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Tipping and the Dynamics of Segregation in Neighborhoods and Schools

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ABSTRACT

In a classic paper, Schelling (1971) showed that extreme segregation can arise from social interactions in preferences: once the minority share in a neighborhood exceeds a "tipping point", all the whites leave. We use regression discontinuity methods and Census tract data from the past four decades to test for the presence of discrete non-linearities in the dynamics of neighborhood racial composition. White mobility patterns in most cities exhibit tipping-like behavior, with a range of tipping points centered around a 13% minority share. These patterns are very pronounced during the 1970s and 1980s, and diminish but do not disappear in the 1990s. We find similar dynamic patterns in neighborhoods and in schools. A variety of specification checks rule out the possibility that the discontinuity in the initial minority share is driven by income stratification or other factors, and underscore the importance of white preferences over neighbors' race and ethnicity in the dynamic process of segregation. Finally, we relate the location of the estimated tipping points in different cities to measures of the racial attitudes of whites, and find that cities with more racially tolerant whites have higher tipping points.

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Is racial segregation in U.S. cities mainly due to preferences or constraints? Many observers have argued that the co-existence of nearly all-white and all-minority neighborhoods – often within a few blocks of each other – can only be explained by discriminatory institutions and practices, such as "steering" by real estate agents. In a classic paper, however, Schelling (1971) observed that extreme segregation can arise solely from individual choice, even when most whites will readily tolerate a high fraction of nonwhite neighbors. Schelling's insight was that social interactions in preferences can generate a non-linear system: once the fraction of minorities in a neighborhood exceeds a critical "tipping point," a cascade of white flight leads to complete racial isolation.[1]

Since Schelling's paper, social interaction models have been used to explain phenomena as diverse as macroeconomic growth (Cooper and John, 1988), restaurant choice (Becker, 1991), and technology adoption (Durlauf, 1993). The unifying feature of these models is that individual choices depend on the choices of others, potentially leading to complex dynamics with multiple equilibria and tipping points (Brock and Durlauf, 2001b; Glaeser and Scheinkman, 2003). Existing empirical studies of social interactions have concentrated on measuring the effects of peer characteristics on individual choices (e.g. Case and Katz, 1991; Evans, Oates and Schwab, 1992; Kling, Ludwig and Katz, 2005); and on testing for excess dispersion in endogenous outcomes across social groups (Glaeser, Sacerdote, and Scheinkman, 1996; Graham 2005).[2] To date, there is no direct evidence of the tipping points or phase transitions predicted by many complex system models.

In this paper we draw on methods from the burgeoning literature on regression

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[1] In the decades before Schelling's paper, sociologists had documented the evolution of neighborhood racial composition in response to the arrival of black families. Grodzins (1958) defined the "tip point" as the percent of black residents that "...exceeds the limits of the neighborhood's tolerance for inter-racial living."

[2] See Manski (1993) for a careful discussion of the difficulties in testing for interaction effects, and Glaeser and Scheinkman (2003) for a review of many existing studies.

discontinuity inference (e.g., Angrist and Lavy, 1999) to test for the existence of tipping behavior in the evolution of the racial and ethnic composition of neighborhoods and schools.[3] We find strong visual and model-based evidence that neighborhoods in most cities exhibit tipping, with rapid declines in the white population of neighborhoods just beyond the tipping point. To illustrate our approach, Figure 1 shows the estimated relationship between the fraction of minorities in a census tract in Chicago in 1970 and the change in the tract-level white population (as a share of the initial population) over the next decade. We fit a local linear regression to the data, allowing a change in both the intercept and the slope at a 5% minority share – the level identified by two alternative search procedures as the most likely potential tipping point. The graph shows clear evidence of tipping: whereas tracts just to the left of the 5% cutoff in 1970 experienced growth in the white population over the next decade, those with over 5% minority share experienced substantial declines. The non-linear dynamics in Figure 1 are consistent with bi-modality in the cross-sectional distribution of minority shares across tracts, and a high level of residential segregation, both common characteristics in American cities.

