White Flight in the 21st Century

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Abstract

I use a national dataset of U.S. elementary school student demographics to show that White Flight - the accelerating emigration of whites from demographically mixed neighborhoods - was still an important dynamic in the first two decades of the 21st century. On average, white schools reached the 'tipping point' - the point at which net white exodus begins and accelerates - at a white share around 95%. Leveraging Mediated Intergroup Contact (MIC) theory and the Obama campaign as a natural experiment, I provide causal evidence through a difference-in-differences approach that MIC measurably reduced the intensity of white flight. This finding challenges the idea that racial preferences may no longer be an important driver of segregation patterns. It highlights the persistent influence of structural and cultural racism in residential mobility. I exploit the theory of Mediated Intergroup Contact to give a lower bound to the impact of anti-black prejudiced stereotypes on White Flight. At the mean white share of 57.5%, 2.2% of white elementary school students will flee the school in the following year. The proportion of this effect attributable to anti-black prejudiced stereotypes can be conservatively lower bounded at 23.6%.

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1 Introduction

In the 1950s, the demographics of U.S. cities began to shift. White families moved to the suburbs while black and often poorer families migrated into urban centers. This phenomenon became known in popular narratives and early academic discussions as White Flight (WF) (Grodzins, 1958; Weaver, 1960). Anti-black prejudice and pro-white sentiments were proposed as key drivers of White Flight but alternate explanations emerged early on, including differential returns on real estate, the effects of race-based housing policies, differential crime rates, and exogenous demographic shifts (Weaver, 1960; Schelling, 1969, 1971). Given the strong correlation between race, income, and socioeconomic status in the U.S., racial prejudice, statistical discrimination, and economic incentives may have created a vicious cycle of White Flight (Derenoncourt, 2022; Frey, 1979; on Civil Disorders, 2016). The result of these twined effects was labeled 'Urban Decay' in early public discourse. This was a welcome euphemism during an era of intense public debates surrounding the civil rights movement and the dismantling of Jim Crow because it shifted attention away from the racial underpinnings of these patterns. The role of race in postwar WF remains a sensitive subject in policy discussions and a subject of ongoing research in academic circles. Empirical studies continue to disentangle the relative influence of subjective racial preferences like prejudice and homophily from quantifiable differences in housing quality, public goods, and real estate returns in shaping these migration patterns (Davis et al., 2023; Daepp et al., 2023; Aliprantis et al., 2022; Bayer et al., 2022; Malone, 2020; Li et al., 2020; Rosenthal and Ross, 2015; Boustan, 2010; Card et al., 2008; Reber, 2005; Quillian and Pager, 2001; Clotfelter, 2001).

Economic models of White Flight have long focused on "tipping," where a neighborhood becomes unstable once it reaches a critical demographic threshold (Grodzins, 1958; Weaver, 1960; Schelling, 1969, 1971; Clark, 1991; Card et al., 2008; Easterly, 2009; Zhang, 2011; Caetano and Maheshri, 2017). Tipping can be driven by racial preferences, socioeconomic status, or both, reinforcing patterns of segregation. Racial-preference-based tipping remains a key explanatory mechanism behind the stubborn persistence of U.S. residential segregation. Tipping based on socioeconomic factors correlated with race can be understood to be a form of statistical discrimination that works through the same channel. Other proposed mechanisms for persistent segregation include place stratification and spatial assimilation models and barriers to black mobility into white neighborhoods such as housing price differentials and limited outside options (Logan et al., 2023; Blair, 2023; Bartik and Mast, 2021; Malone, 2020; Bayer et al., 2017; Shapiro et al., 2004; Charles, 2003; South and Crowder, 1998). The extent to which racial-preference-based tipping still affects the dynamics of the U.S. real estate market is an important question that this paper, along with other recent research, directly addresses (Davis et al., 2023; Blair, 2023; Aliprantis et al., 2022; Bayer et al., 2022; Malone, 2020; Li et al., 2020). Forces of urban renewal and gentrification have begun to work in the opposite direction of post-war Urban Decay and there is some evidence that racial segregation in some U.S. cities is becoming less dominated by the historic white/black dichotomy (Clark et al., 2015; Boustan et al., 2024). In the post-war era, White Flight was easy to discern: the urban-to-suburban emigration of whites and the concomitant urban immigration of blacks was a sectoral sea-change. But today's White Flight is not so much a well defined wave but more a chaotic churn from suburb to suburb and neighborhood to neighborhood. As illustrated in Figure 1, white share in neighborhoods is decreasing nationally. This is partly driven by an overall decrease in white share of the U.S. population, and partly by an increase in the proportion of neighborhoods that are racially integrated (Colby and Ortman, 2015; Ellen et al., 2012).

The potential of White Flight to reinforce and even exacerbate historic racial wealth disparities through lower real estate returns is well documented. Although White Flight may have made black homoeownership more possible (Boustan and Margo, 2013), homes in black neighborhoods are persistently undervalued even after accounting for differences in housing and neighborhood quality. Perry et al. (2018) estimate this undervaluation in majority black neighborhoods to be, on average, $48,000 per home - a cumulative loss of $156 billion nationally. Identified channels of this devaluation include reduced demand due to racial preferences and stereotypes, higher concentrations of distressed home sales, lower rates of owner occupation, racist ideas and actions of brokers, and the fact that neighborhood racial composition is still an implicit determining factor in U.S. real estate appraisals (Akbar et al., 2022; Kermani and Wong, 2021; Howell and Korver-Glenn, 2021; Korver-Glenn, 2021; Perry et al., 2018; Shapiro et al., 2004; Flippen, 2004, 2001; Harris, 1999).

This paper uses OLS regression to show that White Flight persists today and two segment cubic spline regressions to identify the Tipping Point. A second model, using a difference-in-differences approach, shows that a treatment for negative racial stereotypes reduced White Flight. Unlike previous studies that focus on socioeconomic or structural factors, this analysis isolates a single channel of influence — negative racial stereotypes — and quantifies its role in shaping demographic change. The results give evidence that anti-black racial prejudice is still an important driver of White Flight. This is a critical extension of classical tipping models, demonstrating that a cultural intervention can shift the behaviors that contribute to segregation.

The treatment for racial prejudice that this paper leverages is known as Mediated Intergroup Contact. MIC is built upon Gordon Allport's contact hypothesis, which was first published in 1954 (Allport, 1954). In the intervening years, Intergroup Contact has been widely examined and found to be an effective palliative for prejudice against out-groups in general, and racial prejudice in particular (Pettigrew and Tropp, 2006; Paluck et al., 2019; Brown et al., 2022). The effectiveness of Mediated

Intergroup Contact, an extension of Intergroup Contact in which individuals are exposed to the out-group through media portrayals rather than direct social contact, has in turn been well documented (Garretson, 2015; Wojcieszak and Azrout, 2016; Ramasubramanian, 2013; Goldman, 2012; Goldman and Hopkins, 2019; Haynes and Block, 2019; Tukachinsky et al., 2015; Schiappa et al., 2005; Lemmer and Wagner, 2015; Kite et al., 2022). My identification strategy is rooted in the application of MIC theory to the 2008 election as laid out by Goldman (2012) and Goldman and Mutz (2014), who show that the media coverage of the 2008 presidential campaign decreased race-based stereotypes among racially prejudiced individuals. This is, perhaps, counterintuitive because the politically - and sometimes racially - charged rhetoric of conservative media is well documented to have swayed opinions against democrats and President Obama, both inside and outside the ballot box (DellaVigna and Kaplan, 2007; Tope et al., 2014, 2017). Studies that examine prejudice in response to the Obama campaign and presidency do not show that the media portrayals generally decreased Racial Animus among prejudiced voters in the medium to long term (Enns and Jardina, 2021; Pasek et al., 2014; Yadon and Piston, 2019; Schmidt and Axt, 2016; Tesler, 2020). But Barack Obama was portrayed in the media as employed, with a stable family, successful, well dressed, and intelligent. These are all important attributes of a good neighbor. MIC tells us that these portrayals should undermine the most pertinent stereotypes behind White Flight even when they are in the context of negative campaign ads or partisan vitriol and whether or not there is an associated relaxation or heightening of racial tensions among certain segments of the white population. Empirical evidence confirms that this occurred as MIC theory predicts (Goldman, 2012; Goldman and Mutz, 2014; Goldman and Hopkins, 2019).

There are at least five related mechanisms by which White Flight can be connected to racial preference: Homophily, Racial Solidarity, Racial Animus, Statistical Discrimination, and Negative Racial Stereotypes. The distinctions between these five mechanisms are at times subtle. The correlations between these mechanisms - that is, the extent to which a person who exhibits racial preferences driven by one of these mechanisms also exhibits preferences driven by another - are beyond the scope of this paper and are well explored in sociological literature (e.g. Small and Pager (2020); Mijs and Roe (2021).) Importantly, MIC unambiguously treats only one of these channels - Negative Racial Stereotypes.

