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Abstract

How do social group boundaries evolve? Does the appearance of a new outgroup change the ingroup's perceptions of other outgroups? We introduce a conceptual framework of context-dependent categorization, in which exposure to one minority leads to recategorization of other minorities as in- or outgroups depending on perceived distances across groups. We test this framework by studying how Mexican immigration to the US affected White Americans' attitudes and behaviors towards Black Americans. We combine survey and crime data with a difference-in-differences design and an instrumental variables strategy. Consistent with the theory, Mexican immigration improves Whites' racial attitudes, increases support for pro-Black government policies and lowers anti-Black hate crimes, while simultaneously increasing prejudice against Hispanics. Results generalize beyond Hispanics and Blacks and a survey experiment provides direct evidence for recategorization. Our findings imply that changes in the size of one group can affect the entire web of inter-group relations in diverse societies.

Keywords: Immigration, race, ingroup–outgroup relations.

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Distinctions into ingroups and outgroups are a universal feature of human societies. Humans display ingroup favoritism, which supports cooperation and successful collective action, and outgroup prejudice, which often triggers conflict and violence. Yet classifications of others into in- and outgroups are not fixed, but change over time and across contexts. A long tradition in the social sciences studies the forces driving outgroup prejudice (Allport 1954; Blumer 1958) and changes in social group boundaries (Barth 1969), usually focusing on the interaction between two groups. Significantly less work exists that generalizes the focus to multi-group relations in diverse societies.

In this paper, we attempt to fill this gap by studying the effects of immigration on intergroup relations in a society with multiple minorities. While the impact of immigration has received much attention, we know relatively little about how immigrants affect natives' views of racial or other minority groups. Extant work suggests that the size and characteristics of one minority group can change how majority members view other minorities, but the direction of this effect remains indeterminate. On the one hand, new groups may divert natives' prejudice from existing excluded minorities. On the other, attitudes can be driven by generalized ethnocentrism, with all culturally distant groups being lumped together in the minds of natives (Kinder and Kam 2010).

We propose a framework that accommodates both possibilities, and predicts when and how attitudes towards existing minorities change in response to the arrival of new groups. Building on self-categorization theory in social psychology (Turner et al. 1987; 1994), we hypothesize that individuals categorize others as in- or outgroup members based on shared attributes. We introduce the concept of *affective distance* as a key determinant of which attributes will emerge as relevant for social categorization. Affective distance is a summary term for an individual's feelings towards members of different groups relative to their own ingroup. Like social status, it captures a group's relative perceived quality or value (Tajfel and Turner 1986).

In our framework, an increase in the size of one group changes the way the majority classifies other groups, depending on the combination of group size, affective distance and shared attributes. Existing outgroups are reclassified as ingroups, and viewed more positively,

when they differ from the growing group in terms of key attributes that distinguish the latter from the majority, and when their affective distance from the majority is lower *relative* to that of the growing group.

We provide evidence consistent with this theoretical framework in the context of the US, by investigating the impact of Mexican immigration on Whites' attitudes toward Blacks. We combine Census demographic data between 1970 and 2010 with survey data on attitudes toward various minority groups from the American National Election Study (ANES), the General Social Survey (GSS), the Cooperative Elections Study (CCES), and with data on hate crimes from FBI's Uniform Crime Reporting system.

We implement a difference-in-differences design that leverages changes in Mexican immigration across states over time, accounting for states' time-invariant characteristics and for time-variant factors that affect all states within the same census division. To assuage remaining endogeneity concerns, we predict Mexican immigration exploiting the distribution of ethnic enclaves across states in 1960. This strategy builds on the empirical regularity that immigrants tend to locate in areas with an extant immigrant network. We perform several checks to support the identifying assumption that time-varying unobservables correlated with 1960 Mexican shares are not the crucial driver of changes in racial attitudes.

Using this empirical design, we find that Mexican immigration substantively reduces anti-Black prejudice among Whites. The increase in the share of Mexican immigrants experienced by the average US state between 1970 and 2010 can explain up to 59% of the increase in feelings of warmth (as captured by a feeling thermometer) expressed by Whites towards Blacks during the same period. Attitudinal changes among Whites have implications for racial policy preferences, which become significantly more liberal in states that receive more Mexican immigrants. These changes are specific to government interventions that promote Black-White equality, and are not driven by a general increase in liberal ideology. Whites' attitudes towards Hispanics deteriorate with increasing shares of Mexican immigrants, suggesting that Whites become more positive towards Blacks, but not more tolerant of minorities in general. These findings hold regardless of the contextual unit used to measure Mexican group size – from state to county to Census tract – and across a number of different attitudinal surveys. Attitudinal changes are reflected in behavioral patterns, with anti-Black hate crimes registering a larger drop in counties that receive more Mexican immigrants.

Interpreted through the lens of our theoretical framework, Mexican immigration improves attitudes and behaviors of native-born Whites towards Blacks, because Mexicans have a higher affective distance from Whites than do Blacks. Consistent with this hypothesis, using the feeling thermometer in the ANES as a proxy of affective distance, we show that Whites have cooler feelings towards Hispanics as compared to Blacks, for every single survey year between 1980 and 2010.

The data allow us to test three additional implications of the theory. First, the inflow of relatively more distant groups (in our case, Mexican immigrants) increases the salience of attributes along which those groups display maximal difference from the majority (immigration status instead of race). Consistent with this prediction, White respondents in states experiencing a larger increase in the share of Mexicans become more likely to mention immigration policies and less likely to mention race relations as the country's most important problem.

Second, prejudice against Blacks decreases the most for Whites whose baseline views of Hispanics are particularly negative relative to their views of Blacks. In support of this prediction, the effects of Mexican immigration on attitudes towards Blacks are larger in states with larger baseline (i.e. pre-immigration) differences in thermometer ratings between Mexicans and Blacks.

Third, our theory delivers general predictions for how increases in one immigrant group's size will affect Whites' attitudes towards any other minority group. The direction of effects depends on the relative affective distance of the growing immigrant group, and on whether other groups are classified as outgroups based on race or immigrant status. Consistent with this, inflows of distant groups (such as Hispanics or Arabs) increase the salience of immigration and negatively affect attitudes towards other groups perceived as foreign (such as Asians). Inflows of less distant groups (such as Asians), if anything, reduce the salience of immigrant status as a relevant group boundary.

We complement our analysis with an original survey experiment designed to provide direct evidence that the improvement of Whites' attitudes towards Blacks results from recategorization. White respondents primed with the size of the Hispanic population in the US express warmer feelings towards Blacks and hold less stereotypical views of them, confirming our observational findings on the effects of changes in Hispanic population. Crucially, primed respondents also become more likely to view Blacks as "American", consistent with our hy-

pothesized recategorization mechanism.

Our study contributes to four strands of literature. First and most broadly, the fluid nature of group boundaries in multiethnic and multiracial societies has been extensively studied by scholars in both comparative and American politics. To factors like group mixing and shifting self-identification (Davenport 2018; 2020), instrumental identity choices (Laitin 1995; Posner 2005), and institutionalized group classifications (Hochschild and Powell 2008), we add a new theoretical channel through which group categories can change, that of context-dependent classification based on relative distances between groups. Our framework formalizes insights from social identity theory and is close in spirit to Shayo (2009), but our focus and empirical application are on how individuals classify others, rather than on how they view themselves.

Second, we contribute to the literature on racial and ethnic politics in the US context. A majority of works in that literature focus on Black-White relations (Bobo 1983; Glaser 1994; Kinder and Mendelberg 1995; Valentino and Sears 2005; Acharya, Blackwell and Sen 2018), with a smaller but growing set of studies examining inter-minority relations (Bobo and Hutchings 1996; Oliver and Wong 2003; Meier et al. 2004; Gay 2006; McClain et al. 2006; 2007; Masuoka and Junn 2013; Roth and Kim 2013; Hutchings and Wong 2014). Less attention has been paid to the role that other minorities play in affecting Whites' attitudes towards African Americans. Our paper provides new evidence that the increase in the numbers of immigrant minorities may ameliorate Whites Americans' prejudice toward Black Americans, and identify conditions under which this is likely to happen.

Third, our study contributes to a large literature in the social sciences studying the effects of minority group size on majority prejudice starting with Blumer (1958) and Blalock (1967). We add to this literature in two ways. First, we emphasize the importance of affective distance, as a factor that determines majority reactions to minority inflows jointly with group size. Our results indicate that increases in size alone are unlikely to affect prejudice when groups are relatively close to the majority in terms of affective distance. This is consistent with existing observations that certain immigrant groups are more likely to trigger perceptions of threat than others (Ha 2010; Brader, Valentino and Suhay 2008; Newman and Velez 2014). Second, most of the literature examines how increases in the size of a group affect the majority's views towards that group. We instead shift the focus to the majority's views towards other minorities, and thus to the broader implications of growing minority size in a multi-group

society. In this respect, we also add to a small set of studies examining cross-group spillovers of attitudes.[1]

Finally, our study speaks to the politics of immigration. To date, much of this research focuses on the effects of immigration on native backlash and anti-immigrant sentiment (see Hainmueller and Hopkins 2014 for a review). We examine instead how immigration of one group shifts native-born individuals' attitudes toward other minority groups. In work closely related to ours, Hopkins (2010) finds that the anti-Muslim rhetoric that followed 9/11 triggered backlash against all immigrant groups. Our study places this finding in a broader context, by showing that spillovers of attitudes from one minority to others can be positive or negative, depending on groups' relative perceived distances from the majority.

Conceptual framework

We rely on self-categorization theory (Turner et al. 1987; 1994), which studies how individuals classify themselves and others into in- and outgroups. Such categorization has tangible implications, because prejudice is higher towards members of the outgroup (see, for example, Duckitt 1994; Bernhard, Fischbacher and Fehr 2006; Shayo 2020). Social categorization takes place on the basis of shared attributes. The more attributes are shared by two individuals, the more likely it is that one categorizes the other as member of their ingroup. Since people have multiple attributes, and share similarities in some, but not in others, the relevant question is which attributes determine social categorization.

Self-categorization theory posits that this is context-dependent. The same person can be classified as a member of the ingroup or the outgroup, depending on whom they are compared to. This concept is known as 'comparative fit' (McGarty 1999). More precisely, classification is assumed to follow the rule of maximization of the *meta-contrast ratio*, defined as the ratio of *across category differences* over *within category differences* (Turner et al. 1987, p.47). Intuitively, this implies that humans form categories of stimuli, so that within-category differences are small (i.e. a given category is sufficiently homogeneous) and across-category

[1] For example, work on "secondary transfer effects" (Weigert 1976; Pettigrew 1997) suggests that positive contact with one group can spillover to other outgroups.

differences are large (i.e. categories are sufficiently different from each other). Experimental evidence suggests that humans indeed follow such a heuristic for categorization (Tajfel and Wilkes 1963; Turner et al. 1987).

To capture relevant differences between individuals, we use a summary measure, which we term *affective distance*. Affect is a heuristic of decision-making (Zajonc 1980) based on an emotional response. Affective distance from a person or a group of people can be driven by many factors, such as the group's perceived competence or quality, or the degree to which it is perceived to be threatening or in competition with the ingroup (Tajfel and Turner 1986).

Formally, consider the set I of individuals within an area. Each $i \in I$ is characterized by a vector of J binary attributes. Denote by δ^i each individual's affective distance from the ingroup and by I^i_j an indicator equal to 1 if individual i differs from the ingroup along the j^{th} attribute. Then, the attribute used by each individual to categorize others into in- and outgroup solves

$$\max_j R_j = \frac{\frac{\sum_i \delta^i I^i_j}{\sum_i I^i_j}}{\frac{\sum_i \delta^i (1-I^i_j)}{\sum_i (1-I^i_j)}}$$

where R_j is the meta-contrast ratio for attribute j. R_j can be thought of as the salience of attribute j for ingroup–outgroup distinctions.

Defining a group k as the set of individuals with common attributes, we can rewrite the above problem in terms of group-level categorization for K groups:

$$\max_j R_j = \frac{\frac{\sum_{k \in K} \delta^k n^k I^k_j}{\sum_{k \in K} n^k I^k_j}}{\frac{\sum_{k \in K} \delta^k n^k (1-I^k_j)}{\sum_{k \in K} n^k (1-I^k_j)}} \tag{1}$$

where δ^k denotes the average affective distance of members of group k from the ingroup and n^k is the size of group k. The numerator is a weighted average of affective distances across all outgroups $k \in K$, with the weights corresponding to each group's relative size. The denominator is a weighted average of affective distances across all ingroups $k \in K$. Maximization thus implies choosing the attribute that makes the outgroup most different, and the ingroup most similar in terms of affective distance. Section A in the Appendix

provides a concrete example of how this classification rule operates in the case of three groups (White Americans, Black Americans, and Mexican immigrants) and two attributes (nativity and race) that we focus on in the empirical part of the paper.

Equation 1 makes it clear that both relative size and affective distance matter for categorization. We derive testable predictions for the effects of increasing size of a group of given affective distance on the salience of different attributes determining ingroup–outgroup divisions and on the categorization of other groups.

Specifically, consider a group l with $I_m^l = 1$, $I_j^l = 0$ and $\delta^l > 0$. The above formula implies the following results:

Prediction 1 (Salience)**.** *A large enough increase in the size of group l increases the salience of attribute m and decreases the salience of attribute j as long as $\delta^l > \delta^k$ for all $k \in K \setminus l$.*

This follows directly from the fact that $\frac{\partial R_j}{\partial n^l} > 0$. Intuitively, an increase in the size of a group distant in terms of affect shifts the basis of social categorization to the attribute along which that group differs from the ingroup. When an immigrant group that is perceived as distant or threatening grows in size, immigrant status becomes the salient cleavage in a society.

This implies the following for other groups in the society.

Prediction 2 (Recategorization)**.** *(a) For any group k with $I_m^k = 0$ and $I_j^k = 1$ that is categorized as outgroup, a large enough increase in the size of group l leads to recategorization if $\delta^l > \delta^k$. The threshold for recategorization is decreasing in the difference $\delta^l - \delta^k$.*

(b) Consider a group k with $I_m^k = 1$ and $I_j^k = 0$, where j solves equation 1 so that group k is categorized as ingroup. Then a large enough increase in the size of group l leads to recategorization if $\delta^l > \overline{\delta_j}$, where $\overline{\delta_j}$ is the numerator of R_j.

(c) Consider a group k with $I_m^k = 1$ and $I_j^k = 0$, where m solves equation 1 so that group k is categorized as outgroup. Then a large enough increase in the size of group l leads to recategorization if $\delta^l < \overline{\delta_j}$, where $\overline{\delta_j}$ is the numerator of R_j.

Part (a) of Prediction 2 follows directly from Prediction 1, and the fact that, when the increase in n^l is large enough, R_m becomes larger than R_j and attribute m arises as the

determinant of classification into in- and outgroup. Intuitively, an increase in the size of an outgroup of high affective distance draws the majority's attention to the attribute that distinguishes that group from the majority, and away from other attributes. The differences between majority and groups previously classified as outgroups based on attribute j are thus de-emphasized. This leads to recategorization of existing minorities from out- to ingroup status. In the case of immigration and race, an increase in the salience of immigrant status reduces the importance of skin color as a group classifier, and thus reduces prejudice of Whites against Blacks.

It follows from 2(a) that an increase in the size of an outgroup can accentuate existing dimensions of difference between the majority and other outgroups when that group is of lower affective distance to the majority than existing outgroups. When an expanding group is perceived as less threatening than other groups (e.g. Asian immigrants), its comparison with racial minorities does not decrease, and may even increase, prejudice against the latter.

Parts (b) and (c) of Prediction 2 concern groups that share relevant attributes with the group that is growing in size. When affective distance of the growing group is high, and attention is drawn to attributes distinguishing that group from the majority, other groups may see a change in their classification from in- to outgroups if they share said attributes. Conversely, if affective distance is low, groups categorized as outgroups based on the distinguishing attribute of the growing group may find themselves recategorized as ingroups.

Context and group size

What is the relevant spatial unit for measuring group size n^k? Extant theory provides only partial guidance to answering this question. The answer depends on the perceptions of group size formed by ingroup members (Wong et al. 2012). Yet it is not clear which spatial unit individuals consider when forming relevant perceptions. When asked to estimate group size in their local community, individuals provide estimates that are best predicted by size at the level of the zip code (Newman et al. 2015; Velez and Wong 2017). However, people might not always think about their local community or real-life exposure to a racial or ethnic group when assessing its size. Social and informational environments – such as traditional and social media – may be equally important in influencing people's perceptions. Such forces operate at larger scales, such as media markets, states, or even at the national level (Huckfeldt and

Sprague 1995).

Regardless of the relevant context for perception formation, recategorization is more likely to happen when the group growing in size is further away from the ingroup in terms of affective distance. To the extent that affective distance reflects threat, it is likely to peak at larger contextual units, like the MSA or the state (Oliver and Wong 2003; Ha 2010; Tam Cho and Baer 2011). Several studies in the social sciences suggest that perceptions of threat in response to diversity are maximized at units equal to or larger than 500,000 people, with little variation in effects by population size once that threshold is reached (Kaufmann and Goodwin 2018). Instead, effects of positive intergroup contact are more prevalent among studies that examine lower levels of aggregation closer to the neighborhood (Ha 2010; Tam Cho and Baer 2011).[2]

Given this discussion, we expect stronger recategorization at larger levels of aggregation, where growing groups are more likely to be perceived as affectively distant and where size perceptions are influenced by media and social environments likely to further heighten perceptions of threat (Massey and Pren 2012; Valentino, Brader and Jardina 2013). Yet, the mechanism we posit should operate also at lower levels of aggregation. As long as the distance of a group is larger than that of existing outgroups, increases in its size at any spatial unit relevant for people's perceptions should lead to re-categorization of other groups. In our empirical analysis, we focus on the state level, but also evaluate effects at different contextual units, from the county to the census tract.

Data and empirical strategy

Data

We construct a state-level panel of Mexican and overall immigration using data from the US Census (Ruggles et al. 2019) for each decade between 1970 and 2010. Given Census data availability, and for the demographic data to closely match the instrument for predicted immigration introduced below, we focus only on the foreign-born and not the population of

[2]Threat perceptions are not necessarily linear in the size of the spatial unit. *Micro-threat* theories argue that threat may be triggered by demographic changes at the hyper-local level. Dinesen and Sønderskov (2015) show that diversity reduces trust when measured at a radius of up to 180 meters from an individual's residence, but has no effect for larger radii.

second-generation immigrants.

We complement this data with state-level demographic characteristics (Ruggles et al. 2019; Manson et al. 2019). To assess whether immigrant inflows from Mexico affect Whites' attitudes, we rely on survey data from the American National Elections Study (ANES). The ANES is a nationally representative public opinion survey conducted every two or four years since 1948 by the University of Michigan. We focus primarily on attitudes towards African Americans, but also examine attitudes towards Hispanics and Asian Americans when investigating the mechanisms. Because data on immigrant population is decadal, but the ANES is conducted every two years until 2000, and every four years thereafter, we map immigration to survey responses in the years closest to, and centered around, the year when immigrant numbers were recorded. For example, the 1980 Mexican share is mapped to survey responses in 1978, 1980 and 1982.

We use two measures of Whites' racial attitudes. The first one is the feeling thermometer. The scale of responses ranges from 0 to 100, with higher values indicating warmer feelings. The feeling thermometer has the advantage of having been consistently asked over time throughout our period of study. We construct a second measure of attitudes, by combining the feeling thermometer with variables capturing stereotypical views of Blacks. Specifically, we focus on whether the respondent believes that Blacks are hard-working, intelligent, violent or trustworthy (items coded on a 1 to 7 scale). We recode all items so that higher values indicate lower prejudice, and create an index out of all standardized items (including the feeling thermometers) to reduce noise and avoid multiple hypothesis testing. We construct similar measures for Hispanics and Asian Americans.

We focus on the state level because this is a relevant unit of analysis from a theoretical standpoint, but also because it presents a number of empirical advantages. First, county level ANES data is sparser and the repeated cross-section of counties that one can follow over time is not nationally representative. Second, selective migration of Whites in response to Mexican immigration, which is a likely confounder of any estimates of immigration on attitudes, is significantly less pronounced at the state level than at the level of smaller spatial units. Finally, as explained in more detail in the next section, the instrument for Mexican immigration relies on the initial distribution of Mexican enclaves prior to the change in the immigration regime in 1965. This information is accurate and complete at the state level, but

not at lower levels of aggregation. Despite these empirical shortcomings, we nonetheless show that our results are unchanged at the county and census tract levels. We present this data as it becomes relevant.

Table C.1 presents summary statistics for all variables used in our analyses. Tables C.2 and C.3 report the exact wording and years of availability of ANES survey questions.

Empirical strategy

We start from a generalized difference-in-differences design. We compare changes in racial attitudes across states experiencing differential changes in the fraction of Mexican immigrants over time, absorbing any time-invariant state and any time-varying census division characteristics. Focusing on White respondents, we estimate:

$$Y_{irst} = \beta_1 M_{rst} + \beta_2 S_{rst} + \gamma_{rs} + \mu_{rt} + \mathbf{X}_{irst} + \eta_{irst} \tag{2}$$

where M_{rst} is the fraction of the total population that is born in Mexico in census division r and state s in time t. The key parameter of interest, β_1, captures the impact of Mexican immigration on attitude Y_{irst} for individual i. γ_{rs} and μ_{rt} represent state and decade by census division fixed effects. Their inclusion implies that β_1 is estimated from changes in Mexican immigration within a state over time, as compared to other states within the same division in the same decade. To account for the potential correlation between Mexican and overall immigration to the US, we control for S_{rst} – the share of (non-Mexican) immigrants in a state and decade. Finally, we control for a set of baseline individual-level characteristics (age, age squared, and gender) collected in the vector $\mathbf{X}_{irst}$. We cluster standard errors at the state level.