A major difficulty in testing the tipping hypothesis is in specifying the location of a potential tipping point. We consider two complementary approaches. First, we select the potential tipping point that leads to the best fitting version of a parametric model for the change in the white population share over a ten year period.[4] Our second approach exploits the fact that a tipping point represents an unstable equilibrium or fixed point in the differential equation

[3] Recent studies by Easterly (2005) and Clotfelter (2001) of the evolution of the fraction of whites in neighborhoods and schools, respectively, turned up little evidence of tipping behavior. As discussed in Section II, we believe that these studies smooth away tipping effects by pooling data from cities with heterogeneous dynamics and, in the Easterly case, by failing to account for substantial heterogeneity in neighborhood growth rates.

[4] This is similar to a procedure for identifying the timing of a structural change in a stationary time series model (e.g. Piehl et al, 2003; Bai, 1997).

describing the evolution of the neighborhood minority share. We fit a flexible model of racial dynamics to each city and find the level of the initial minority share at which the predicted rate of change of the white share equals the city-wide average. Both approaches involve intensive "data mining" and are vulnerable to specification search bias (Leamer, 1978). To avoid this bias, we adopt a split sample approach, using a random sub-sample of tracts in a city to identify the potential tipping points and the remaining tracts to estimate regression discontinuity (RD) style models conditional on the identified point.[5] The potential tipping points identified by the alternative methods are highly correlated, and in many cases correspond exactly. Estimated tipping points for a given city are also highly correlated over successive decades in our sample, which ranges from 1970 to 2000.

Having identified potential tipping points we turn to an analysis of the dynamic behavior of white shares around these points. We pool the data from different cities by deviating the minority share in a given tract or school from the corresponding city-specific potential tipping point. As suggested by the pattern in Figure 1, our analysis provides strong evidence of tipping behavior, in the form of large discontinuities in the white population growth rate at the potential tipping points. These discontinuities are robust to the inclusion of flexible controls for other neighborhood characteristics, including poverty, unemployment, and housing attributes. We find similar though slightly weaker evidence of tipping in the composition of elementary schools.

While Schelling's (1971) original model treated racial composition as the source of externalities in location choices, people may also care about their neighbors' incomes (Schelling, 1978; Bond and Coulson, 1989). Since minorities have lower average incomes than whites, such

[5] Our method is similar in spirit to the split-sample method proposed by Angrist, Imbens, and Krueger (1999) for eliminating the bias in instrumental variables procedures with weak instruments.

preferences will lead to some degree of segregation. Moreover, even in the absence of social interaction effects, standard models of spatial equilibrium imply that households will sort into neighborhoods with similar incomes, again leading to some segregation. To distinguish race-based tipping from these alternative explanations, we conduct a parallel investigation of tipping in the tract-level poverty rate. Even when we allow for highly nonlinear responses to neighborhood poverty rates we continue to find strong evidence of a discontinuity in white mobility rates at the racial tipping point, suggesting that preferences over race and ethnicity strongly influence whites' location choices.

We also consider several other neighborhood characteristics that might change when a neighborhood tips, including the average value of owner-occupied homes. Home values show a modest (insignificant) discontinuity at the tipping point, with some evidence of anticipatory price reductions.[6] Specifically, we find that tracts that tipped during the 1990s had (insignificantly) lower home values at the beginning of the decade than those that did not, perhaps reflecting forward-looking assessments of future rents. Most of the housing market response to tipping seems to be met by changes in quantities: we find that the population and housing stock of tracts beyond the tipping point tend to shrink relative to other tracts in the same city.

We conclude our empirical analysis by relating the location of the neighborhood tipping point in each city to the racial attitudes of white residents. Specifically, we construct an index of racial attitudes based on responses to four questions in the General Social Survey regarding

[6] A large body of work in urban economics has established that home values depend on the racial composition of neighborhoods. Recent studies have emphasized that sorting across neighborhoods is informative about different groups' *relative* demand (see, e.g., Bayer and Ross, 2006; Bayer, Ferreira, and MacMillan, 2003; Bajari and Kahn, 2003), though these papers do not focus on the highly nonlinear reactions that arise from social interactions.

inter-racial marriage, school busing, and housing segregation.[7] Controlling for other city characteristics (including region dummies, racial composition, and the mean incomes of different racial/ethnic groups), we find a robust and quantitatively important link between white residents' racial attitudes and the location of the average tipping point. This adds support to the conclusion that the tipping behavior identified in our main analysis is driven by white preferences over minority contact.