The distinction between Negative Racial Stereotypes and Statistical Discrimination can be subtle - but important. Take, for instance, the belief that an African American's presence in the neighborhood will decrease a white household's property value due to the practice of "comping" - the process of comparing a property to similar properties to determine its value. Statistical Discrimination would support this belief. A rational homeowner may recognize that appraisers systematically undervalue homes owned by blacks (Flippen, 2004). If a black neighbor sells their home before an existing white household leaves the neighborhood, this systematic undervaluation of black-owned properties will be shared with their white neighbors in the next appraisal of the white family's dwelling through comping. The existing white homeowner may calculate the estimated differential to their property value from this channel and choose to leave the neighborhood before their black neighbor sells in order to avoid capturing this loss of real estate value. This act would be a component of White Flight attributable to Statistical Discrimination. MIC theory does not posit that a treated white homeowner would change any behaviors that are based on this mechanism. MIC does not convince them to take a rationally estimated financial loss. Nor does MIC posit that a treated white homeowner's estimation of the financial loss would become incorrectly biased after treatment. MIC does not change rational and calibrated assessments that treated ingroup members make of the outgroup. Rather, MIC treats the irrational and/or incorrectly biased assumptions of ingroup members that are based on inaccurate racial stereotypes.

Imagine instead that a white homeowner has a new black neighbor and the white homeowner believes that blacks are in some way inferior employees or less likely to keep their job. In this case, the white homeowner may fear that the new black neighbor will lose their job and sell their home as a distressed property, thereby lowering the white homeowner's real estate value through comping. This belief is not rational because the new black neighbor must have cleared similar institutional hurdles as the white homeowner with their mortgage lender to confirm income stability. If the white homeowner were to preemptively exit the neighborhood in order to avoid capturing this incorrectly anticipated loss of real estate value, this would be White Flight attributable to anti-black racial stereotypes. This channel is directly treated by MIC. MIC can undermine the stereotype and convince the existing white homeowner that blacks can be hardworking, intelligent, and successful in their careers. But this is the only one of the five racial preference mechanisms for White Flight that is treated by MIC. The fact that MIC can undermine negative racial stereotypes does not imply that it decreases Racial Animus. Recognizing that blacks can be stable and successful does not equate to wanting to to have a black neighbor over for a cookout or a block party. Socially undesirable neighbors may drive an existing homeowner to exit a neighborhood. An ingroup member may have a history of disliking people of a particular race for any number of reasons. And there is no reason to believe that intergroup contact, mediated or otherwise, systematically undermines these preferences. It is always possible that the ingroup member will especially dislike the particular exemplar of the outgroup. And this could even increase - rather than decrease - Racial Animus. In fact, in the context of the Obama campaign, there is evidence that media coverage may have increased Racial Animus even while it decreased anti-black prejudiced stereotypes (Enns and Jardina, 2021; Pasek et al., 2014; Yadon and Piston, 2019;

Schmidt and Axt, 2016; Tesler, 2020). Similarly, there are no mechanisms by which MIC directly treats Homophily - the subjective preference for members of the ingroup - or feelings of Racial Solidarity within the ingroup.

In this paper, I establish that white flight was still an important phenomenon throughout the first two decades of the 21st century. The intensity of white flight remained stable during the 1990s. It may have decreased slightly in the 2000s and it clearly decreased significantly in the 2010s. I establish that an event occurs which causes the White Flight Tipping Point to vanish for the 2009-2010 school year. The tipping point returns the following school year, but measures of White Flight intensity remain at a lower level after this disruption. Controls, placebo tests, and the timing of the events allow me to argue that despite structural changes due to the great recession and the 2007 housing crisis, the most plausible explanation for this disruption is Mediated Intergroup Contact from the 2008 presidential campaign - the so-called "Obama Effect." In my interpretation, White Flight responded to MIC treatment in the form of media portrayals of the Obama family as black exemplars. Alternative explanations - which rely on confounds such as the great recession (illustrated in Figure 5), regional unemployment patterns (which are controlled for with State fixed effects), and structural changes to the housing market (illustrated in Figure 5) - are less plausible than my interpretation. MIC impacts Negative Racial Stereotypes, but has no theoretical impact on other mechanisms for White Flight such as Homophily, In-group Solidarity, Racial Animus, or Statistical Discrimination. If I am, as I propose, capturing the effects of MIC on White Flight, my analysis can provide a lower bound on the percent of White Flight that was caused in the first two decades of the 21st century by the racist stereotypes undermined by MIC.

2 Data

In order to measure demographics at a spatial and temporal resolution sufficient to identify the neighborhood-to-neighborhood churn of present day White Flight, this paper uses elementary school demographics as a proxy for neighborhood demographics. Census data is only available every ten years, and the finest spatial resolution in Census data is the Public Use Microdata Area (PUMA), which contains at least 100,000 people. There were 13,452 regular elementary schools in the US in 2020 and 2,487 PUMAs, so the spatial resolution based on elementary school data is better than five times higher. Figure 1 illustrates one reason elementary school demographics are a good proxy for neighborhood demographics. There is a strong linear relationship between average white shares of enrollment in elementary schools and the average white shares of PUMA population as derived from Census and ACS data. The fact that the school average is lower and has a more negative slope can be at least partially explained by the higher rates of fertility in the non-white population and higher rates of private school attendance among whites (Passel et al., 2012; Reardon et al., 2006). The linearity of this relationship implies that the white share of elementary school population is a good proxy for the white share of residential population in this context. But there is an even stronger argument to be made for using elementary school data: the racial demographics of the local public elementary school is such an important factor in White Flight that it may not be a proxy at all. Americans have long been deeply concerned with the skin color of their children's schoolmates, and market-enabled segregation of elementary schools by way of migration may be the very heart of the issue. In the context of White Flight, real estate transactions might rightly be understood primarily as a method families use to choose which school their children will attend. The National Association of Realtors found that 29% of 2013 home buyers cited school district quality as a primary factor in choosing a home (NAR, 2014). Malone (2020) finds evidence that an income-based tipping mechanism is the primary driver of White Flight from schools - postulating that families flee due to concerns that public schools will become underprovisioned once families of lower socioeconomic status move in. But Chin (2022) finds evidence that race-based school preferences are more stable than preferences based on school quality. White Flight's long and intimate connection to preferences for segregated public schooling is well studied (Clotfelter, 2001; Caetano and Maheshri, 2017), and the historical role of racial prejudice and homophily in the context of schooling cannot be reasonably refuted.

I use K-12 public elementary school district data from all 50 states plus Washington D.C. Unified districts - that is, school districts that combine elementary schools with middle or high schools - are excluded because they draw from a larger catchment than elementary school districts. Magnet schools such as vocational-technical or agricultural schools as well as private and charter schools are excluded because they draw students from outside their local neighborhood. I use the National Center for Education Statistics (NCES) dataset obtained from The Institute of Education Sciences (IES) website for the 2000-2001 school year through the 2019-2020 school year for every state and D.C. This includes enrollment data by gender and race, school characteristics, and location data for each school. The demographic trend toward greater diversity is evident in the summary statistics reported in Table 1. Both white share and black share decrease after 2008, while Hispanic share and share of other race (non-Asian, white, or black) increase.

3 Evidence for White Flight In the Years 2000 through 2020

3.1 Identification and Estimation

Figure 2 illustrates the average percent change in elementary school white share between years t and $t+1$ with respect to the white share in year t. In the middle three quintiles, there is a positive correlation between white share and the rate of change in white share. That is, the loss of white share accelerates as white share drops. Under the assumption that the total number of students remains constant, the lower the white share, the greater percentage of white students are replaced by non-white students the following year. This is White Flight. The tipping point is within the top quintile. Above this point is a reversal, where white share is negatively correlated with year-over-year change. A similar reversal happens in the middle of the bottom quintile, around 15% white share. In this range other forces, such as reversion to the mean and the effects of gentrification, begin to dominate.

$$\%\Delta WhiteShare_{est} = \beta_0 + \beta_1 WhiteShare_{et} + \beta_2 WFtrend_{et} + X'_{et} + \zeta_{st} + \epsilon_{et} \tag{1}$$

