Black/White race IAT, the Quad model assumes that either White people are evaluated positively and Black people are evaluated negatively, or White people are evaluated negatively and Black people are evaluated positively. In contrast, the PDP is more flexible, and can model positive or negative evaluations of both Black and White people. Because the present research represents the first application of MPT models to regional data, we prioritized parsimony and adopted the PDP as the more flexible model with fewer assumptions.

Additionally, we sought to cast a wide net by using data spanning 2005-2019. Analyzing these data one year at a time (e.g., 2005, 2006, 2007…) would provide insight into heterogeneity across years, which is likely to be especially important given the 2008 financial crisis and its relevance to economic conditions like unemployment, poverty, and income inequality. However, analyzing each of 14 years individually would also inflate Type I error. In contrast, analyzing all data in a single model would maximize statistical power but potentially obscure important differences across years. To strike a balance between flexibility and parsimony, we separated the data into three-year blocks and calibrated our confidence more strongly in effects that replicate across multiple blocks. Furthermore, we operationalized state-level economic conditions using data from the American Community Survey (ACS) one-year estimates which occasionally contain missing data for specific state-level variables (e.g., North Dakota Black poverty rate was available in 2011 but not 2012). By aggregating our data into three-year blocks, we reduce the impact of any missingness and improve data completeness.

6.1. Predictions

From the perspective of previous research demonstrating that adverse economic conditions reduce individuals' cognitive control, we predict that regional cognitive control estimates will be lower in states where higher proportions of the population experience adverse economic conditions. We do not have strong predictions about whether the hypothesized negative relationship between cognitive control and adverse economic conditions will depend on whether participants' ingroup versus an outgroup experience those conditions.

Previous research has also demonstrated that adverse economic conditions increase individuals' intergroup biases. Consequently, we expect a complementary pattern of effects for the relationship between regional intergroup bias and adverse economic conditions, such that intergroup bias estimates will reflect more positive evaluations of the ingroup and more negative evaluations of the outgroup in states where higher proportions of the population experience adverse economic conditions. This prediction depends on separate bias estimates for Black versus White populations, and is what motivates us to model each populations' data separately. For example, the PDP parameter reflecting White evaluations corresponds with the ingroup for White participants but with the outgroup for Black participants.

Taken together, we have theoretically-grounded and straightforward predictions about general relationships among regional economic conditions, regional cognitive control, and regional intergroup bias. Guided by previous research, we cast a broad net in terms of how we operationalized economic conditions as objective disadvantage versus relative inequality, and also operationalized objective disadvantage in terms of both poverty rates and unemployment rates. Given this exploratory approach, we do not have predictions about which specific operationalization of economic conditions will be more strongly related to either cognitive control or intergroup bias. One possibility is that the predicted relationships hold for one (or each) operationalization of economic conditions, which would appear as main effects in our models. However, another possibility is that the relationships are strongest when both operationalizations of adverse economic conditions are high, which would appear as interaction effects in our models. Thus, the present research should be viewed as theoretically motivated but at the same time exploratory.[3]

[3] This project has gone through many iterations over its life. We initially posted a series of pre-registrations, but our analytic plans have changed a number of times due to data availability issues, modeling constraints, and other unforeseen circumstances. Consequently, we refrain from describing the present research as preregistered, but for the sake of full transparency the preregistrations along with analysis scripts and other materials can be viewed at https://osf.io/xhqc6/?view_only=96460ad8d34f44eb9ef152aa010a6c91.

7. Methods

7.1. Participants

Participants were visitors to the Project Implicit demonstration website (implicit.harvard.edu) who completed a race IAT between January 1, 2005-December 31, 2019 and self-reported that they resided in the U.S. We separated these data into three-year blocks – 2005-2007, 2008-2010, 2011-2013, 2014-2016, 2017-2019 – and aggregated participants' responses into $N = 51$ state-level estimates (including District of Columbia) based on their geolocation. Table 1 summarizes state-level sample sizes across years.

7.2. Measures

7.2.1. Implicit association test

Participants completed a Black-White Race IAT (Greenwald et al., 1998) consisting of pictures of Black and White people, and pleasant and unpleasant words, as described in Nosek et al. (2007). IAT performance is traditionally operationalized in terms of the D-score (Greenwald et al., 2003), which quantifies the difference in how quickly a participant can respond to one block of trials (e.g., in which 'White' and 'pleasant' share a response key) versus the other block of trials (e.g., in which 'White' and 'unpleasant' share a response key). D-scores are generally interpreted to indicate the strength of evaluative associations stored in memory: if a participant responds more quickly or accurately when White and pleasant stimuli share a response key than when White and unpleasant stimuli share a response key, then they are assumed to more strongly associate White people with pleasant than unpleasant concepts. However, D-scores are not pure indices of racial evaluations but instead reflect the contributions of multiple processes (for reviews, see Calanchini, 2020; Hütter and Klauer, 2016). To the extent that multiple processes contribute to responses on the IAT, any interpretation of D-scores lacks precision – precision that can be provided by process models like the PDP.

7.2.2. Process dissociation procedure

Table 1
Participant demographic information.

Race	Time Period	*Total N*	Average *N* per State	*SD*	Range
Black	2005-2007	61,992	1,215.53	1,462.74	12 - 5,441
	2008-2010	75,674	1,483.80	1,725.61	21 - 6,068
	2011-2013	63,161	1,238.45	1,379.44	17 - 4,839
	2014-2016	80,516	1,578.75	1,862.26	8 - 6,618
	2017-2019	133,856	2,624.63	2,927.48	20 - 10,825
White	2005-2007	376,774	7,387.73	6,986.62	608 - 31,367
	2008-2010	429,919	8,429.78	7,859.88	568 - 35,721
	2011-2013	341,986	6,705.61	6,182.20	368 - 27,161
	2014-2016	541,170	10,611.18	10,931.29	590 - 52,865
	2017-2019	802,977	15,744.65	14,952.88	695 - 74,002

The PDP (Payne, 2001) posits that responses on implicit measures like the IAT are the result of the joint influence of two qualitatively distinct types of cognitive processes: controlled and automatic processing.[4] In the context of the IAT, controlled processing reflects cognitive processes that lead to the correct categorization of target stimuli. PDP estimates of cognitive control in the IAT are related to the executive functions of task-set switching and working memory updating (Ito et al., 2015). Thus, controlled processing is related to correct perception and self-regulation (e.g., target discrimination, inhibition of interfering information, motivation to respond correctly). Automatic processing reflects cognitive processes that bias responses towards one option versus the other. Thus, automatic processing is related to racial evaluations (e.g., intergroup bias; Ito et al., 2015; Klauer and Voss, 2008) as well as other response tendencies (e.g., directional preferences; Nisbett and Wilson, 1977). Importantly, the PDP assumes that successful controlled processing always results in a correct response, whereas automatic processing drives either correct or incorrect responses when controlled processing does not succeed (Payne, 2001; Klauer and Voss, 2008; Laukenmann et al., 2023).