II. Previous Literature

a. Theoretical Models of Social Interactions and Tipping

Although Veblen (1934), Duesenberry (1949) and Leibenstein (1950) all presented models with interdependent preferences, Schelling (1969, 1971, 1978) was the first to introduce social interaction effects that lead to tipping behavior, and to link this behavior explicitly to segregation.[8] His 1971 paper presents a simple model of residential location with heterogeneity in white's preferences. Miyao (1979) and Kanemoto (1980) extended Schelling's framework and derived tipping-like behavior in models with explicit land markets. Bond and Coulson (1989) present a model that combines neighborhood externalities with the Muth (1973) – Brueckner (1977) model of "filtering". We discuss a variant of this model in the next section.

In the last decade there has been an explosion of new theoretical research on social interaction models (see Glaeser and Scheinkman, 2003 and Durlauf, 2003 for recent surveys).

[7] A similar approach is taken by Cutler, Glaeser, and Vigdor (1999), who correlate white attitudes with the levels of segregation in different cities.

[8] An earlier model of the boundary externality between rich and poor neighborhoods was developed by Baily (1959). Schelling (1969) is closer to Baily's model. Granovetter (1978) presents a model of the choice to participate in a riot that is formally similar to Schelling (1971). This is referred to as a "critical mass" model in sociology.

Among the key insights of this work are the links between social interaction effects, statistical mechanics (Blume, 1993), and game-theoretic models of strategic complementarity (Cooper and John, 1988; Milgrom and Roberts, 1990; Heal and Kunreuther, 2006). Durlauf (2003) notes that social interactions models are often characterized by multiple equilibria and phase transitions. For example, in Brock and Durlauf's (2001a) model, each agent chooses between two actions. Depending on whether the social interaction effect exceeds a certain threshold, there may be one or three distinct equilibria.[9] In the latter case, two are stable; in dynamic versions of the model, each has a large attracting zone. The third equilibrium lies between the first two on the boundary of the attracting zones. This unstable equilibrium can be interpreted as a tipping point: points on opposite sides converge to different long-run equilibria.

Becker and Murphy (2000) consider social interaction effects in a variety of market settings, including a neighborhood choice model with two types of agents and two neighborhoods. (An earlier analysis is presented by Benabou, 1993, 1996). They show that multiple equilibria are possible, and that a market equilibrium will exhibit greater segregation than is socially optimal if the willingness to pay for neighborhood composition is concave.[10]

b. Empirical Studies of Social Interactions

Empirical studies of social interactions have generally taken one of two approaches.[11]

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[9] Glaeser and Scheinkman (2003) present an upper bound on the relative size of social influences that is sufficient to guarantee a unique equilibrium in a model with continuous actions and finitely many agents. Horst and Scheinkman (2006) extend this analysis to models with an infinite number of agents and "global" social interactions.

[10] Becker and Murphy (2000) also consider a competitive multi-neighborhood model with two types of agents and show that tipping behavior will emerge when there are some neighborhoods that contain only one group, and that group has a higher willingness to pay for a marginal increase in the fraction of the *other* group.

[11] Several studies calibrate the Schelling model with survey data on white families' preferences over the racial composition of their neighborhoods. These studies (see, e.g., Clark, 1991) typically conclude that the preference distribution is such that *no* integrated neighborhood is stable. Vigdor (2003) performs a similar analysis.

The first is to relate individual choices to the average choices and/or characteristics of the peer group (an early example is Case and Katz, 1991). Given the reflection problem described by Manski (1993), identifying the effect of the average choice of the peer group – a so-called endogenous peer effect – is difficult, and many researchers have focused on identifying the reduced-form effect of the peer group's exogenous characteristics.[12] Even here, non-random selection of peer groups can lead to biases. Two alternative solutions to this problem are an aggregation strategy (Evans, Oates, and Schwab, 1992; Cutler and Glaeser, 1997; Card and Rothstein, 2006), or an experimental or quasi-experimental manipulation of peer assignment (e.g., Mas and Moretti, 2006; Kling, Ludwig and Katz, 2005; Duflo and Saez, 2003; Oreopoulos, 2003; Sacerdote, 2001). Although some empirical studies have estimated significant social interaction effects, others find statistically insignificant effects, or effects in limited domains.[13]

The second approach to identifying peer effects starts from the observation that if the outcome of an individual depends on the mean outcome of his/her social group, then the variance of mean outcomes across groups will be "too big" relative to the variance of outcomes within groups (see Graham, 2005 for a careful explication). This excess variance approach is used by Glaeser, Sacerdote and Scheinkman (1996) and Topa (2001) to detect social interaction effects within neighborhoods in crime and unemployment, respectively, and by Boozer and Cacciola (2001) and Graham (2005) to measure within-classroom effects. These studies all find evidence of endogenous social interactions.

