Online Appendix for Changing Ingroup Boundaries: The Effect of Immigration on Race Relations in the US

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

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B Details on ANES dataset

Table B.1: Summary statistics, state-level ANES dataset

Variable	Mean	Std. Dev.	Min	Max	Obs.
State-level (ANES)					
Feeling thermometer Blacks	63.312	20.302	0	100	17,283
Blacks intelligent	4.264	1.22	1	7	8,147
Blacks hard-working	3.920	1.29	1	7	8,177
Blacks violent	3.445	1.22	1	7	1,791
Blacks trustworthy	4.065	1.17	1	7	1,186
Average attitudes Blacks	-0.129	0.868	-3.123	2.289	17,546
Feel close to Blacks	0.112	0.32	0	1	7,548
Feeling thermometer Hispanics	61.542	20.785	0	100	11,469
Hispanics intelligent	4.337	1.19	1	7	8,055
Hispanics hard-working	4.671	1.35	1	7	8,089
Hispanics violent	3.779	1.13	1	7	1,718
Hispanics trustworthy	4.162	1.162	1	7	1,169
Average attitudes Hispanics	-0.065	0.807	-2.939	2.085	11,747
Feel close to Hispanics	0.130	0.34	0	1	4,128
Feeling thermometer Asian Americans	63.497	19.497	0	100	8,984
Feeling thermometer Muslims	43.587	23.227	0	100	4,999
Problem: Immigration policies	0.005	0.07	0	1	10,753
Problem: Racial problems (positive)	0.004	0.07	0.00	1.00	10,753
Problem: Racial problems (negative)	0.001	0.03	0	1	10,753
Should gov. help Blacks	3.066	1.67	1	7	9,940
School integration	0.409	0.49	0	1	5,841
Gov. guarantee FEP	2.803	1.99	1	5	8,925
Pref. hiring for Blacks	1.519	1.34	1	5	9,449
Racial policy average	-0.156	0.80	-1.31	2.04	16,455
Increase gov. spending	4.060	1.63	1	7	12,765
Conservative	4.299	1.40	1	7	15,995
Female	0.542	0.50	0	1	21,689
Age	47.095	17.72	17	99	21,570
Share Mexican	0.021	0.03	0.00	0.12	21,689
Share non-Mexican	0.064	0.05	0.00	0.20	21,689

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

C 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

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

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 C.1 above to

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

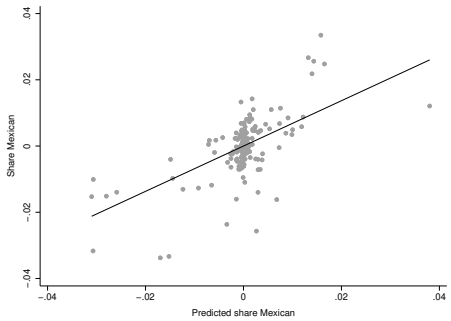
where n indexes immigrant nationalities. In this case, α_s^n is the share of immigrants of nationality n living in state s in 1960 (relative to all immigrants of that nationality in the US).

Table C.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)
Baseline controls × Year FE		Yes	
Predicted share other immigrants			Yes
R-squared	0.98	0.99	0.98
Observations	21,570	21,570	21,570
Number of states	51	51	51
Mean dep. var.	0.021	0.021	0.021

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.

Figure C.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 C.1 displays graphically the relationship between the fraction of Mexican immigrants and the corresponding instrument at the state level. Table C.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.

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 these 1960 state characteristics interacted with year fixed effects. These interactions 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 substantively 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)
R-squared	0.40
Observations	51
Mean dep. var.	0.006

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.

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.

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.

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	78.940	162.402	4.294	10.560
	(36.965)	(103.026)	(1.773)	(4.142)
F-stat	131.3	21.81	132.1	22.28
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
Mean dep. var.	63.31	63.31	-0.129	-0.129

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.

Table D.3: Entropy balance

Dependent variable	Feeling thermometer Blacks		Average attitudes	
	Baseline	Ebalance weights	Baseline	Ebalance weights
	(1)	(2)	(3)	(4)
Share Mexican	78.940	83.212	4.294	6.698
	(36.965)	(29.814)	(1.773)	(2.438)
F-stat	131.3	221.2	132.1	220.7
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
Mean dep. var.	63.31	63.29	-0.129	-0.128

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.