Fig. 1 depicts the structure of the PDP as a multinomial processing tree for trials in which Black faces share a response key with pleasant or unpleasant words. Control parameters are defined as the probability of the participant successfully categorizing target stimuli in the IAT. Automatic parameters are defined as the extent to which responses are biased towards either positive or negative responses. In the PDP, Control (C) and Automatic (A) process parameters jointly produce responses on the IAT. Each path in the tree represents the probability that a response is driven by a process or the combination of processes. For example, there are two ways in which a correct response can be returned on an IAT trial in which 'Black' and 'pleasant' share a response key. The first is the possibility that the correct response is driven by controlled processing (with probability C). The second possibility is that controlled processing does not succeed to produce a correct response (with probability 1-C), and Automatic processing linking 'Black' with pleasant evaluations drives the response (with probability A), which leads to a correct response represented by the joint probability: (1-C) × A. As such, the overall probability of producing a correct response on this trial type is the sum of these two conditional probabilities: C + (1-C) × A. The respective equations for each item category (i.e., White, Black, pleasant, and unpleasant, in both blocks of trials) are then used to estimate Control and Automatic process parameters from the observed number of correct and incorrect responses in a given data set.

In the present research, we specified six parameters for the PDP: four Control parameters corresponding to each IAT stimulus type (i.e., Control Black, Control White, Control Pleasant, Control Unpleasant) and two Automatic parameters corresponding to each target race (i.e., Automatic Black, Automatic White), thus reflecting Racial Evaluations towards the respective target group. We estimated four Control parameters to maximize the flexibility and, thus, fit of the model. However, we have no predictions that some but not other Control parameters will be related to regional economic conditions. Instead, Control parameters estimated from the PDP reflect domain-general processes that operate similarly across different stimuli (Volpert-Esmond et al., 2020). Moreover, the four Control parameters correlated very strongly with each other for both Black (mean $r = .78$, range = .58 - .95) and White (mean $r = .86$, range = .68 - .98) populations (see Supplement for a full table of Control parameter correlations). Consequently, for each population, we averaged their four Control parameters into a single Control parameter which we used for analysis.

[4] We use the terms Controlled and Automatic to refer to the PDP's parameters in correspondence with the terminology of Payne (2001). However, we expressly refrain from assuming that the processes assessed by either parameter possess features of controllability (e.g., conscious, intentional, resource-dependent, slow) or automaticity (e.g., unconscious, unintentional, efficient, fast) as articulated in traditional dual-process perspectives of cognition (e.g., Metcalfe and Mischel, 1999; Shiffrin and Schneider, 1977).

7.2.3. Economic conditions and demographic covariate variables

State-level Economic Conditions. We relied on state-level data from the American Community Survey (ACS; U.S. Census Bureau, 2006-2019) from the years 2006-2019[5] to operationalize economic conditions. We aggregated one-year estimates into three-year blocks. We quantified objective disadvantage in two ways: the unemployment rate and the poverty rate. To align with our approach of estimating separate MPT parameters for Black and White populations, we included separate unemployment rates and poverty rates for Black and White populations. We quantified relative inequality in terms of the Gini coefficient, which measures the wealth distribution among the population within each state. The Gini coefficient ranges from 0 to 1, with 0 indicating perfect equality and 1 indicating perfect inequality. None of the economic condition variables were correlated above $r = .69$, nor did they show any indication of multicollinearity. See Supplement for a full table of correlations and multicollinearity indices.

State-level Demographic Covariates. We accounted for median age, high school drop-out rates, and percentage of Black and White (non-Hispanic/Latine) citizens based on the 2006-2019 ACS estimates (U.S. Census Bureau, 2006-2019). The demographic variables were not correlated above $r = .65$. See Supplement for a full table of correlations.

7.2.4. MPT modeling

To estimate the process parameters of the PDP, we implemented a hierarchical latent-trait MPT model using Bayesian estimation (Klauer, 2010). This hierarchical approach models individuals nested within states, which accounts for individual-level heterogeneity and at the same time estimates statistically-precise state-level parameters informed by individual-level parameters. We fit the PDP using default priors in *TreeBUGS* (Heck et al., 2018) in R Programming Environment v.4.1.2., which draws posterior samples of the parameters using Markov chain Monte Carlo methods. Our specification of the PDP model estimates six parameters: four Control parameters, one for each target stimulus (i.e., Black faces, White faces, pleasant words, unpleasant words); and two Automatic parameters reflecting Racial Evaluations of each target race (i.e., Black, White). We estimated Control and Racial Evaluation parameters for each state, separately for Black and White participants, based on participants' self-reported race/ethnicity and geolocation. After estimating parameters for each year, we averaged the four Control parameters into a single Control parameter and then aggregated the average Control, Black Racial Evaluations, and White Racial Evaluations parameters into three-year blocks.

To interpret differences in parameter estimates between the Black and White populations, we relied on 95% Bayesian credibility intervals (BCIs). BCIs represent the range that most likely contains the true parameter value based on the data and prior assumptions (Hespanhol et al., 2019). Parameters can be interpreted as meaningfully different from one another if their BCIs do not overlap.

8. Results

Table 2 summarizes Control and Racial Evaluations parameters for Black and White populations for each time period. We report these parameters on a probability scale ranging [0,1], which represents the probability of a process against its counter probability. Control parameters are anchored at 0, such that values closer to 1 reflect the greater influence of controlled processing. In contrast, Racial Evaluations parameters are anchored at .5, such that values above .5 reflect positive evaluations, values below .5 reflect negative evaluations, and .5 reflects neutral evaluations.

Control parameters did not differ between Black and White populations across any of the five time periods. Averaging across states,

[5] The ACS 2005 one-year estimates did not include all of our variables of interest, so we aggregated data from 2006 to 2007 for the first time period.

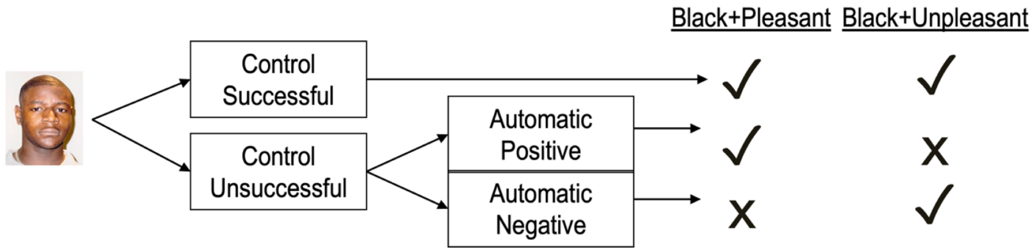

Fig. 1. The process dissociation procedure.
Note. The table on the right depicts correct (✓) and incorrect (**X**) responses across trials in which Black stimuli share a response key with pleasant (left column) versus unpleasant (right column) stimuli.

Table 2
MPT parameter differences.

Parameter	Time Period	Black Population [95% *BCI*]	White Population [95% *BCI*]	Credible Difference?
Control Average	2005-2007	.87 [.79, .92]	.88 [.87, .89]	No
	2008-2010	.87 [.81, .91]	.88 [.87, .89]	No
	2011-2013	.86 [.78, .90]	.87 [.86, .88]	No
	2014-2016	.86 [.79, .90]	.89 [.88, .90]	No
	2017-2019	.89 [.86, .92]	.91 [.91, .92]	No
Black Racial Evaluations	2005-2007	.58 [.46, .69]	.42 [.39, .45]	Yes
	2008-2010	.58 [.48, .67]	.42 [.39, .44]	Yes
	2011-2013	.56 [.46, .66]	.41 [.39, .44]	Yes
	2014-2016	.56 [.46, .65]	.43 [.40, .45]	Yes
	2017-2019	.53 [.46, .60]	.37 [.35, .39]	Yes
White Racial Evaluations	2005-2007	.56 [.44, .67]	.76 [.73, .78]	Yes
	2008-2010	.56 [.46, .65]	.73 [.71, .76]	Yes
	2011-2013	.55 [.45, .65]	.72 [.70, .75]	Yes
	2014-2016	.54 [.44, .63]	.72 [.70, .75]	Yes
	2017-2019	.50 [.43, .58]	.71 [.69, .73]	Yes

Black populations' Black Racial Evaluations were neutral (i.e., their BCIs included .5) across all five time periods. White populations' Black Racial Evaluations were reliably negative and reliably more negative than Black populations' Black Racial Evaluations in all five time periods. Black populations' White Racial Evaluations were neutral in all five time periods. White populations' White Racial Evaluations were reliably positive and reliably more positive than Black populations' White Racial Evaluations in all five time periods. Thus, White populations demonstrated ingroup bias in their pattern of racial evaluations, with White evaluations that were more positive than Black evaluations. However, Black populations demonstrated a different pattern of bias, with Black and White evaluations that both overlapped with the neutral midpoint. That said, Black evaluations were more positive among Black than White populations, and White evaluations were more positive among White than Black populations.