The OLS regression specified in equation 1 estimates the magnitude of White Flight in the period between fall 2000 and spring 2020. It is estimated on the middle three quintiles, by white share, of the elementary school data. $\%\Delta WhiteShare_{et}$ is the percent change in the share of enrolled students identifying as white in elementary school e between year t and $t+1$. It is calculated $(WhiteShare_{e,t+1} - WhiteShare_{et})/WhiteShare_{et}$. $WhiteShare_{et}$ is the share of enrolled students identifying as white in elementary school e during year t. The coefficient of interest is β_1. A positive coefficient indicates White Flight. The larger the coefficient, the greater the intensity of White Flight. $WFtrend_{et}$ is the interaction between $Year_t$ and $WhiteShare_{et}$. It controls for linear trends in the prevalence of White Flight. A negative value of β_3 is evidence that White Flight is decreasing over time (as the US becomes more diverse and possibly more tolerant of diversity.) ζ are state-year fixed effects, and X'_{et} is a vector of controls at the elementary-year level including: share of students receiving free lunch, number of students in the school, share of Hispanic students, share of Asian or Other Race students, latitude, longitude, and indicators for city (small, medium, and large), suburb (s,m,l), town (small, large), and rural.

$$
\begin{aligned}
&\%\Delta WhiteShare_{est} = \gamma_0 + \gamma_1 WhiteShare_{et} + \gamma_2 WhiteShare_{et}^2 + \gamma_3 WhiteShare_{et}^3 + \\
&\delta_0 D_{et} + \delta_1 (D_{et} \times WhiteShare_{et}) + (D_{et} \times \delta_2 WhiteShare_{et}^2) + (D_{et} \times \delta_3 WhiteShare_{et}^3) + \\
&\beta_2 WFtrend_{et} + X'_{et} + \zeta_{st} + \epsilon_{et}
\end{aligned} \tag{2}
$$

The two-region cubic spline regression specified in equation 2 is used to estimate the Tipping Point. In general, a higher Tipping Point is associated with greater White Flight intensity. Here the indicator variable D_{et} takes the value of 1 if $WhiteShare_{et}$ is above the knot placed at the boundary between the third and fourth quintiles. Results are generally robust to alternative knot placement, as is reported in Appendix Table A1. The remaining variables are as defined in Equation 1. The regression is constrained such that the value and first derivative of the regression estimates are equal at the knot. The maximum of the top region, calculated using the first-order-condition that the first derivative equal zero, is the estimated tipping point. The bootstrap algorithm is performed on 1000 resamples to estimate the confidence intervals. A detailed discussion of the algebra is included in Appendix B

3.2 Results and Interpretation

The results of estimating equations 1 and 2 are reported in Table 2. The uncontrolled regression in column (1) is illustrated overlaying the data (shown as means of 2% white share bins for visual clarity) in Figure 2. The uncontrolled estimate of the Tipping Point is 95.1%. Below the Tipping Point, white share decreases at an accelerating rate.

Consider an elementary school that maintains an enrollment of 500 students and opened the century with 90.0% white share, 450 white students. Using the estimate in column (1) of Table 2 and assuming the school was exactly average, this school lost 43 white students between 2000 and 2010 to close the decade with a white share of 81.4%. The losses accelerated and the school lost an additional 68 white students between 2010 and 2020, closing the decade with a white share of 67.8%. If the dynamics of White Flight remain unchanged, the school will lose an additional 108 white students and have a white share of 46.2% by 2030. Calculating at the sample mean white share of 57.5%, 11.1 white students, 2.2% of the student population, flee the average elementary school within the first year during the sample period.

4 The "Obama Effect": MIC as a Treatment for White Flight

The intensity of White Flight can be measured in at least two ways. First, by the percent change in white share in the middle three quintiles as illustrated by the slope in Figure 2. Second, by the location of the Tipping Point. A less steep slope and lower Tipping Point are both associated with lower intensity of White Flight. During the first two decades of the 21st century, both the slope diminished and the Tipping Point moved downward. Figure 3 illustrates the White Flight curve and tipping point for every school year between 1990 and 2019. The year 2009 is clearly an outlier. It is the only school year in which no Tipping Point can be discerned. The years following 2009 have a noticeably lower slope and Tipping Point than the years of the previous decade. Figure 4 shows the absence of a tipping point in 2009 by illustrating years 2008, 2009, and 2010 in residuals after controls.

The disruption of tipping in 2009, followed by the marked decrease in White Flight intensity, is likely due to Mediated Intergroup Contact from the 2008 presidential campaign - the so-called "Obama Effect." For economists, MIC's framing as a treatment — akin to interventions in labor or education economics — offers a novel approach to understanding prejudice as a dynamic economic factor. By conceptualizing MIC as an exogenous shock to stereotype-driven preferences, this paper bridges a methodological gap between sociological theories of prejudice and economic models of mobility.

If the 2008 presidential campaign indeed had an effect on White flight as I postulate, a one-year lag would be expected. The real estate market is generally illiquid and rental leases are typically annual. School terms begin in September and a family changing schools mid-term would cause educational disruption. The MIC treatment of the Obama campaign ramped up through the summer and reached its peak in September and October of 2008. The primary impact that the Obama campaign had on school demographics should therefore be maximized starting the following school year: fall 2009. The suggestion that there may be a confound with the 2007-2008 financial crisis is easily addressed. First, there is no obvious mechanism by which the crisis would have affected racial biases in relocation. And, if a hidden mechanism exists, it is difficult to argue that it would have a persistent influence on demographic self-selection after the market recovered. Furthermore, the timing is incorrect. Figure 5 shows that there are no significant disruptions to national relocation patterns during the years surrounding 2009. Finally, the housing sales crash associated with the great recession had reached bottom by 2008 - a year too early.

4.1 Identification and Estimation

$$
\begin{aligned}
\%\Delta WhiteShare_{est} = &\beta_0 + \beta_1 ObamaEffect_{et} + \beta_2 WhiteShare_{et} + \beta_3 Post2008_t + \\
&\beta_4 WFtrend_{et} + \beta_5 Year_t + X'_{et} + \eta_s + \epsilon_{et}
\end{aligned}
\tag{3}
$$

The difference-in-differences regression specified in equation 3 estimates the extent to which Mediated Intergroup Contact due to the Barack Obama 2008 campaign affected rates of White Flight from elementary schools after 2008. $\%\Delta WhiteShare$ is the percent change in the share of enrolled students identifying as white in elementary school e between year t and $t+1$. It is calculated $(WhiteShare_{t+1} - WhiteShare_t)/WhiteShare_t$. $ObamaEffect_{et}$ is the interaction term $WhiteShare_{et} \times Post2008_t$. The coefficient of interest is β_1. It is an estimate of the extent to which the Obama Effect impacted anti-black stereotype driven White Flight. A negative coefficient shows that MIC diminished White Flight. $WhiteShare$ is the white share of students enrolled in elementary school e during year t. $Post2008_t$ is an indicator for the year being 2009 or later. $Year_t$ controls for linear trends in the rate of racial diversification and $WFtrend_{et}$ is the interaction between $Year_t$ and $WhiteShare_{et}$. It controls for linear trends in the intensity of White Flight. η_s are state fixed effects, and X'_{et} is a vector of controls at the elementary-year level including: share of students receiving free lunch, number of students in the school, share of Hispanic students, share of Asian and other race students, latitude, longitude, and indicators for city (small, medium, and large), suburb (s,m,l), town (small, large), and rural. Table 3 shows these results.

4.2 Results and Interpretation

The results reported in Table 3 are calculated using observations between the 2000/2001 school year and 2019/2020 school year. The school year starting in the fall of 2008 is excluded. Results are robust to time ranges as narrow as 2006/2007 to 2010/2011 - two years before and after the 2008 school year - and as wide as 1987/1988 to 2019/2020, which is the entirety of the observed data. These results refine existing economic models of white flight by showing how tipping behavior can be influenced by cultural interventions. While Schelling's classical models highlight the role of racial preferences in creating segregation equilibria, the findings here demonstrate that these equilibria are not fixed. By quantifying the impact of MIC, I show that tipping points, often viewed as static thresholds, can shift when specific stereotypes are challenged. This aligns with recent work emphasizing dynamic models of segregation (e.g. Card et al. (2008); Caetano and Maheshri (2017)) but uniquely isolates a causal pathway for stereotype-driven behavior.

Consider two elementary schools that each maintain an enrollment of 500 students and begin the decade in 2010 with 80.0% white share. One of the elementary schools exists in a universe where the 2008 Obama campaign occurred, but the other exists in a counterfactual universe where it did not. Both schools begin the period with 400 white students. By the year 2020, the school in the counterfactual universe has lost 80 white students to have a white share of 64%. The school that experienced the MIC treatment has only lost 69 students to have a white share of 66.2%. And the differential accelerates. By 2030, the counterfactual school will lose another 150 white students and have a white share of 34.0%. The school that experienced the MIC treatment will only have lost an additional 100 white students to end the decade with a white share of 46.2%.