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

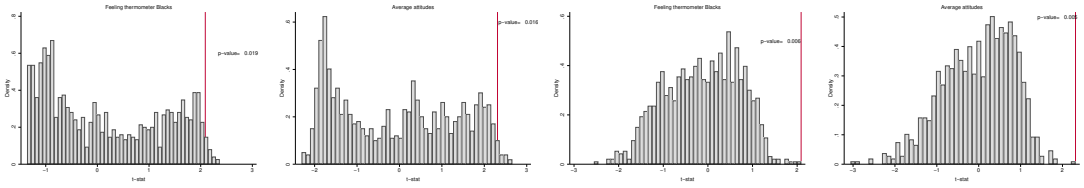
Table D.4: Accounting for the time-varying effect of 1960 Mexican shares

Dep. variable	Feeling thermometer Blacks				Average attitudes			
	Predicted share Mexican		Placebo		Predicted share Mexican		Placebo	
	Reduced form (1)	2SLS (2)	Reduced form (3)	2SLS (4)	Reduced form (5)	2SLS (6)	Reduced form (7)	2SLS (8)
Predicted share Mexican	53.677				2.917			
	(23.636)				(1.208)			
Share Mexican		72.361		24.226		3.968		-0.157
		(34.639)		(35.019)		(1.717)		(1.541)
Placebo predicted share Mexican			11.768				-0.076	
			(17.008)				(0.747)	
R-squared	0.034	0.014	0.034	0.014	0.032	0.010	0.032	0.011
F-stat		87.71		78.57		88.04		78.92
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
Mean dep. var.	63.31	63.31	63.31	63.31	-0.129	-0.129	-0.129	-0.129

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.

time. This indicates that our results are unlikely to be driven by the endogeneity of Mexican inflows.

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.

D.2 Additional robustness checks

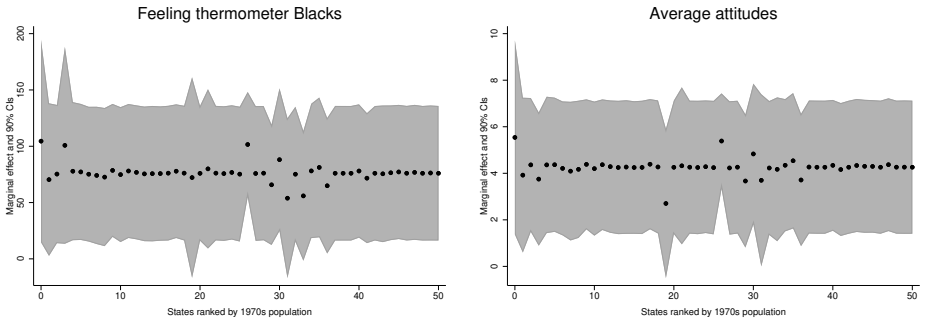
Spatial models. Betz, Cook and Hollenbach (2020) demonstrate that spatial interdependence in the outcome variable may bias 2SLS estimates even when instruments are as good as randomly assigned. To account for potential interdependence in attitudes across states, we estimate spatial autoregressive models in Table D.5. 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 close to zero.

Table D.5: 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	78.940	91.234	120.625	4.294	5.615	15.214
	(36.965)	(40.086)	(75.534)	(1.773)	(1.865)	(9.528)
Share Mexican (spatial lag)		-40.797			-4.527	
		(72.605)			(3.400)	
Feeling thermometer Blacks (spatial lag)			-0.192			
			(0.341)			
Average attitudes (spatial lag)						-1.244
						(1.094)
F-stat	131.3	20	12.22	132.1	19.39	2.615
Observations	17,188	17,188	17,188	17,446	17,446	17,446
Number of states	51	51	51	51	51	51
Mean dep. var.	63.31	63.31	63.31	-0.129	-0.129	-0.129

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.

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.

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. In Table D.6 we show that, even after removing from the sample each of the states that experienced the higher change in their share of Mexicans between 1970 and 2010, as well as all three of them simultaneously, the Mexican share continues to have a positive effect on attitudes towards Blacks.