8.1. Regression models

We specified a series of linear regression models consisting of regional economic conditions and demographic covariates to predict, separately, regional Control and Racial Evaluations parameters. Bayesian hierarchical latent-trait modeling (Heck et al., 2018; Klauer, 2010) estimates MPT parameters on the probit scale, which positions us to treat parameter estimates as normally distributed in our regression models. We ran separate linear regression models for each three-year time period (five time periods), for each model parameter (three model parameters: one Control and two Racial Evaluations), and for each Black and White populations (two populations) resulting in a total of thirty models. As a conservative safeguard against Type I error, we only interpret effects that replicate across a majority (i.e., at least three) of the five three-year time periods. See Fig. 2 for a summary of the full analytic plan.

Control in Black Populations. The proportion of Black residents in poverty was consistently negatively related to Control: across all five time periods, Black populations' cognitive control was stronger in states where fewer Black residents live in poverty (Table 3). Conversely, the proportion of White residents in poverty was positively related to Control, such that Black populations' cognitive control was stronger in states where more White residents live in poverty. The relationship between White poverty and Control was significant at $p < .05$ in four of five time periods (2005-2007, 2008-2010, 2014-2016, 2017-2019), and the effect size in the fifth time period (2011-2013) was in the same direction and of the same magnitude but not significantly different from zero.

In addition, the Gini coefficient interacted with the Black unemployment rate to predict Control across the three earliest time periods (2005-2007, 2008-2010, 2011-2013). The interaction revealed a

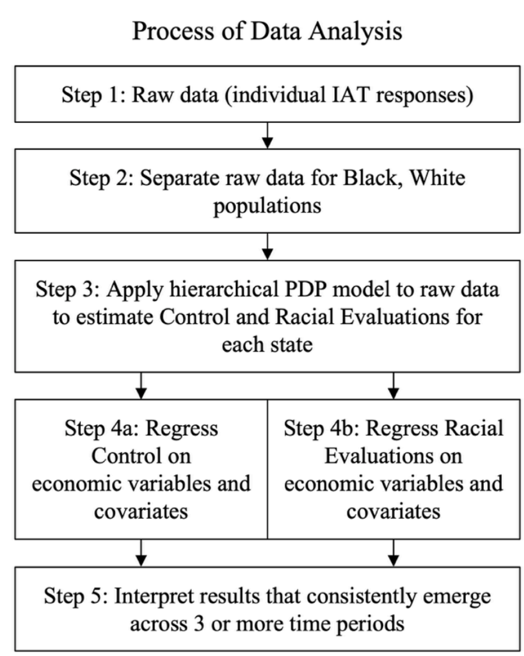

Fig. 2. Summary of analytic plan.

Table 3
Control parameter regression coefficients for black populations.

	2005-07 β (SE)	2008-10 β (SE)	2011-13 β (SE)	2014-16 β (SE)	2017-19 β (SE)
% Black	.032†	.034	.022	.020	.008
	(.018)	(.023)	(.019)	(.016)	(.013)
% White	.017	-.040	-.017	.008	-.042*
	(.024)	(.030)	(.028)	(.019)	(.017)
High School Dropout	-.016	-.016	.018	.018	.006
	(.015)	(.019)	(.013)	(.014)	(.008)
Gini	.020	-.029	-.007	.018	-.014
	(.016)	(.021)	(.019)	(.019)	(.012)
Black Unemployment	.034†	.019	.043*	.024	.011
	(.017)	(.018)	(.016)	(.017)	(.009)
White Unemployment	-.007	-.017	-.024	-.031	-.002
	(.012)	(.017)	(.017)	(.019)	(.011)
Black Poverty	**-.055****	**-.045***	**-.057*****	**-.076****	**-.022***
	(.018)	**(.017)**	**(.015)**	**(.023)**	**(.010)**
White Poverty	**.034***	**.059***	.030	**.043***	**.034****
	(.016)	**(.022)**	(.019)	**(.019)**	**(.012)**
Gini x Black Unemployment	**-.053*****	**-.033**†	**-.033***	.008	.004
	(.013)	**(.016)**	**(.015)**	(.012)	(.007)
Gini x White Unemployment	-.004	.013	.017	.016	-.008
	(.008)	(.013)	(.016)	(.014)	(.011)
Gini x Black Poverty	.054**	.018	.005	-.000	-.011
	(.017)	(.019)	(.019)	(.019)	(.012)
Gini x White Poverty	-.033	-.035	-.024	-.018	.000
	(.020)	(.026)	(.025)	(.018)	(.014)
Adj. R^2	0.65	0.47	0.52	0.44	0.60

Note.
*** $p < .001$,
** $p < .01$,
* $p < .05$,
† $p < .10$.
Black (White) Poverty = Proportion of Black (White) residents below the poverty line in a state. Black (White) Unemployment = Black (White) Unemployment rate. Bold type indicates effects that emerge consistently across three or more time periods.

spreading pattern (Fig. 3), such that in regions with high economic inequality, Black populations' cognitive control was weaker in regions with lower levels of Black unemployment (-1 *SD*) compared to regions with higher levels of Black unemployment (+1 *SD*). However, in regions with low economic inequality, Black populations' cognitive control did not consistently vary as a function of Black unemployment rates.

Control in White Populations. The Black unemployment rate was negatively related to Control: in four of five time periods (2005-2007, 2008-2010, 2011-2013, 2017-2019), White populations' cognitive

Table 4
Control parameter regression coefficients for white populations.