This approach differences out all time-invariant unobservable characteristics of states that could affect both immigrant location choices and racial prejudice. However, local time-varying factors may still be influencing both immigrants' settlements and the social integration of minorities. To overcome these concerns, we predict the number of Mexican immigrants settling in a given state over time using a version of the shift-share instrument commonly adopted in the immigration literature (Card 2001). The instrument assigns decadal immigration flows from Mexico between 1970 and 2010 to destinations within the US proportionally to the shares

of Mexican immigrants who had settled there in 1960, prior to the change in immigration regime introduced in 1965. We predict the number of non-Mexican immigrants using a similar approach and averaging across immigrant origin countries. Details on the construction of the instrument are provided in Section B. The first stage relationship, which is strong, is displayed in Figure B.1 and Table B.1.

The key identifying assumption behind the instrument is that places that received more Mexican immigrants before 1960 are not on differential trajectories in terms of changes in Whites' attitudes or other factors correlated with the latter (Goldsmith-Pinkham, Sorkin and Swift 2020). We provide multiple pieces of evidence in support of this assumption.

Main results

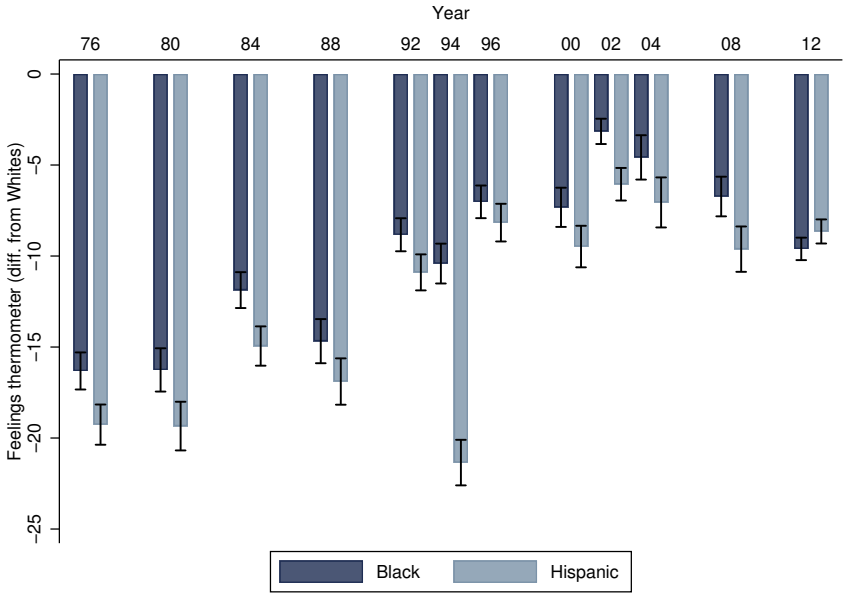
Affective distance

A fundamental premise in our argument is that Mexican immigrants have a higher affective distance from native Whites than do Blacks. Using thermometer ratings relative to the White ingroup as a measure of affective distance supports this assumption. Figure 1 plots Whites' relative thermometer ratings of Blacks and Hispanics for every survey year in the ANES. Whites consistently express warmer feelings towards Blacks, as compared to Hispanics, and differences between the two groups are always statistically significant.[3]

The high affective distance of Hispanics from Whites traces its origins to the 1970s. The large influx of undocumented Mexican immigrants that followed the abrupt ending of the Bracero program was exploited by opportunistic politicians to construct a narrative around a "Latino threat" (Massey and Pren 2012). Since that time, Hispanic immigration has captured a disproportional amount of media attention (Valentino, Brader and Jardina 2013). Other factors, such as the direct proximity of Mexico to the US, have also contributed to perceptions of Mexican immigration as a unique challenge for American society and culture (Huntington 2004), possibly explaining the patterns in Figure 1.

[3] An alternative – but not consistently available across years and groups – measure of affective distance, reported closeness to a group, produces similar results (Figure D.4).

Figure 1. Feeling thermometer ratings of White ANES respondents



Effects on attitudes

Table 1 presents our main results. 2SLS estimates suggest that Mexican immigration increases both the feeling thermometer (column 2) and the average of standardized Whites' racial attitudes (column 4). OLS coefficients are negative, implying that Mexican immigrants moved to states where Whites' racial views were improving more slowly over time.[4]

The magnitude of the estimates is substantive. One percentage point increase in the Mexican share raises the Black feeling thermometer by 1.2% relative to its baseline mean. Between 1970 and 2010 the fraction of Mexicans increased, on average, by 2 percentage points. According to our estimates, this accounts for 58.8% of the average increase in the Black thermometer (2.57) and 60% of the average increase in the mean (0.14) over the same time frame.

[4]This bias is consistent with our theoretical mechanism. If Mexican immigrants tended to move to states with more positive views towards Hispanics, reductions in anti-Black prejudice in those states would be smaller, consistent with Prediction 2(a). As expected, OLS coefficients increase after interacting baseline state controls with decade indicators, as in Table D.2, consistent with omitted variable bias.

Table 1. Effects on Whites' attitudes towards Blacks

Dependent variable	Feeling thermometer Blacks		Average attitudes	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Share Mexican	-15.751	76.030	-1.747	4.224
	(28.663)	(36.305)	(1.304)	(1.733)
Mean dep. variable	63.067	63.067	-0.139	-0.139
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
R-squared	0.034	0.033	0.033	0.031
F-stat		131.3		132.1

We conduct several checks to verify that these estimates represent causal effects, reported in detail in Section D.1 of the Appendix. Our results are robust to allowing states to be on differential trajectories depending on a number of 1960 characteristics potentially correlated with Mexican shares, such as racial composition or urbanization (Table D.2). Falsification tests and permutation exercises confirm that 1960 Mexican shares do not alone drive the evolution of racial attitudes we estimate (Table D.4 and Figure D.1). Our results go through after accounting for potential bias due to spatial interdependence (Table D.6), for the potential influence of outliers (Figure D.2 and Table D.7) and for serial correlation in the instrument for predicted immigration (Table D.8).

Our results are orders of magnitude larger in states with above-median share of Blacks in 1970 and improvements in attitudes are driven primarily by states with below-median residential segregation (Table D.14). This indicates that immigration changes racial attitudes particularly for Whites more likely to be exposed to and interact with Blacks. This heterogeneity is also consistent with our framework. States with more Blacks and lower segregation in 1970 may have been characterized by more positive racial attitudes among Whites and thus lower affective distance between Blacks and Whites at the start of our study period. This increases the likelihood of recategorization (Prediction 2(a)).

We examine whether changes in attitudes also translate into policy preferences. Ex ante, it is unclear what to expect. Policy preferences related to race are crucially shaped by factors such as political ideology and views on the role of government, which may be harder to change and orthogonal to racial attitudes. Table D.16 in the Appendix documents that Mexican immigration increases support for government interventions that advance racial equality, such

as fair employment practices or preferential hiring. These patterns are specific to race-related policies and not part of a broader package of more liberal views spurred by immigration (Table D.17).

Can our results be explained by a broader improvement of Whites' attitudes towards minorities? In Table 2 we estimate the effects of Mexican immigration on attitudes towards Hispanics and find this to not be the case. 2SLS estimates, reported in columns 2 and 4, indicate that Mexican immigration increases Whites' prejudice towards Hispanics.[5] These patterns are consistent with Prediction 2(b) of our theoretical framework and suggest that Mexican immigration leads Whites to change the definition of the ingroup so as to include Blacks and exclude Hispanics.

Table 2. Effects on Whites' attitudes towards Hispanics

Dependent variable	Feeling thermometer		Average attitudes	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Share Mexican	42.587	-320.526	1.037	-10.984
	(59.578)	(182.423)	(2.945)	(6.017)
Mean dep. variable	61.288	61.288	-0.112	-0.112
Number of states	51	51	51	51
Observations	11,399	11,399	11,672	11,672
R-squared	0.061	0.056	0.073	0.070
F-stat		90.70		89.40

Factors beyond recategorization, could explain our findings. In Section D.3 of the Appendix we rule out several prominent alternatives. Changes in racial attitudes are not driven by changes in the numbers of Black or White residents (Table D.9). Using data from the 2004 ANES panel study, we provide evidence against selective out-migration of Whites with more anti-Black and less anti-Hispanic attitudes (Table D.11). We show that our results are not driven by the effect of 9/11 on anti-immigrant sentiment (Table D.12). We also assess the possibility, identified by prior work (Green, Strolovitch and Wong 1998; Hopkins 2009; 2010; Newman and Johnson 2012; Newman 2012), that *changes* instead of *levels* of Mexican group size drive changes in attitudes. We do not find strong evidence that changes in group size

[5] OLS coefficients are upwards biased, suggesting that Mexican immigrants were moving to states where attitudes towards Hispanics were improving.

have a larger impact on racial prejudice than size itself (Table D.13), but our identification strategy does not allow us to cleanly distinguish between the two.

A likely pathway for the results we observe is that changing political discourse or media narratives contribute to a shift in attention from race-related issues to immigration and the role of Hispanics in the US. Massey and Pren (2012) document an explosion of media mentions of Hispanic immigration in the period we study. Rising volume of media coverage of Hispanics could crowd out mentions of other groups, increasing perceptions of threat from the former and reducing them for the latter. We view this mechanism as consistent with our framework. Media reports are responsive to readers' demand (Gentzkow and Shapiro 2010), and the increased focus on Hispanics is as much a driver as it is an outcome of White Americans' anxiety about immigrant population growth. Indeed, Valentino, Brader and Jardina (2013) show that media coverage of Hispanics mirrors trends of immigration from Latin America, suggesting that the media respond to real demographic changes in the US population. According to our framework, increases in the size of an immigrant group endogenously increase the salience of immigration. Increased media mentions are both a reflection of this endogenous salience and an amplifying mechanism for its effects on group recategorization and prejudice.

Local-level evidence

Studies on local demographics and majority attitudes frequently yield conflicting results depending on the spatial unit of analysis (Tam Cho and Baer 2011; Pottie-Sherman and Wilkes 2017). To avoid aggregation bias – the "modifiable aerial unit" problem (Fotheringham and Wong 1991) – the literature emphasizes the importance of choosing units of analysis that closely correspond to the theoretical mechanisms analyzed (Wong et al. 2012; Newman et al. 2015). We argued that the state is a relevant unit for perceptions of group size, particularly those perceptions that trigger macro-threat. Yet other contextual units may be relevant for size perceptions at the local community level (Velez and Wong 2017) and those perceptions could also affect re-categorization. We investigate these possibilities empirically.

We estimate a county-level variant of equation 2, controlling for state by decade (rather than division by decade) fixed effects. That is, we restrict comparisons to counties within the same state that experience differential increases in their Mexican populations. County-level estimates are similar to those of the state-level analysis (Table E.5). A one percentage point

increase in the share of Mexicans raises the feeling thermometer for Blacks by 1% relative to the baseline mean, very close to the 1.2% effect estimated at the state level. The effect on the summary measure of attitudes is somewhat smaller and less significant than the equivalent state-level estimate, but still amounts to 38% of the average increase in the mean during the period of interest – a substantive effect. Attitudes towards Hispanics worsen in response to increasing Mexican group size, with the magnitude of the effect for the Hispanic thermometer corresponding to 2.7% of the baseline mean – not far from the 5.2% estimated at the state level. Similar results obtain in a county-level panel of attitudes from the General Social Survey (Table E.6). The consistency of estimates across state and county-level analyses is perhaps not surprising given that similar mechanisms may operate at both these levels of aggregation (Kaufmann and Goodwin (2018)).

We also examine a contextual unit smaller than the county, the census tract.[6] Using data from the Cooperative Election Study (CCES) between 2007 and 2018, and estimates of local demographics from the American Community Survey (ACS), we find that Mexican population size significantly reduces symbolic racism (Kinder and Sears 1981) and negatively, though not significantly, impacts immigration policy preferences (Table E.10). These estimates compare census tracts within the same county, conditional on the evolution of a number of tract-level demographic and socioeconomic characteristics, thus representing particularly stringent local estimates of the effect of Mexican immigration on attitudes. Details on this analysis are provided in Section E.2 of the Appendix.

Taken together, our results suggest consistency of effects across spatial units. For the remainder of the analysis, we focus attention on state-level estimates that provide us empirically with the most traction to test additional empirical implications of our framework.

[6]The population size of census tracts ranges between 1,200 and 8,000 people, for an average of 4,000 residents.

Testing the mechanisms

Increase in the salience of immigration

As per Prediction 1, Mexican inflows lower prejudice against Blacks because they reduce the salience of race and increase that of immigrant status. We provide evidence for this mechanism by exploiting ANES responses to the question "What do you think are the most important problems facing the country?". This is an open-ended question, but the ANES reclassified the answers of respondents into broader categories. We focus on two categories that do not change over time: immigration policies and racial problems. For the latter, we can further identify the exact position the respondent takes on various racial issues and whether it indicates positive or negative attitudes towards African Americans (e.g. supports vs opposes fair employment practices). We construct an indicator for respondents who mentioned a category as the single most important problem facing the country at the time.

Table 3 shows that Mexican immigration significantly increases the share of White respondents who mention immigration policies as the most important problem in the country. The share of respondents who mention race-related problems and place themselves in opposition to the expansion of rights for Blacks decreases (columns 3–4). Conversely, the share of those who mention race-related problems and express support for Black-White equality increases (columns 5–6). As immigration becomes a salient problem, White Americans appear to shift their attention to issues that unite, rather than divide, them from Black Americans.

Table 3. Most important problem in the country

Dependent variable	Immigration policies		Racial problems (negative)		Racial problems (positive)	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Share Mexican	0.290	0.154	-0.096	-0.143	0.406	0.478
	(0.125)	(0.078)	(0.118)	(0.176)	(0.092)	(0.088)
Observations	10,726	10,726	10,726	10,726	10,726	10,726
Number of states	46	46	46	46	46	46
R-squared	0.012	0.012	0.022	0.022	0.015	0.015
F-stat		154.7		154.7		154.7

Effects increasing in the difference of affective distances

Prediction 2(a) states that the effect of immigration on attitudes towards Blacks is higher the more distant immigrants are perceived to be by Whites, compared to Blacks. We test this empirically by exploring heterogeneity patterns within the ANES sample.

We construct state-level averages of the difference in thermometer values between Blacks and Hispanics in 1980 – the first survey decade for which attitudes on Hispanics began to be systematically collected. Larger values indicate that White respondents have warmer feelings towards Blacks than they do towards Hispanics. We then interact the effect of the share of Mexicans with this variable. Table 4 presents heterogeneous effects by baseline difference in affective distance between Blacks and Hispanics. The results indicate that a significantly larger improvement in Whites' feelings towards Blacks comes from states whose residents viewed Mexicans more coolly than Blacks in 1980 (column 2). A similar positive, though not statistically significant, interaction effect is found for average prejudice (column 4).[7]

Table 4. Effects by baseline difference in Black-Hispanic thermometer ratings

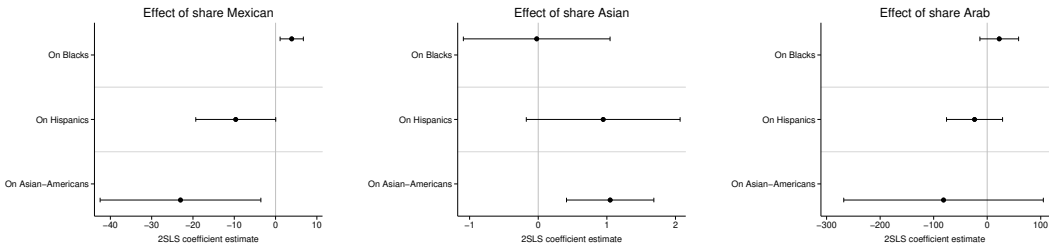
Dependent variable	Feeling thermometer Blacks		Average	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Share Mexican	-42.074	45.634	-3.049	6.288
	(62.348)	(57.539)	(2.790)	(3.444)
Share Mexican × 1980	9.331	16.663	0.349	0.117
diff. Black-Hispanic thermometer	(5.128)	(3.920)	(0.240)	(0.175)
Mean dep. variable	63.314	63.314	-0.127	-0.127
Observations	14,818	14,818	15,062	15,062
Number of states	39	39	39	39
R-squared	0.034	0.033	0.032	0.030
AP F-Stat Share Mexican		147.8		144.8
AP F-Stat interaction		45.24		41.94

[7]We find similar patterns of heterogeneity when splitting the sample by partisanship. As compared to Republicans, Democrats view Hispanics less warmly *relative* to Blacks in the baseline. Consistent with Prediction 2, increases in the share of Mexicans improve attitudes towards Blacks more for Democrats than for Republicans (Appendix Figure D.5 and Table D.15).

Generalized cross-group effects

Beyond a prediction for the effect of Mexican immigration on Whites' attitudes towards Blacks, our framework has broader implications for how the growth in the size of one group affects the majority's attitudes towards other social groups. Prediction 2(b) implies that growth in the size of immigrant groups of higher affective distance from Whites not only leads to recategorization of non-immigrant outgroups as ingroups, but that it also has the opposite effect on other immigrant groups, increasing prejudice against them. Further, Prediction 2(c) predicts that growth in the size of immigrant groups that are less distant, in terms of affect, from Whites than are Blacks, does not decrease, and may even increase, prejudice towards the latter. In this section, we provide evidence supportive of both patterns.

Figure 2. Cross-group effects by affective distance and shared attributes



Notes: The figures plot 2SLS coefficient estimates and 90% confidence intervals of the effect of group size from equation 2 for each of the groups indicated in the subplot titles. The dependent variable is the feeling thermometer rating of White ANES respondents for each of the groups indicated on the y-axis. Full estimates reported in Table D.18 in the Appendix.

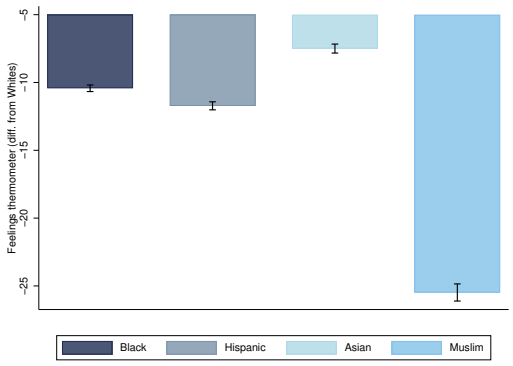
The left panel of Figure 2 plots the effects of the share of Mexicans on Whites' feeling thermometer ratings of different groups. The first two estimates correspond to 2SLS coefficients from Tables 1 and 2. The third estimate shows how an increase in the Mexican share affects Whites' thermometer ratings of Asians. Consistent with Prediction 2(b), Mexican immigration has negative effects on attitudes of Whites towards groups perceived as foreign-born.

The particular effects of Mexican immigration on Whites' views of other groups result from the fact that Mexicans' relative affective distance from Whites is high. Inflows of relatively less distant groups de-emphasize immigrant status as a classifier and, if large enough, may have the effect of redirecting prejudice away from immigrants.

Next to Central and South America, Asia was the second largest immigrant-sending region

during the 1970-2010 period. Figure 3 reveals that White respondents have warmer feelings towards Asian Americans than they do towards either Blacks or Hispanics. This lower distance can be a result of Asian Americans being on average more educated and highly skilled, or perceived as less of a threat than other minorities.[8]

Figure 3. Average thermometer ratings of White ANES respondents



The impact of Asian immigration on Whites' attitudes towards Blacks is consistent with this ranking.[9] The middle panel of Figure 2 shows that an increase in the share of Asian immigrants has no effect on Whites' thermometer ratings of Blacks. Instead, effects on thermometer ratings of Hispanics and Asians are positive, consistent with prediction 2(c).

Finally, we examine how inflows of another group of high relative affective distance affects minority recategorization. After 9/11, the ANES introduced questions on thermometer ratings of Muslims. This group's ratings relative to Whites are more negative than those of Hispanics (Figure 3).[10] In the right panel of Figure 2, we measure the Muslim (primarily

[8]Studies asking Americans to evaluate various groups in terms of competence and warmth – two dimensions that have emerged as explanatory of attitudes towards minorities in social psychology – consistently find that Asians are scored as high-competence low-warmth, while Hispanics score low on both categories (Fiske, Cuddy and Glick 2007).

[9]We measure Asian immigration using all East and Southeast Asian countries identifiable in the 1960 Census microdata (China, Japan, Korea and the Philippines).

[10]Thermometer rating for Muslims are only available in 2004, 2008 and 2012, so they may not accurately capture Whites' views of the group in earlier periods. There are other difficulties, both conceptual and empirical, when examining the effects of Muslim immigration on other groups in the US. 20% of US Muslims are Black, blurring the conceptual distinction of immigrant status and (Black-White) racial classification that was clear in the case of Hispanics. Empirically, the majority of Muslims in the US arrived after 2000, with only 6% and 10% having arrived in the 1970s and 1980s, respectively. This limits the power of our empirical strategy, which relies on decadal changes in immigration over a long time period. Finally, to construct an instrument for Muslim immigration using 1960 immigrant shares we are required to rely only on the few Muslim-majority countries or regions identified in the 1960 US census, most of them in the Middle East and North Africa. The measure of Arab immigration is only a poor proxy of changes in the population of Muslims in the US over time, resulting

Arab) share of the population as the share of people born in any of the following countries or regions, which we can identify in all decades in the census: Syria, Lebanon, Palestine, Turkey, Egypt, or unspecified countries in North Africa. Arab immigration increases Whites' thermometer ratings of Blacks and lowers those for Hispanics and Asians. This is consistent with recategorization operating as in the case of Hispanic immigration: increased salience of foreign-born status as a classifier leads to reclassification of immigrant groups as outgroups and racial minorities as ingroups, with divergent effects on Whites' attitudes for each type of group.[11]

Micro-level evidence on reclassification

The previous sections show that immigration changes Whites' attitudes, but only test our theory indirectly, by providing evidence consistent with the framework's implications. To establish the posited mechanism more directly, we conduct an online survey experiment priming respondents with the share of Hispanics in the US population. This allows us to tailor the questions we ask, so as to examine not only whether Whites' racial attitudes change, but also whether Blacks are more likely to be perceived as ingroup members when the size of the Hispanic population becomes more salient.