Table D.6: Dropping outlier states

Sample	Baseline	Drop CA	Drop NV	Drop TX	Drop all three
	(1)	(2)	(3)	(4)	(5)
	Panel A. Dependent variable: Feeling thermometer Blacks				
Share Mexican	78.940	108.232	79.611	102.858	287.948
	(36.966)	(55.433)	(37.064)	(53.816)	(135.234)
F-stat	131.3	61.61	133.8	43.42	11.54
Observations	17,188	15,476	17,111	15,996	14,207
Number of states	51	50	50	50	48
Mean dep. var.	63.31	63.16	63.30	63.17	62.97
	Panel B. Dependent variable: Average attitudes				
Share Mexican	4.294	5.600	4.398	3.759	8.378
	(1.773)	(2.585)	(1.770)	(1.766)	(5.917)
F-stat	132.1	62.33	134.6	43.60	11.20
Observations	17,446	15,704	17,365	16,231	14,408
Number of states	51	50	50	50	48
Mean dep. var.	-0.129	-0.133	-0.129	-0.134	-0.139

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.

Table D.7: 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	36.083	166.195	1.985	10.626
	(61.077)	(81.809)	(2.777)	(4.162)
Lagged share Mexican	-51.879	-132.520	-3.736	-9.069
	(66.889)	(82.114)	(3.146)	(4.115)
R-squared	0.03	0.03	0.03	0.03
F-stat		39.24		40.66
AP F-Stat Share Mexican		236.4		241.6
AP F-Stat Lagged share Mexican		76.65		78.17
Observations	15,334	15,334	15,592	15,592
Number of states	51	51	51	51
Mean dep. var.	63.58	63.58	-0.116	-0.116

Notes: Years 1980-2010. 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 C.2. Standard errors clustered at the state level.

Serial correlation in the instrument. Jaeger, Ruist and Stuhler (2019) 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 (2019) and augment our baseline specification with a lag of the Mexican share, using

both contemporaneous and lagged values of predicted Mexican inflows as instruments. The results in Table D.7 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.

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.8 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.[1]

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 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 (ANES Panel, 2016).[2] 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

[1] 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.

[2] 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.

change state in between.[3] This leaves us with 760 individuals and a total of 2,052 observations – 691 for 2000, 709 for 2002, and 652 for 2004.[4]

Table D.8: 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)
R-squared	0.995	0.006	0.995	0.156
F-stat		22.81		22.81
Observations	255	255	255	255
Number of states	51	51	51	51
Mean dep. var.	11.94	11.94	14.69	14.69

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 C.2. Standard errors clustered at the state level.

In Table D.9, 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 B.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 44 percent of respondents being female (as compared to an average age of 47 and 54 percent of females in the cross-sectional sample). The average Mexican and non-Mexican immigrant share in 2000 is 2.7 and 7.4 percent respectively.

Table D.9: Summary statistics, ANES panel study

Variable	Mean	Std. Dev.	Min	Max	Obs.
Feeling thermometer Blacks	66.113	19.537	0	100	2,336
Feeling thermometer Whites	71.152	18.843	0	100	2,330
Feeling thermometer Hispanics	63.886	19.668	0	100	2,317
Feeling thermometer Asians	65.125	18.973	0	100	2,317
Age	49.770	16.437	18	97	2,633
Female	0.438	0.496	0	1	2,646
Share Mexican	0.027	0.037	0	0.116	2,646
Share Non-Mexican	0.074	0.056	0.010	0.195	2,646

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

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

[3] 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.

[4] 532 of the 760 individuals were interviewed in all of the three years.

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.[5]

Table D.10 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.10: 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)
R-squared	0.62	0.62	0.64	0.64
F-stat		34.33		33.20
Observations	2,052	2,052	2,044	2,044
Number of states	43	43	43	43
Mean dep. var.	66.05	66.05	63.93	63.93

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, 2021), 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.11 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.

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.12, where we compare our estimates to identical specifications using the *change* in Mexican share across two consecutive decades as dependent variable.[6] We estimate

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

[6]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.

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.[7]

Table D.11: 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	46.673	86.842	157.523	1.371	4.240	10.427
	(34.076)	(41.994)	(104.420)	(1.987)	(2.429)	(3.848)
R-squared	0.042	0.013	0.013	0.042	0.013	0.012
F-stat		131.3	22.29		136.1	24.62
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
Mean dep. var.	62.84	62.84	62.84	-0.155	-0.155	-0.155

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.