	2005-07 β (SE)	2008-10 β (SE)	2011-13 β (SE)	2014-16 β (SE)	2017-19 β (SE)
% Black	-.002	-.016	**-.024***	**-.017***	**-.017**†
	(.009)	(.010)	**(.011)**	**(.008)**	**(.010)**
% White	**-.021**†	**-.044****	**-.035***	**-.020***	**-.040****
	(.012)	**(.013)**	**(.016)**	**(.010)**	**(.013)**
High School Dropout	-.001	-.001	-.003	-.007	-.011
	(.007)	(.008)	(.008)	(.007)	(.006)
Gini	.013	.007	.015	.022*	-.004
	(.008)	(.009)	(.011)	(.010)	(.009)
Black Unemployment	**-.016**†	**-.015**†	**-.018**†	-.011	**-.019****
	(.008)	**(.008)**	**(.009)**	(.009)	**(.007)**
White Unemployment	.004	.011	.020†	.021*	.009
	(.006)	(.007)	(.010)	(.010)	(.008)
Black Poverty	.003	.002	.002	.012	.007
	(.009)	(.007)	(.009)	(.012)	(.007)
White Poverty	-.002	.001	-.006	-.017	.002
	(.008)	(.009)	(.011)	(.010)	(.009)
Gini x Black Unemployment	-.001	.005	.011	-.007	.001
	(.006)	(.007)	(.009)	(.007)	(.005)
Gini x White Unemployment	-.004	-.004	**-.036*****	**-.029*****	**-.027****
	(.004)	(.006)	**(.009)**	**(.007)**	**(.008)**
Gini x Black Poverty	.010	.006	-.020†	-.001	.001
	(.008)	(.008)	(.011)	(.010)	(.009)
Gini x White Poverty	.009	.006	.033*	.023*	.004
	(.010)	(.011)	(.015)	(.010)	(.010)
Adj. R^2	0.63	0.68	0.63	0.49	0.57

Note.
*** $p < .001$,
** $p < .01$,
* $p < .05$,
† $p < .10$.
Black (White) Poverty = Proportion of Black (White) residents below the poverty line in a state. Black (White) Unemployment = Black (White) Unemployment rate. Bold type indicates effects that emerge consistently across three or more time periods.

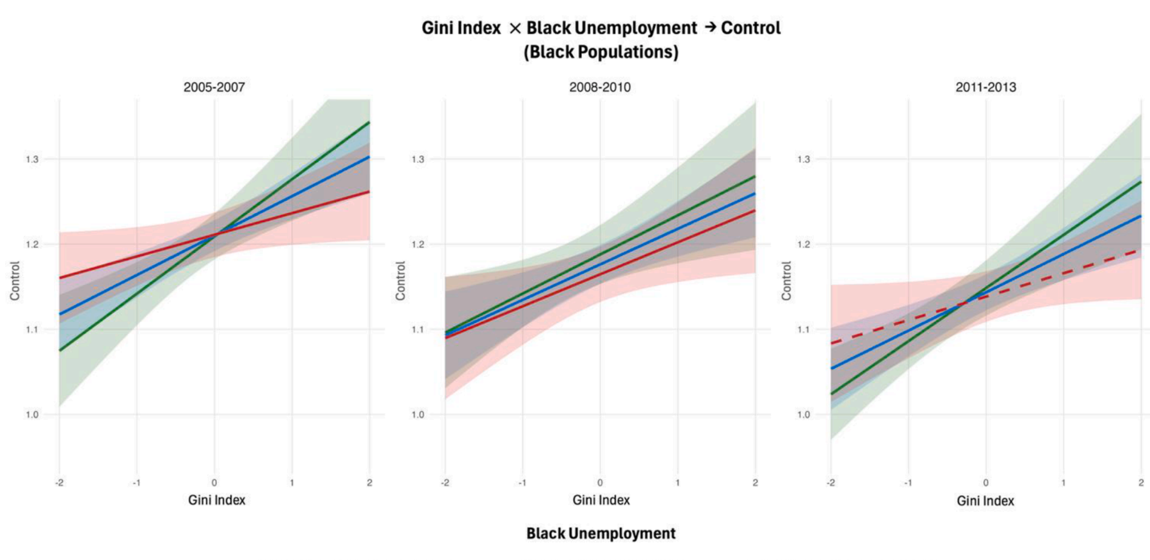

Fig. 3. Interaction between Gini and black unemployment predicting control in black populations 2005-2007, 2008-2010, 2011-2013.
Note. Solid lines indicate slopes that are different from zero $p < .05$, dashed lines indicate slopes that are not different from zero $p > .05$. Control parameter estimates are displayed on the probit scale.

control was stronger in states where fewer Black residents are unemployed (Table 4). The effect size in the fifth period (2014-2016) was in the same direction and of the same magnitude but not significantly different from zero. The percentage of Black residents in a state was negatively related to Control: across the three most recent time periods (2011-2013, 2014-2016, 2017-2019), White populations' cognitive control was stronger in states with fewer Black residents. The effect size was in the same direction and of the same magnitude but not significantly different from zero in 2008-2010, but was an order of magnitude smaller in 2005-2007. The percentage of White residents in a state was also consistently negatively related to Control: in all five time periods, White populations' cognitive control was stronger in states with fewer White residents.

In addition, the Gini coefficient interacted with the White unemployment rate to predict Control across the three most recent time periods (2011-2013, 2014-2016, 2017-2019). The interaction revealed a spreading pattern (Fig. 4), such that in regions with low economic inequality, White populations' cognitive control was higher in regions with lower levels of White unemployment (-1 *SD*) compared to regions with higher levels of White unemployment (+1 *SD*). However, in regions with high economic inequality, White unemployment was not consistently related to cognitive control.

Black Racial Evaluations in Black Populations. No consistent effects emerged for Black populations' Racial Evaluations of Black people (Table 5).

White Racial Evaluations in Black Populations. The proportion of White residents in poverty was negatively related to White Racial Evaluations: across the three most recent time periods (2011-2013, 2014-2016, 2017-2019), Black populations' evaluations of White people were more negative in states where more White residents live in poverty (Table 6).

Black Racial Evaluations in White Populations. The percentage of Black residents in a state was negatively related to Black Racial Evaluations: across four time periods (2005-2007, 2008-2010, 2014-2016, 2017-2019), White populations' evaluations of Black people were more negative in states with more Black residents (Table 7). The effect size was in the same direction in 2011-2013 but was an order of magnitude smaller and not significantly different from zero.

The Gini coefficient interacted with the Black unemployment rate to predict Black Racial Evaluations across the three most recent time periods (2011-2013, 2014-2016, 2017-2019). Although the interaction terms were significant in each year, the shape of the interactions were different across time periods and follow-up analyses indicated that none of the slopes (-1 *SD*, mean, +1 *SD*) were different from zero (Fig. 5).

White Racial Evaluations in White Populations. The White unemployment rate was positively related to White Racial Evaluations: across three time periods (2008-2010, 2011-2013, 2017-2019) White

Table 5
Black racial evaluations parameter regression coefficients for black populations.

	2005-07 β (SE)	2008-10 β (SE)	2011-13 β (SE)	2014-16 β (SE)	2017-19 β (SE)
% Black	-.003 (.024)	.007 (.020)	.026 (.024)	.015 (.014)	-.003 (.008)
% White	.004 (.031)	-.042 (.026)	-.004 (.034)	-.012 (.017)	-.033** (.010)
High School Dropout	.006 (.019)	-.018 (.016)	-.036* (.016)	-.006 (.012)	.002 (.005)
Gini	-.007 (.021)	-.002 (.018)	-.011 (.023)	-.011 (.017)	-.004 (.007)
Black Unemployment	.011 (.022)	-.002 (.016)	-.013 (.020)	.009 (.015)	.003 (.005)
White Unemployment	.014 (.016)	.009 (.014)	.017 (.021)	-.032† (.017)	-.010 (.006)
Black Poverty	-.012 (.023)	.014 (.015)	.009 (.019)	-.032 (.020)	.016* (.006)
White Poverty	-.011 (.021)	.027 (.019)	.006 (.023)	.029 (.017)	.003 (.007)
Gini x Black Unemployment	.026 (.017)	-.018 (.014)	-.002 (.018)	-.012 (.011)	-.004 (.004)
Gini x White Unemployment	-.012 (.011)	.003 (.012)	-.004 (.019)	.012 (.012)	-.015* (.006)
Gini x Black Poverty	-.013 (.022)	.016 (.016)	.019 (.023)	.012 (.017)	-.006 (.007)
Gini x White Poverty	.023 (.026)	-.008 (.023)	-.016 (.030)	-.011 (.016)	.019* (.008)
Adj. R^2	-0.13	0.20	0.01	0.09	0.54

Note. *** $p < .001$,
** $p < .01$,
* $p < .05$,
† $p < .10$.
Black (White) Poverty = Proportion of Black (White) residents below the poverty line in a state. Black (White) Unemployment = Black (White) Unemployment rate. Bold type indicates effects that emerge consistently across three or more time periods.