Modest social interaction effects are potentially consistent with the existence of a unique

[12] "Exogenous" peer effects do not give rise to multiple equilibria. In the absence of exogenous effects, however, the reduced form relation between peer characteristics and individual choices can be used to identify "endogenous" peer effects (Case and Katz, 1991).

[13] See Moffitt (2001), Glaeser and Scheinkman (2003) and Durlauf (2003) for more detailed reviews.

equilibrium (Glaeser and Scheinkman, 2003; Horst and Scheinkman 2006). While the existing literature provides some evidence of interactions, we are unaware of any direct evidence of multiple equilibria.[14] Tipping behavior is perhaps the most readily observable indicator of multiplicity.

c. Empirical Studies of Neighborhood Change

Building on the work of the Chicago school sociologists (Park, Burgess, and McKenzie, 1925), Duncan and Duncan (1957) and Taeuber and Taeuber (1965) used Census tract data linked across decades to correlate changes in the white population share in a tract to the initial fraction of nonwhites, finding a generally negative effect.[15] A similar approach is taken by Easterly (2005), who tests for nonlinearity in the effects of initial minority shares using the same data that we use here. Specifically, Easterly relates the change in the white share of tract residents between Censuses (or over multiple decades) to a fourth order polynomial in the initial white share. He finds strong evidence of "mean regressive" behavior, particularly for tracts with initial white shares under 20 percent, but little or no evidence of discontinuous tipping. Our exploration of the data points to two aspects of Easterly's empirical specification that appear to have masked the strong evidence of tipping that we identify below. First, Easterly focuses exclusively on changes in the white and minority shares of neighborhoods, neglecting substantial

[14] Glaeser and Scheinkman (2003, p. 361) note that with existing approaches "it is difficult to separate out extremely high variances from multiple equilibria."

[15] More recent studies by sociologists include Lee and Wood (1991) and Denton and Massey (1991). A few recent studies, including South and Crowder (1998), Quillian (2002), and Mare and Bruch (2003), have used panel data to examine how neighborhood composition affects individual mobility. All three of these studies conclude that a higher fraction of black neighbors leads to increasing outflows of white families. Unfortunately the sample sizes in these studies are modest and given the uneven distribution of minority shares they have limited power to detect nonlinear or discontinuous effects.

heterogeneity in population growth rates. We find that tipping toward reduced white demand generally coincides with a relative decline in the neighborhood's population, attenuating the change in the observed minority share. Second, Easterly assumes that dynamic behavior is similar in all cities (or in large groups of cities), whereas we find considerable heterogeneity in tipping points. By pooling the data from cities with different tipping points Easterly inadvertently smooths away the discontinuous dynamics that we identify below.

A closely related set of studies examines the racial composition of schools. Coleman, Kelley, and Moore (1975) study changes in white enrollment shares in larger school districts that underwent desegregation in the late 1960s, and find a significant negative effect of increased exposure to black schoolmates.[16] Welch and Light (1987) and Reber (2005) likewise find significant declines in white enrollment following implementation of court-ordered desegregation plans. A recent study by Clotfelter (2001) examines district-level data for larger metropolitan areas of the US over the 1987-96 period, and explicitly tests for nonlinear dynamics. Clotfelter concludes that the response of the white enrollment share to increasing minority exposure is essentially linear over the relevant range. In the analysis below we extend this analysis by studying data at the school level, and by allowing tipping points to vary across cities. As in our neighborhood analyses, we find that this flexibility is important.