Our survey experiment was conducted online in a sample of 499 White non-Hispanic respondents recruited through Lucid Theorem. The survey opened with two questions asking respondents to provide their best estimate of certain demographic characteristics of the US population. All respondents were asked to estimate the number of US residents. Respondents in the treatment group were asked to estimate what share of the US population consists of people of Hispanic origin. Respondents in the control group were instead asked to provide their best guess on the average age of US residents. We did not provide respondents with the correct answers to these questions, as we do not want to estimate the effect of information or of correcting misperceptions. Our goal was to lead respondents to reflect on the size of the Hispanic population.

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in noisy empirical estimates.

[11] The magnitudes of the estimates on Arab share are also orders of magnitude larger than those of Hispanic immigration, though we refrain from direct quantitative comparisons of 2SLS estimates due to the limited power of the instrument for Arab inflows.

We collect a number of outcomes that mirror the survey questions we analyze in the previous sections. We ask respondents to rate their feelings towards each of five groups in the US (Blacks, Hispanics, Asians, Muslims, Whites) using a feeling thermometer, with identical wording as in the ANES. We also ask for respondents' agreement with a number of statements associating groups with the same stereotypical attributes recorded in the ANES: intelligent, hardworking, trustworthy, violent. To measure recategorization, we follow Levendusky (2018) and include an additional item asking participants to rate how well the attribute "American" describes each group. Details on variables, sample characteristics, success of randomization and our survey instrument can be found in Section F of the Appendix. Our theory predicts that priming the size of the Hispanic population leads White respondents to recategorize Blacks as Americans, and express more positive attitudes towards them.

The upper left panel of Figure 4 plots our measure of affective distance, thermometer ratings relative to Whites, for respondents in the control group. All groups are viewed as more distant than Whites. Consistent with patterns in the ANES, Muslims are viewed as most distant. Unlike patterns in the ANES, Asians are the second most distant group, and Hispanics are viewed very similarly to Blacks.[12] The ranking of groups in terms of how American they are perceived to be is less surprising: the top right panel of Figure 4 shows that Whites rank highest, followed by Blacks. Asians and Hispanics are in the same position, while Muslims are perceived as the least American of all five groups.

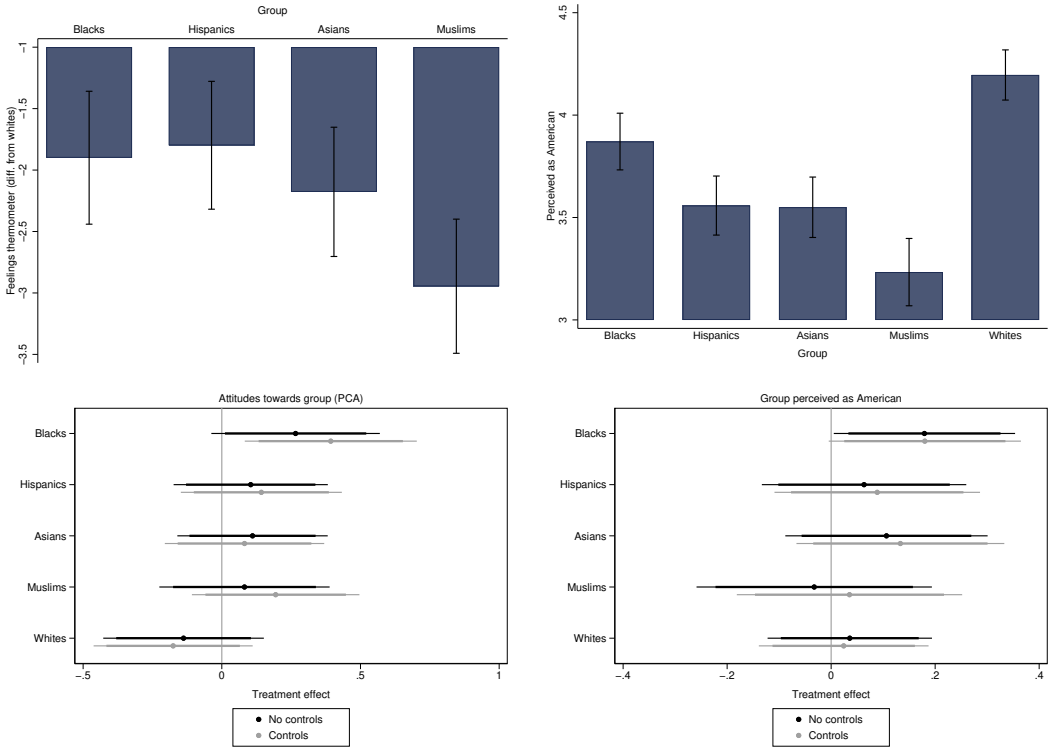
The bottom panel of the figure displays the effects of the treatment. Priming respondents with the size of the Hispanic population increases positive attitudes towards Blacks, measured as the principal component of the thermometer and all four stereotypes. It also significantly increases ratings of Blacks as American. No statistically significant effect is estimated for any other group and magnitudes for Blacks are always larger than for other groups.[13] Interestingly, the treatment does not worsen attitudes towards Hispanics or other immigrant groups, nor

[12]The differences between Blacks, Hispanics and Asians are not statistically significant. The low thermometer values for Asians could be a result of using the term "Asians" instead of "Asian Americans" as is the case for the ANES. We avoid using the term "Americans", as perceptions of groups as American are our outcome of interest.

[13]When controls are included, the estimated treatment effect on the principal component of attitudes towards Blacks is statistically different from coefficients for all other groups, with the exception of Muslims (p-value = 0.106).

does it lead respondents to perceive them as less American, possibly because immigration is already a salient group classifier in respondents' minds.

Figure 4. Priming respondents with share of Hispanics in the US



Notes: The top two subfigures plot averages among respondents in the control group. The bottom figures plot standardized beta coefficients of treatment effects on a principal component of attitudinal measures (left) and on perceptions of groups as American (right), with and without the inclusion of baseline controls. Thin and thick lines denote 95% and 90% confidence intervals respectively. For more details on the experimental setup, sample and estimation process see Section F of the Appendix.

Mexican immigration and changes in Whites' behavior

Our analysis so far relied on attitudinal variables, since the theoretical mechanism we propose is one of changes in perceptions and attitudes. Here, we turn to real-world behavior. Besides being of substantive interest, use of behavioral outcomes addresses potential concerns that our effects are driven by social desirability bias changing differentially across groups. To assess whether reduction in anti-Black prejudice among Whites implies changes in behavior, we examine rates of prejudice-motivated violence.

We use data on hate crimes available between 1992 and 2016, compiled by the FBI as part of the Uniform Crime Reporting (UCR) program, distributed by the Inter-University Consortium for Social Research at the University of Michigan (FBI and ICPSR 2018). The data comprises all reported hate crimes, defined as

> "[...] criminal offenses that are motivated, in whole or in part, by an offender's bias against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity." (FBI 2015, p.5)

Section G of the Appendix provides more details on the dataset and the FBI's procedure for recording hate crimes. It is important to highlight two relevant features of the hate crimes measure here. First, FBI records are not accurate measures of bias-motivated violence, and likely underestimate violence, though over-reporting is also a possibility (Freilich and Chermak 2013). At the same time, they constitute the most complete dataset of hate crimes and the only dataset that allows for systematic comparisons across minority groups, space, and time. Second, hate crimes are an extreme measure of prejudice and as such may not necessarily reflect changes in the average behavior among Whites. They capture the behavior of "extreme" individuals – those with high levels of prejudice or propensity to violence. There is no obvious reason why our framework of re-categorization should not equally apply to this population, in which case hate crimes are a valid and informative behavioral measure.[14]

The data contains information on the race of the perpetrator and on the crime's motivating bias. Based on the location of the reporting agency, as provided through the Originating Agency Identifier (ORI), incidents are matched to counties. We average crimes across decades and estimate a county-level version of equation 2 controlling for state by decade fixed effects. The dependent variable is hate crimes against Blacks per 100,000 people. The construction of the instrument for Mexican immigration follows the procedure detailed in Section E.1 of the Appendix.

Table 5 reports the results. 2SLS estimates in Panel A indicate that Mexican immigration

[14] Figure G.2 in the Appendix shows that hate crimes against a group and attitudes towards that group are not strongly correlated at the county level. The correlation is strong and significant for counties at the 90th percentile of hate crimes, where there is arguably a closer correspondence between hate crime perpetrators and ANES respondents (as hate crimes are a more common behavior and thus perpetrators more representative of the population's values).

reduces anti-Black hate crimes (column 2). This effect is higher relative to the baseline mean when restricting attention to crimes committed by White offenders (column 4). Effects on hate crimes against Latinos are noisily estimated, but if anything tend to increase in response to Mexican immigration, especially when focusing on White offenders (columns 2 and 4, Panel B). In Section G of the Appendix we subject these estimates to several robustness checks similar to those of our baseline analysis, and verify that they do not reflect overall reductions in criminality in response to Hispanic immigration (Table G.5).

The effects are substantive in magnitude. The coefficient in column 4 suggests that one percentage point increase in the Mexican share leads to almost 6 fewer anti-Black hate crimes per 100,000 people, or 97% of the baseline mean. For the average county in our sample, our estimates imply that an increase in the share of Mexicans leads to about 8 fewer hate crimes per 100,000 people against Blacks and 3.1 more hate crimes against Hispanics, though the latter quantity is not statistically significant.

Table 5. Mexican immigration and hate crimes

Dependent variable	Hate crimes per 100,000 people			
	All offenders		White offenders	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Panel A: Black victims				
Share Mexican	0.004	-1.437	0.049	-2.221
	(19.125)	(263.633)	(14.303)	(299.869)
	{16.994}	{258.265}	{12.136}	{267.384}
Mean dep. variable	8.255	8.255	5.345	5.345
Observations	4,301	4,301	3,507	3,507
Number of counties	1,642	1,642	1,359	1,359
R-squared	0.666	-0.273	0.681	-0.674
F-stat		13.847		10.050
Panel B: Hispanic victims				
Share Mexican	0.221	0.840	0.203	1.861
	(35.577)	(171.455)	(35.206)	(211.620)
	{31.735}	{157.996}	{33.368}	{211.351}
Mean dep. variable	1.734	1.734	1.277	1.277
Observations	4,301	4,301	3,507	3,507
Number of counties	1,642	1,642	1,359	1,359
R-squared	0.586	-0.036	0.608	-0.291
F-stat		13.847		10.050

Notes: Beta coefficients reported. Standard errors clustered at the county level reported in parentheses; Conley standard errors using a distance cutoff of 500 km reported in curly brackets.

Discussion and conclusion

Due to rising immigration, over the past five decades, the US and Europe have become increasingly diverse. How does this trend contribute to shaping social group boundaries in these societies? To answer this question, we introduce a conceptual framework where group boundaries are endogenous and context-dependent, and provide evidence for it by studying how Mexican immigration in the US between 1970 and 2010 influenced native Whites' attitudes towards African Americans.

We provide evidence in support of recategorization, whereby Mexican immigration induces Whites to reclassify Blacks as "American", and thus as members of their ingroup. This does not mean – either conceptually or in our data – that Blacks are assigned the same classification Whites reserve for other Whites. For clarity, our framework makes a stylized distinction between "us" and "them", and assumes ingroup homogeneity in terms of affective distance. Yet ingroups can be heterogeneous. Carbado (2005) discusses how Blacks have historically participated in an American identity, without necessarily being granted either formal citizenship – during the period of slavery – or equality – during the period of Jim Crow and later. In other words, Whites have historically viewed Blacks as American, an identity that they were less willing to confer to other groups like Asians or Latinos. At the same time, Black American identity may be understood in terms of marginalization and "[remain] directly linked to racial subordination" (Carbado 2005). In our data, Blacks are viewed by Whites as more American than other groups, but are not assigned the same degree of American identity nor the same affective distance as Whites do. We highlight that recategorization may take place without a complete elimination of racial group boundaries erected by prejudice and discrimination.

A complementary explanation behind Whites' reactions towards Blacks in response to Mexican immigration is that of uniting against a common enemy. Lab-based evidence in evolutionary psychology indicates that coalitional considerations determine the importance of race as a social category (Kurzban, Tooby and Cosmides 2001). However, a coalitional theory does not explain why majority members would form coalitions with certain groups (Blacks), but not others (Asians).

A distinct, but related, framework is the common ingroup identity model (Gaertner et al.

1993), which predicts that priming a superordinate group identity can reduce outgroup prejudice.[15] In our context, Mexican inflows may prime a superordinate "American" identity, thereby reducing the importance of race as a social cleavage. Yet the fact that non-Mexican immigrants do not achieve the same effect necessitates that this theory be extended with additional assumptions in order to explain our empirical findings in their entirety.

Our conceptual framework helps reconcile conflicting results in the literature. On the one hand, Rasul and McConnell (2020) find that 9/11, and the associated Islamophobic reaction among Americans, worsened attitudes towards Hispanics. On the other, Fouka, Mazumder and Tabellini (Forthcoming) find that 1915-1930 Black in-migration to the US North, and the associated increase in racism among northern Whites, improved the relative standing of (White European) immigrants. Our framework can explain these seemingly contradictory findings. By raising the salience of dimensions related to immigration and foreign-born threat, 9/11 had negative spillovers on all groups differing from natives on such dimensions, including Hispanics.[16] Instead, by raising the salience of skin color, Black in-migration to the US North reduced the importance of ethnicity as a dimension relevant for social categorization, thus helping White immigrants.

Finally, we highlight implications of our study that travel beyond the US context. A large constructivist tradition in ethnic politics (Fearon and Laitin 2000; Posner 2005; Chandra 2006) examines the conditions under which ethnicity emerges as a relevant cleavage in a society. This literature has focused primarily on group members' identification with their own ethnicity. Our study highlights a complementary dimension to ingroup identity that matters for the salience of ethnicity: majority attitudes towards minorities. We suggest that whether majorities discriminate on the basis of ethnicity or of another attribute is endogenous to the composition of outgroups in a society, primarily in terms of perceived affective distance from the majority. When the affective distance of majorities from groups differing on the basis of ethnicity is large, ethnicity endogenously emerges as a basis for discrimination or allocation

[15] Many studies provide evidence for the effectiveness of this mechanism in reducing prejudice (e.g. Charnysh, Lucas and Singh 2015; Levendusky 2018; Dinas, Fouka and Schläpfer Forthcoming and Siegel and Badaan 2020).

[16] Consistent with our framework and findings, Rasul and McConnell (2020) find no negative spillover of 9/11 on federal judges' behavior towards Blacks.

of privileges in a society. Ethnicity can then become salient because members of ethnic groups rationally choose their ethnic identity – as the constructivist literature suggests – or because majorities discriminate on the basis of ethnicity – as our framework would indicate. We leave the full development and empirical test of this idea to future work.

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Online Appendix

Table of Contents

A An example of reclassification

We illustrate the general principle expressed in equation 1 of the paper with a stylized example from our specific empirical context. Consider three groups, $k \in \{W, B, M\}$, for Whites, Blacks and Mexicans, and two binary attributes $j \in \{rac, nat\}$, for race and nativity. Suppose we are interested in how native-born Whites classify Blacks. Blacks differ from Whites in terms of skin color ($I^B_{rac} = 1$), but not in terms of native status ($I^B_{nat} = 0$). Is nativity or race the relevant attribute for ingroup classification? Assuming that Mexicans are not Black, and normalizing δ^W to zero, we can write the meta-contrast ratio for nativity as

$$R_{\text{nat}} = \frac{\frac{\delta^M n^M}{n^M}}{\frac{\delta^B n^B}{n^W + n^B}}$$

and for race as

$$R_{\text{rac}} = \frac{\frac{\delta^B n^B}{n^B}}{\frac{\delta^M n^M}{n^W + n^M}}$$

The principle of meta-contrast ratio maximization implies that race will be the relevant attribute for categorization whenever

$$\left(\frac{\delta^B}{\delta^M}\right)^2 > \frac{\frac{n^M}{n^W + n^M}}{\frac{n^B}{n^W + n^B}} \tag{A.1}$$

or whenever the affective distance of Blacks (from Whites) is larger than that of Mexicans, and Blacks are a relatively large group. Conversely, the likelihood that nativity becomes the attribute that divides in- from outgroup increases in the difference between δ^M and δ^B and in the relative size of the Mexican group.

This is a stylized example with two attributes. More generally, if Mexicans are of higher affective distance from Whites than Blacks, increases in their size will accentuate any attribute shared between Blacks and Whites that is not shared between Whites and Mexicans (e.g. language).

B Details on instrument construction

We predict the share of Mexican immigrants in a state using a version of the shift-share instrument commonly adopted in the immigration literature (Card 2001).

Formally, the predicted number of Mexican immigrants in state s in decade t is computed as

$$Z_{st} = \alpha_s^{Mex} O_t^{Mex} \tag{B.1}$$

where α_s^{Mex} is the share of Mexican immigrants living in state s in 1960 (relative to all Mexican immigrants in the US in that year), and O_t^{Mex} is the number of Mexican immigrants entering the United States between year t and $t-10$, for decades 1970 to 2010. We scale Z_{st} by a state's population. To avoid dividing with an endogenous variable, we use predicted population based on 1970 state population and post-1970 national population growth rate.

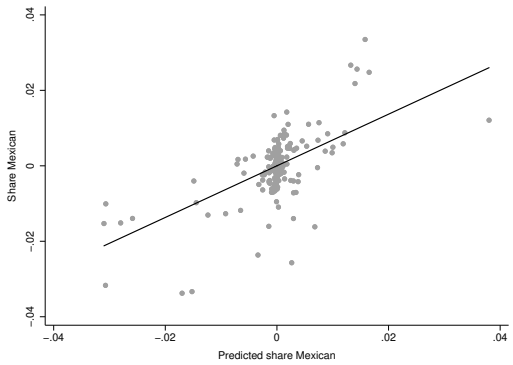
In our analysis, we always control for the predicted share of non-Mexican immigrants, to ensure that our instrument for Mexican immigration does not capture changes in immigrant inflows more generally. We construct predicted immigrant inflows by generalizing equation B.1 above to

$$Z_{st}^{NM} = \sum_n \alpha_s^n O_t^n \tag{B.2}$$

where n indexes immigrant nationalities. In this case, α_s^n is the share of immigrants of nationality n living in state s in 1960 (relative to all immigrants of that nationality in the US).

Controlling for instrumented (instead of predicted) share of non-Mexican immigrants does not qualitatively affect our results, but the presence of multiple instruments reduces the predictive power of the first stage. We report robustness checks with this alternative specification in Table D.5.

Figure B.1. First stage



Notes: The figure shows the relationship between the change in actual and predicted fraction of immigrants of Mexican origin for the years 1970 to 2010. Each point represents the coefficient from a regression of actual on predicted fraction of Mexican immigrants, after partialling out state and year by Census division fixed effects, and the predicted fraction of non-Mexican immigrants. Regressions are weighted by the number of observations in the ANES sample.

Figure B.1 displays graphically the relationship between the fraction of Mexican immigrants and the corresponding instrument at the state level. Table B.1 shows that the first stage relationship is strong and insensitive to controlling for predicted immigration from countries other than Mexico or to the inclusion of interactions between year dummies and a number of 1960 variables that could conceivably have a time-varying effect on both immigration and racial attitudes.

Table B.1. First stage

Dep. Variable	Share Mexican		
	(1)	(2)	(3)
Predicted share Mexican	0.800	0.488	0.748
	(0.076)	(0.105)	(0.061)
Observations	21,570	21,570	21,570
Number of states	51	51	51
R-squared	0.980	0.993	0.981
Baseline controls × Year FE		Yes	
Predicted share other immigrants			Yes

Notes: The sample consists of White ANES respondents. Years 1970-2010. All regressions control for state and census year by division fixed effects. Baseline controls include distance from Mexico and the following variables measured in 1960: share Black, share foreign-born, share rural, share high school graduates and unemployment rate. Standard errors in parentheses, clustered at the state level.

C Details on ANES dataset

Table C.1. Summary statistics, state-level ANES dataset

Variable	Mean	Std. Dev.	Min	Max	Obs.
State-level (ANES)					
Feeling thermometer Blacks	63.066	19.872	0	97	17,277
Blacks intelligent	4.264	1.224	1	7	8,141
Blacks hard-working	3.920	1.288	1	7	8,171
Blacks violent	3.445	1.217	1	7	1,791
Blacks trustworthy	4.065	1.174	1	7	1,186
Average attitudes Blacks	-0.139	0.871	-3.199	2.280	17,540
Feel close to Blacks	0.112	0.315	0	1	7,548
Feeling thermometer Hispanics	61.286	20.327	0	97	11,463
Hispanics intelligent	4.338	1.186	1	7	8,049
Hispanics hard-working	4.671	1.353	1	7	8,083
Hispanics violent	3.779	1.129	1	7	1,718
Hispanics trustworthy	4.162	1.162	1	7	1,169
Average attitudes Hispanics	-0.112	0.806	-3.012	2.085	11,,741
Feel close to Hispanics	0.130	0.336	0	1	4,128
Feeling thermometer Asian Americans	63.258	19.070	0	97	8,978
Problem: Immigration policies	0.004	0.065	0	1	12,545
Problem: Racial problems (positive)	0.008	0.088	0	1	12,545
Problem: Racial problems (negative)	0.001	0.028	0	1	12,545
Should gov. help Blacks	3.185	1.707	1	7	14,580
School integration	0.409	0.492	0	1	5,841
Gov. guarantee FEP	2.803	1.990	1	5	8,921
Pref. hiring for Blacks	1.519	1.344	1	5	9443
Racial policy average	-0.077	0.808	-1.351	2.590	18,182
Conservative	4.299	1.394	1	7	15,995
Increase gov. spending	4.060	1.627	1	7	12,765
Female	0.542	0.498	0	1	21,683
Age	47.093	17.716	17	99	21,564
Share Mexican	0.021	0.032	0	0.116	21,683
Share non-Mexican	0.063	0.052	0.004	0.203	21,683

Notes: Years 1970–2010. Sample restricted to White respondents.