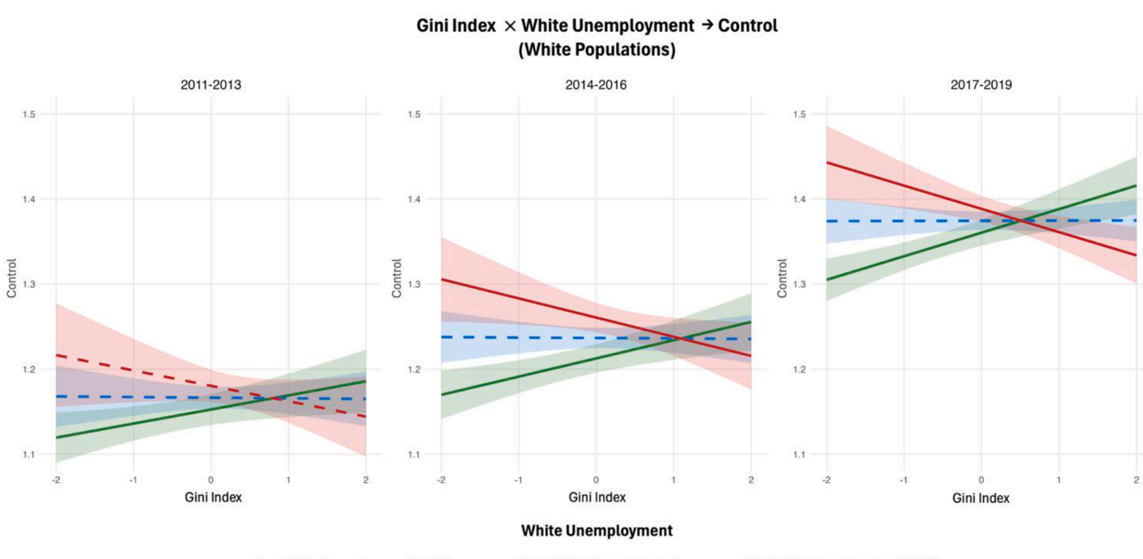

Fig. 4. Interaction between Gini and white unemployment predicting control in white populations 2011-2013, 2014-2016, 2017-2019.
Note. Solid lines indicate slopes that are different from zero $p < .05$, dashed lines indicate slopes that are not different from zero $p > .05$. Control parameter estimates are displayed on the probit scale.

Table 6
White racial evaluations parameter regression coefficients for black populations.

	2005-07 *β (SE)*	2008-10 *β (SE)*	2011-13 *β (SE)*	2014-16 *β (SE)*	2017-19 *β (SE)*
% Black	-.009	-.042*	-.008	-.007	.012
	(.022)	(.016)	(.021)	(.012)	(.013)
% White	.013	-.047*	.026	.018	.046*
	(.029)	(.022)	(.031)	(.014)	(.017)
High School Dropout	-.022	-.015	-.023	-.004	.019*
	(.018)	(.013)	(.015)	(.011)	(.009)
Gini	.001	.004	.009	.022	.018
	(.019)	(.015)	(.021)	(.014)	(.012)
Black Unemployment	.019	-.022	-.016	-.017	.013
	(.021)	(.013)	(.018)	(.013)	(.009)
White Unemployment	-.016	.029*	.020	.025	.013
	(.015)	(.012)	(.019)	(.015)	(.011)
Black Poverty	-.041†	.011	.020	.020	-.009
	(.021)	(.012)	(.017)	(.017)	(.010)
White Poverty	.005	-.019	**-.040**†	**-.054*****	**-.042****
	(.019)	(.016)	**(.021)**	**(.015)**	**(.013)**
Gini x Black Unemployment	-.009	-.031*	-.004	-.003	.017*
	(.015)	(.012)	(.016)	(.010)	(.007)
Gini x White Unemployment	-.009	-.026*	-.001	-.025*	-.015
	(.010)	(.010)	(.017)	(.011)	(.011)
Gini x Black Poverty	.026	.016	-.008	-.038*	-.038**
	(.020)	(.014)	(.021)	(.015)	(.012)
Gini x White Poverty	.008	.001	-.005	.036*	.056***
	(.024)	(.019)	(.027)	(.014)	(.014)
Adj. R^2	0.09	0.44	0.49	0.44	0.47

Note.
*** $p < .001$,
** $p < .01$,
* $p < .05$,
† $p < .10$.
Black (White) Poverty = Proportion of Black (White) residents below the poverty line in a state. Black (White) Unemployment = Black (White) Unemployment rate. Bold type indicates effects that emerge consistently across three or more time periods.

Table 7
Black racial evaluations parameter regression coefficients for white populations.

	2005-07 *β (SE)*	2008-10 *β (SE)*	2011-13 *β (SE)*	2014-16 *β (SE)*	2017-19 *β (SE)*
% Black	**-.018**†	**-.038*****	-.009	**-.016***	**-.032*****
	(.009)	**(.010)**	(.011)	**(.006)**	**(.006)**
% White	-.008	-.024†	.011	-.011	-.016*
	(.012)	(.013)	(.015)	(.008)	(.008)
High School Dropout	-.005	-.000	-.005	.007	.004
	(.008)	(.008)	(.007)	(.006)	(.004)
Gini	-.006	-.010	.005	.003	.000
	(.008)	(.009)	(.010)	(.008)	(.006)
Black Unemployment	-.012	.008	.000	-.008	-.006
	(.009)	(.008)	(.009)	(.007)	(.004)
White Unemployment	.005	-.010	.002	-.008	.002
	(.006)	(.007)	(.009)	(.008)	(.005)
Black Poverty	.006	-.002	-.000	.005	.003
	(.009)	(.008)	(.008)	(.009)	(.005)
White Poverty	.008	.010	.001	.014†	.001
	(.008)	(.010)	(.010)	(.008)	(.006)
Gini x Black Unemployment	-.002	-.002	**.020***	**.010**†	**.009****
	(.007)	(.007)	**(.008)**	**(.005)**	**(.003)**
Gini x White Unemployment	-.003	-.009	-.010	.004	-.012*
	(.004)	(.006)	(.009)	(.006)	(.005)
Gini x Black Poverty	-.013	-.007	-.013	.012	.000
	(.009)	(.009)	(.010)	(.008)	(.005)
Gini x White Poverty	-.004	-.015	.019	-.008	.005
	(.010)	(.012)	(.014)	(.007)	(.006)
Adj. R^2	0.54	0.57	0.20	0.37	0.62

Note.
*** $p < .001$,
** $p < .01$,
* $p < .05$,
† $p < .10$.
Black (White) Poverty = Proportion of Black (White) residents below the poverty line in a state. Black (White) Unemployment = Black (White) Unemployment rate. Bold type indicates effects that emerge consistently across three or more time periods.

populations' evaluations of White people were more positive in states where more White residents are unemployed (Table 8). The effect size was in the same direction and of the same magnitude but not significantly different from zero in 2014-2016 but was an order of magnitude smaller in 2005-2007.