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.3 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.

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.

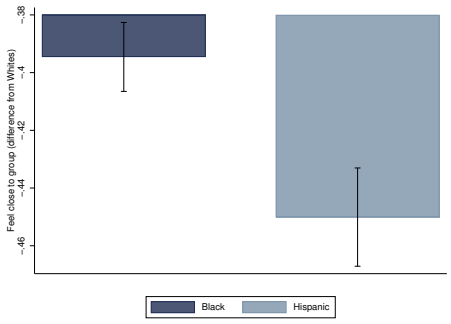
[7]Existing work estimates the effects of change conditional on size. Given that we would be using two instruments that exploit nearly identical variation to simultaneously estimate the effect of changes and level, we are not able to directly replicate this approach of earlier work.

Table D.12: 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	123.646		7.506	
	(62.822)		(3.452)	
Change in share Mexican		118.875		8.450
		(88.906)		(4.358)
F-stat	131.5	95.87	130.7	97.89
Observations	15,334	15,334	15,592	15,592
Number of states	51	51	51	51
Mean dep. var.	63.58	63.58	-0.116	-0.116
	Panel A: Hispanics			
Share Mexican	-329.182		-11.050	
	(183.880)		(5.994)	
Change in share Mexican		-159.000		-3.260
		(68.258)		(2.544)
F-stat	90.71	102.5	89.42	104.7
Observations	11,399	11,399	11,672	11,672
Number of states	51	51	51	51
Mean dep. var.	61.52	61.52	-0.0661	-0.0661

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.

Figure D.3: Average feelings of closeness, by group



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

In Table D.13 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 larger in states with above-median share of Blacks in 1970, but differences are not significant. Improvements in attitudes are driven primarily by states with below-median residential segregation.

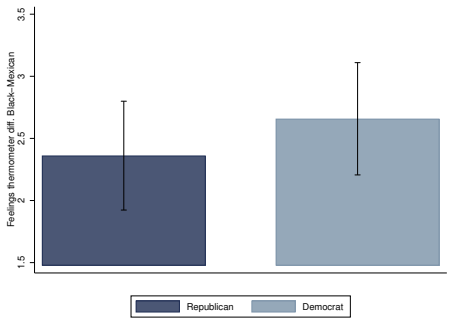
Table D.13: Heterogeneity by degree of contact with Blacks

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	60.364	407.422	-90.476	329.620	60.198	463.766
	(54.665)	(258.729)	(63.538)	(150.154)	(54.112)	(276.187)
F-stat	85.39	18	65.19	75.78	84.12	16.90
Observations	12,570	4,618	12,887	4,159	11,848	5,198
Number of states	26	25	24	23	24	23
Mean dep. var.	63.06	63.99	63.32	63.28	63.08	63.86
	Panel B. Dependent variable: Average attitudes					
Share Mexican	4.729	10.868	-2.672	6.501	4.779	13.366
	(2.832)	(11.474)	(2.458)	(6.095)	(2.836)	(12.279)
F-stat	85.15	17.60	66.08	76.21	83.81	16.54
Observations	12,764	4,682	13,081	4,222	12,035	5,268
Number of states	26	25	24	23	24	23
Mean dep. var.	-0.148	-0.0760	-0.129	-0.129	-0.147	-0.0858

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 C.2. Standard errors clustered at the state level.

We also explore heterogeneity by partisanship. Figure D.4 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.14 shows that increases in the share of Mexicans improve attitudes towards Blacks more for Democrats than for Republicans.

Figure D.4: 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.

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

Table D.14: Heterogeneity by party affiliation

Dependent variable	Feeling thermometer Blacks		Average attitudes	
	(1)	(2)	(3)	(4)
Share Mexican	67.013	89.362	3.827	4.642
	(36.423)	(36.370)	(1.742)	(1.767)
Share Mexican × Democrat	38.220		1.501	
	(8.910)		(0.441)	
Share Mexican × Republican		-19.743		-0.639
		(7.070)		(0.273)
F-stat	65.64	65.99	66.06	66.47
AP F-Stat Share Mexican	285.5	232.9	280.4	226.3
AP F-Stat Interaction	43.34	25.20	42.61	25.28
Observations	17,188	17,188	17,446	17,446
Number of states	51	51	51	51
Mean dep. var.	63.31	63.31	-0.129	-0.129

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.

scale), and whether they are for or against preferential hiring for Blacks (agreement level on a 1-5 scale). We recode all items so that higher values indicate higher support for government intervention in favor of Black people.