At the sample mean white share of 57.5%, the annual rate of White Flight was -2.64% before the Obama campaign. After the campaign, the same rate was -2.02%. This 0.62% decrease in magnitude - 23.6% of the total effect - is attributable to the MIC treatment of the Obama campaign. If we make the unrealistically strong assumption that the MIC of the Obama Campaign and Presidency was a 100% effective palliative for anti-black prejudice driven White Flight, this becomes an estimate for the component of white flight attributable to anti-black prejudiced stereotypes at the mean white share. When we allow for lower effectiveness rates of MIC, the estimate of anti-black driven prejudice as a driver of White Flight must *increase*. Therefore 23.6% is a conservative estimate of the lower bound of the proportion of the entire White Flight effect from public elementary schools that can be attributed to anti-black prejudiced stereotypes. The remainder, 76.4%, is the upper bound of the proportion of White Flight that is connected to Homophily, Racial Solidarity, Racial Animus, and Statistical Discrimination.

In addition to the effect on the slope in the middle quintiles, Table 3 reports the change in the Tipping Point that is attributable to the Obama Effect. The Tipping Point decreases by around 3% of white share. Using the estimates from the uncontrolled specification in column (1), let us compare the tipping dynamics. Before 2008, the average elementary school would fall into tipping once white share fell below 95.8%. In a school of 500, that's 21 non-white students. After 2008, the tipping point falls to 92.4%, increasing the number of non-white students to 38. That is, 81.0% more non-white students are tolerated before the school falls into tipping.

I perform three "placebo" tests to support the validity of these results. In 2001, Colin Powell became the first black Secretary of State and he was immediately succeeded by Condoleezza Rice, a black woman, in 2005. Due to Powell and Rice's media presence, I hypothesize that there may be an MIC-powered "Powell-Rice Effect" centered on 2001 which is smaller than the Obama Effect centered on 2008. The results of my regressions weakly support this possibility. The sign of the variable of interest on the slope in the middle quintiles is correct in all specifications. It is statistically significant in the uncontrolled specification and the specification with state fixed effects, where the magnitude of the point estimate is about half of the estimates of the Obama Effect reported in Table 3. The estimated effect on the Tipping Point, however, is ambiguous. I center a placebo test on 1994, in which I expect null results, and report the results in Appendix Table A3. It yields estimates of an effect on the slope with mixed signs. Tipping Point results are not statistically significant. A second placebo with expected null results is centered on 1991 and reported in Appendix Table A4. The estimated effects on the slope of the middle quintiles are strong, statistically significant, and positive - indicating a possible increase in the intensity of White Flight over these years. The estimated effects on the Tipping Point, however, are ambiguous and statistically insignificant.

5 Conclusion

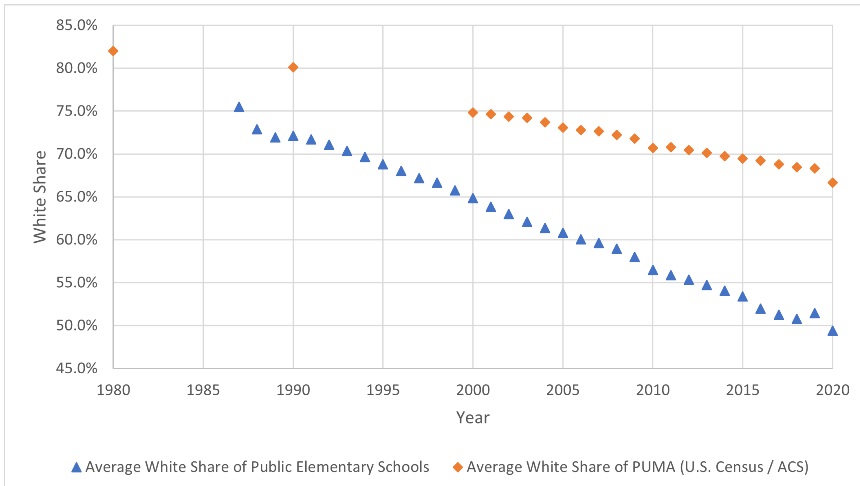
White Flight was still an important dynamic in US elementary schools during the first two decades of the 21st century. Because school enrollment is a function of residential location in the US system, residential White Flight and White Flight from schools are interconnected. Indeed, the demographic correlation between neighborhood and school population is so strongly linear that conclusions about the dynamics of White Flight drawn from schools and neighborhoods can be roughly equivalent.

On average, schools begin tipping into White Flight at a white share around 95%. As white share decreases, the rate of the decrease accelerates. By the time a school reaches the mean white share of 57.5%, 2.2% of white elementary school students will flee the school in the following year. The exodus continues to accelerate until the school is well within the bottom quintile of the white share distribution.

Leveraging the theory of Mediated Intergroup Contact and the media coverage of the 2008 Barack Obama campaign and presidency, I identify a lower bound for the proportion of white flight that is attributable to anti-black prejudiced stereotypes. At the mean white share of 57.5%, 10.1 white students will flee a treated school the first year while 13.2 will flee an untreated school. This is a decrease in White Flight intensity of 23.6%. Because MIC only treats anti-outgroup prejudiced stereotypes and cannot be 100% effective, this becomes the lower bound for the proportion of White Flight that is attributable to anti-black prejudiced stereotypes.

These findings underscore that white flight remains a multifaceted phenomenon influenced by intersecting channels, including statistical discrimination, racial animus, and homophily. While MIC effectively reduces negative racial stereotypes, it does not address the other mechanisms driving segregation. This limitation highlights the need for future research to explore complementary interventions targeting these other channels. The persistence of white flight and its measurable reduction through MIC serves as a rebuttal to claims that racism's importance in shaping contemporary economic and social behaviors is diminishing. This evidence highlights the importance of cultural and structural factors in driving migration patterns that underlie racial segregation, reinforcing the need for ongoing empirical research to further disentangle these effects.

Figure 1: Average White Share in US Elementary Schools and Public Use Microdata Areas (PUMAs).



The PUMA is the highest resolution geographic delineation in US Census and American Community Survey (ACS) data. Sources: Author's calculations based on decennial Census, ACS, and NCES data.

Table 1: Elementary School Data: Summary Statistics

	2000-2019	2000-2007	2009-2019
Mean Total Enrollment	466 (215)	455 (223)	475 (210)
Mean White Share	0.575 (0.332)	0.623 (0.337)	0.539 (0.324)
Mean Black Share	0.141 (0.225)	0.152 (0.242)	0.133 (0.210)
Mean Hispanic Share	0.206 (0.264)	0.172 (0.253)	0.233 (0.268)
Mean Asian Share	0.043 (0.089)	0.040 (0.087)	0.045 (0.089)
Mean Other Race Share	0.077 (0.118)	0.054 (0.107)	0.095 (0.122)
Mean Share Free Lunch	0.423 (0.266)	0.370 (0.251)	0.464 (0.270)
% Rural	0.239 (0.427)	0.263 (0.440)	0.218 (0.413)
% Small Town	0.092 (0.289)	0.091 (0.288)	0.092 (0.289)
% Large Town	0.023 (0.150)	0.021 (0.143)	0.022 (0.148)
% Small Suburb	0.012 (0.111)	0.005 (0.073)	0.017 (0.129)
% Midsize Suburb	0.055 (0.228)	0.092 (0.288)	0.030 (0.170)
% Large Suburb	0.258 (0.438)	0.265 (0.441)	0.252 (0.434)
% Small City	0.044 (0.206)	0.020 (0.140)	0.060 (0.237)
% Midsize City	0.079 (0.270)	0.124 (0.330)	0.048 (0.213)
% Large City	0.100 (0.301)	0.119 (0.323)	0.085 (0.279)
Number of Schools	55,073	49,467	47,624
Number of Observations	805,923	326,840	438,280

Standard errors in parentheses.

Table 2: Year-Over-Year % Change in White Enrollment Among Elementary School Students