Table C.2. Wording of questions in ANES

Variable Name	Wording
Feeling thermometer [Group]	I'd like to get your feelings toward some people in the news these days. I'll read the name of a person and I'll ask you to rate that person on a thermometer that runs from 0 to 100 degrees. Rating above 50 means that you feel favorable and warm toward the person. Rating below 50 means that you feel unfavorable and cool toward the person. Rating right at the 50 degree mark means you don't feel particularly warm or cold. You may use any number from 0 to 100 to tell me how favorable or unfavorable your feelings are. Still using the thermometer how would you rate the following groups? [Group]
[Group] intelligent	The next set asks if people in each group tend to be "intelligent" or "unintelligent". Where would you rate [Group] (in general) on this scale? [1. Intelligent - 7. Unintelligent]
[Group] hard-working	Now I have some questions about different groups in our society. I'm going to show you a seven-point scale on which the characteristics of the people in a group can be rated. In the first statement a score of 1 means that you think almost all of the people in that group tend to be "hard-working". A score of 7 means that almost all of the people in the group are "lazy". A score of 4 means that you think that most people in the group are not closer to one end or the other, and of course you may choose any number in between. Where would R rate [group]'s work ethic on this scale?
[Group] violent	Do people in these groups tend to be violent or do they tend to be peaceful? Where would R rate the group's disposition? [Group] [1. Peaceful - 7. Violent]
[Group] trustworthy	Where would you rate [Group] on this scale? [1. Untrustworthy - 7. Trustworthy]
Feel close to [Group]	Please read over this list and tell me which of these groups you feel particularly close to– people who are most like you in their ideas and interests and feelings about things.
Problem: Immigration policies	Of those [problems] you've mentioned, what would you say is the single most important problem the country faces? Answers: immigration policy; against open immigration; immigration policies for open immigration; relaxation of immigration quotas; problems relating to the influx of political/economic refugees (Cubans, Haitians, Mexicans, etc.), prohibiting specified types of persons from entering the US.

Table C.2. – continued from previous page

Variable Name	Wording
Problem: Racial problems (positive)	Of those [problems] you've mentioned, what would you say is the single most important problem the country faces? Answers: protection (expansion) of negro civil rights; pro-busing; school, housing integration, fair employment practices; right to vote; fair treatment by police; other specific programs/proposals/legislation for (extending) civil rights; civil rights/racial problems; programs to enable Blacks to gain social/economic/educational/ political equality; relations between Blacks and Whites.
Problem: Racial problems (negative)	Of those [problems] you've mentioned, what would you say is the single most important problem the country faces? Answers: protection (expansion) of White majority; prevention of race mixing; maintenance of segregated schools, anti-busing; right to choose own neighbors; right to discriminate in employment, against other specific programs/proposals/legislation for (extending) civil rights.
Should gov. help Blacks	Some people feel that the government in Washington should make every effort to improve the social and economic position of Blacks. Others feel that the government should not make any special effort to help Blacks because they should help themselves. Where would you place yourself on this scale, or haven't you thought much about this? [1. Government should help Blacks - 7. Blacks should help themselves]
School integration	Do you think the government in Washington should see to it that White and Black children go to the same schools or stay out of this area as it is not its [the government's] business?
Gov. guarantee FEP	How do you feel? Should the government in Washington see to it that Black people get fair treatment in jobs or is this not the federal government's business?
Pref. hiring for Blacks	Some people say that because of past discrimination, Blacks should be given preference in hiring and promotion. Others say that such preference in hiring and promotion of Blacks is wrong because it gives Blacks advantages they haven't earned. What about your opinion – are you FOR or AGAINST preferential hiring and promotion of Blacks?
Conservative	We hear a lot of talk these days about liberals and conservatives. Here is a seven-point scale on which the political views that people might hold are arranged from extremely liberal to extremely conservative. Where would you place yourself on this scale, or haven't you thought much about this? [1. Extremely liberal - 7. Extremely conservative]

Table C.2. – continued from previous page

Variable Name	Wording
Increase gov. spending	Some people think the government should provide fewer services even in areas such as health and education in order to reduce spending. Suppose these people are at one end of a scale, at point 1. Other people feel it is important for the government to provide many more services even if it means an increase in spending. Suppose these people are at the other end, at point 7. And, of course, some other people have opinions somewhere in between, at points 2,3,4,5 or 6.

Notes: [Group] intelligent: for year 1992 the scale was [1. Unintelligent - 7. Intelligent] and has been reversed. *[Group] violent:* the scale was [1. Violent - 7. Peaceful] and has been reversed. *[Group] trustworthy:* the scale was [1. Trustworthy - 7. Untrustworthy] and has been reversed. *Most important problem questions*: For 1980 and 1982 the question reads: "Of those you've mentioned, which would you say is the single most important problem the government in Washington should try to take care of?". *Gov. guarantee FEP*: For 1972 the question reads: "How do you feel? Should the government in Washington see to it that Black people get fair treatment in jobs or leave these matters to the states and local communities?" *Pref. hiring for Blacks*: For 1988 the question reads: "Some people say that because of past discrimination, Blacks should be given preference in hiring and promotion. Others say that such preference in hiring and promotion of Blacks is wrong because it discriminates against Whites. What about your opinion–are you for or against preferential hiring and promotion of Blacks?". *Increase gov.spending:* the scale was reversed to [1. Government should provide many fewer services; reduce spending a lot - 7. Government should provide many fewer services; reduce spending a lot]. For years 1980, 1982 the question reads "Some people think the government should provide fewer services, even in areas such as health and education, in order to reduce spending. Other people feel it is important for the government to continue the services it now provides even if it means no reduction in spending. Where would you place yourself on this scale, or haven't you thought much about this?". *Problem: Immigration policies*: In some years, possible responses to this question distinguish between positive and negative immigration attitudes, but no White respondents in the ANES list pro-immigration issues as the most important problem facing the country. Hence, we group all responses to this question in a single category expressing concerns about immigration or support for more restrictive immigration policies.

Table C.3. Question availability across survey years in ANES

Variable Name	1972	1978	1980	1982	1988	1990	1992	1998	2000	2002	2008	2012
Feeling thermometer Blacks	X		X	X	X	X	X	X	X	X	X	X
Blacks intelligent							X		X		X	X
Blacks hard-working							X		X		X	X
Blacks violent							X					
Blacks trustworthy									X			
Feel close to Blacks	X		X		X		X		X			
Feeling thermometer Hispanics			X		X		X		X	X	X	X
Hispanics intelligent							X		X		X	X
Hispanics hard-working							X		X		X	X
Hispanics violent							X					
Hispanics trustworthy									X			
Feel close to Hispanics			X				X		X			
Feeling thermometer Asian-Am.							X		X	X	X	X
Problem: Immigration policies	X	X	X	X	X	X	X	X	X			
Problem: Racial problems (positive)	X	X	X	X	X	X	X	X	X			
Problem: Racial problems (negative)	X	X	X	X	X	X	X	X	X			
Should gov. help Blacks					X	X	X	X			X	X
School integration	X	X				X	X		X			
Gov. guarantee FEP					X	X		X	X		X	X
Pref. hiring for Blacks	X				X		X		X		X	X
Conservative	X	X	X	X	X	X	X	X	X	X	X	X
Increase gov. spending			X	X	X	X	X	X	X		X	X

D Additional analyses

D.1 Addressing threats to identification

In Table D.1 we examine the correlation between the population share of Mexicans in 1960 and a number of state-level baseline characteristics. States with a higher share of Mexican immigrants in 1960 have a significantly lower Black population, and are more likely to have a college educated population. Not surprisingly, they are also closer to Mexico. Given these patterns, in Table D.2 we control for a number of 1960 state characteristics interacted with year fixed effects. These are meant to account for the fact that states that received more Mexican immigrants in 1960 might have been on differential trends in terms of their economies, population composition, or social and political conditions, that could have also affected the evolution of racial attitudes. Reassuringly, the inclusion of these controls does not significantly affect our results.

Table D.1. Predictors of 1960 share of Mexican immigrants

Dep. Variable	Share Mexican
Share Black 1960	-0.044
	(0.021)
Share foreign-born 1960	0.029
	(0.023)
Share rural 1960	0.252
	(1.514)
Share high school graduates 1960	-0.079
	(0.072)
Share college graduates 1960	0.605
	(0.281)
Unemployment rate 1960	0.161
	(0.147)
Distance from Mexico	-0.001
	(0.000)
Observations	51
R-squared	0.404

Notes: Data on share foreign-born and share rural are from NHGIS. Data on the share of high school and college graduates and the unemployment rate are from the 5% IPUMS sample. Distance from Mexico measured in hundred kilometers. Robust standard errors in parentheses.

Table D.2. Robustness to the inclusion of baseline controls

Dep. variable	Feeling thermometer Blacks		Average	
	Baseline	State controls×Year FE	Baseline	State controls×Year FE
	(1)	(2)	(3)	(4)
Share Mexican	76.030	159.208	4.224	10.522
	(36.304)	(100.746)	(1.733)	(4.145)
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
R-squared	0.033	0.036	0.031	0.034
F-stat	131.3	21.81	132.1	22.28

Notes: Years 1970-2010. The sample is restricted to White ANES respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects, and predicted share (non-Mexican) immigrants. Columns (2) and (4) further include interactions of the following state-level variables with census year fixed effects: share Blacks in 1960, share immigrants in 1960, share rural in 1960, share high school graduates in 1960, unemployment rate in 1960, distance from Mexico. Standard errors clustered at the state level.

As an additional robustness exercise, we use entropy balancing (Hainmueller 2012) to ensure comparability of states differing on their Mexican population. Since our main independent variable of interest is continuous, we split states into low (below median) and high (above median) Mexican share averaged across all decades in our data and reweigh them using entropy balance weights in order to match the means of a number of baseline (1960) controls. Results are reported in Table D.3 and reveal little sensitivity of our estimates to this check.

Table D.3. Entropy balance

Dependent variable	Feeling thermometer Blacks		Average attitudes	
	Baseline	Ebalance weights	Baseline	Ebalance weights
	(1)	(2)	(3)	(4)
Share Mexican	76.030	82.554	4.224	6.425
	(36.305)	(31.226)	(1.733)	(1.836)
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
R-squared	0.033	0.031	0.031	0.028
F-stat	131.3	148.8	132.1	149

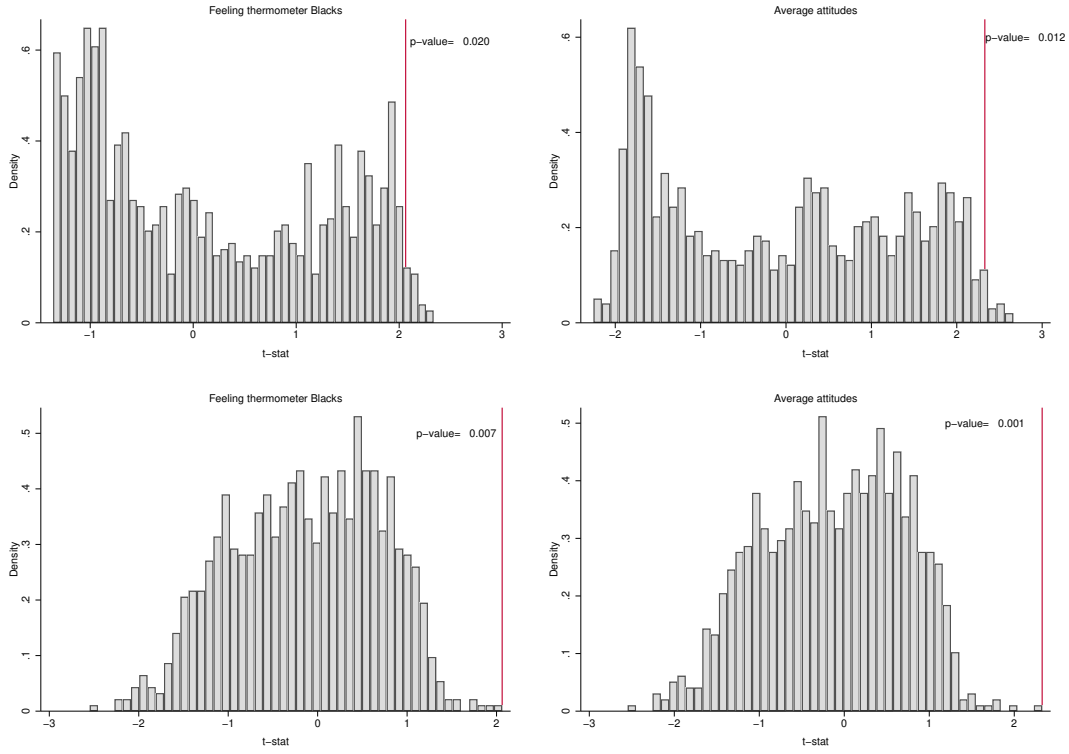
Notes: Years 1970-2010. The sample is restricted to White ANES respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects, and predicted share (non-Mexican) immigrants. In columns (2) and (4) entropy balance weights are applied, matching states with above- and below-median Mexican share along the mean of the following state-level variables: share Blacks in 1960, share immigrants in 1960, share rural in 1960, share high school graduates in 1960, unemployment rate in 1960, distance from Mexico. Standard errors clustered at the state level.

Even after controlling for the time-varying effect of observables, there may still be time-variant unobservable factors correlated with both Whites' attitudes and the initial spatial distribution of Mexican immigrants. We provide evidence against this concern in two ways. First, we show that a linear trend based on the 1960 fraction of Mexican immigrants has no explanatory power for racial attitudes. To perform this placebo test, we interact the state-level fraction of Mexicans in 1960 with the average inflow of Mexican immigrants over the period 1970-2010 and create a stock version of the instrument by recursively summing up predicted inflows constructed in this way. If the baseline distribution of Mexican immigrants was correlated with time-varying unobservables affecting racial attitudes, we would expect this

instrument to positively and significantly predict our outcomes of interest. Results are shown in Table D.4. Columns 1–2 and 3–4 display reduced form and 2SLS coefficients for our actual and placebo instrument, respectively. Placebo Mexican inflows have a small, insignificant effect on both the feeling thermometer (columns 3–4) and average prejudice (columns 7–8).

Second, we take a more systematic approach to rule out a persistent effect of the 1960 state-level fraction of Mexican immigrants by conducting a randomization inference exercise (Young 2018). We reconstruct predicted immigrant inflows at the state level by randomly assigning national-level immigrant inflows from different nationalities to the 1960 shares of Mexican immigrants within states and decades (without replacement). We randomly draw 1,000 sets of placebo assignments of inflows to shares and re-estimate our baseline equation. The upper panel of Figure D.1 plots the distribution of t-statistics resulting from this exercise for the feeling thermometer (left) and average prejudice (right). We report empirical p-values as the share of t-statistics that are larger than the actual one. This approach yields t-statistics lower than our baseline estimates 98% of the time.

Figure D.1. Randomization inference



Notes: The figure plots, for each of the main outcomes, the distribution of t-statistics resulting from 1,000 iterations of estimating equation 2 with alternative computations of the instrument for Mexican immigrants. In the upper panel, predicted numbers of Mexicans are computed using 1960 Mexican shares and randomly assigned inflows of immigrants from different nationalities within state and decade. In the lower panel, predicted numbers of Mexicans are computed using Mexican inflows and randomly assigned 1960 shares of immigrants from different nationalities within state and decade. Vertical lines are drawn at the value of the t-statistic for our actual treatment effect. P-values are computed as the share of t-statistics whose value is more extreme than the value estimated using actual assignment of 1960 Mexican shares and decade-specific Mexican inflows.

Table D.4. Accounting for the time-varying effect of 1960 Mexican shares

Dep. variable	Feeling thermometer Blacks				Average attitudes			
	Predicted share Mexican		Placebo		Predicted share Mexican		Placebo	
	Reduced form	2SLS	Reduced form	2SLS	Reduced form	2SLS	Reduced form	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predicted share Mexican	51.836				2.874			
	(23.103)				(1.182)			
Share Mexican		69.881		10.145		3.910		-0.792
		(33.876)		(37.785)		(1.679)		(1.683)
Placebo predicted share Mexican			-5.331				0.416	
			(19.808)				(0.886)	
Observations	17,188	17,188	17,188	17,188	17,446	17,446	17,446	17,446
Number of states	51	51	51	51	51	51	51	51
R-squared	0.034	0.033	0.034	0.033	0.033	0.031	0.032	0.032
F-Stat		87.70		74.80		88.03		75.15

Notes: Years 1970-2010. The sample is restricted to White respondents. *Placebo predicted share Mexican* is constructed by assigning the average Mexican inflow over the period 1970-2010 to 1960 state-level shares of Mexicans. All columns include controls for age, age squared, gender, state and year by division fixed effects. Standard errors clustered at the state level.

We repeat this procedure by randomly assigning 1960 shares of immigrants from different nationalities to actual (decade-specific) Mexican inflows and recomputing the instrument for Mexican immigration. This exercise is meant to address the concern that the push component of our instrument (the size of immigrant inflows) may be driven by unobserved time-varying shocks to states with large Mexican enclaves in 1960. The lower panel of Figure D.1 plots the distribution of t-statistics resulting from 1,000 iterations of this procedure. T-statistics are lower than those in our baseline regressions over 99% of the time. This indicates that our results are unlikely to be driven by the endogeneity of Mexican inflows.

D.2 Additional robustness checks

Share of non-Mexican immigrants. To account for the fact that the share of Mexican immigrants may be capturing broader patterns of immigration, all 2SLS regressions control for the share of non-Mexican immigrants predicted by equation B.2. Including instrumented, instead of predicted, share of non-Mexican immigrants lowers the power of the first stage somewhat, but does not meaningfully affect our estimates. Table D.5 presents these results.

Table D.5. Robustness to instrumenting the share of non-Mexican immigrants

Dep. variable	Feeling thermometer Blacks		Average attitudes	
	Baseline	Instrumented other imm.	Baseline	Instrumented other imm.
	(1)	(2)	(3)	(4)
Share Mexican	76.030	84.230	4.224	4.642
	(36.305)	(43.006)	(1.733)	(2.124)
Mean dep. variable	63.067	63.067	-0.139	-0.139
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
R-squared	0.033	0.033	0.031	0.031
F-stat	131.3	6.167	132.1	6.245
AP F-Stat Share Mexican		90.57		91.81

Notes: Years 1970-2010. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects. Columns 1 and 3 control for predicted and columns 2 and 4 for instrumented share of (non-Mexican) immigrants. Standard errors clustered at the state level.

Spatial models. Betz, Cook and Hollenbach (2020) demonstrate that spatial interdependence in the outcome variable may bias 2SLS estimates even when instruments are as good as randomly assigned. To account for potential interdependence in attitudes across states, we estimate spatial autoregressive models in Table D.6. We use the `spegen` function in Stata 15 to create spatial lags of outcome variables and regressors using a spatial weight matrix of power functional form following Kondo (2016). Columns (2) and (5) spatially lag the share of Mexicans and show that there is no spillover effect of Mexican populations on attitudes of neighboring states. Columns (3) and (6) estimate S-2SLS models as suggested by Betz, Cook and Hollenbach (2020) and show that results are not driven by bias caused by spatial interdependence in the dependent variables. In all instances, spatial lags are not statistically significant, and in the case of spatially lagged outcomes the magnitude of estimates is essentially zero.