Table D.15: 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	7.011
	(174.651)	(0.820)	(3.295)	(26.002)	(1.314)
F-stat	0.159	119.6	119.9	8.637	113.5
Observations	9,875	5,825	8,868	9,378	16,358
Number of states	51	45	51	51	51
Mean dep. var.	3.067	0.409	2.804	1.519	-0.156

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.

Table D.15 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.[8] 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.16 examines the effect of Mexican immigration on broader ideology and policy preferences. The outcome in columns 1–2 is the respondent's self-placement on a 1–7 liberal-conservative scale, with higher values indicating higher conservatism. In columns 3–4 the

[8]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.

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.16: 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)	(3.158)	(8.750)
Number of states	51	51	51	51
R-squared	0.05	0.05	0.05	0.05
F-stat		139.69		63.84
Observations	15,916	15,916	12,700	12,700
Number of States	51	51	51	51
Mean dep. var.	4.299	4.299	4.062	4.062

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 C.2. Standard errors clustered at the state level.

Taken together, results from Tables D.15 and D.16 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.[9]

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.17 presents the full set of estimates corresponding to the analysis of Figure 2 in the main paper.

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

[9]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 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.17: Cross-group effects

Dependent variable	Feeling thermometer			Average attitudes		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Effect on Blacks					
Share Mexican	72.361	52.867	43.864	3.968	4.312	2.860
	(34.639)	(56.205)	(47.820)	(1.717)	(2.517)	(2.228)
Share Asian		101.712			-1.804	
		(122.311)			(5.798)	
Share Arab			493.801			19.304
			(401.442)			(20.220)
F-stat	87.71	27.83	12.05	88.04	28.60	12.19
Observations	17,188	17,188	17,188	17,446	17,446	17,446
Number of states	51	51	51	51	51	51
Mean dep. var.	63.31	63.31	63.31	-0.129	-0.129	-0.129
	Panel B: Effect on Hispanics					
Share Mexican	-301.072	-367.081	-305.341	-9.706	-10.961	-9.638
	(170.654)	(189.937)	(168.412)	(5.750)	(6.443)	(5.756)
Share Asian		607.270			11.946	
		(341.481)			(12.080)	
Share Arab			297.133			-5.248
			(822.454)			(28.048)
F-stat	55.21	40.72	15.97	54.78	39.99	15.42
Observations	11,399	11,399	11,399	11,672	11,672	11,672
Number of states	51	51	51	51	51	51
Mean dep. var.	61.52	61.52	61.52	-0.0661	-0.0661	-0.0661
	Panel C: Effect on Asian-Americans					
Share Mexican	-183.012	-148.951	-251.040	-22.898	-20.564	-28.693
	(256.227)	(234.716)	(349.154)	(11.642)	(10.322)	(17.952)
Share Asian		390.265			26.168	
		(255.045)			(15.156)	
Share Arab			-596.775			-50.324
			(1,301.947)			(91.310)
F-stat	21.11	10.55	1.589	21.18	10.61	1.531
Observations	8,917	8,917	8,917	9,201	9,201	9,201
Number of states	51	51	51	51	51	51
Mean dep. var.	63.50	63.50	63.50	-0.0309	-0.0309	-0.0309

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.

of counties sampled in at least two decades (Table E.1). Summary statistics are displayed in Table E.2.

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 (Smith et al., 2018), for years 1993-2010 for which county identifiers are available. The GSS covers a somewhat wider set of counties across multiple decades (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 of the extended appendix available with replication materials. 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.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	154	384	4,476	12,520
Counties available in three decades	225	294	7,744	7,681