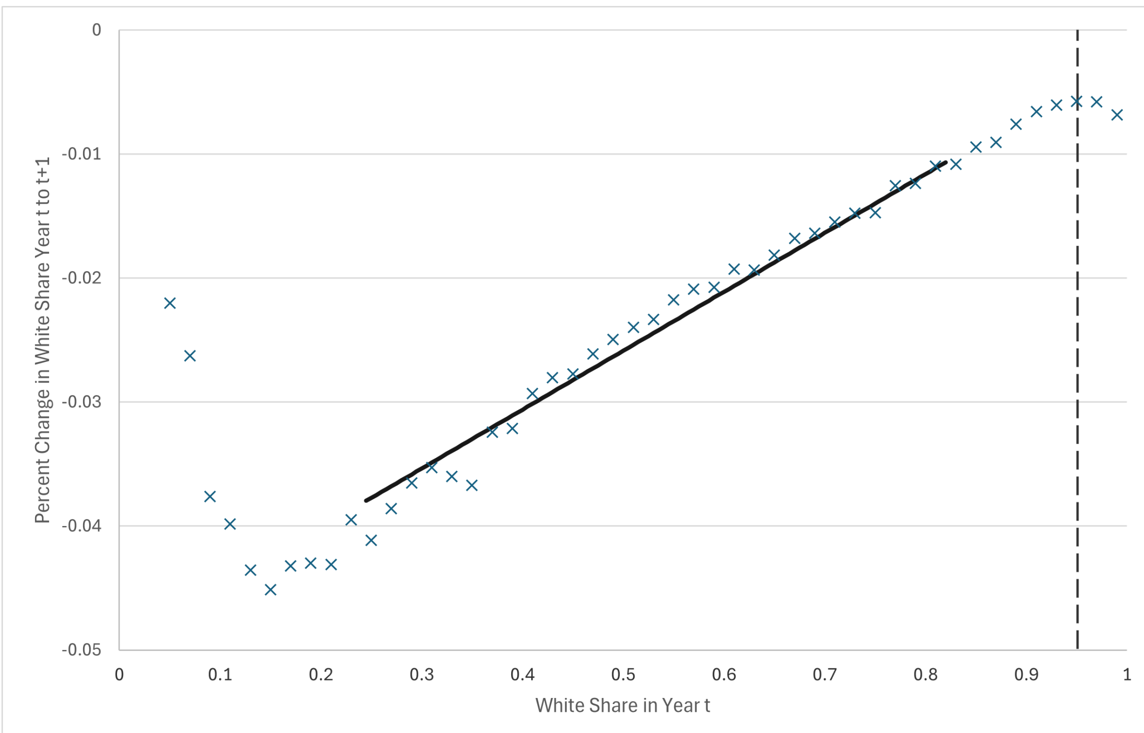
	(1)	(2)	(3)
White Share	0.047***	0.047***	0.080***
	(0.002)	(0.002)	(0.006)
White Flight Trend			-0.002***
			(0.000)
State-Year FE	No	Yes	Yes
Controls	No	No	Yes
N	516,120	516,120	516,120
r2	0.026	0.062	0.071
Tipping Point	0.951	0.952	0.911
	(0.946, 0.957)	(0.943, 0.964)	(0.903, 0.92)

Standard errors and 95% confidence intervals in parentheses

Observations are of elementary school districts with white shares in the middle three quintiles in the school years starting fall 2000 through fall 2019. *White Share* is the share of white students in the elementary school in the observation year. School/year observations that show a total enrollment change greater than 25% are excluded. Controls include: share of students receiving free lunch, number of students in the school, share of Hispanic students, share of Asian or Other race students, latitude, longitude, indicators for city (small, medium, large), suburb (small, medium, large), town (small, large) and rural. Standard errors are clustered at the county level. Tipping Point is estimated on the top four quintiles and is the peak of a cubic-cubic spline with knot between the third and fourth quintile. Confidence intervals and standard errors of Tipping Point estimated by bootstrap on 1000 resamples, clustered at the county level.

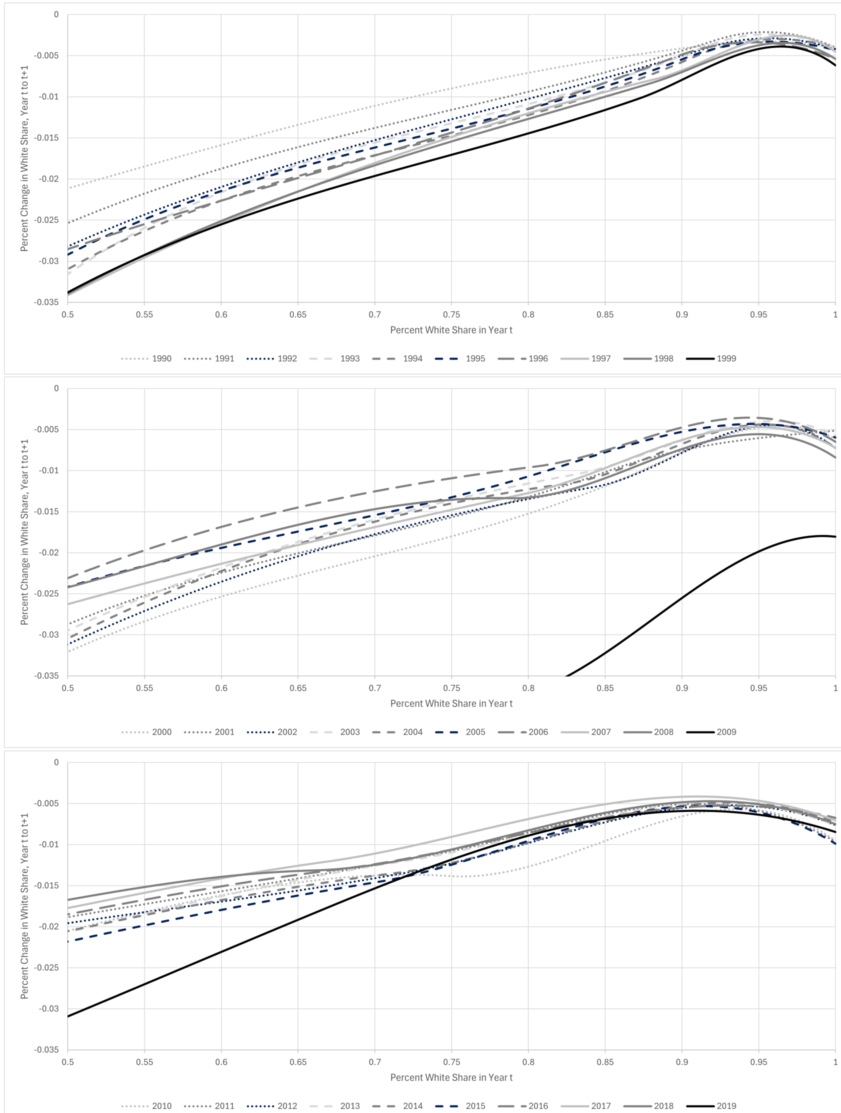
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2: White Flight from US Public Elementary Schools in 2000 to 2019.



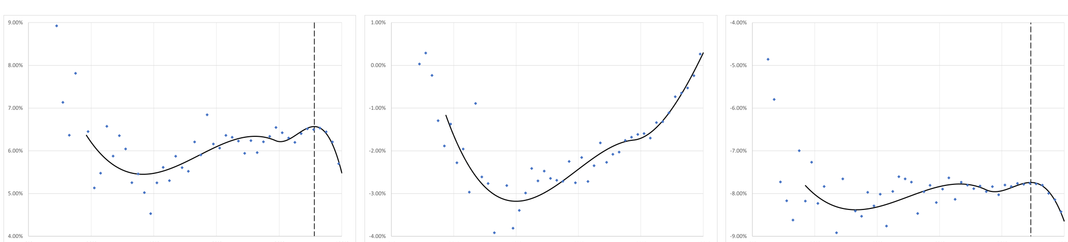
Each data point shows the mean $\%\Delta WhiteShare$ within 2% wide white share bins in years 2000 through 2019. The solid black line represents the predicted values after estimating the uncontrolled regression specified in equation 1. Dashed vertical line is the predicted Tipping Point calculated as the peak value of a cubic-cubic spline regression on the top four quintiles with a knot between the 3rd and 4th quintiles.

Figure 3: The Tipping Point by Year (grouped in decades 1990s, 2000s, 2010s)



Percent change in white share in year t+1 by white share in year t. Fitted cubic-cubic spline on the top 4 quintiles of uncontrolled data with knot between the 3rd and 4th quintiles.

Figure 4: The Tipping Point in Residuals 2008, 2009, and 2010



Percent change in white share in year t+1 by white share in year t. Fitted cubic-cubic spline on the top 4 quintiles of controlled data with knot between the 3rd and 4th quintiles. Controls include: state fixed effects, share of students receiving free lunch, number of students in the school, share of Hispanic students, share of other race students, latitude, longitude, indicators for city (small, medium, large), suburb (small, medium, large), town (small, large) and rural. Dashed vertical line is the Tipping Point. Left panel is 2008, middle is 2009, and right is 2010.

Figure 5: The Tipping Point, White Flight Slope, Home Sales, and Relocations

Tipping point and White Flight slope in the middle three quintiles with 95% confidence interval. Tipping Points are calculated using bootstrap on 1000 resamples of a fitted cubic-cubic spline on the top 4 quintiles of uncontrolled data with knot between the 3rd and 4th quintiles. White flight slopes are calculated using the uncontrolled version of equation 1 on a single year. The red line in 2009 indicates that no tipping point is in evidence. Recessions are shaded gray. Controls include: state fixed effects, share of students receiving free lunch, number of students in the school, share of Hispanic students, share of Asian and other race students, latitude, longitude, indicators for city (small, medium, large), suburb (small, medium, large), town (small, large) and rural. Home Sales data is the sum of existing home sales, provided by the National Association of Realtors, and new one-family home sales provided by FRED (HSN1F). Percent population relocated data source is the Current Population Survey. Recession data source is FRED (JHDUSRGDPBR).