Outliers. Next, we investigate whether our results are sensitive to omitting individual states from the sample. Figure D.2 replicates results in Table 1 by dropping one state at a time. Excluding larger states like New York affects estimate precision, but point estimates remain positive and large for both the thermometer and average prejudice. One may be concerned that the effect is driven by a few states that experienced disproportionately large increases in their Mexican population over the period of study. Figure D.3 shows that California, Texas and Arizona stand out in terms of average change in the share of Mexicans over the 1970-2010 period. In Table D.7 we show that, even after removing each of these states from the sample,

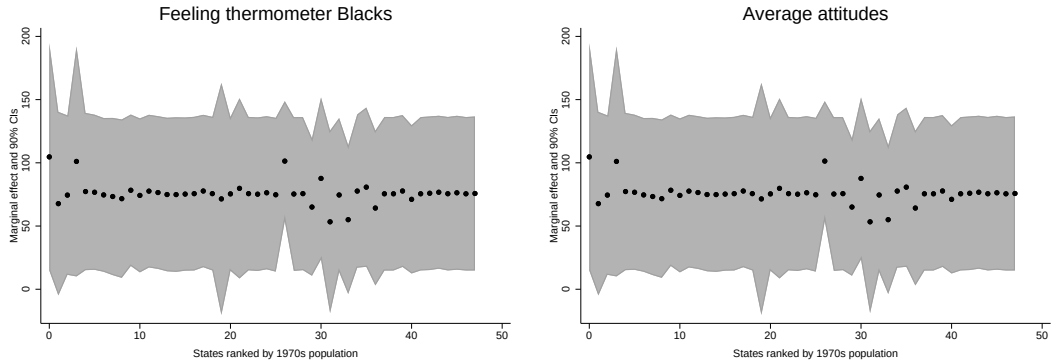
Table D.6. Accounting for spatial interdependence

Dependent variable	Feeling thermometer Blacks			Average attitudes		
	Baseline	Spatial models		Baseline	Spatial models	
	(1)	(2)	(3)	(4)	(5)	(6)
Share Mexican	76.030	89.840	111.819	4.224	5.602	9.766
	(36.305)	(40.939)	(68.956)	(1.733)	(1.851)	(4.578)
Share Mexican (spatial lag)		-40.928			-4.370	
		(75.444)			(3.524)	
Feeling thermometer Blacks (spatial lag)			-0.204			
			(0.373)			
Averag (spatial lag)						-0.734
Observations	17,188	17,188	17,188	17,446	17,446	17,446
Number of states	51	51	51	51	51	51
R-squared	0.033	0.033	0.034	0.031	0.031	0.030
F-stat	131.3	16.55	14.52	132.1	16	10.53

Notes: Years 1970-2010. 2SLS estimates reported. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects. Columns including spatial lags of the independent (columns (2) and (5) and of the dependent (columns (3) and (6)) variables include as additional instrument the spatial lag of the predicted share Mexican. Spatial weight matrix is of power functional type with parameter 4. Standard errors clustered at the state level.

Mexican share continues to have a positive effect on attitudes towards Blacks.[17]

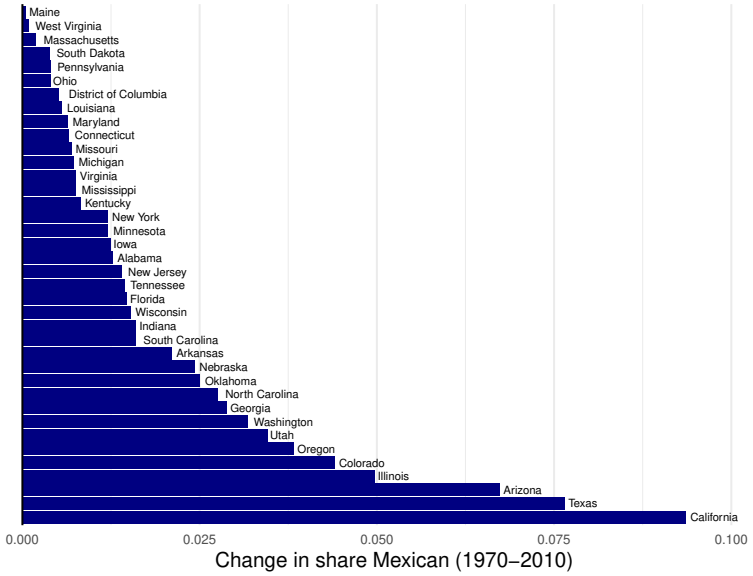
Figure D.2. Assessing the influence of outliers



Notes: The figure plots point estimates and 90% confidence intervals for the share of Mexican immigrants, by estimating equation 2 after dropping one state at a time. States are ordered by their population in 1970.

[17] In column (5) of Table D.7 we estimate a regression that drops all three states simultaneously. As can be seen from the F-statistic, this exercise leaves us underpowered and second stage estimates do not have a proper interpretation due to bias from weak instruments. We nonetheless report them for completeness.

Figure D.3. Change in Mexican population by state



Notes: The figure plots the 1970-2010 change in the fraction of total state population that is born in Mexico.

Table D.7. Dropping outlier states

Sample	Baseline	Drop CA	Drop TX	Drop AZ	Drop all three
	(1)	(2)	(3)	(4)	(5)
	Panel A. Dependent variable: Feeling thermometer Blacks				
Share Mexican	76.030	104.549	100.809	55.928	289.027
	(36.304)	(54.620)	(53.113)	(35.012)	(390.811)
Observations	17,188	15,476	15,996	16,966	14,062
Number of states	51	50	50	50	48
R-squared	0.013	0.012	0.014	0.014	0.011
F-stat	131.278	61.615	43.424	166.409	0.946
	Panel B. Dependent variable: Average attitudes				
Share Mexican	4.224	5.478	3.734	4.137	12.726
	(1.733)	(2.528)	(1.730)	(1.873)	(17.554)
Observations	17,446	15,704	16,231	17,220	14,263
Number of states	51	50	50	50	48
R-squared	0.010	0.008	0.011	0.010	0.008
F-stat	132.123	62.334	43.605	163.265	0.956

Notes: Years 1970-2010. The sample is restricted to White ANES respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects, and predicted share (non-Mexican) immigrants. Standard errors clustered at the state level.

Serial correlation in the instrument. Jaeger, Ruist and Stuhler (2018) show that shift-share instruments may conflate short and long-run responses to immigration shocks. If the spatial distribution of immigrant inflows is stable over time, predicted immigration is likely to be correlated with responses to previous immigration shocks. This concern is particularly

relevant when studying wage responses to labor supply shocks, as the short-run (plausibly negative) wage effects may be conflated with longer-run (plausibly positive) wage adjustments producing downward biased estimates of the effects of immigration shocks on wages. Such concerns are less relevant in our setup, since we are not interested in distinguishing short from longer-run responses and we have no theoretical reason to believe that these responses will move in opposite directions as in the case of wage adjustments in response to labor supply shocks. Nonetheless, we follow the procedure of multiple instrumentation proposed by Jaeger, Ruist and Stuhler (2018) and augment our baseline specification with lagged Mexican share, using both contemporaneous and lagged values of predicted Mexican inflows as instruments. The results in Table D.8 suggest that the immediate effects of Mexican immigration on racial attitudes are even more positive after accounting for lagged values of immigration. The coefficients on the lagged Mexican share are negative but smaller in size than the contemporaneous estimates, suggesting that the positive effect of recategorization decays, but does not entirely disappear within the period of a decade.

Table D.8. Accounting for serial correlation in predicted Mexican immigration

Dependent variable	Feeling thermometer Blacks		Average attitudes	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Share Mexican	60.999	190.662	3.330	12.471
	(62.944)	(60.544)	(2.840)	(2.529)
Lagged share Mexican	-62.203	-143.018	-4.500	-10.106
	(69.019)	(75.942)	(3.297)	(3.583)
Observations	14,952	14,952	15,203	15,203
Number of states	51	51	51	51
R-squared	0.032	0.032	0.030	0.030
F-stat		41.95		42.36
AP F-Stat Share Mexican		100.3		100.9
AP F-Stat Lagged Share Mexican		48.77		48.77

Notes: Years 1970-2010. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects. Columns 1 and 3 control for contemporaneous and lagged share of non-Mexican immigrants. Columns 2 and 4 include contemporaneous and lagged values of the instrument, as well as controls for contemporaneous and lagged non-Mexican immigration predicted by equation B.2. Standard errors clustered at the state level.

D.3 Ruling out alternative explanations

Selective migration. An obvious concern with the interpretation of our estimates is that they reflect changes in the population composition of states where the share of Mexicans increased, perhaps as a direct result of Mexican immigration. Hispanic immigration could lead to outflows of White residents with intolerant attitudes towards immigrants and other minorities. In that case, lower prejudice would reflect a change in sample composition rather than genuine attitudinal changes. Black outmigration could similarly affect our interpretation of the results, but in a different way. If Mexican immigrants lead Black residents to leave their states, for instance because of rising labor market competition, then the drop in the number of Blacks could have a direct effect on Whites' attitudes towards the latter. This would be consistent with theories of group threat, and not the result of the recategorization mechanism we propose. As argued in the case of White out-migration, such population outflows are unlikely to happen at a level of aggregation as large as the state. In Table D.9 we rule out this possibility directly by showing that Mexican immigration has no effect on the size of either the Black or the White population of the state.[18]

Table D.9. Assessing state-level changes in Black and White population

Dependent variable	Log Black population		Log White population	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Share Mexican	2.985	0.104	4.755**	1.851
	(3.358)	(3.241)	(2.246)	(2.672)
Observations	255	255	255	255
Number of states	51	51	51	51
R-squared	0.995	0.995	0.995	0.995
F-stat		22.70		22.70

Notes: Years 1970-2010. All regressions control for state and year by census division fixed effects. Columns 1 and 3 control for share of non-Mexican immigrants. Columns 2 and 4 control for share of non-Mexican immigrants predicted by equation B.2. Standard errors clustered at the state level.

Despite the lack of evidence pointing to out-migration of Whites from states with large Mexican inflows, we acknowledge that selective sorting could still take place, with more intolerant Whites leaving a state and less intolerant ones moving in, with no impact on average population numbers. It is worth pointing out that the effects we estimate for Blacks and Hispanics are not easy to explain with selective sorting. Our estimates would imply that Mexican immigration drives out-migration of Whites with more positive attitudes towards Hispanics and more negative attitudes towards Blacks. Nonetheless, selective sorting could operate on

[18] Notice that, since the size of the Black population does not change, but that of the Mexican population increases, the share of Black residents mechanically drops. The changing relative sizes of groups are not a confounder of our result, but rather part of the mechanism driving recategorization. As seen in equation 1, meta-contrast ratios are influenced by both relative sizes and affective distances.

characteristics unknown to the researcher, and that could be correlated with attitudes towards the two groups in unexpected ways.

To address this concern, we take advantage of the fact that, in 2004, the ANES re-interviewed participants who had been already interviewed in 2000 and 2002.[19] For the panel time-series study, the ANES asked only questions on feeling thermometers, but not other attitudinal variables. As in our main analysis, we restrict attention to White respondents with non-missing values for feeling thermometers. Since we are interested in the panel dimension of the dataset, we keep only individuals who were surveyed at least twice over the 2000-2002-2004 study period and who did not change state in between.[20] This leaves us with 760 individuals and a total of 2,052 observations – 691 for 2000, 709 for 2002, and 652 for 2004.[21]

In Table D.10, we report summary statistics for the ANES panel dataset. Blacks are viewed slightly more favorably relative to Hispanics, with an average thermometer rating of 66, compared to 63 for the latter. These values are slightly higher than those in the cross-sectional sample (see Table C.1), but convey a similar pattern of White attitudes. For what concerns the key demographic characteristics, the panel dataset is similar to the cross-sectional one, with an average age of 50, and 51 percent of respondents being female (as compared to an average age of 47 and 52 percent of females in the cross-sectional sample). The average Mexican and non-Mexican immigrant share in 2000 is 2.5 and 7.1 percent respectively.

Table D.10. Summary statistics, ANES panel study

Variable	Mean	Std. Dev.	Min	Max	Obs.
Feeling thermometer Blacks	66.045	19.351	0	100	2,052
Feeling thermometer Whites	70.959	18.564	4	100	2,028
Feeling thermometer Hispanics	63.933	19.327	0	100	2,008
Feeling thermometer Asians	65.302	18.582	0	100	2,007
Age	50.611	15.636	18	93	2,041
Female	0.508	0.500	0	1	2,052
Share Mexican	0.025	0.036	.000265	.116	2,052
Share Non-Mexican	0.071	0.054	.0102	.195	2,052

Notes: Years 2000, 2002, and 2004. Sample restricted to White respondents who did not change state of residence between surveys.

[19] Interviews were conducted on the phone between November 3, 2004, and December 20, 2004. The order of questions was randomized within batteries or question series. See `https://electionstudies.org/data-center/2004-panel-study/` for additional details on the sampling methodology.

[20] 83 individuals moved across states during the period. We omit them because it is not clear how to assign relevant Mexican shares to these individuals; moreover, the decision to move may be endogenous. Including these individuals does not change our results.

[21] 532 of the 760 individuals were interviewed in all of the three years.

Since we lack data on the size of the Mexican group in 2002 and 2004, we use an alternative approach. We rely on 9/11 as an exogenous shock that increases the salience of immigration in the US (Massey and Pren 2012; Hopkins 2010). The effect of the shock on priming the presence of Mexican immigrants should be higher in states with a larger share of those immigrants in 2000. We thus use the interaction of Mexican share in 2000 and an indicator for interviews conducted after 2000 as a time-varying measure of perceived, rather than actual, size.[22]

Table D.11 shows that this measure has a positive effect on thermometer ratings of Blacks and a negative (though not statistically significant) effect on thermometer ratings of Hispanics. Importantly, these regressions include individual fixed effects, and thus estimate changes in attitudes for the same individual over time, assuaging any concerns related to selective sorting.

Table D.11. Individual-level panel estimates

Dependent variable	Feeling thermometer Blacks		Feeling thermometer Hispanics	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Share Mexican × Post 2000	28.878	23.979	-14.580	-18.990
	(16.964)	(13.880)	(18.911)	(17.832)
Mean dep. variable	66.045	66.045	63.933	63.933
Observations	2,052	2,052	2,044	2,044
Number of states	43	43	43	43
R-squared	0.622	0.622	0.643	0.643
F-stat		34.35		33.22

Notes: Years 2000 and 2004. The sample is restricted to a panel of White ANES respondents who were interviewed in both 2000 and 2004. All columns include state, individual, and survey wave fixed effects. Standard errors clustered at the state level.

The effect of 9/11. Consistent with existing work (Hopkins 2010; Massey and Pren 2012; Rasul and McConnell 2020), the panel analysis demonstrates that 9/11 played an important role in driving attitudes towards Hispanics and Blacks in the US. Its effect is consistent with our theory. Our framework posits that increases in the size of a group lead to recategorization, raising the salience of a new category (immigration status, foreign birthplace) at the expense of an old one (race). While salience in our model is endogenous to size, exogenous shocks to the salience of a category, like 9/11, may have similar effects on prejudice. Yet we verify that our results are not driven by the effects of 9/11 in the latter part of our data. In Table D.12 we re-estimate baseline effects on racial attitudes (as in Table 1) after dropping all surveys conducted after 9/11, with little effect on the magnitude of our estimates.

[22] This builds on the findings of Hopkins (2010), who finds the interaction of national-level salience with local-level demographics to affect immigration attitudes.

Table D.12. Drop survey years after 9/11

Dependent variable	Feeling thermometer Blacks			Average attitudes		
	OLS	2SLS	2SLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Share Mexican	43.532	84.804	156.310	1.303	4.208	10.398
	(33.568)	(41.247)	(101.779)	(1.969)	(2.388)	(3.853)
	(33.568)	(41.247)	(101.779)	(1.969)	(2.388)	(3.853)
Baseline controls × Year FE			✓			✓
Observations	11,197	11,197	11,197	11,309	11,309	11,309
Number of states	47	47	47	47	47	47
R-squared	0.042	0.013	0.013	0.041	0.012	0.012
F-stat		131.258	22.290		136.076	24.616

Notes: Years 1970-2000. The sample is restricted to White ANES respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects, and predicted share (non-Mexican) immigrants. Standard errors clustered at the state level.

The role of changes in group size. Existing work in political science has suggested that changes may be more important than levels of group size for shaping people's perceptions of and attitudes towards immigrants (Green, Strolovitch and Wong 1998; Hopkins 2009; 2010; Newman and Johnson 2012; Newman 2012). To the extent that sudden demographic changes correspond more closely to natives' perceptions of immigrant group size than actual size itself (Newman and Velez 2014), we would expect re-categorization and prejudice reduction towards Blacks to be driven more by growth than by size. We examine this possibility in Table D.13, where we compare our estimates to identical specifications using the *change* in Mexican share across two consecutive decades as dependent variable.[23] We estimate a qualitatively similar effect of change as of size. The magnitude of coefficients is very similar for attitudes towards Blacks, though significance is lower for change than for levels (Panel A). The effect of change on attitudes towards Hispanics is smaller than that of size (Panel B). Overall, we do not find strong evidence that changes have a larger impact on re-categorization and racial prejudice. We do highlight however that the nature of our instrument may be isolating very similar variation for level and changes, making it hard to independently identify the effects of each in this context.[24]

[23] Since computing the change implies losing the first period in our dataset, we restrict the data to decades 1980-2010 so that estimates for levels and changes are comparable.

[24] Existing work estimates the effects of change conditional on size. Given that we would be using two instruments that exploit nearly identical variation to simultaneously estimate the effect of changes and level, we are not able to directly replicate this approach of earlier work.

Table D.13. Relative effects of group size and change in group size

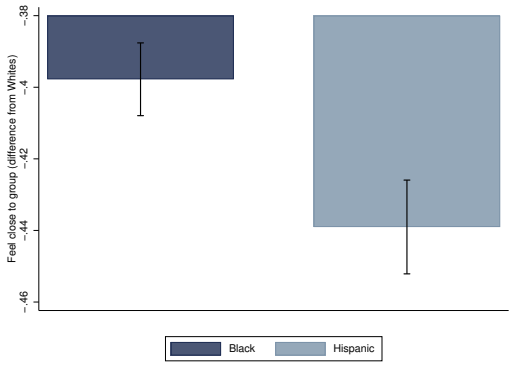
Dependent variable	Feeling thermometer		Average attitudes	
	(1)	(2)	(3)	(4)
	Panel A: Blacks			
Share Mexican	118.390		7.381	
	(60.936)		(3.351)	
Change in share Mexican		116.345		8.360
		(87.905)		(4.399)
Mean dep. variable		63.308	-0.127	-0.127
Observations	15,334	15,334	15,592	15,592
Number of states	51	51	51	51
R-squared	0.014	0.015	0.009	0.011
F-stat	131.449	95.865	130.647	97.886
	Panel A: Hispanics			
Share Mexican	-320.526		-10.984	
	(182.414)		(6.017)	
Change in share Mexican		-154.446		-3.460
		(67.430)		(2.518)
Mean dep. variable	61.261	61.261	-0.113	-0.113
Observations	11,399	11,399	11,672	11,672
Number of states	51	51	51	51
R-squared	0.001	0.006	-0.000	0.003
F-stat	90.706	102.510	89.408	104.659

Notes: Years 1980-2010. 2SLS estimates reported. The sample is restricted to White ANES respondents. *Change in share Mexican* is the change from the previous decade in the number of Mexicans as fraction of total state population. All columns include controls for age, age squared, gender, state and year by division fixed effects, and predicted share (non-Mexican) immigrants. Standard errors clustered at the state level.

D.4 Additional results

Affective distance. Figure 1 shows that affective distance of Whites from Hispanics is larger than that from Blacks using relative thermometer ratings as a proxy. In Figure D.4 we verify this result using an alternative measure of affective distance. Respondents were asked to indicate whether they feel close to various groups, in terms of their ideas, interests and feelings about things. We average binary responses over time and compute the difference from the average value White respondents assign to their own group. Consistent with thermometer ratings, Hispanics are perceived by Whites as more distant than Blacks. In our main analysis, we use the feeling thermometer as a measure of affective distance, since this variable is available for more years and groups than the measure of closeness.

Figure D.4. Average feelings of closeness, by group



Notes: Sample restricted to White respondents. Black lines are 95% confidence intervals.

Heterogeneous effects. An important question is whether Mexican immigration changes attitudes of Whites who encounter Black people in their everyday lives or whether the effect is more present among those with little contact with Blacks. The answer to this question can help us understand the real-life implications of the observed changes in prejudice – attitudinal changes among Whites are potentially more meaningful and impactful in areas with a large Black population and a high degree of interracial contact.

In Table D.14 we split the data by share of Black population (columns 1 and 2), and by two measures of racial residential segregation: an index of dissimilarity (columns 3 and 4) and an index of isolation (columns 5 and 6). The state-level index of dissimilarity (Duncan and Duncan 1955) captures the share of a group that needs to change states for the groups to be evenly distributed within a state. The index of isolation captures the probability with which minority members will only be exposed to other minority members (Massey and Denton 1988). We compute these indices at the state level starting from tract-level Black and White populations and applying the formulas in Cutler, Glaeser and Vigdor (1999). In all cases we use baseline (1970) measures of population and segregation that are exogenous to later changes in Mexican immigration. Estimated effects are orders of magnitude larger in states with above-median share of Blacks in 1970 and improvements in attitudes are driven primarily

by states with below-median residential segregation.

Table D.14. Heterogeneity by degree of contact with Blacks

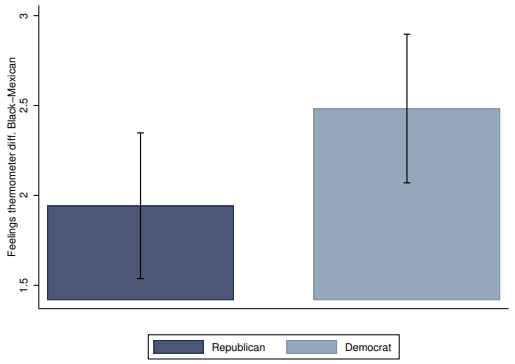
Sample (rel. to median)	Share Black		Racial dissimilarity index		Racial isolation index	
	Above	Below	Above	Below	Above	Below
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Dependent variable: Feeling thermometer Blacks					
Share Mexican	141.712	72.714	-226.994	453.205	-10.533	460.828
	(26.414)	(190.477)	(35.923)	(244.185)	(70.612)	(247.694)
Mean dep. variable	62.845	63.241	63.170	62.951	63.009	63.147
Observations	7,611	9,577	9,003	8,185	10,150	7,038
Number of states	28	23	19	32	24	27
R-squared	-0.002	0.000	-0.001	-0.004	0.000	-0.004
F-stat	61.438	17.491	68.713	15.458	38.356	15.422
	Panel B. Dependent variable: Average attitudes					
Share Mexican	8.608	1.681	-7.662	13.320	3.271	13.233
	(2.283)	(5.550)	(1.268)	(11.171)	(4.238)	(11.057)
Mean dep. variable	-0.154	-0.127	-0.148	-0.129	-0.153	-0.118
Observations	7,744	9,702	9,149	8,297	10,316	7,130
Number of states	28	23	19	32	24	27
R-squared	-0.004	0.000	-0.000	-0.003	-0.000	-0.002
F-stat	60.389	16.614	77.382	15.099	40.366	15.106

Notes: 2SLS estimates reported. Years 1970-2010. The sample is restricted to White respondents. Share Black and segregation indices used for sample splits are measured in 1970. Dissimilarity and isolation computed starting from tract-level information on Black and White populations and following Cutler, Glaeser and Vigdor (1999). All columns include controls for age, age squared, gender, state and year by division fixed effects and share of non-Mexican immigrants predicted by equation B.2. Standard errors clustered at the state level.