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

Variable	Mean	Std. Dev.	Min	Max	Obs.
ANES					
Feeling thermometer Blacks	63.636	19.956	0	100	12,066
Feeling thermometer Hispanics	58.811	20.267	0	100	9,268
Average attitudes Blacks	-0.114	0.887	-3.155	2.448	12,216
Average attitudes Hispanics	-0.115	0.871	-2.925	2.470	9,445
Age	46.568	17.823	17	99	13,581
Female	0.543	0.498	0	1	13,616
Share mexican	0.018	0.040	0	0.283	13,616
Share Non-Mexican	0.048	0.055	0.001	0.444	13,616
GSS					
Attitudes towards Blacks	-0.072	0.622	-2.759	1.797	15,143
Attitudes towards immigrants	-0.059	0.909	-1.730	2.472	6,178
Age	47.586	17.374	18.000	89.000	20,565
Female	0.548	0.498	0.000	1.000	20,619
Share Mexican	0.022	0.039	0.000	0.240	20,619
Share Non-Mexican	0.058	0.069	0.001	0.464	20,619

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

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.[10] 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 C.1 and C.2, where α_c^{Mex} and α_c^n are computed using the procedure just described.

[10]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.3: 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	-28.110	64.532	64.177	10.522	-1.794	2.212	2.267	12.551
	(37.723)	(34.069)	(33.982)	(653.698)	(1.845)	(1.427)	(1.384)	(27.539)
R-squared	0.085	0.017	0.016	0.017	0.085	0.018	0.018	0.016
F-stat		15.59	15.60	1.793		15.05	15.06	1.907
Observations	11,780	11,780	11,780	11,780	11,912	11,912	11,912	11,912
Number of counties	239	239	239	239	244	244	244	244
Mean dep. var.	63.62	63.62	63.21	63.62	-0.116	-0.116	-0.124	-0.116
	Panel B: Hispanics							
Share Mexican	-56.152	-75.529	-71.457	-446.912	-2.855	-7.056	-6.940	13.537
	(38.539)	(63.075)	(67.248)	(717.856)	(2.237)	(2.519)	(2.762)	(25.532)
R-squared	0.098	0.005	0.004	0.000	0.092	0.004	0.006	-0.000
F-stat		12.37	12.26	1.869		12.31	12.21	2.098
Observations	8,995	8,995	8,995	8,995	9,155	9,155	9,155	9,155
Number of counties	237	237	237	237	241	241	241	241
Mean dep. var.	58.76	58.76	60.62	58.76	-0.117	-0.117	-0.0288	-0.117

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 C.2. In columns (3) and (7) 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.

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.3 and E.4. 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.3). We report these results for completeness, but we obviously cannot interpret any of the estimated 2SLS coefficients.

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 (Kuriwaki, 2018). The CCES contains identifiers for respondents' zip codes. To match zip codes to tract-level demographics we use yearly crosswalks 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

Table E.4: 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	5.139	5.421	9.610	-1.084	-6.087	-5.957	-7.030
	(0.808)	(2.280)	(2.368)	(3.851)	(3.252)	(7.079)	(7.025)	(25.846)
R-squared	0.159	0.052	0.047	0.048	0.127	0.005	0.007	0.005
F-stat		18.82	18.31	15.66		22.17	22.22	3.095
Observations	15,102	15,102	15,102	15,102	6,153	6,153	6,153	6,153
Number of counties	322	322	322	322	308	308	308	308
Mean dep. var.	-0.0720	-0.0720	-0.0644	-0.0720	-0.0585	-0.0585	-0.0270	-0.0585

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 C.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.

randomly assign individuals relying on zip-tract overlaying weights.[11] 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 (U.S. Census Bureau ACS, 2019). 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.[12] 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 (C.1) and (C.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.

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

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

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 of the extended appendix provided with the replication materials. 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 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.

Table E.5: Summary statistics, tract-level

Variable	Mean	Std. Dev.	Min	Max	Obs.
Racial attitudes					
Racial resentment	0.115	0.885	-1.960	1.419	12,5591
Age	53.542	15.719	18	96	12,5591
Female	0.520	0.500	0	1	12,5591
Share Mexican	0.022	0.049	0	0.523	12,5535
Share Non-Mexican	0.075	0.091	0	0.816	12,5535
Immigration attitudes					
Immigration policy	0.459	0.364	0	1	15,7054
Age	52.484	15.880	17	98	15,7054
Female	0.517	0.500	0	1	15,7054
Share Mexican	0.022	0.049	0	0.536	15,6989
Share Non-Mexican	0.076	0.093	0	1	15,6989

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

Table E.6: 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)
F-stat		45.75	53.32	53.39		98.57	96.21	96.21
Observations	115,341	115,334	115,252	115,252	145,877	145,869	145,745	145,745
Number of tracts	24659	24658	24640	24640	27960	27959	27935	27935
Mean dep. var.	0.119	0.119	0.119	0.119	0.459	0.459	0.459	0.459
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 C.2. Standard errors clustered at the census tract level.