Table 3: Year-Over-Year % Change in White Enrollment Among Elementary School Students

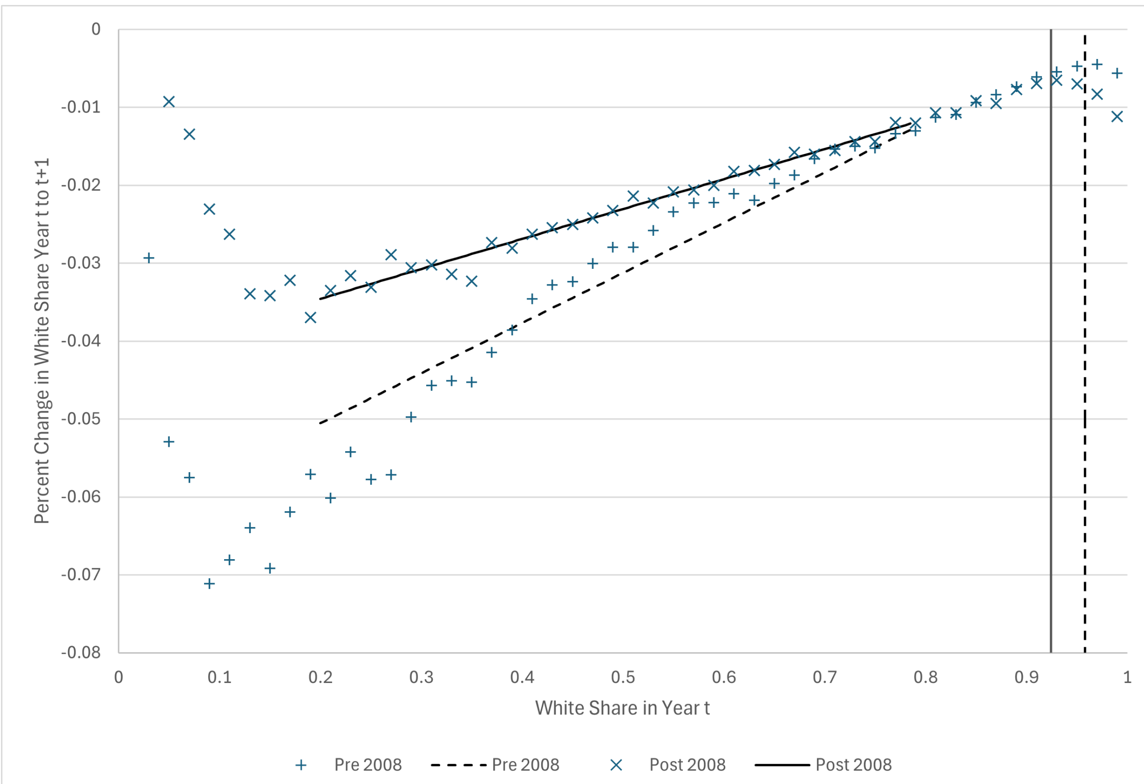
	(1)	(2)	(3)
Obama Effect	-0.026***	-0.027***	-0.021***
	(0.003)	(0.003)	(0.004)
White Share	0.064***	0.062***	0.055***
	(0.003)	(0.002)	(0.007)
Post 2008	0.021***	0.021***	0.006
	(0.002)	(0.002)	(0.003)
White Flight Trend			-0.001
			(0.000)
State FE	No	Yes	Yes
Controls	No	No	Yes
N	490,790	490,790	490,790
r2	0.030	0.034	0.044
Pre 2008 Tipping Point	0.958	0.943	0.939
	(0.952, 0.966)	(0.935, 0.951)	(0.928, 0.949)
Post 2008 Tipping Point	0.924	0.920	0.904
	(0.920, 0.929)	(0.915, 0.925)	(0.882, 0.922)
Δ Tipping Point	-0.034	-0.023	-0.035
	(-0.041, -0.027)	(-0.031, -0.015)	(-0.059, -0.015)

Standard errors and 95% confidence intervals in parentheses

Observations are of elementary school districts with white shares in the middle three quintiles in the school years starting fall 2000 through fall 2019 and excluding 2008. *Obama Effect* is the interaction between *White Share* and *Post 2008*. *White Share* is the share of white students in the elementary school in the observation year. *Post 2008* is an indicator taking the value of 1 if the observation is after 2008. *White Flight Trend* is the interaction of time (in years) and *White Share*. School/year observations that show a total enrollment change greater than 25% are excluded. Controls include: linear time trend, share of students receiving free lunch, number of students in the school, share of Hispanic students, share of Asian or Other race students, latitude, longitude, indicators for city (small, medium, large), suburb (small, medium, large), town (small, large) and rural. Standard errors are clustered at the county level. Tipping Point is estimated on the top four quintiles and is the peak of a cubic-cubic spline with knot between the third and fourth quintile. Confidence intervals and standard errors of the Tipping Point is estimated by bootstrap on 1000 resamples, clustered at the county level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6: The Obama Effect: White Flight before and after 2008



Each data point shows the mean $\%\Delta WhiteShare$ within 2% wide white share bins. Years 2000 through 2007 are denoted with pluses and 2009 through 2019 are denoted with x's. The semi-horizontal lines are the predicted values after estimating the uncontrolled regression specified in equation 3. The vertical lines are the predicted Tipping Points calculated as the peak value of a cubic-cubic spline regression on the top four quintiles with a knot between the 3rd and 4th quintiles. The dashed lines refer to years 2000 through 2007 while the solid lines refer to years 2009 through 2019.

Appendix A

Table A1: Tipping Point Sensitivity to Knot Placement

	(1)	(2)	(3)	(4)	(5)
White Share at Knot	0.658	0.711	0.763	0.822	0.881
Tipping Point	0.964	0.955	0.951	0.951	0.956
	(0.953, 0.977)	(0.948, 0.964)	(0.946, 0.957)	(0.947, 0.955)	(0.953, 0.960)

95% confidence intervals in parentheses

Tipping Point is estimated on the top four quintiles and is the peak of a cubic-cubic spline with knot at the specified white share. Column (1) places the knot at the median white share, Column(3) places the knot between the third and fourth quintiles, and Column (5) places the knot between the third and fourth quartiles. Columns (2) and (4) place the knots at the midpoints between columns (1) and (3) and (3) and (5) respectively. Confidence intervals estimated by bootstrap on 1000 resamples, clustered at the county level.

Table A2: Placebo Test: MIC treatment in 2001, A Powell-Rice Effect?

	(1)	(2)	(3)
White Share × Post	-0.014***	-0.015***	-0.005
	(0.002)	(0.002)	(0.004)
White Share	0.076***	0.075***	0.076***
	(0.003)	(0.003)	(0.007)
Post	0.013***	0.013***	0.007*
	(0.002)	(0.002)	(0.003)
White Flight Trend			-0.002**
			(0.000)
State FE	No	Yes	Yes
Controls	No	No	Yes
N	316,544	316,544	316,544
r2	0.048	0.053	0.065
Pre 2008 Tipping Point	0.966	0.948	0.918
	(0.959, 0.975)	(0.941, 0.956)	(0.907, 0.927)
Post 2008 Tipping Point	0.952	0.94	0.945
	(0.947, 0.958)	(0.933, 0.947)	(0.932, 0.956)
Δ Tipping Point	-0.014	-0.008	0.027
	(-0.022, -0.007)	(-0.015, -0.001)	(0.011, 0.042)

Standard errors in parentheses

Observations are of elementary school districts with white shares in the middle three quintiles in the school years starting fall 1994 through fall 2007 and excluding 2001. *White Share* × *Post* is the interaction between *White Share* and *Post*. *White Share* is the share of white students in the elementary school in the observation year. *Post* is an indicator taking the value of 1 if the observation is after 2001. *White Flight Trend* is the interaction of time (in years) and *White Share*. School/year observations that show a total enrollment change greater than 25% are excluded. Controls include: linear time trend, share of students receiving free lunch, number of students in the school, share of Hispanic students, share of other race students, latitude, longitude, indicators for city (small, medium, large), suburb (small, medium, large), town (small, large) and rural. Standard errors are clustered at the county level. Tipping Point is estimated on the top four quintiles and is the peak of a cubic-cubic spline with knot between the third and fourth quintile. Confidence intervals and standard errors of the Tipping Point is estimated by bootstrap on 1000 resamples, clustered at the county level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Placebo Test: MIC treatment in 1994