We also explore heterogeneity by partisanship. Figure D.5 shows that Democrats have a higher affective distance from Hispanics relative to Blacks, while Republicans tend to have equally cool feelings towards both groups. Consistent with Prediction 2(a), Table D.15 shows that increases in the share of Mexicans improve attitudes towards Blacks more for Democrats than for Republicans.

Effects on policy preferences. To what extent do changes in racial attitudes brought about by immigration affect Whites' policy preferences? The question of whether racial prejudice has political effects has long concerned scholars of American political behavior (Huddy and Feldman 2009). We turn to a number of questions in the ANES that capture preferences for government intervention to achieve Black-White equality and have been consistently asked in at least three out of four decades in our sample. Respondents are asked whether they believe that the government should intervene to help Blacks (agreement level on a 1-7 scale), whether Black and White schools should be integrated, whether the government should see to it that Blacks get fair treatment protection in jobs (agreement level on a 1-5 scale), and whether they are for or against preferential hiring for Blacks (agreement level on a 1-5 scale). The precise question wording is reported in Table C.2. We recode all items so that higher values indicate higher support for government intervention in favor of Black people.

Figure D.5. Difference in feelings between Blacks and Hispanics, by party affiliation



Notes: The figures plot the average difference between Black and Hispanic feeling thermometer, by partisanship. Black lines are 95% confidence intervals. Sample restricted to White respondents.

Table D.15. Heterogeneity by party affiliation

Dependent variable	Feeling thermometer Blacks		Average attitudes	
	(1)	(2)	(3)	(4)
Share Mexican	-2.056	21.574	0.361	1.243
	(32.535)	(31.717)	(1.237)	(1.252)
Share Mexican × Democrat	36.895		1.483	
	(9.314)		(0.495)	
Share Mexican × Republican		-21.312		-0.703
		(4.974)		(0.168)
Mean dep. variable	63.067	63.067	-0.139	-0.139
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
R-squared	0.031	0.030	0.030	0.029
AP F-Stat Share Mexican	270.3	50.68	272.9	51.84
AP F-Stat Interaction	20.60	105	20.58	105.6

Notes: 2SLS estimates reported. Years 1970-2010. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects, and predicted share of non-Mexican immigrants. Standard errors clustered at the state level.

Table D.16 reports 2SLS coefficients from our main specification for each of these outcomes (Columns 1-4) as well as for an average of all four (standardized) items. Mexican inflows lead to increased support for intervention in favor of African Americans for three out of four policy measures.[25] The average of all measures is highly significant and indicates that Mexican immigration induces more liberal views among White respondents.

These changes in policy preferences concerning Blacks are not part of a broader package of more liberal views spurred by immigration. Table D.17 examines the effect of Mexican immigration on broader ideology and policy preferences. The outcome in columns 1–2 is the

[25]Support for government aid for Blacks is negative, but, given the low first stage F-statistic in that regression, the coefficient cannot be readily interpreted.

Table D.16. Effects on policy preferences

Dependent variable	Should gov. help Blacks	School integration	Gov. guarantee FEP	Pref. hiring for Blacks	Racial policy average
	(1)	(2)	(3)	(4)	(5)
Share Mexican	-63.150	0.905	13.505	39.937	7.135
	(174.660)	(0.820)	(3.296)	(26.003)	(1.321)
Mean dep. variable	3.185	0.409	2.803	1.519	-0.077
Number of states	51	45	51	51	51
Observations	9,875	5,825	8,868	9,378	16,358
R-squared	0.045	0.090	0.033	0.011	0.044
F-stat	0.159	119.6	119.8	8.636	113.5

Notes: 2SLS estimates reported. Years 1970-2010. The sample is restricted to white respondents. All variables are coded so that higher values indicate higher support of respondents for the policy mentioned. All columns include controls for age, age squared, gender, state and year by division fixed effects, and predicted share of non-Mexican immigrants. Standard errors clustered at the state level.

respondent's self-placement on a 1–7 liberal-conservative scale, with higher values indicating higher conservatism. In columns 3–4 the dependent variable is the respondent's preference for provision of government services in exchange for government spending coded in a 1–7 scale, with higher values denoting lower preference for the role of government. Effects are not statistically significant, but, if anything, Mexican immigration tends to induce less liberal attitudes.

Table D.17. Effects on ideology

Dependent variable	Conservative		Lower gov. spending	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Share Mexican	-2.531	5.538	-5.239	6.323
	(2.045)	(3.333)	(3.159)	(8.751)
Observations	15,916	15,916	12,700	12,700
Number of states	51	51	51	51
R-squared	0.045	0.043	0.053	0.052
F-stat		139.7		63.84

Notes: Years 1970-2010. The sample is restricted to White respondents. All columns include controls for age, age squared, gender and state and year by division fixed effects. Columns 1 and 3 control for share of non-Mexican immigrants and columns 2 and 4 control for share of non-Mexican immigrants predicted by equation B.2. Standard errors clustered at the state level.

Taken together, results from Tables D.16 and D.17 imply that Mexican immigration makes White respondents willing to demand or accept a bigger role for government specifically when intervention is aimed at helping Blacks. Changes in attitudes appear to translate into changes in racial policy preferences, which may even go against respondents' general ideology or views of government's role.[26]

[26]Sniderman and Carmines (1997) show that White Americans' support for policies promoting racial equality increases with appeals that reach "beyond race" to broader moral values. Our findings suggest the reverse

The results provide an additional insight: immigration and anti-immigrant sentiment need not shift voting behavior to a more anti-immigrant or conservative direction when party platforms are multidimensional. This observation is consistent with recent findings, showing that increases in the Hispanic population at the local level need not increase Republican voting in US Presidential elections (Hill, Hopkins and Huber 2019).

Cross-group effects. Table D.18 presents the full set of estimates corresponding to the analysis of Figure 2 in the main paper.

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pattern; in response to Mexican immigration, appeals for policies targeted to Blacks may elicit more support from Whites than appeals for policies that are not group-specific.

Table D.18. Cross-group effects

Dependent variable	Feeling thermometer			Average attitudes		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Effect on Blacks					
Share Mexican	69.885	68.866	39.891	3.910	3.912	-1.136
	(33.897)	(34.457)	(69.583)	(1.680)	(1.695)	(3.615)
Share Asian		11.513			-0.022	
		(12.475)			(0.637)	
Share Arab			381.412			24.252
			(405.637)			(20.119)
Mean dep. variable		63.064	63.064	-0.139	-0.139	-0.139
Observations	17,182	17,182	17,182	17,440	17,440	17,440
Number of states	49	49	49	49	49	49
R-squared	-0.000	-0.000	-0.000	-0.001	-0.001	0.000
F-stat	87.625	26.774	6.300	87.961	27.494	6.330
	Panel B: Effect on Hispanics					
Share Mexican	-292.477	-197.918	180.548	-9.642	-7.404	4.883
	(169.340)	(135.920)	(110.067)	(5.770)	(4.655)	(3.721)
Share Asian		40.737			0.947	
		(17.956)			(0.668)	
Share Arab			-110.255			-14.753
			(459.257)			(16.908)
Mean dep. variable	61.260	61.260	61.260	-0.113	-0.113	-0.113
Observations	11,393	11,393	11,393	11,666	11,666	11,666
Number of states	49	49	49	49	49	49
R-squared	-0.003	-0.001	0.001	-0.001	-0.001	0.001
F-stat	55.157	25.783	5.477	54.724	25.620	5.468
	Panel C: Effect on Asian-Americans					
Share Mexican	-181.540	13.839	507.588	-23.019	-13.530	14.649
	(256.185)	(219.398)	(239.316)	(11.604)	(9.532)	(9.293)
Share Asian		21.685			1.048	
		(8.798)			(0.379)	
Share Arab			330.511			11.203
			(910.945)			(30.848)
Mean dep. variable	63.263	63.263	63.263	-0.076	-0.076	-0.076
Observations	8,911	8,911	8,911	9,195	9,195	9,195
Number of states	49	49	49	49	49	49
R-squared	0.000	0.001	-0.006	-0.007	-0.002	-0.004
F-stat	21.092	7.215	2.669	21.157	7.162	2.670

Notes: Years 1970-2010. 2SLS coefficients reported. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, state and year by division fixed effects. Standard errors clustered at the state level.

E County and tract-level analysis

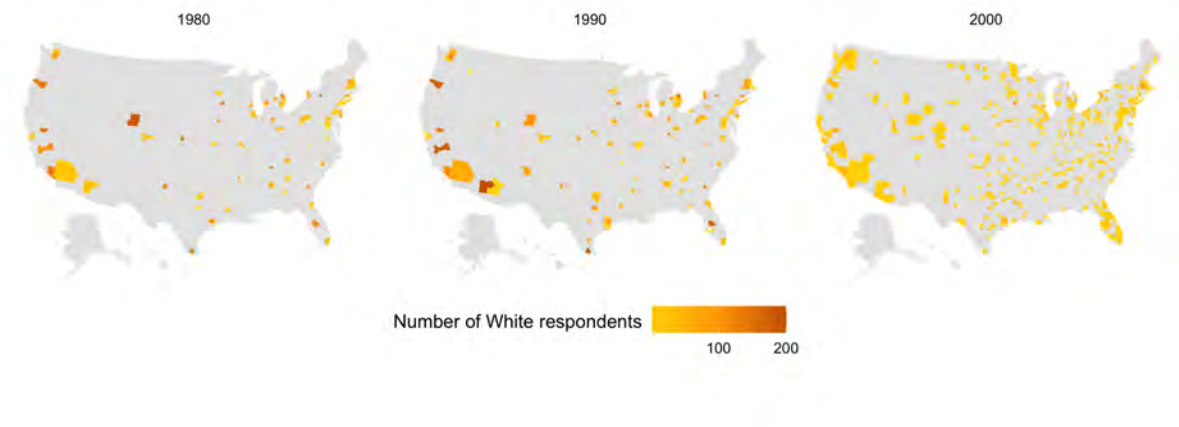
E.1 County-level analysis

We replicate our analysis at the county level using years 1984-1998, 2000 and 2004 of the ANES. These are years in which the ANES follows a consistent sampling framework with SMSAs and counties as primary sampling units. Given the panel nature of our analysis, the resulting dataset comprises only of counties sampled in at least two decades (Table E.1). The spatial distribution of available counties by sample size is shown in Figure E.1 and summary statistics are displayed in Table E.2.

Table E.1. Variation in ANES and GSS county-level datasets

	Number of counties		Number of White respondents	
	ANES	GSS	ANES	GSS
Counties available in two decades	76	191	3,311	12,382
Counties available in three decades	105	102	10,793	7,822

Figure E.1. Counties in the ANES



Notes: The maps depict the number of White respondents per county and decade in the ANES dataset.

Because the county-level ANES dataset is sparse, with approximately 28 White respondents per county and decade, we also use information from the General Social Survey (GSS), for years 1993-2010 for which county identifiers are available. The GSS covers a somewhat wider set of counties across multiple decades (Figure E.2 and Table E.1). We measure racial attitudes using all relevant questions that have been asked in at least two decades. Questions and response scales are listed in Table E.3. We recode responses so that higher values indicate more positive attitudes towards Blacks, and take the average of all standardized items as

a summary measure of prejudice. Questions capturing attitudes towards Hispanics are only asked in a single decade and we are unable to use them in our panel analysis. We focus instead on attitudes towards immigrants and use the average of all relevant (standardized) variables asked in at least two decades. Summary statistics for the GSS dataset are displayed in the bottom panel of Table E.2.

Table E.2. Summary statistics, county-level datasets

Variable	Mean	Std. Dev.	Min	Max	Obs.
ANES					
Feeling thermometer Blacks	63.351	19.638	0	97	13,766
Feeling thermometer Hispanics	71.944	17.901	0	97	10,512
Average attitudes Blacks	-0.072	0.622	-2.76	1.8	15,143
Average attitudes Hispanics	-0.059	0.909	-1.73	2.47	6,178
Age	47.586	17.374	18	89	20,565
Female	0.548	0.498	0	1	20,619
Share Mexican	0.022	0.039	0	.24	20,619
Share Non-Mexican	0.058	0.069	.000737	.464	20,619
GSS					
Attitudes towards Blacks	-0.004	0.624	-2.76	1.8	19,101
Attitudes towards immigrants	0.019	0.934	-1.92	2.47	7,963
Age	46.304	17.153	18	89	26,143
Female	0.558	0.497	0	1	26,222
Share Mexican	0.024	0.042	0	.24	26,222
Share Non-Mexican	0.066	0.078	.000737	.464	26,222

Notes: Years 1980-2000 (upper panel) and 1990-2010 (lower panel). Sample restricted to White respondents.

Figure E.2. Counties in the GSS

Notes: The maps depict the number of White respondents per county and decade in the GSS dataset.

Table E.3. Wording of questions in GSS

Variable Name	Wording
	Attitudes towards Blacks
Vote Black president	If your party nominated a (Negro/Black/African-American) for President, would you vote for him if he were qualified for the job? [1: Yes; 2: No.]
Differences due to inborn ability	On the average (Negroes/Blacks/African-Americans) have worse jobs, income, and housing than White people. Do you think these differences are . . . B. Because most (Negroes/Blacks/African-Americans) have less in-born ability to learn? [1: Yes; 2: No.]
Differences due to discrimination	On the average (Negroes/Blacks/African-Americans) have worse jobs, income, and housing than White people. Do you think these differences are . . . A. Mainly due to discrimination? [1: Yes; 2: No.]
Differences due to lack of will	On the average (Negroes/Blacks/African-Americans) have worse jobs, income, and housing than White people.Do you think these differences are . . . D. Because most (Negroes/Blacks/African-Americans) just don't have the motivation or will power to pull themselves up out of poverty? [1: Yes; 2: No.]
Blacks shouldn't push	Here are some opinions other people have expressed in connection with (Negro/Black)-White relations. Which statement on the card comes closest to how you, yourself, feel? The first one is . . . A. (Negroes/Blacks/African-Americans) shouldn't push themselves where they're not wanted. [1: Agree strongly - 4: Disagree strongly.]
Laws against racial intermarriage	A. Do you think there should be laws against marriages between (Negroes/Blacks/African-Americans) and Whites? [1: Yes; 2: No.]

Table E.3. – continued from previous page

Variable Name	Wording
Blacks - Hardworking or lazy	Now I have some questions about different groups in our society. I'm going to show you a seven-point scale on which the characteristics of people in a group can be rated. In the first statement a score of 1 means that you think almost all of the people in that group are "rich." A score of 7 means that you think almost everyone in the group are "poor." A score of 4 means you think that the group is not towards one end or another, and of course you may choose any number In between that comes closest to where you think people in the group stand. B. The second set of characteristics asks if people in the group tend to be hard-working or if they tend to be lazy. 3. Blacks? [1 Hardworking – 7 Lazy]
Blacks - Unintelligent or intelligent	Now I have some questions about different groups in our society. I'm going to show you a seven-point scale on which the characteristics of people in a group can be rated. In the first statement a score of 1 means that you think almost all of the people in that group are "rich." A score of 7 means that you think almost everyone in the group are "poor." A score of 4 means you think that the group is not towards one end or another, and of course you may choose any number In between that comes closest to where you think people in the group stand. D. Do people in these groups tend to be unintelligent or tend to be intelligent? 3. Blacks? [1 Unintelligent – 7 Intelligent]
Close relative marry Black	What about having a close relative marry a Black person? Would you be very in favor of it happening, somewhat In favor, neither in favor nor opposed to it happening, somewhat opposed, or very opposed to it happening? [1: Strongly favor - 5: Strongly oppose.]
Favor preference in hiring Blacks	A. Some people say that because of past discrimination, Blacks should be given preference in hiring and promotion. Others say that such preference in hiring and promotion of Blacks is wrong because it discriminates against Whites. What about your opinion – are you for or against preferential hiring and promotion of Blacks? IF FAVORS: A. Do you favor preference in hiring and promotion strongly or not strongly? IF OPPOSES: B. Do you oppose preference in hiring and promotion strongly or not strongly? [1: Strongly support pref - 4: Strongly oppose.]
	Attitudes towards Immigrants
Number of immigrants should be...	Do you think the number of immigrants from foreign countries who are permitted to come to the United States to live should be increased a lot, increased a little, left the same as it is now, decreased a little, or decreased a lot? [1: Increased a lot - 5: Decreased a lot.]

Table E.3. – continued from previous page

Variable Name	Wording
Immigrants increase crime rates	There are different opinions about immigrants from other countries living in America. (By "immigrants" we mean people who come to settle in America.) How much do you agree or disagree with each of the following statements? A. Immigrants increase crime rates [1: Agree strongly - 5: Disagree strongly.]
Immigrants good for America	There are different opinions about immigrants from other countries living in America. (By "immigrants" we mean people who come to settle in America.) How much do you agree or disagree with each of the following statements? B. Immigrants are generally good for America's economy [1: Agree strongly - 5: Disagree strongly.]
Immigrants take jobs away	There are different opinions about immigrants from other countries living in America. (By "immigrants" we mean people who come to settle in America.) How much do you agree or disagree with each of the following statements? C. Immigrants take jobs away from people who were born in America [1: Agree strongly - 5: Disagree strongly.]

Table E.4. Question availability across survey years in GSS

Variable Name	1993	1994	1996	1998	2000	2002	2004	2006	2008	2010
Vote Black president	X	X	X						X	X
Differences due to inborn ability	X	X	X	X	X	X	X	X	X	X
Differences due to discrimination	X	X	X	X	X	X	X	X	X	X
Differences due to lack of will	X	X	X	X	X	X	X	X	X	X
Blacks shouldn't push		X	X	X	X	X				
Laws against racial intermarriage	X	X	X	X	X	X				
Blacks - Hardworking or lazy		X	X	X	X	X	X	X	X	X
Blacks - Unintelligent or intelligent			X	X	X	X	X	X	X	X
Close relative marry Black			X	X	X	X	X	X	X	X
Favor preference in hiring Blacks		X	X	X	X	X	X	X	X	X
Number of immigrants should be...			X				X	X	X	X
Immigrants increase crime rates			X				X			
Immigrants good for America			X				X			
Immigrants take jobs away			X				X			

To construct an instrument at the county level, we modify our state-level approach to account for data limitations. Census tabulations for 1960 do not provide population counts by country of birth, and census microdata are only available for 1% and 5% samples, restricting the overlap between counties in our survey datasets and counties for which 1960 share of Mexicans can be computed. To circumvent this problem, we turn to the full count of the 1930 US census, which is publicly available and contains micro-level information on the universe of US residents (Ruggles et al. 2015). To maximize predictive power, we compute initial shares at the county level using information on foreign-born residents from Mexico as well as on US-born individuals with at least one Mexican-born parent.[27] We then use these county-level shares to predict baseline shares of Mexicans in 1960, by allocating the total number of Mexican immigrants in that year to counties proportional to 1930 Mexican population shares. We repeat the same procedure for non-Mexican immigrants and construct predicted flows of Mexican and non-Mexican immigrants by decade following county analogs of equations B.1 and B.2, where α_c^{Mex} and α_c^n are computed using the procedure just described.

We estimate the following county-level analog of equation 2:

$$Y_{isct} = \beta_1 M_{sct} + \beta_2 S_{sct} + \gamma_{sc} + \mu_{st} + \mathbf{X}_{isct} + \eta_{isct} \tag{E.1}$$

where s indexes states and c indexes counties. γ_{sc} and μ_{st} denote county and state by decade fixed effects. Our identifying variation thus comes from changes in the share of Mexicans across counties within the same state. We cluster standard errors at the county level. Throughout, we instrument the share of Mexicans with the predicted flow based on 1930 county shares and control directly for the predicted number of immigrants from origin countries other than Mexico. The first stage is strong in most of our analysis as indicated by the F-statistics in Tables E.5 and E.6. The exception is in specifications including 1960 controls interacted with decade fixed effects when the ANES dataset is used, where the predictive power of the instrument entirely collapses (columns 4 and 8 in Table E.5). We report these results for completeness, but we obviously cannot interpret any of the estimated 2SLS coefficients.

[27] This differs from the instrument constructed from the state level analysis, where we only consider first generation immigrants. Because of the smaller unit of analysis, using only first generation immigrants at the county level would result in a significantly sparser "migration matrix".