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 of the extended appendix available with replication materials. 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.5.

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.[13] 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.[14] 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.

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

[13] 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.

[14] 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.

thermometer and all (recoded) attributes with the exception of "American".[15] Summary statistics of variables used in the analysis are provided in Table F.1.

Table F.1: Summary statistics

	Mean	Std	Min	Max	N
Respondent characteristics					
Age	48.82	16.27	18	90	499
Female	0.499	0.501	0	1	499
Democrat	0.407	0.492	0	1	499
Republican	0.297	0.457	0	1	499
Independent	0.265	0.442	0	1	499
Other	0.032	0.176	0	1	499
Northeast	0.194	0.396	0	1	499
Midwest	0.206	0.405	0	1	499
South	0.397	0.490	0	1	499
West	0.202	0.402	0	1	499
Education: Less than college	0.413	0.493	0	1	499
Education: College or higher	0.585	0.493	0	1	499
Household income <$50,000	0.321	0.467	0	1	499
Household income $50,000 - $99,000	0.383	0.487	0	1	499
Household income $100,000 - $149,000	0.068	0.252	0	1	499
Household income $150,000 - $199,000	0.102	0.303	0	1	499
Household income > $200,000	0.126	0.332	0	1	499
Attitudes towards Blacks					
American	3.964	0.985	1	5	499
Thermometer	5.771	2.901	0	10	476
Principal component	0.000	1.678	-4.867	2.841	476
Attitudes towards Hispanics					
American	3.591	1.115	1	5	499
Thermometer	5.621	2.956	0	10	488
Principal component	0.000	1.553	-5.393	2.630	488
Attitudes towards Asians					
American	3.605	1.101	1	5	499
Thermometer	5.458	3.022	0	10	480
Principal component	0.000	1.505	-5.995	2.326	480
Attitudes towards Muslims					
American	3.216	1.284	1	5	499
Thermometer	4.619	3.045	0	10	475
Principal component	0.000	1.699	-4.558	3.025	475
Attitudes towards Whites					
American	4.214	0.892	1	5	499
Thermometer	7.299	2.521	0	10	478
Principal component	0.000	1.604	-6.156	2.481	478

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

[15]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).

we aggregate into four categories (Democrat, Republican, Independent, Other).

Table F.3 presents average treatment effects on attitudes and views of a group as American, for all groups in the survey.

Table F.2: Randomization check

	Control	Treatment	Difference	P-value
Age	48.12	49.48	-1.362	0.351
Female	0.512	0.486	0.026	0.562
Democrat	0.450	0.367	0.083	0.059
Republican	0.279	0.313	-0.034	0.413
Independent	0.254	0.274	-0.020	0.614
Other	0.017	0.046	-0.030	0.060
Northeast	0.221	0.170	0.051	0.151
Midwest	0.192	0.220	-0.028	0.434
South	0.383	0.409	-0.026	0.555
West	0.204	0.201	0.003	0.925
Education: Less than college	0.392	0.432	-0.041	0.356
Education: College or higher	0.608	0.564	0.045	0.313
Household income <50,000	0.354	0.290	0.065	0.123
Household income 50,000 – 99,000	0.358	0.405	-0.047	0.281
Household income 100,000 – 149,000	0.063	0.073	-0.011	0.631
Household income 150,000 – 199,000	0.100	0.104	-0.004	0.876
Household income >200,000	0.125	0.127	-0.002	0.936

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	0.158	0.234	0.067	0.092	0.074	0.054	0.048	0.114	-0.086	-0.109
	(0.092)	(0.094)	(0.091)	(0.095)	(0.092)	(0.097)	(0.092)	(0.090)	(0.092)	(0.091)
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	0.182	0.183	0.057	0.080	0.097	0.121	-0.025	0.027	0.040	0.027
	(0.090)	(0.095)	(0.090)	(0.090)	(0.090)	(0.092)	(0.090)	(0.086)	(0.090)	(0.093)
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.

G Analysis of hate crimes

G.1 Data on hate crimes

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.