Table 9 summarizes all findings as they relate to our hypotheses.

9. Discussion

Building on previous research linking individuals' experience of adverse economic conditions with lower levels of cognitive control and higher levels of intergroup bias, the present research investigated relationships among regional economic conditions, cognitive control, and racial evaluations. We aggregated IAT responses from 2.9 million participants to the level of the U.S. state and decomposed responses into their component processes using MPT modeling. In states with more adverse objective economic conditions, we generally found support for our hypotheses that cognitive control is lower, and partially found support for our hypothesis that racial evaluations are more biased in favor of the ingroup. However, these relationships were moderated in important ways that we discuss in detail below.

9.1. Economic conditions and cognitive control

Because previous research has demonstrated that economic stress negatively impacts individuals' cognitive control, we predicted that residents of states with more adverse economic conditions would demonstrate weaker cognitive control. Aligning with our prediction, Black populations' control was weaker in states where more Black people live in poverty. However, in contrast to our predictions, Black populations' control was also weaker in states where Black unemployment is low but inequality is high. Moreover, Black populations' control was stronger in states where more White people live in poverty. In the present research, we only interpreted effects that replicated across multiple time periods, thus, the likelihood is low that the unpredicted relationships among Black populations' control and some adverse economic conditions are spurious. Instead, these findings likely reflect meaningful variation that warrants further investigation. We speculate here about what some of that meaningful variation might be.

The finding that Black populations' cognitive control was weaker in states with high inequality and low Black unemployment is consistent with theories of relative deprivation. In these states, relatively low ingroup unemployment signals that economic opportunities should translate into fair outcomes. At the same time, high inequality makes gaps in resources, status, and returns on effort highly visible. This mismatch between expectations of opportunity and the continued presence of structural disadvantage reflects relative deprivation, which arises when people perceive their outcomes as undeserved relative to others (Smith and Pettigrew, 2014; Smith et al., 2011). At the individual level, relative deprivation is related to decreased control (i.e. Mishra and Novakowski, 2016; Zhang et al., 2023) and exposure to economic uncertainty is related to poorer executive functioning and weaker cognitive control, particularly when material hardship is ambiguous rather than overt (Mani et al., 2013; Payne et al., 2017). More broadly, these findings suggest that contexts characterized by ambiguous disadvantage, where opportunity is implied but equity is absent, may be particularly detrimental for Black populations' cognitive control.

In contrast, Black populations had stronger cognitive control in regions where more White people experience adverse economic conditions. From a structural perspective, we might expect for states in which

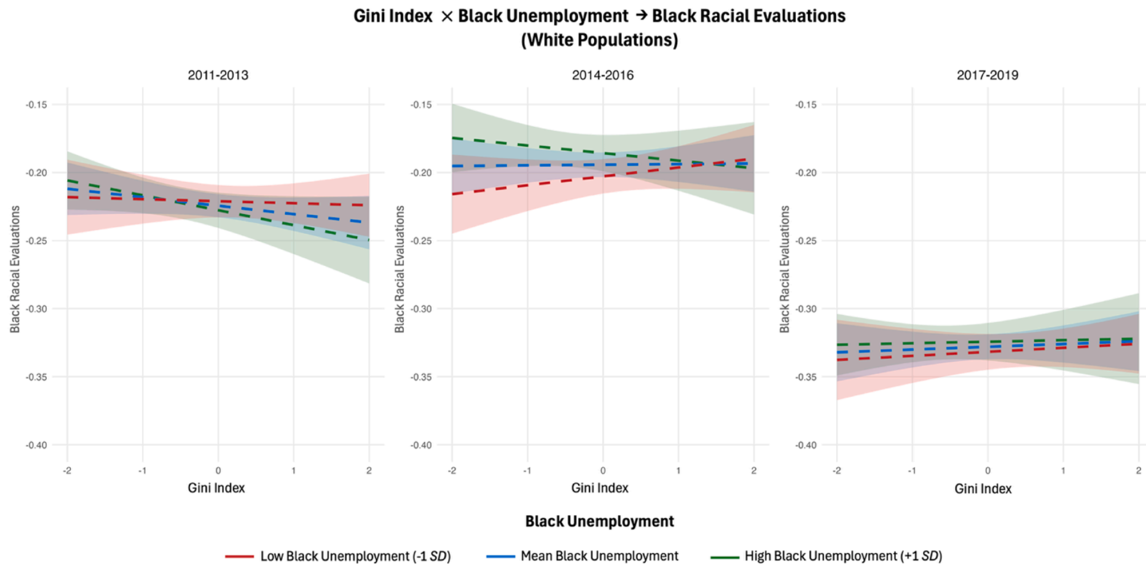

Fig. 5. Interaction between Gini and black unemployment predicting black evaluations in white populations 2011-2013, 2014-2016, 2017-2019.
Note. Solid lines indicate slopes that are different from zero $p < .05$, dashed lines indicate slopes that are not different from zero $p > .05$. Black Racial Evaluation parameter estimates are displayed on the probit scale.

Table 8
White racial evaluations parameter regression coefficients for white populations.

	2005-07 *β (SE)*	2008-10 *β (SE)*	2011-13 *β (SE)*	2014-16 *β (SE)*	2017-19 *β (SE)*
% Black	-.000	.030*	.005	.008	.010
	(.012)	(.012)	(.012)	(.008)	(.007)
% White	-.020	-.019	-.024	-.018†	-.014
	(.016)	(.016)	(.017)	(.010)	(.009)
High School Dropout	-.000	-.002	-.008	.000	-.003
	(.010)	(.010)	(.008)	(.007)	(.005)
Gini	.032**	-.006	.011	.007	-.002
	(.011)	(.011)	(.011)	(.010)	(.007)
Black Unemployment	-.013	-.016†	-.014	-.009	-.026***
	(.011)	(.009)	(.010)	(.009)	(.005)
White Unemployment	.001	**.019***	**.018†**	.016	**.029*****
	(.008)	**(.009)**	**(.010)**	(.011)	**(.006)**
Black Poverty	.001	-.002	-.002	-.002	.017**
	(.012)	(.009)	(.009)	(.012)	(.005)
White Poverty	-.006	-.007	-.001	-.003	-.020**
	(.011)	(.011)	(.011)	(.010)	(.007)
Gini x Black Unemployment	-.015†	-.011	.002	-.011	-.004
	(.009)	(.009)	(.009)	(.007)	(.004)
Gini x White Unemployment	.008	.005	-.015	.000	-.027***
	(.005)	(.007)	(.009)	(.008)	(.006)
Gini x Black Poverty	.015	-.002	-.006	.006	-.008
	(.011)	(.010)	(.011)	(.010)	(.006)
Gini x White Poverty	.012	-.003	.016	-.008	.007
	(.013)	(.014)	(.015)	(.010)	(.008)
Adj. R^2	0.59	0.63	0.56	0.45	0.70

Note.
*** $p < .001$,
** $p < .01$,
* $p < .05$,
† $p < .10$.
Black (White) Poverty = Proportion of Black (White) residents below the poverty line in a state. Black (White) Unemployment = Black (White) Unemployment rate. Bold type indicates effects that emerge consistently across three or more time periods.

more White people struggle economically to also have better social safety nets, which in turn could benefit Black residents. This explanation dovetails with psychological research demonstrating that White Americans' beliefs about White poverty specifically predict more positive attitudes toward welfare recipients and increased support for welfare policies (Cooley et al., 2022). More direct evidence for this explanation comes from sociological research linking higher White poverty rates with increased social services (Kelly and Lobao, 2021). Taken together, our findings complement a growing body of interdisciplinary research highlighting disparities in social welfare support. Nevertheless, we recognize that these explanations are post hoc and contrast with the predictions we derived from the psychological literature – and perhaps also highlights the pitfall of making predictions about an inherently interdisciplinary research question based primarily on one literature. Consequently, future research should continue to investigate the relationship between public policy and population differences in cognitive control.