	(1)	(2)	(3)
White Share × *Post*	0.014***	0.013***	-0.013*
	(0.004)	(0.003)	(0.005)
White Share	0.062***	0.062***	0.032***
	(0.004)	(0.003)	(0.005)
Post	-0.014***	-0.014***	0.013**
	(0.003)	(0.003)	(0.004)
White Flight Trend			0.004***
			(0.001)
State FE	No	Yes	Yes
Controls	No	No	Yes
N	277,770	277,770	277,770
r2	0.042	0.048	0.058
Pre 2008 Tipping Point	0.960	0.933	0.898
	(0.953, 0.968)	(0.923, 0.942)	(0.886, 0.908)
Post 2008 Tipping Point	0.965	0.947	0.911
	(0.958, 0.973)	(0.94, 0.955)	(0.896, 0.923)
Δ Tipping Point	0.005	0.014	0.013
	(-0.003, 0.013)	(0.005, 0.023)	(-0.004, 0.028)

Standard errors in parentheses

Observations are of elementary school districts with white shares in the middle three quintiles in the school years starting fall 1988 through fall 2000 and excluding 1994. *White Share* × *Post* is the interaction between *White Share* and *Post*. *White Share* is the share of white students in the elementary school in the observation year. *Post* is an indicator taking the value of 1 if the observation is after 1994. *White Flight Trend* is the interaction of time (in years) and *White Share*. School/year observations that show a total enrollment change greater than 25% are excluded. Controls include: linear time trend, share of students receiving free lunch, number of students in the school, share of Hispanic students, share of other race students, latitude, longitude, indicators for city (small, medium, large), suburb (small, medium, large), town (small, large) and rural. Standard errors are clustered at the county level. Tipping Point is estimated on the top four quintiles and is the peak of a cubic-cubic spline with knot between the third and fourth quintile. Confidence intervals and standard errors of the Tipping Point is estimated by bootstrap on 1000 resamples, clustered at the county level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Placebo Test: MIC treatment in 1991

	(1)	(2)	(3)
White Share × *Post*	0.028***	0.028***	0.027***
	(0.004)	(0.003)	(0.007)
White Share	0.048***	0.048***	0.033***
	(0.005)	(0.004)	(0.005)
Post	-0.025***	-0.025***	-0.025***
	(0.003)	(0.003)	(0.005)
White Flight Trend			-0.000
			(0.001)
State FE	No	Yes	Yes
Controls	No	No	Yes
N	177,113	177,113	177,113
r2	0.038	0.044	0.055
Pre 2008 Tipping Point	0.965	0.928	0.911
	(0.956, 0.976)	(0.913, 0.938)	(0.897, 0.921)
Post 2008 Tipping Point	0.963	0.946	0.922
	(0.955, 0.973)	(0.938, 0.954)	(0.909, 0.932)
Δ Tipping Point	-0.002	0.018	0.011
	(-0.012, 0.008)	(0.007, 0.033)	(-0.005, 0.026)

Standard errors in parentheses

Observations are of elementary school districts with white shares in the middle three quintiles in the school years starting fall 1987 through fall 1995 and excluding 1991. *White Share* × *Post* is the interaction between *White Share* and *Post*. *White Share* is the share of white students in the elementary school in the observation year. *Post* is an indicator taking the value of 1 if the observation is after 1994. *White Flight Trend* is the interaction of time (in years) and *White Share*. School/year observations that show a total enrollment change greater than 25% are excluded. Controls include: linear time trend, share of students receiving free lunch, number of students in the school, share of Hispanic students, share of other race students, latitude, longitude, indicators for city (small, medium, large), suburb (small, medium, large), town (small, large) and rural. Standard errors are clustered at the county level. Tipping Point is estimated on the top four quintiles and is the peak of a cubic-cubic spline with knot between the third and fourth quintile. Confidence intervals and standard errors of the Tipping Point is estimated by bootstrap on 1000 resamples, clustered at the county level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B Algebra: Calculating the Tipping Point

The tipping point is estimated as the maximum, using the First Order Condition that the first derivative equal 0, of a cubic regression in the fourth and fifth quintiles. Importantly, this cubic regression is constrained to match a cubic regression on the second and third quintiles - with the same value and first derivative at the "knot." This makes the regression a cubic-cubic spline. Ramsay (1988) states "In general the shape of a spline function is not very sensitive to knot placement." This is borne out by the sensitivity analysis presented in Appendix Table A1. It shows that my estimation of the Tipping Point is robust to alternative choices of knot placement.

Equation 1, with simplified notation and suppressed controls is the simple OLS regression:

$$Y_i = \beta_0 + \beta_1 x1_i + \epsilon_i \tag{4}$$

We can make this a cubic regression by adding third-order polynomial terms:

$$Y_i = \beta_0 + \beta_1 x1_i + \beta_2 x1_i^2 + \beta_3 x1_i^3 + \epsilon_i \tag{5}$$

This can be transformed into a cubic-cubic spline, at knot value k, by introducing an indicator variable, D that takes the value of 1 if $x1_i > k$ and running a constrained regression (e.g. using cnsreg in stata.)

$$\begin{aligned} Y_i =& \beta_0 + \beta_1 x1_i + \beta_2 x1_i^2 + \beta_3 x1_i^3 + \\ & \beta_4 D + \beta_5 (D \times x1_i) + \beta_6 (D \times x1_i^2) + \beta_7 (D \times x1_i^3) + \epsilon_i \end{aligned} \tag{6}$$

With the following two constraints.

First, we constrain the value to match at the knot k:

$$0 = \beta_4 + k\beta_5 + k^2\beta_6 + k^3\beta_7 \tag{7}$$

Second, we constraint the first derivative with respect to k to match at the knot:

$$0 = \beta_5 + (2 \times k)\beta_6 + (3 \times k^2)\beta_7 \tag{8}$$

The first derivative of the estimated equation can then be plugged into the quadratic equation to find two candidate Tipping Points. The highest value is the estimated Tipping Point.

$$
\begin{aligned}
TippingPoint =& \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \\
& a := 3 \times (\beta_7 + \beta_3) \\
& b := 2 \times (\beta_6 + \beta_2) \\
& c := \beta_5 + \beta_1
\end{aligned}
\tag{9}
$$

The same algebra can be used for the diff-in-diff specification in Equation 3 in section 4 by separately estimating the pre and post periods.

References

Akbar, P. A., S. L. Hickly, A. Shertzer, and R. P. Walsh (2022). Racial segregation in housing markets and the erosion of black wealth. *Review of Economics and Statistics*, 1–45.

Aliprantis, D., D. R. Carroll, and E. R. Young (2022). What explains neighborhood sorting by income and race? *Journal of Urban Economics*, 103508.

Allport, G. W. (1954). *The nature of prejudice.* Addison-Wesley.

Bartik, A. W. and E. Mast (2021). Black suburbanization and the evolution of spatial inequality since 1970. Technical report, Upjohn Institute Working Paper.

Bayer, P., M. Casey, F. Ferreira, and R. McMillan (2017). Racial and ethnic price differentials in the housing market. *Journal of Urban Economics 102*, 91–105.

Bayer, P., M. D. Casey, W. B. McCartney, J. Orellana-Li, and C. S. Zhang (2022). Distinguishing causes of neighborhood racial change: A nearest neighbor design. Technical report, National Bureau of Economic Research.

Blair, P. Q. (2023). Beyond racial attitudes: The role of outside options in the dynamics of white flight. Technical report, National Bureau of Economic Research.

Boustan, L., C. Cai, and T. Tseng (2024). Jue insight: White flight from asian immigration: Evidence from california public schools. *Journal of Urban Economics 141*, 103541.

Boustan, L. P. (2010). Was postwar suburbanization "white flight"? evidence from the black migration. *The Quarterly Journal of Economics 125*(1), 417–443.

Boustan, L. P. and R. A. Margo (2013). A silver lining to white flight? white suburbanization and african–american homeownership, 1940–1980. *Journal of Urban Economics 78*, 71–80.

Brown, T. N., A. Bento, J. Culver, R. S. Casarez, and H. J. Duffy III (2022). Intergroup contact and white racial apathy: Findings from the national study of youth and religion (nsyr). *Sociological Perspectives 65*(6), 1188–1207.

Caetano, G. and V. Maheshri (2017). School segregation and the identification of tipping behavior. *Journal of Public Economics 148*, 115–135.

Card, D., A. Mas, and J. Rothstein (2008). Tipping and the dynamics of segregation. *The Quarterly Journal of Economics 123*(1), 177–218.

Charles, C. Z. (2003). The dynamics of racial residential segregation. *Annual review of sociology 29*(1), 167–207.

Chin, M. J. (2022). The stability of families' revealed preferences for schools. *Educational Researcher 51*(9), 588–592.

Clark, W. A. (1991). Residential preferences and neighborhood racial segregation: A test of the schelling segregation model. *Demography 28*, 1–19.

Clark, W. A., E. Anderson, J. Östh, and B. Malmberg (2015). A multiscalar analysis of neighborhood composition in los angeles, 2000–2010: A location-based approach to segregation and diversity. *Annals of the Association of American Geographers 105*(6), 1260–1284.