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, crime data

	Mean	Std	Min	Max	N
Hate crimes					
Against Blacks, all offenders	7.915	12.874	0	283	4,981
Against Hispanics, all offenders	1.741	4.967	0	124	4,981
Against Blacks, White offenders	5.245	8.077	0	158	4,220
Against Hispanics, White offenders	1.362	4.362	0	99	4,220
Index crimes					
All	26,440	17734.711	0	335,120	6,876
Violent	2,807	2692.417	0	85,165	6,876
Property	23,633	15652.377	0	249,956	6,876

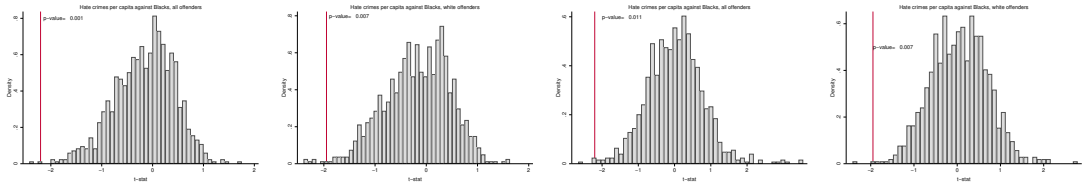
Notes: Numbers reported are crimes per 100,000 people, averaged over decades. Years 1990-2010.

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.1). 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.

Figure G.1: 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.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	-1.405	-1.436	-0.707	-2.410	-2.448	-1.075
	(0.635)	(0.665)	(0.402)	(1.231)	(1.286)	(0.585)
	{0.656}	{0.678}	{0.428}	{1.146}	{1.193}	{0.567}
F-stat	10.36	9.689	19.01	7.572	6.940	20.97
Observations	4,350	4,350	4,350	3,547	3,547	3,547
Number of counties	1662	1662	1662	1376	1376	1376
Mean dep. var.	0.0254	0.000898	0.0254	0.0108	0.0695	0.0108
	Panel B: Hispanic victims					
Share Mexican	0.395	0.252	0.591	1.227	1.244	1.026
	(0.926)	(0.977)	(0.753)	(1.359)	(1.403)	(0.945)
	{0.855}	{0.898}	{0.676}	{1.381}	{1.425}	{0.965}
F-stat	10.36	9.689	19.01	7.572	6.940	20.97
Observations	4,350	4,350	4,350	3,547	3,547	3,547
Number of counties	1662	1662	1662	1376	1376	1376
Mean dep. var.	0.00365	0.0711	0.00365	-0.0124	0.0388	-0.0124
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 C.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.

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 homi-

cide, rape, robbery and aggravated assault. Property crimes include burglary, theft and motor vehicle theft.

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	0.047	-1.170	0.068	-1.158
	(0.048)	(0.580)	(0.054)	(0.840)
	{0.044}	{0.643}	{0.057}	{0.806}
R-squared	0.550	-0.192	0.588	-0.216
F-stat		10.36		7.572
Observations	4,350	4,350	3,547	3,547
Number of counties	1662	1662	1376	1376
Mean dep. var.	-0.00393	-0.00393	-0.0136	-0.0136
	Panel B: Hispanic victims			
Share Mexican	0.046	0.012	0.073	0.213
	(0.138)	(0.383)	(0.182)	(0.535)
	{0.115}	{0.434}	{0.168}	{0.633}
R-squared	0.554	0.000	0.587	-0.002
F-stat		10.36		7.572
Observations	4,350	4,350	3,547	3,547
Number of counties	1662	1662	1376	1376
Mean dep. var	0.00202	0.00202	-0.00438	-0.00438

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 C.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.

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).

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	0.447	-9.550	-0.029	-5.940
	(0.941)	(14.180)	(0.197)	(3.865)
R-squared	0.984	-0.058	0.996	-0.342
F-stat		26.87		23.13
Observations	6,812	6,812	6,876	6,876

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 C.2. Standard errors clustered at the county level.

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	-0.126	-0.269	-0.065	-0.109	-0.131	-0.286
	(0.026)	(0.341)	(0.021)	(0.410)	(0.027)	(0.334)
F-stat		23.13		23.13		23.13
Observations	6,876	6,876	6,876	6,876	6,876	6,876
Number of counties	2292	2292	2292	2292	2292	2292

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 C.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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