We also found support for our hypothesis among White populations, whose control was weaker in states with higher Black unemployment, and in states where White unemployment is high but income inequality is low. These findings generally align with our prediction that adverse economic conditions are associated with weaker cognitive control at the regional level. Moreover, this pattern of results suggests that White populations' cognitive control is sensitive to economic conditions affecting both their ingroup and the outgroup. However, the finding that control is weaker in states with high White unemployment and low inequality differs from what we observed for Black populations, for whom weaker control was associated with low Black unemployment and high inequality. For White populations, the pattern more straightforwardly reflects weaker cognitive control in direct economic hardship. The differing patterns may reflect the distinct positions that Black versus White racial groups occupy within hierarchical social systems in which dominant and marginalized groups have fundamentally different relationships to structural inequality and economic opportunity (Darity, 2022). Future research designed specifically to test these mechanisms is necessary to understand why similar economic indicators predict regional cognitive control differently for Black and White populations.

9.2. Economic conditions and intergroup bias

Because previous research has demonstrated that economic stress increases individuals' intergroup biases, we predicted that residents of states with more adverse economic conditions would also demonstrate more pro-ingroup and anti-outgroup evaluations. We found mixed evidence for these predictions. Supporting our predictions, we found that

Table 9
Hypothesis support by population.

Hypothesis	Population	Support	Significant Economic Conditions	Results
Regional control estimates will be lower in states with more adverse economic conditions	Black	Partial	Black Poverty, Black Unemployment x Inequality White Poverty	Weaker cognitive control in states with more ingroup poverty, more inequality but less ingroup unemployment. Stronger cognitive control in states with more outgroup poverty.
	White	Partial	Black Unemployment, White Unemployment x Inequality	Weaker cognitive control in states with more outgroup unemployment, less inequality but more ingroup unemployment.
Positive ingroup evaluations in states with more adverse economic conditions	Black	Not Supported		No significant relationships between ingroup evaluations and economic conditions.
	White	Supported	White Unemployment	More positive ingroup evaluations in states with more ingroup unemployment.
Negative outgroup evaluations in states with more adverse economic conditions	Black	Supported	White Poverty	More negative outgroup evaluations in states with more outgroup poverty.
	White	Not supported		No significant relationships between outgroup evaluations and economic conditions.

Black populations' racial evaluations of the outgroup (i.e., White people) are more negative in states where more White people live in poverty. Additionally, White populations' racial evaluations of the ingroup (i.e., White people) are more positive where more White people are unemployed. However, no consistent effects emerged for Black population's evaluations of the ingroup (i.e. Black people), nor for White population's evaluations of the outgroup (i.e. Black people).

Interestingly, relationships between economic conditions and the racial evaluations of both Black and White populations were limited to evaluations of White people. Though we did not predict this pattern of results, it dovetails with previous research demonstrating that lab-based interventions to reduce individuals' implicit racial bias were much more likely to affect evaluations of White than Black people (Calanchini et al., 2020). One possible explanation for these findings is that White people, as the numerical majority group in America, are more visible than members of minority groups – to both White and non-White people alike. Additionally, as the higher-status group in America, White people are relatively more likely to hold positions of power – social, economic, or otherwise. White people's higher visibility in positions of power may make them especially salient and thus the target of evaluations by both the ingroup and outgroup when economic conditions are challenging. Future research should investigate this possibility.

9.3. Black and white demographic effects

Though the focus of the present research was on regional economic conditions, we also found consistent relationships among state-level demographics, cognitive control, and intergroup bias. White populations' cognitive control was consistently weaker in states with higher proportions of White people and higher proportions of Black people. These unexpected findings suggest that demographic composition relates to cognitive control through mechanisms we did not directly account for. States with larger Black populations tend to offer weaker social services (Kelly and Lobao, 2021), illustrating how structural racism can be a barrier to resources and opportunities (Yearby, 2018). However, states with larger White populations generally provide stronger social safety nets and public resources (Grogan and Park, 2017; Schuler et al., 2021), making the negative relationship with White populations' control more difficult to explain. We also found that White populations evaluate Black people more negatively in states with larger Black populations, which replicates the findings of Rae and colleagues (2015) and is consistent with group threat theory such that larger outgroup populations increase perceived competition and negative attitudes (Quillian, 1995; Schneider, 2008). Taken together, the relationships we observed between demographics and intergroup bias are relatively more straightforward and align with previous psychological theory. However, the relationships we observed between demographics and cognitive control remain less clear and warrant further investigation.

9.4. Regional rather than individual effects

Given that psychological scientists traditionally focus on individuals, the interested reader may reasonably wonder whether the individual participants whose data are reflected in the present research experienced adverse economic conditions themselves. In this manuscript we operationalized economic conditions in terms of unemployment rates, poverty rates, and income inequality. Importantly, these metrics are properties of places rather than people. For example, an individual can be employed or unemployed, live above or below the poverty line, or have high or low income. However, unemployment rates, poverty rates, and income inequality metrics can only describe groups of individuals. Consequently, the question guiding this work is not whether economic conditions are related to individuals' cognitive control and racial bias – as previous research has investigated. Instead, in the present research we investigated whether regional economic conditions are related to regional aggregates of cognitive control and racial bias. To our knowledge, this research question is both theoretically and empirically novel, but we can nevertheless speculate here on potential mechanisms by which regional economic conditions might relate to cognitive control and racial bias.

For example, you yourself might be doing well financially, but living in a place characterized by adverse economic conditions can nevertheless be stressful. Perhaps your family members or neighbors are struggling. Maybe there are people who sleep on the side of the street you drive to work each morning. Your local infrastructure – streetlights, parks, schools – might be in disrepair because of a declining local tax base. Thus, despite your own secure financial situation, these situational cues to the economic state of your community may nevertheless weigh on your mind. Will I get robbed if I drive through this part of town? Will my friend who just lost his job get evicted from his home? To the extent that you ruminate on these concerns, your cognitive control and racial bias should be affected in the ways demonstrated at the individual level by Caluori et al., (2021) and Mani et al., (2013), among others. And to the extent that some proportion of your neighbors ruminate on similar concerns – either because they directly experience adverse economic conditions or are routinely exposed to contextual cues of them – then these relationships among economic conditions, cognitive control, and racial bias should emerge in the aggregate.

We recognize that the mechanism we propose here is causal, and at the same time acknowledge that we cannot test such a causal claim given the present data. However, methods to infer causality from observational data are becoming more commonplace in psychological science (e.g., Primbs et al., 2025). Thus, the present research provides a foundation upon which future research can examine causal relationships among regional economic conditions, cognitive control, and racial bias.