Table E.5. County-level analysis, ANES

Dependent variable	Feeling thermometer				Average attitudes			
	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)	OLS (5)	2SLS (6)	2SLS (7)	2SLS (8)
	Panel A: Blacks							
Share Mexican	-24.398	64.144	69.279	3,660.154	-0.576	1.423	1.767	165.808
	(27.611)	(37.841)	(38.399)	(12544.506)	(0.993)	(1.290)	(1.308)	(482.046)
Mean dep. variable	63.604	63.604	62.716	63.604	-0.092	-0.092	-0.130	-0.092
Observations	15,520	15,520	15,520	15,520	16,309	16,309	16,309	16,309
Number of counties	440	440	440	440	465	465	465	465
R-squared	0.089	0.088	0.097	-0.302	0.080	0.080	0.086	-0.316
F-stat		14.571	14.734	0.088		13.807	13.944	0.118
	Panel B: Hispanics							
Share Mexican	-62.150	-157.416	-164.382	222.937	-2.540	-10.898	-11.188	43.870
	(35.213)	(78.717)	(78.779)	(694.367)	(2.109)	(3.526)	(3.563)	(47.588)
Mean dep. variable	59.285	59.285	59.923	59.285	-0.143	-0.143	-0.113	-0.143
Observations	11,044	11,044	11,044	11,044	11,903	11,903	11,903	11,903
Number of counties	435	435	435	435	460	460	460	460
R-squared	0.113	0.113	0.128	0.113	0.094	0.093	0.115	0.065
F-stat		10.357	10.211	0.993		10.078	9.936	1.058

Notes: Years 1980-2000. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, county and year by state fixed effects. Columns 1 and 3 control for share of non-Mexican immigrants and columns 2 and 4 control for share of non-Mexican immigrants predicted by equation B.2. In columns (3) and (6) entropy balance weights are applied, matching counties with above- and below-median Mexican share along the mean of the following state-level variables: share Blacks in 1960, share immigrants in 1960, share rural in 1960, median years of education in 1960, unemployment rate in 1960, distance from Mexico. In columns (4) and (7) the same controls are included interacted with decade fixed effects. Standard errors clustered at the county level.

Table E.6. County-level analysis, GSS

	Attitudes towards Blacks				Attitudes towards immigrants			
	OLS (1)	2SLS (2)	2SLS. (3)	2SLS (4)	OLS (5)	2SLS (6)	2SLS (7)	2SLS (8)
Share Mexican	-0.716	5.367	5.469	9.552	-1.719	-7.851	-7.381	-11.320
	(0.808)	(2.261)	(2.234)	(3.893)	(3.318)	(6.906)	(6.699)	(25.809)
Mean dep. variable	-0.072	-0.072	-0.059	-0.072	-0.055	-0.055	-0.036	-0.055
Observations	15,102	15,102	15,102	15,102	6,154	6,154	6,154	6,154
Number of counties	322	322	322	322	308	308	308	308
R-squared	0.159	0.157	0.141	0.154	0.126	0.126	0.121	0.127
F-stat		17.612	17.861	14.431		21.662	21.656	3.291

Notes: Years 1990-2010. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, county and year by state fixed effects. Columns 1 and 3 control for share of non-Mexican immigrants and columns 2 and 4 control for share of non-Mexican immigrants predicted by equation B.2. In columns (3) and (6) entropy balance weights are applied, matching counties with above- and below-median Mexican share along the mean of the following state-level variables: share Blacks in 1960, share immigrants in 1960, share rural in 1960, median years of education in 1960, unemployment rate in 1960, distance from Mexico. In columns (4) and (7) the same controls are included interacted with decade fixed effects. Standard errors clustered at the county level.

E.2 Tract-level analysis

To examine the effects of Mexican immigration on racial attitudes at a contextual unit finer than the county, we conduct an analysis at the census tract level using information from the Cooperative Congressional Election Study (CCES). The CCES contains identifiers for respondents' zip codes. To match zip codes to tract-level demographics we use yearly cross-walks from the Department of Housing and Urban Development of the US Postal Service to assign individuals in a given year and zip code to the corresponding census tract. Whenever zip codes do not uniquely map to a census tract, we randomly assign individuals relying on zip-tract overlaying weights.[28] This procedure yields a cross-sectional dataset of individual respondents interviewed in years 2007-2018, each uniquely matched to a census tract.

We merge this dataset with demographic data from the American Community Survey (ACS). To maximize precision, and as suggested by ACS for small population subgroups, we use 5-year "period" population estimates (total and by country of birth) and construct a tract-level panel dataset with three periods: 2005 to 2009, 2010 to 2014 and 2015 to 2019.[29] We then map CCES responses to ACS periods as follows: CCES surveys until 2009 are mapped to ACS data for 2005, surveys from 2010 to 2014 are mapped to ACS data for 2010 and CCES surveys from 2015 onwards are mapped to ACS data for 2015.

We predict the number of Mexican and non-Mexican immigrants at the tract level following the same procedure as in our main analysis (see equations (B.1) and (B.2)). We construct baseline Mexican and non-Mexican shares for the year 2000 and interact them with five-year flows of immigrants by country of birth for each of the periods in the ACS. We estimate the following tract-level analog of equation 2:

$$Y_{icjt} = \beta_1 M_{cjt} + \gamma_{cj} + \mu_{ct} + \mathbf{X}_{icjt} + \beta_3 \theta_t \mathbf{Z}_{cj} + \eta_{icjt} \tag{E.2}$$

where c indexes counties and j indexes census tracts. γ_{cj} and μ_{ct} denote, respectively, tract and county by year fixed effects, and $\mathbf{Z}_{cj}$ is a vector of tract-level demographic and economic variables from the 2000 decennial Census, which we interact with period fixed effects θ_t. The set of baseline controls is comprehensive and includes the following variables: Black and urban population share, employment to population ratio, the manufacturing share of employment, share of individuals aged 25 or higher with at least a college degree, share of tract population below the poverty line, median value of owner-occupied housing units, and population density. We cluster standard errors at the tract level.

The CCES contains three questions on symbolic racism, which are asked in various years between 2010 and 2018. The text of the questions is listed in Table E.7. We opt for not using the question on preferences for affirmative action, which has previously been employed by Acharya, Blackwell and Sen (2016) to proxy for racial attitudes. The text of the question

[28] The cross-walk are available at: `https://www.huduser.gov/portal/datasets/usps_crosswalk.html`

[29] See `https://www.census.gov/programs-surveys/acs` for more details.

is not specific to Blacks, but refers to programs that "give preference to racial minorities and to women in employment and college admissions in order to correct for discrimination." As our framework suggests and our results indicate, Mexican immigration has different effects on preferences for affirmative action in favor of different minority groups, making this question an inappropriate measure of racial attitudes in our context. We thus restrict attention to racial resentment questions, averaging all three standardized questions into a single measure, with higher values indicating more resentment.

To measure respondents' attitudes on immigration, we combine answers to a series of questions on immigration policy preferences, asked consistently between 2007 and 2017. The questions are listed in the lower panel of Table E.7. We recode each variable so that higher values denote more favorable views towards immigration, and compute an average of standardized responses to all questions. Summary statistics for the CCES dataset are provided in table E.9. Figure E.3 depicts the spatial distribution of White respondents across census tracts for years in which the racial resentment average can be computed.

Table E.7. Wording of questions in CCES data

Variable Name	Wording
	Racial resentment
Racial Resentment A	The Irish, Italians, Jews and many other minorities overcame prejudice and worked their way up. Black should do the same without any special favors. [1: Strongly agree - 5: Strongly disagree.]
Racial Resentment B	Generations of slavery and discrimination have created conditions that make it difficult for Blacks to work their way out of the lower class. [1: Strongly agree - 5: Strongly disagree.]
Racial Resentment C	It's really a matter of some people not trying hard enough, if Blacks would only try harder they could be just as well off as Whites. [1: Strongly agree - 5: Strongly disagree.]
	Immigration policy
Immigration	What do you think Congress and the President should do about immigration? Select all that apply. [Answers: a) Fine US businesses that hire illegal immigrants; b) Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years, and not been convicted of any felony crimes; c) Increase the number of guest workers allowed to come legally to the U. S; d) Build a wall between the US and Mexico; Increase the number of guest workers allowed to come legally to the U. S.; e) Allow police to question anyone they think may be in the country illegally; f) Deny automatic citizenship to American-born children of illegal immigrants; g) Identify and deport illegal immigrants

Table E.8. Question availability across survey years in CCES

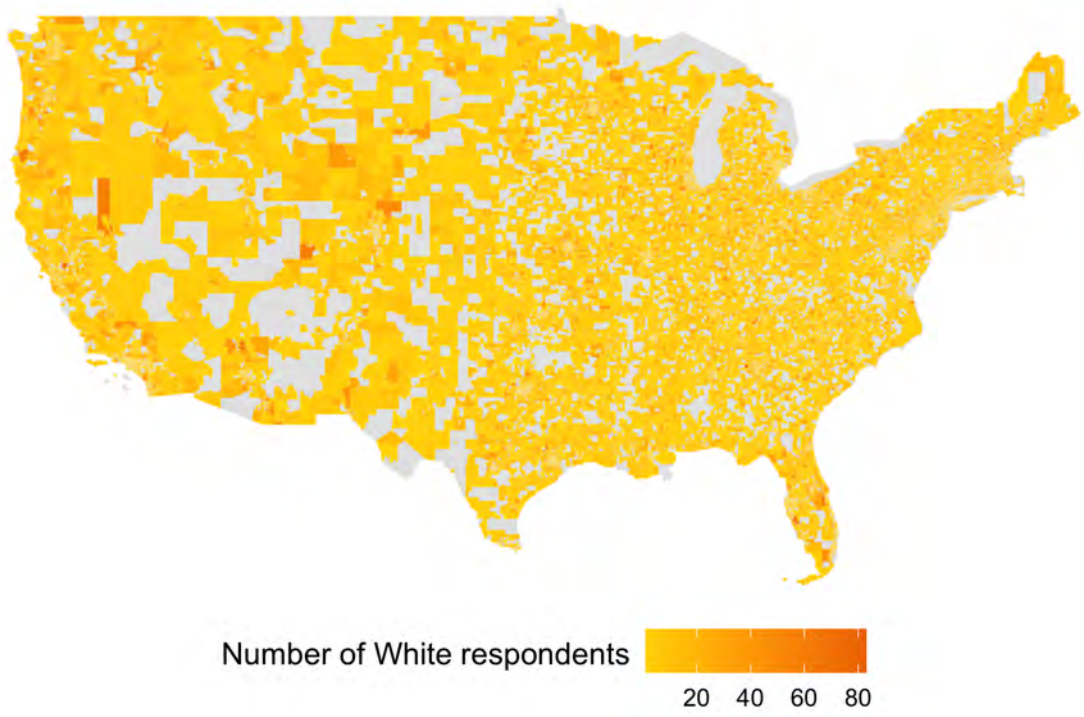
Variable Name	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Racial resentment A				X	X	X		X				X
Racial resentment B				X		X	X	X				X
Grant legal status	X			X	X	X	X	X	X	X	X	
Build a wall	X			X	X	X	X	X	X	X	X	
Increase guest workers	X			X							X	
Allow police questioning	X				X	X	X	X	X		X	
Deny automatic citizenship						X	X					
Identify and deport								X	X	X	X	

Table E.9. Summary statistics, tract-level

Variable	Mean	Std. Dev.	Min	Max	Obs.
Racial attitudes					
Racial resentment	0.119	0.883	-1.96	1.42	115,341
Age	53.633	15.684	18	95	115,341
Female	0.520	0.500	0	1	115,341
Share Mexican	0.021	0.046	0	.511	115,341
Share Non-Mexican	0.073	0.088	0	.816	115,341
Immigration attitudes					
Immigration policy	0.459	0.364	0	1	145,877
Age	52.573	15.879	18	96	145,877
Female	0.517	0.500	0	1	145,877
Share Mexican	0.021	0.047	0	.515	145,877
Share Non-Mexican	0.075	0.091	0	.802	145,877

Notes: CCES data 2007-2018. Sample restricted to White respondents.

Figure E.3. Census tracts in the CCES



Notes: The map depicts the number of White respondents per census tract for years in which questions on racial resentment were asked.

Table E.10. Tract-level analysis, CCES

Dependent variable	Racial resentment				Immigration policy			
	OLS	2SLS	2SLS	2SLS	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share Mexican	0.104	-3.218	-4.304	-4.457	0.007	-0.907	-0.727	-0.721
	(0.390)	(2.292)	(2.425)	(2.434)	(0.111)	(0.571)	(0.633)	(0.635)
Mean dep. variable	0.119	0.119	0.119	0.119	0.459	0.459	0.459	0.459
Observations	115,341	115,334	115,252	115,252	145,877	145,869	145,745	145,745
Number of tracts	24,659	24,658	24,640	24,640	27,960	27,959	27,935	27,935
R-squared	0.335	-0.001	-0.001	-0.002	0.309	-0.001	-0.000	-0.000
F-stat		45.749	53.322	53.388		98.569	96.214	96.210
Baseline controls			✓	✓			✓	✓
Other immigrants				✓				✓

Notes: Years 2005-2015. The sample is restricted to White respondents. All columns include controls for age, age squared, gender, census tract and county by period fixed effects. Columns 3-4 and 7-8 include 2000 tract-level controls interacted with period fixed effects. Columns 4 and 8 control for share of non-Mexican immigrants predicted by equation B.2. Standard errors clustered at the census tract level.

F Survey experiment

We conducted an online survey experiment in winter 2021 using the respondent pool of Lucid's Theorem. Lucid is frequently employed by political scientists in the implementation of survey experiments in the US context (Tomz and Weeks 2020; Hill and Huber 2019; Orr and Huber 2020), and research suggests that it is an appropriate platform for evaluating a wide range of social scientific theories and comparable to other commonly used platforms like Amazon's MTurk (Coppock and McClellan 2019). Lucid aggregates respondents from many different sources and matches demographic margins of the US Census. According to Coppock and McClellan (2019), Lucid respondents are closer to ANES ones in terms of demographics than are respondents sampled through MTurk. We aimed for 500 White non-Hispanic respondents and achieved a number close to that target.[30] Summary statistics for our sample are displayed in Table F.1.

After consenting to take the survey, respondents were asked two questions on the demographic profile of the US population. The first one, common to all participants, asked respondents to estimate the number of residents of the United States. The following question was randomized. Respondents in the treatment group were asked to estimate the share of US residents that are of Hispanic origin. Respondents in the control group were asked to estimate the average age of the US population.[31] Table F.2 compares demographics of the treatment and control group confirming that randomization was successful. Imbalances in partisanship are small in magnitude. In our empirical analysis, we present specifications both with and without controls to correct for any imbalances and improve estimate precision. The inclusion of controls does not have any qualitative impact on our conclusions.

[30] Theorem does not allow for pre-filtering of respondents based on demographics. Given that Lucid matches target population quotas from the US census and its samples consist of 68% non-Hispanic Whites, we fielded the survey to 740 participants and excluded non-Whites from our final sample.

[31] Estimates may deviate from the true size of the Hispanic population in ways that correlate with attitudes towards minority groups. We do not use the endogenous size estimates in our analysis, but only rely on the comparison between those who were asked to reflect on size and those who were not.

Table F.1. Summary statistics

	Mean	Std	Min	Max	N
Respondent characteristics					
Age	48.8236	16.268	18	90	499
Female	0.4990	0.501	0	1	499
Democrat	0.4068	0.492	0	1	499
Republican	0.2966	0.457	0	1	499
Independent	0.2645	0.442	0	1	499
Other	0.0321	0.176	0	1	499
Northeast	0.1944	0.396	0	1	499
Midwest	0.2064	0.405	0	1	499
South	0.3968	0.490	0	1	499
West	0.2024	0.402	0	1	499
Education: Less than college	0.4128	0.493	0	1	499
Education: College or higher	0.5852	0.493	0	1	499
Household income <$50,000	0.3206	0.467	0	1	499
Household income $50,000 - $99,000	0.3828	0.487	0	1	499
Household income $100,000 - $149,000	0.0681	0.252	0	1	499
Household income $150,000 - $199,000	0.1022	0.303	0	1	499
Household income > $200,000	0.1263	0.332	0	1	499
Attitudes towards Blacks					
Intelligent	3.719	1.021	1	5	499
Trustworthy	3.515	1.085	1	5	499
Violent	2.988	1.191	1	5	499
Hardworking	3.677	1.111	1	5	499
American	3.964	0.985	1	5	499
Thermometer	5.771	2.901	0	10	476
Principal component	-0.000	1.678	-5	3	476
Attitudes towards Hispanics					
Intelligent	3.633	0.996	1	5	499
Trustworthy	3.567	1.010	1	5	499
Violent	3.299	1.143	1	5	499
Hardworking	4.096	0.918	1	5	499
American	3.591	1.115	1	5	499
Thermometer	5.621	2.956	0	10	488
Principal component	-0.000	1.553	-5	3	488
Attitudes towards Asians					
Intelligent	4.156	0.843	1	5	499
Trustworthy	3.707	0.956	1	5	499
Violent	3.625	1.191	1	5	499
Hardworking	4.076	0.884	1	5	499
American	3.605	1.101	1	5	499
Thermometer	5.458	3.022	0	10	480
Principal component	-0.000	1.505	-6	2	480
Attitudes towards Muslims					
Intelligent	3.689	1.017	1	5	499
Trustworthy	3.305	1.184	1	5	499
Violent	2.990	1.282	1	5	499
Hardworking	3.651	1.062	1	5	499
American	3.216	1.284	1	5	499
Thermometer	4.619	3.045	0	10	475
Principal component	-0.000	1.699	-5	3	475
Attitudes towards Whites					
Intelligent	3.918	0.903	1	5	499
Trustworthy	3.711	0.934	1	5	499
Violent	3.132	1.149	1	5	499
Hardworking	3.920	0.917	1	5	499
American	4.214	0.892	1	5	499
Thermometer	7.299	2.521	0	10	478
Principal component	0.000	1.604	-6	2	478

Table F.2. Randomization check

	Control	Treatment	Difference	P-value
Age	48.117	49.479	-1.362	0.351
Female	0.512	0.486	0.026	0.562
Democrat	0.45	0.367	0.083	0.059
Republican	0.279	0.312	-0.034	0.413
Independent	0.254	0.274	-0.02	0.615
Other	0.017	0.046	-0.03	0.06
Northeast	0.221	0.17	0.051	0.151
Midwest	0.192	0.22	-0.029	0.434
South	0.384	0.41	-0.026	0.555
West	0.204	0.201	0.004	0.925
Education: Less than college	0.392	0.432	-0.041	0.356
Education: College or higher	0.609	0.564	0.044	0.313
Household income <$50,000	0.354	0.289	0.065	0.123
Household income $50,000 - $99,000	0.358	0.406	-0.047	0.281
Household income $100,000 - $149,000	0.062	0.073	-0.011	0.632
Household income $150,000 - $199,000	0.1	0.104	-0.004	0.876
Household income > $200,000	0.125	0.128	-0.003	0.935
Observations	240	259		

After the treatment block, we elicited attitudes of respondents towards five different groups in the US: Blacks, Hispanics, Asians, Muslims, and Whites. We asked two sets of questions. The first one asked respondents to rate their feelings for each group using a standard feeling thermometer and wording following that of the ANES. The second one asked respondents to rate how well different attributes described each group. We inquire on the four stereotypical attributes measured in the ANES (intelligent, violent, hardworking, trustworthy) and on a fourth attribute, "American", which serves to test our mechanism of group recategorization. The wording of these questions and the choice of American as the relevant ingroup identity follows Levendusky (2018). Within each set of questions (thermometers, attributes) the order in which groups were presented to respondents was randomized. For each group, we constructed a summary measure of prejudice as the principal component of the thermometer and all (recoded) attributes with the exception of "American".[32] Summary statistics on all outcomes are provided in Table F.1. Table F.4 lists all questions asked as part of our survey.

The following demographic variables were provided by Lucid: age, gender, education (10 categories), household income (25 brackets), region of residence and political party affiliation (10 categories). Tables F.1 and Table F.2 present some of these demographics in aggregated form for readability. In our regressions, we control for the full set of indicators, with the exception of partisanship, which we aggregate into four categories (Democrat, Republican,

[32]Our main analysis with ANES data uses the average instead of the principal component to account for the fact that many variables have missing values. We do not face this problem here. The principal component is a superior way of reducing data dimensionality since it assigns optimal ways to underlying components in order to reduce the variance of the lower-dimension representation of the data. The average instead assigns equal weights to all components. Results are similar, but magnitudes and significance for effects on Blacks are larger, when using a simple average instead of the principal component (available upon request).

Independent, Other).

Table F.3 presents average treatment effects on attitudes and views of a group as American, for all groups in the survey. Figure F.1 displays the distribution of thermometer ratings and perceptions for Blacks in the treatment and control group. It shows that the effect is present across the entire distribution, uniformly shifting responses to the right for the treated group.

Figure F.1. Histograms of perceptions of Blacks by treatment status

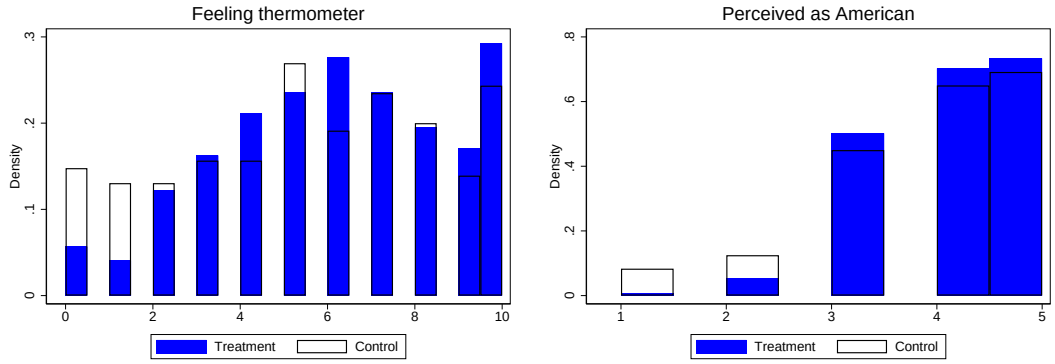


Table F.3. Effects of priming respondents with share of Hispanics in the US

Group	Blacks		Hispanics		Asians		Muslims		Whites	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Attitudes towards group (principal component)									
Treatment	0.079	0.117	0.034	0.046	0.037	0.027	0.024	0.057	-0.043	-0.055
	(0.155)	(0.158)	(0.141)	(0.148)	(0.138)	(0.146)	(0.156)	(0.154)	(0.147)	(0.146)
Observations	476	475	488	487	480	479	475	474	478	477
R-squared	0.006	0.172	0.001	0.109	0.001	0.114	0.001	0.192	0.002	0.167
	Panel B: Group perceived as American									
Treatment	0.091	0.091	0.028	0.040	0.048	0.061	-0.013	0.014	0.020	0.014
	(0.089)	(0.094)	(0.100)	(0.101)	(0.099)	(0.102)	(0.115)	(0.110)	(0.080)	(0.083)
Observations	499	498	499	498	499	498	499	498	499	498
R-squared	0.008	0.109	0.001	0.162	0.002	0.141	0.000	0.223	0.000	0.118
Controls		✓		✓		✓		✓		✓

Notes: Beta coefficients reported. The dependent variable in Panel A is the principal component of a feeling thermometer and agreement with the groups having the following attributes: intelligent, violent (inversely coded), trustworthy, hardworking. Controls include age and age squared, gender, four indicators for region of residence, eight indicators for educational attainment, three indicators for party affiliation (Democrat, Republican, Independent) and twenty-five income bracket indicators. Robust standard errors in parenthesis.