Clotfelter, C. T. (2001). Are whites still fleeing? racial patterns and enrollment shifts in urban public schools, 1987–1996. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management 20*(2), 199–221.

Colby, S. L. and J. M. Ortman (2015). Projections of the size and composition of the us population: 2014 to 2060. population estimates and projections. current population reports. p25-1143. *US Census Bureau*.

Daepp, M. I., J. W. Hsu, et al. (2023). The effect of racial composition on neighborhood housing prices: Evidence from hurricane katrina-induced migration. *Journal of Urban Economics 134*, 103515.

Davis, M. A., J. Gregory, and D. A. Hartley (2023). Preferences over the racial composition of neighborhoods: Estimates and implications. *Available at SSRN 4495735*.

DellaVigna, S. and E. Kaplan (2007). The fox news effect: Media bias and voting. *The Quarterly Journal of Economics 122*(3), 1187–1234.

Derenoncourt, E. (2022). Can you move to opportunity? evidence from the great migration. *American Economic Review 112*(2), 369–408.

Easterly, W. (2009). Empirics of strategic interdependence: the case of the racial tipping point. *The BE Journal of Macroeconomics 9*(1).

Ellen, I. G., K. Horn, and K. O'Regan (2012). Pathways to integration: Examining changes in the prevalence of racially integrated neighborhoods. *Cityscape*, 33–53.

Enns, P. K. and A. Jardina (2021). Complicating the role of white racial attitudes and anti-immigrant sentiment in the 2016 us presidential election. *Public Opinion Quarterly 85*(2), 539–570.

Flippen, C. (2004). Unequal returns to housing investments? a study of real housing appreciation among black, white, and hispanic households. *Social Forces 82*(4), 1523–1551.

Flippen, C. A. (2001). Racial and ethnic inequality in homeownership and housing equity. *Sociological Quarterly 42*(2), 121–149.

Frey, W. H. (1979). Central city white flight: Racial and nonracial causes. *American Sociological Review*, 425–448.

Garretson, J. J. (2015). Does change in minority and women's representation on television matter?: a 30-year study of television portrayals and social tolerance. *Politics, Groups, and Identities 3*(4), 615–632.

Goldman, S. K. (2012). Effects of the 2008 obama presidential campaign on white racial prejudice. *Public Opinion Quarterly 76*(4), 663–687.

Goldman, S. K. and D. J. Hopkins (2019). When can exemplars shape white racial attitudes? evidence from the 2012 us presidential campaign. *International Journal of Public Opinion Research 31*(4), 649–668.

Goldman, S. K. and D. C. Mutz (2014). *The Obama effect: How the 2008 campaign changed white racial attitudes.* Russell Sage Foundation.

Grodzins, M. (1958). *The Metropolitan Area as a Racial Problem.* University of Pittsburgh Press.

Harris, D. R. (1999). "property values drop when blacks move in, because...": Racial and socioeconomic determinants of neighborhood desirability. *American sociological review 64*(3), 461–479.

Haynes, C. S. and R. Block (2019). Role-model-in-chief: understanding a michelle obama effect. *Politics & Gender 15*(3), 365–402.

Howell, J. and E. Korver-Glenn (2021). The increasing effect of neighborhood racial composition on housing values, 1980–2015. *Social Problems 68*(4), 1051–1071.

Kermani, A. and F. Wong (2021). Racial disparities in housing returns. Technical report, National Bureau of Economic Research.

Kite, M. E., B. E. Whitley Jr, and L. S. Wagner (2022). *Psychology of prejudice and discrimination.* Routledge.

Korver-Glenn, E. (2021). *Race brokers: Housing markets and segregation in 21st century urban America.* Oxford University Press.

Lemmer, G. and U. Wagner (2015). Can we really reduce ethnic prejudice outside the lab? a meta-analysis of direct and indirect contact interventions. *European Journal of Social Psychology 45*(2), 152–168.

Li, S., K.-L. Chang, and L. Wang (2020). Racial residential segregation in multiple neighborhood markets: a dynamic sorting study. *Journal of Economic Interaction and Coordination 15*, 363–383.

Logan, J. R., S. Kye, H. J. Carlson, E. Minca, and D. Schleith (2023). The role of suburbanization in metropolitan segregation after 1940. *Demography 60*(1), 281–301.

Malone, T. (2020). There goes the neighborhood does tipping exist amongst income groups? *Journal of Housing Economics 48*, 101667.

Mijs, J. J. and E. L. Roe (2021). Is america coming apart? socioeconomic segregation in neighborhoods, schools, workplaces, and social networks, 1970–2020. *Sociology Compass 15*(6), e12884.

NAR (2014). 2014 national association of realtors home buyer and seller generational trends. *National Association of Realtors Research Division*.

on Civil Disorders, T. N. A. C. (2016). *The Kerner Report*. Princeton University Press.

Paluck, E. L., S. A. Green, and D. P. Green (2019). The contact hypothesis re-evaluated. *Behavioural Public Policy 3*(2), 129–158.

Pasek, J., T. H. Stark, J. A. Krosnick, T. Tompson, and B. Keith Payne (2014). Attitudes toward blacks in the obama era: Changing distributions and impacts on job approval and electoral choice, 2008–2012. *Public Opinion Quarterly 78*(S1), 276–302.

Passel, J. S., G. Livingston, and D. Cohn (2012). Explaining why minority births now outnumber white births. *Pew Research Center*.

Perry, A., J. Rothwell, and D. Harshbarger (2018). The devaluation of assets in black neighborhoods. *Library Catalog: www. brookings. edu*.

Pettigrew, T. F. and L. R. Tropp (2006). A meta-analytic test of intergroup contact theory. *Journal of personality and social psychology 90*(5), 751.

Quillian, L. and D. Pager (2001). Black neighbors, higher crime? the role of racial stereotypes in evaluations of neighborhood crime. *American journal of sociology 107*(3), 717–767.

Ramasubramanian, S. (2013). Intergroup contact, media exposure, and racial attitudes. *Journal of Intercultural Communication Research 42*(1), 54–72.

Ramsay, J. O. (1988). Monotone regression splines in action. *Statistical science*, 425–441.

Reardon, S. F., J. T. Yun, and G. Orfield (2006). Private school racial enrollments and segregation. *The Civil Rights Project*.

Reber, S. J. (2005). Court-ordered desegregation: Successes and failures integrating american schools since brown versus board of education. *Journal of Human resources 40*(3), 559–590.

Rosenthal, S. S. and S. L. Ross (2015). Change and persistence in the economic status of neighborhoods and cities. *Handbook of regional and urban economics 5*, 1047–1120.

Schelling, T. C. (1969). Models of segregation. *The American economic review 59*(2), 488–493.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of mathematical sociology 1*(2), 143–186.

Schiappa, E., P. B. Gregg, and D. E. Hewes (2005). The parasocial contact hypothesis. *Communication monographs 72*(1), 92–115.

Schmidt, K. and J. R. Axt (2016). Implicit and explicit attitudes toward african americans and barack obama did not substantively change during obama's presidency. *Social Cognition 34*(6), 559–588.

Shapiro, T. M. et al. (2004). *The hidden cost of being African American: How wealth perpetuates inequality*. Oxford University Press, USA.

Small, M. L. and D. Pager (2020). Sociological perspectives on racial discrimination. *Journal of Economic Perspectives 34*(2), 49–67.

South, S. J. and K. D. Crowder (1998). Leaving the'hood: Residential mobility between black, white, and integrated neighborhoods. *American sociological review*, 17–26.

Tesler, M. (2020). *Post-racial or most-racial? Race and politics in the Obama era.* University of Chicago Press.

Tope, D., J. T. Pickett, R. J. Cobb, and J. Dirlam (2014). Othering obama: Racial attitudes and dubious beliefs about the nation's first black president. *Sociological Perspectives 57*(4), 450–469.

Tope, D., B. D. Rawlinson, J. T. Pickett, A. M. Burdette, and C. G. Ellison (2017). Religion, race, and othering barack obama. *Social Currents 4*(1), 51–70.

Tukachinsky, R., D. Mastro, and M. Yarchi (2015). Documenting portrayals of race/ethnicity on prime-time television over a 20-year span and their association with national-level racial/ethnic attitudes. *Journal of Social Issues 71*(1), 17–38.

Weaver, R. C. (1960). Class, race and urban renewal. *Land Economics 36*(3), 235–251.

Wojcieszak, M. and R. Azrout (2016). I saw you in the news: Mediated and direct intergroup contact improve outgroup attitudes. *Journal of Communication 66*(6), 1032–1060.

Yadon, N. and S. Piston (2019). Examining whites' anti-black attitudes after obama's presidency. *Politics, Groups, and Identities 7*(4), 794–814.

Zhang, J. (2011). Tipping and residential segregation: a unified schelling model. *Journal of Regional Science 51*(1), 167–193.