9.5. Strengths and open questions

In the present research, we estimated cognitive control and intergroup bias from participants' responses on the IAT – a measure that has been reasonably criticized on both statistical and theoretical grounds (e.g., Blanton et al., 2009; Schimmack, 2021). For example, two common criticisms of the IAT are that the measure demonstrates low test-retest reliability and predicts behaviors only modestly (Oswald et al., 2013). However, these criticisms focus on individuals' IAT responses rather than regionally aggregated IAT responses, and on the D-score rather than formal modeling parameters. The regional approach we adopted here shores up several of these issues. Our analyses are high in statistical validity because aggregating the responses of hundreds or thousands of participants to the state level helps to minimize the influence of measurement error (Rushton et al., 1983). As a result, regionally aggregated IAT scores reflect a more stable indicator of regional norms, collective psychological tendencies, and shared cultural attitudes (Hehman et al., 2019) that may be reinforced through media, social interactions, and institutional practices (Calanchini et al., 2022; Leitner et al., 2016; Payne et al., 2019). Additionally, our analyses are high in theoretical precision because process modeling decomposes IAT responses into relatively more process-pure estimates of cognitive control and racial evaluations than can be provided by summary statistics like the D-score. In doing so, our findings extend the work of Connor and colleagues (2019) who found a positive relationship between the Gini coefficient and explicit racial bias, but not implicit racial bias as quantified by the IAT D-score. Thus, the present research capitalizes on the strengths of two complementary methodologies in a way that is, to our knowledge, entirely novel.

With that said, open questions remain about what regional operationalizations of cognitive control and racial evaluations reflect specifically. Considerable theorizing and empirical research at the individual level connect PDP Control parameters to executive functions like task-set shifting and working memory updating (Ito et al., 2015; Klauer et al., 2010). PDP Automatic parameters estimated from individuals are conceptualized to reflect mental associations between social groups (e.g., White) and attributes (e.g., pleasant) that contribute to biased responding. However, parameter estimates based on regional aggregates cannot be interpreted in the same way as individuals' parameter estimates. Regional aggregation not only reduces measurement error, but also minimizes the influence of any sources of variance not shared by a substantial proportion of people within a region (e.g., idiosyncratic learning histories and other individual differences). Consequently, regional parameter estimates reflect different constructs than individual parameter estimates, and primarily correspond with whatever shared influences are present in regions.

Building on the arguments of Calanchini and colleagues (2022), regional racial evaluations may reflect social structures like laws, norms, institutions, and segregation patterns that shape residents' intergroup biases. Regional cognitive control is relatively newer psychological territory, so to speak, which we hypothesize to reflect the prevalence of institutions that attract people with strong executive function, such as higher education opportunities, skilled labor jobs, or small business incubators. Moreover, geographic aggregation may provide a lens to study racial historical context (Bonilla-Silva, 1997) and socioeconomic disparities (Crescenzi and Rodríguez-Pose, 2013) that also affect regional variation in cognitive control and intergroup bias. Future research should continue to investigate the roots and correlates of regional operationalizations of psychological constructs such as cognitive control and intergroup bias that have traditionally been the purview of individual-level investigation.

A further strength of the present research is its longitudinal scope. Rather than drawing inferences from a single snapshot in time, we modeled 15 years of data (2005-2019), aggregated into three-year blocks, to examine whether associations between economic conditions, cognitive control, and intergroup bias were stable or variable across time. By using this approach, we reduced the risk that any of our observed effects were driven by idiosyncrasies of any one time period (e.g., the 2008 financial crisis). Instead, we focus our interpretations on patterns that emerge consistently over time. That said, discrete events certainly matter. For example, racial attitudes in the United States became more egalitarian after versus before the Black Lives Matter protests (Primbs et al., 2024; Sawyer and Gampa, 2018). Future theory-driven research might use our findings as a roadmap to make more fine-grained temporal predictions about how cognitive control and racial evaluations changed over time in the United States. Similarly, we analyzed each time period using simple linear regressions and looked for consistency over time. Future research might instead rely on more sophisticated longitudinal statistical techniques (e.g., latent growth curve modeling; regression discontinuity designs) to identify additional effects in these or similar data. Nevertheless, our findings illustrate important relationships among regional economic conditions, cognitive control, and intergroup bias, and further demonstrate that these effects are not confined to a single moment, but instead persist across multiple time periods.

9.6. Limitations

Though the present research represents novel contributions to both the regional intergroup bias and process modeling literatures, it is limited in several ways. Our analyses are relatively high in generalizability because we rely on representative data from the U.S. Census Bureau. However, Project Implicit data are not representative of the U.S. population; instead, Project Implicit visitors are relatively young, female, educated, and politically left-leaning compared to the general population (Ratliff and Smith, 2021). That said, Project Implicit visitors are more diverse on a wide variety of demographics than the typical university sample, and previous research has demonstrated a strong correlation between regional demographics in the Project Implicit sample and demographics as assessed by the U.S. Census (Hehman et al., 2018). Additionally, the Project Implicit data are much larger than other administrative data sources that also include measures of intergroup bias and, thus, are high in statistical validity. However, to our knowledge, no administrative data source (representative or otherwise) includes measures of cognitive control. Nevertheless, future research should seek to replicate and further generalize our findings with data from other sources.

The present research is also limited because it is correlational, so we refrain from making strong claims about causal relationships among economic conditions, regional cognitive control, and regional racial evaluations. Though our predictions are based on individual-level theorizing and empirical findings demonstrating that economic stressors influence cognitive control and intergroup biases, bidirectional and recursive relationships likely exist among these constructs at regional levels. Moreover, we accounted for several regional demographic variables that may be related to economic conditions, cognitive control, and intergroup bias – such as race and education – but cannot rule out the influence of other unobserved variables. Future research should incorporate data and analytic methods that are better positioned to provide more comprehensive insight into relationships among economic conditions, regional cognitive control, and regional racial evaluations.

One interesting and unanticipated finding to emerge from our analyses is an overall disparity in the amount of variance our models explain in the responses of Black versus White populations. Our models explained more variance in the cognitive control and racial evaluations of White populations (average adj. $R^2 = .60$ for Control, .52 for Racial Evaluations) compared to Black (average adj. $R^2 = .54$ for Control, .26 for Racial Evaluations) populations. Our intent was not to prioritize one population over the other; indeed, we specified separate models for each population subsample rather than aggregating them all together to provide theoretically-precise insight into the patterns of results among each group. Nevertheless, we recognize that we formulated our hypotheses and specified our models by drawing from psychological literatures that have been criticized for centering Whiteness (e.g., Roberts and Mortenson, 2023; Thomas et al., 2023). To the extent that our predictors and covariates did not explain as much variance among Black populations as they did among White populations, we hope that our findings can inspire research into factors related to the cognitive control and racial evaluations of Black and other non-White populations specifically.

10. Conclusion

Economic insecurity is a pressing issue that affects millions of people across the U.S. and around the world. By identifying correlations among economic conditions, regional cognitive control, and regional racial evaluations, the present research is positioned to inform policy that better supports people living in economically-challenged regions. Marginalized and disadvantaged groups are especially likely to suffer under adverse economic conditions, so the present research may provide a foundation for stakeholders to develop programs aimed at interrelationships among economic conditions, cognitive control, and intergroup bias – especially among vulnerable populations.

Ethics & informed consent statement

Data used in this research were collected from the Project Implicit demonstration website, where participants voluntarily completed measures and provided informed consent for the use of their data in research. This secondary data analysis was approved by the Institutional Review Board at the University of California, Riverside.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cresp.2026.100271.

Data availability

Data and code are available via an OSF link in the manuscript.

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