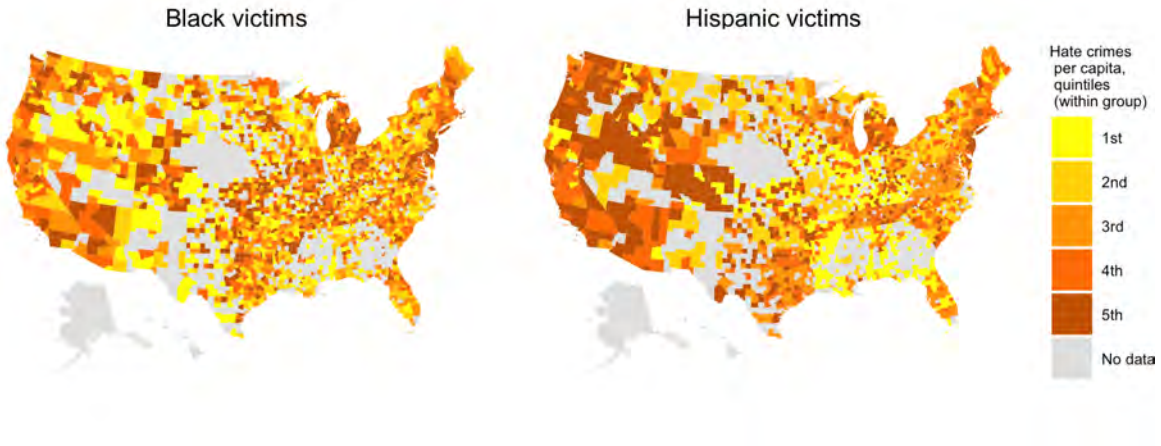
Table F.4. Survey instrument

	Treatment block
	We would like to start by asking you a few questions about the demographic characteristics of the population of the United States. Click the arrow to continue.
Q.1	How many million residents does the US have? Please provide your best guess.
Q.2A	[Treatment group only] What share of the US population is of Hispanic origin? Please provide your best guess.
Q.2B	[Control group only] What is the average age of the US population? Please provide your best guess.
	Feeling thermometers
Q.3	Now, we would like to get your feelings toward some groups of people in the United States. In the following pages, you'll see the name of a group next to a feeling thermometer. Please rate that group using the sliding bar next to the thermometer. Ratings between 5 and 10 degrees mean that you feel favorably and warm toward that group; ratings between 0 and 5 degrees mean that you don't feel favorably toward that group. You would rate the person at the 5 degree mark if you don't feel particularly warm or cold toward the group. Click the arrow to continue.
	Group attributes
	Now we'd like to know what you think about [group]. Below, we've given a list of words that some people might use to describe [group]. For each item, please indicate how well you think it applies to them: extremely well, very well, somewhat well, not too well, or not at all well.
Q.4	What about "American"? Does that apply to [group] extremely well, very well, somewhat well, not too well, or not at all well?
Q.5	What about "intelligent"? Does that apply to [group] extremely well, very well, somewhat well, not too well, or not at all well?
Q.6	What about "hard-working"? Does that apply to [group] extremely well, very well, somewhat well, not too well, or not at all well?
Q.7	What about "violent"? Does that apply to [group] extremely well, very well, somewhat well, not too well, or not at all well?
Q.8	What about "trustworthy"? Does that apply to [group] extremely well, very well, somewhat well, not too well, or not at all well?

G Analysis of hate crimes

G.1 Data on hate crimes

Figure G.1. Hate crimes against Blacks and Hispanics by county



Notes: The maps depict the quintiles for the mean number of hate crimes against Blacks and Hispanics for the decades of 1990, 2000, and 2010.

Data on hate crimes come from the FBI's Uniform Crime Reporting System (UCR), for the years 1992 to 2016. The FBI compiles data from agencies that report to it on a voluntary basis. Data is available at the level of the reporting agency and agencies are mapped to counties based on an Originating Agency Identifier (ORI). In a small set of cases (approximately 4% in our data) a single agency is assigned to more than one counties. When that occurs, we assign the hate crimes of the agency to all counties in the jurisdiction of that agency.

The procedure followed by the FBI to decide whether a crime is bias-motivated is described below:

> "Once the development of this collection was complete, the FBI UCR Program surveyed state UCR Program managers on hate crime collection procedures used at various law enforcement agencies which collected hate crime data employing a two-tier decision-making process. The first level is the law enforcement officer who initially responds to the alleged hate crime incident, i.e., the responding offi-

cer (or first-level judgment officer). It is the responsibility of the responding officer to determine whether there is any indication that the offender was motivated by bias. If a bias indicator is identified, the officer designates the incident as a suspected bias-motivated crime and forwards the case file to a second-level judgment officer/unit. (In smaller agencies this is usually a person specially trained in hate crime matters, while in larger agencies it may be a special unit.) It is the task of the second-level judgment officer/unit to review the facts of the incident and make the final determination of whether a hate crime has actually occurred. If so, the incident is to be reported to the FBI UCR Program as a bias-motivated crime." (Federal Bureau of Investigation (FBI) 2015, p.2-3)

There are 27 distinct bias motivations, belonging to one of the following broad categories: race/ethnicity/ancestry, religion, sexual orientation, disability, gender, and gender identity. Additional information recorded in the data is the date and type of crime, the number of victims and offenders, and the race of the offender.

To map the yearly FBI data to decadal information on the share of Mexicans, we sum all hate crimes that occur in a given decade and assign them to census population information in the beginning of the decade. For instance, we sum up all hate crimes committed between 1990 and 1999 and map them to census information on Mexican population shares in 1990. Table G.1 reports summary statistics for hate crimes against Blacks and Hispanics from our resulting county-decade-level dataset.

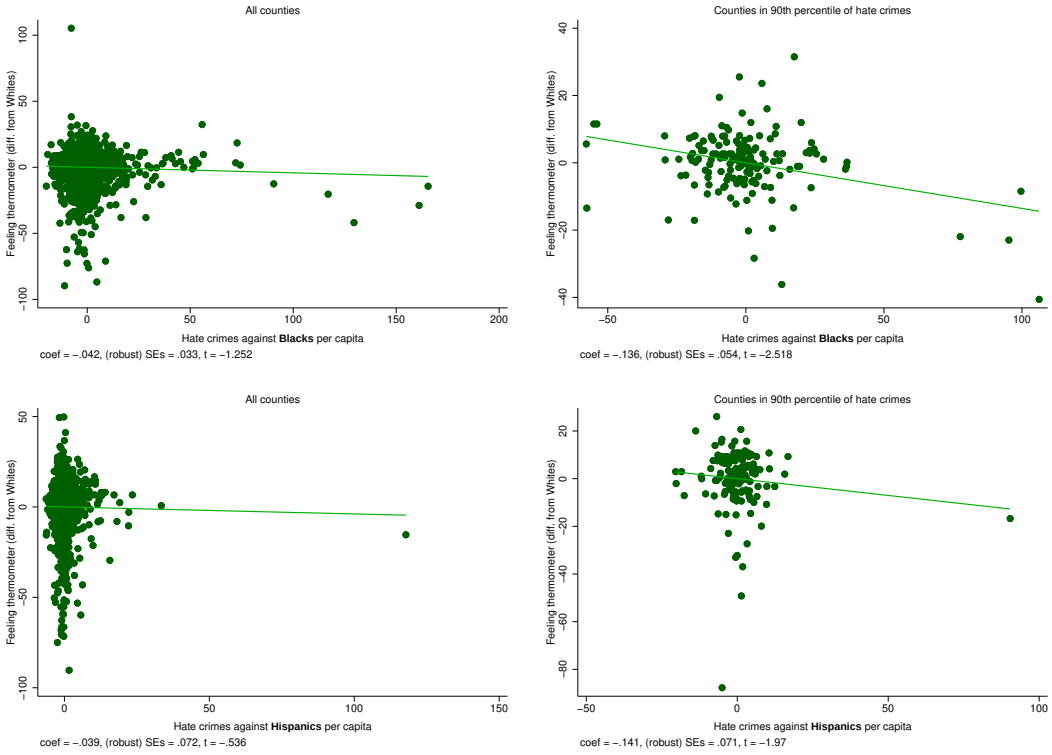
Table G.1. Summary statistics of crime data

	Mean	Std	Min	Max	N
Hate crimes					
Against Blacks, all offenders	7.9	12.902	0	283	4913
Against Hispanics, all offenders	1.7	4.847	0	124	4913
Against Blacks, all offenders	5.25	8.078	0	158	4166
Against Hispanics, White offenders	1.3	4.216	0	99	4166
Index crimes					
All	26494	17763	0	335120	6756
Violent	2830	2699	0	85165	6756
Property	23663	15672	0	249956	6756

Notes: Numbers reported are crimes per 100,000 people, averaged over decades. Years 1990-2010.

Figure G.2 shows that hate crimes against a group and attitudes towards that group are not strongly correlated at the county level. The correlation is strong and significant for counties at the 90th percentile of hate crimes, where there is arguably a closer correspondence between hate crime perpetrators and ANES respondents (as hate crimes are a more common behavior and thus perpetrators more representative of the population's values).

Figure G.2. Correlation of hate crimes and attitudes



Notes: Binned scatterplots of per capita hate crimes against Blacks (top) and Hispanics (bottom) at the county-decade level against feelings towards the respective group (relative to feelings towards Whites). Values are residualized from year and state fixed effects and standard errors are clustered at the county level.

G.2 Robustness checks

The jurisdictions of agencies that report to the FBI do not directly correspond to county boundaries. As a result, for about 4% of the observations, an agency may be mapped to more than one county, in which case we assign incidents reported by that agency to all counties the agency is mapped to. To account for resulting spatial correlation, we always report standard errors adjusted following Conley (1999) using a distance cutoff of 500 km. Our inferences are little affected by this adjustment.

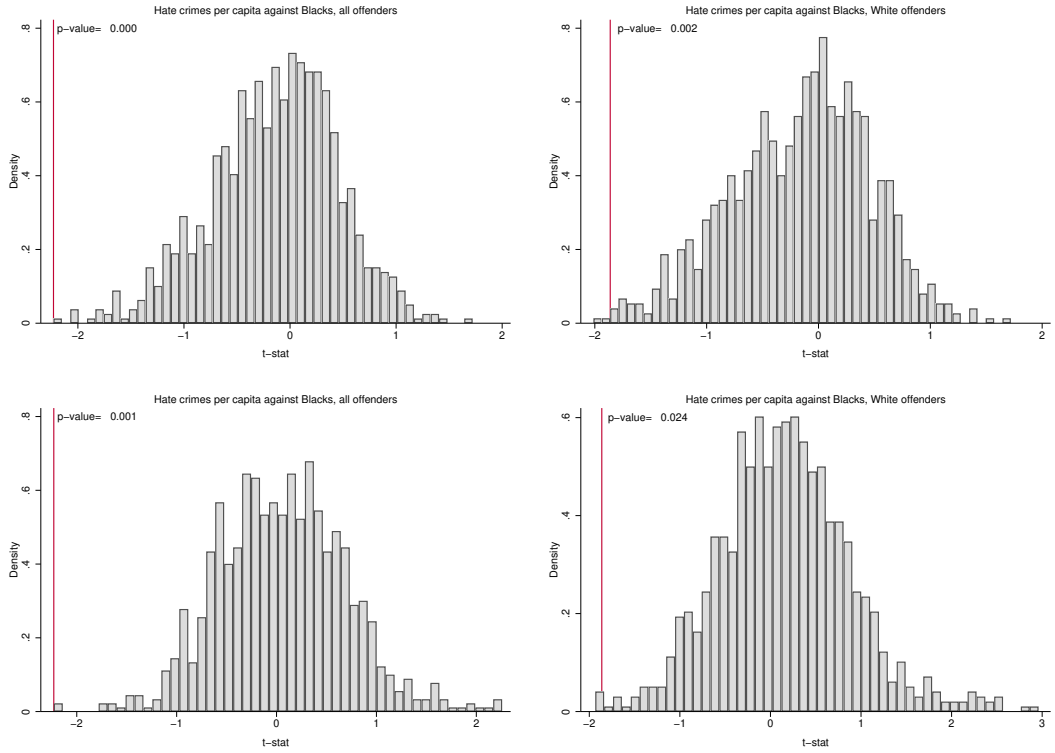
Our estimates are robust to the inclusion of baseline county-level controls interacted with year fixed effects and to entropy balance weighting (Table G.2). Using placebo exercises identical to the ones conducted for the state-level analysis of the ANES data, we show that the estimated coefficients are unlikely to arise from a persistent effect of initial Mexican shares (Figure G.3). The patterns of changes in anti-Black and anti-Hispanic crimes are also present when restricting the analysis to violent hate crimes, which are more likely to be accurately recorded by the FBI (Table G.3). We also provide evidence that these effects are not due to selective migration and changing population demographics in response to Mexican immigration – a concern more pronounced at the county than at the state level. Table G.4 shows that changes in the share of Mexicans at the county level do not significantly affect the numbers of either Black or White residents.

Table G.2. Robustness to baseline controls and entropy balance weights

Dependent variable	Hate crimes per 100,000 people					
	All offenders			White offenders		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Black victims					
Share Mexican	-1.437	-1.448	-0.790	-2.221	-2.085	-1.047
	(263.633)	(273.863)	(172.268)	(299.869)	(311.576)	(157.160)
	{258.265}	{266.341}	{175.969}	{267.384}	{277.558}	{146.334}
Mean dep. variable	8.255	8.014	8.255	5.345	5.856	5.345
Observations	4,301	4,301	4,301	3,507	3,507	3,507
Number of counties	1,642	1,642	1,642	1,359	1,359	1,359
R-squared	0.574	0.612	0.644	0.464	0.505	0.636
F-stat	13.85	12.84	24.03	10.05	9.095	25.43
	Panel B: Hispanic victims					
Share Mexican	0.840	0.685	0.968	1.861	1.934	1.528
	(171.455)	(179.952)	(140.081)	(211.620)	(217.523)	(156.122)
	{157.996}	{165.222}	{129.017}	{211.351}	{217.250}	{156.226}
Mean dep. variable	1.734	2.024	1.734	1.277	1.496	1.277
Observations	4,301	4,301	4,301	3,507	3,507	3,507
Number of counties	1,642	1,642	1,642	1,359	1,359	1,359
R-squared	0.568	0.570	0.564	0.492	0.489	0.541
F-stat	13.85	12.84	24.03	10.05	9.095	25.43
Entropy balance weights		✓			✓	
Year x Baseline FEs			✓			✓

Notes: Years 1990-2010. Beta coefficients reported. All columns control for county and year by state fixed effects as well as for the share of non-Mexican immigrants predicted by equation B.2. In columns (2) and (4) entropy balance weights are applied, matching counties with above- and below-median Mexican share along the mean of the following county-level variables: share Blacks in 1960, share immigrants in 1960, share rural in 1960, median years of education in 1960, unemployment rate in 1960, distance from Mexico. Columns (3) and (5) include interactions of this list of baseline controls with year fixed effects. Standard errors clustered at the county level. Standard errors clustered at the county level reported in parentheses; Conley standard errors using a distance cutoff of 500 km reported in curly brackets.

Figure G.3. Randomization inference



Notes: The figure plots, for each of the outcomes listed in the titles of individual graphs, the distribution of t-statistics resulting from 1,000 iterations of estimating equation E.1 with alternative computations of the instrument for Mexican immigrants. In the upper panel, predicted numbers of Mexicans are computed using Mexican shares and randomly assigned inflows of immigrants from different nationalities within county and decade. In the lower panel, predicted numbers of Mexicans are computed using Mexican inflows and randomly assigned shares of immigrants from different nationalities within county and decade. Vertical lines are drawn at the value of the t-statistic for our actual treatment effect. P-values are computed as the share of t-statistics whose value is more extreme than the value estimated using actual assignment of Mexican shares and decade-specific Mexican inflows.

Table G.3. Effects on violent hate crimes

Dependent variable	Violent hate crimes per 100,000 people			
	All offenders		White offenders	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
	Panel A: Black victims			
Share Mexican	0.064	-1.261	0.080	-1.214
	(4.769)	(58.243)	(4.829)	(74.164)
	{4.460}	{58.555}	{5.218}	{68.719}
Mean dep. variable	1.080	1.080	0.967	0.967
Observations	4,301	4,301	3,507	3,507
Number of counties	1,642	1,642	1,359	1,359
R-squared	0.551	-0.171	0.588	-0.167
F-stat		13.847		10.050
	Panel B: Hispanic victims			
Share Mexican	0.058	0.102	0.095	0.246
	(7.689)	(21.010)	(9.538)	(25.862)
	{6.406}	{19.795}	{8.806}	{30.147}
Mean dep. variable	0.356	0.356	0.280	0.280
Observations	4,301	4,301	3,507	3,507
Number of counties	1,642	1,642	1,359	1,359
R-squared	0.555	0.000	0.587	-0.001
F-stat		13.847		10.050

Notes: Years 1990-2010. Beta coefficients reported. Violent hate crimes are: murder or non-negligent manslaughter, rape, robbery, and aggravated assault. Columns include controls for county and year by state fixed effects. Columns 1, 3 and 5 control for share of non-Mexican immigrants and columns 2, 4 and 6 control for predicted share of non-Mexican immigrants predicted by equation B.2. Standard errors clustered at the county level reported in parentheses; Conley standard errors using a distance cutoff of 500 km reported in curly brackets.

Table G.4. Assessing county-level changes in Black and White population

Dependent variable	Log Black population		Log White population	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Share Mexican	0.150	-3.678	-0.012	-2.459
	(0.936)	(14.059)	(0.202)	(3.270)
Observations	6,699	6,699	6,759	6,759
R-squared	0.984	0.984	0.996	0.996
F-stat		31.97		25.97

Notes: Years 1990-2010. All columns control for county and year by state fixed effects. Columns 1 and 3 control for share of non-Mexican immigrants and columns 2 and 4 control for share of non-Mexican immigrants predicted by equation B.2. Standard errors clustered at the county level.

Finally, we address the possibility that Mexican immigration may lead to overall reductions in criminality, including hate crimes. Prior work has found that Latino immigrants are less likely to engage in criminal behavior than comparable Blacks and Whites (Sampson, Morenoff and Raudenbush 2005), and that Hispanic immigration may have additional spillover effects on crime rates of other groups through neighborhood revitalization (Sampson 2017).

To examine whether Mexican immigration affects criminality or crime reporting more

broadly we use information on Offenses Known and Clearances By Arrest from FBI's Uniform Crime Reporting System compiled by Jacob Caplan (Kaplan 2020). The dataset records seven types of serious crimes (Part I index crimes), further classified into violent and property crimes. Violent crimes include homicide, rape, robbery and aggravated assault. Property crimes include burglary, theft and motor vehicle theft.

As with data on hate crimes, we sum all crimes within a decade and assign the resulting number to population information at the beginning of the decade. Summary statistics for all index crimes, and separately for violent and property crimes are reported in Table G.1. The estimated effect of Mexican population share on other types of crime is close to zero and far from statistical significance (Table G.5).

It is worth noting that the county-level data collected by the FBI are not complete, as reporting of agencies to the FBI is voluntary and not all agencies consistently report their crime statistics. For data disseminated at the county level, the FBI imputes missing values using procedures that may produce inaccurate estimates (Maltz and Targonski 2002). These issues are generally more pronounced for earlier periods than the ones we analyze.

Table G.5. Mexican immigration and other types of crime

	Index crimes per capita					
	All		Violent crime		Property crime	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Share Mexican	-0.130	-0.418	-0.071	-0.170	-0.136	-0.445
	(0.155)	(2.111)	(0.019)	(0.395)	(0.143)	(1.817)
Mean dep. variable	0.265	0.265	0.028	0.028	0.237	0.237
Observations	6,756	6,756	6,756	6,756	6,756	6,756
Number of counties	2,252	2,252	2,252	2,252	2,252	2,252
R-squared	0.900	0.004	0.864	0.059	0.899	-0.009
F-stat		18.702		18.702		18.702

Notes: Years 1990-2010. Beta coefficients reported. The dependent variable is crimes divided by total population. Violent crimes include homicide, rape, robbery and aggravated assault. Property crimes include burglary, theft and motor vehicle theft. All columns include controls for county and year by state fixed effects. Columns 1, 3 and 5 control for share of non-Mexican immigrants and columns 2, 4 and 6 control for predicted share of non-Mexican immigrants predicted by equation B.2. Standard errors clustered at the county level reported in parentheses; Conley standard errors using a distance cutoff of 500 km reported in curly brackets.

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