III. Theoretical Models of Tipping Behavior

a. A Basic Model

It is useful to begin by restating Schelling's simplified (1971) model. Schelling assumes

[16] Clotfelter (1979) and Farley, Richards, and Wurdock (1980) reach similar conclusions.

that whites are indifferent between neighborhoods with minority shares less than m^* but are unwilling to tolerate a minority share above m^*. He also assumes that minorities do not care about neighborhood composition. Ignoring for the moment any heterogeneity in m^*, an equilibrium then has the property that families are distributed across two types of neighborhoods: integrated neighborhoods (with $m<m^*$) and all-minority neighborhoods. This equilibrium exhibits discontinuous "tipping" behavior. A neighborhood with a minority share $m<m^*$ is stable, but if for any reason an integrated neighborhood receives an injection of minorities that raises the minority share above m^*, all the whites will leave.

Similar dynamics arise with heterogeneous white preferences. Let m^* be a random variable, distributed across the white population with distribution function F[ ]. The fraction of the white population willing to live in a neighborhood with minority share m is 1-F[m]. Thus, if a neighborhood that initially contains a random sample of whites sees its minority share rise to the point that $1-F[m] < 1-m$ (i.e. $F[m] > m$), the fraction of whites willing to remain in the neighborhood will fall below 1-m, and m will rise. Assuming a conventional shape for F, this leads to the situation shown in Figure 2. Any minority share less than the point m^{**} – where the distribution function F cuts the 45 degree line from below– is a potential equilibrium. Once m exceeds the tipping point m^{**}, however, a cascade of white flight is initiated, and the neighborhood will become 100% minority.[17]

Although Schelling's model ignores housing prices, it is straightforward to include land markets so long as white preferences—and bid-rent functions—are discontinuous in m. It is perhaps not surprising, however, that such preferences produce discontinuous responses. To

[17] Note that in general $m^{**} \neq E[m^*]$, though the two are related: Rightward shifts in F[] will in general lead to increases in m^{**}.

demonstrate that similar results can obtain in a model with continuous preferences, we present a modified version of the model developed by Bond and Coulson (1989).[18]

b. A Model with Quality Heterogeneity

Consider a city with many neighborhoods and two race groups, whites (denoted by W) and minorities (denoted by M). Assume that a family in race group $r \in \{M,W\}$ has preferences represented by the function $U^r(X, q, m)$, where X is a numeraire consumption good, q is housing quality (with $\partial U/\partial q>0$), and m is the minority share in the neighborhood (with $\partial U/\partial m<0$). For simplicity, assume that all whites have income Y^W and all minorities have income $Y^M<Y^W$.[19]

With free mobility, families of race group r must achieve the same utility U^r in any neighborhood that they choose to live in. This yields a pair of equilibrium bid-rent functions $b^r(q, m, U^r, Y^r)$, implicitly defined by the equality $U^r = U^r(Y^r - b^r(q, m, U^r, Y^r), q, m)$. We make two assumptions about these functions:

(1a) $\partial b^W(q, m, U^W, Y^W)/\partial m < \partial b^M(q, m, U^M, Y^M)/\partial m$.

(1b) $\partial b^W(q, m, U^W, Y^W)/\partial q > \partial b^M(q, m, U^M, Y^M)/\partial q$.

These inequalities imply that white families have a higher willingness-to-pay than minorities for marginal increases in q or marginal decreases in m. If whites and minorities have identical preferences but whites have higher incomes, (1a) and (1b) are ensured by a standard "single crossing" assumption on preferences.

Consider the demand for houses in a neighborhood with minority share m. Define the

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[18] Examples of similar models include Miyao (1979) and Benabou (1996).

[19] The results below also hold in a more complex model with overlapping income distributions where the white share is increasing in income. The assumption that minority families' utility is declining in m is also unnecessary but convenient.

quality threshold a(m) such that whites and minorities would bid an equal amount for a house of quality q=a(m):

$$b^W(a(m), m, U^W, Y^W) = b^M(a(m), m, U^M, Y^M).$$

By assumption (1b), minority families outbid whites for any lower-quality houses (houses with $q<a(m)$), while whites outbid minorities for higher-quality houses ($q>a(m)$). Equations (1a) and (1b) ensure that a(m) is upward-sloping and invertible. Let H denote the distribution function of quality q in a given neighborhood. If the neighborhood has a minority share m, a fraction H(a(m)) of houses will attract higher bids from minorities than from whites. Thus, for the housing market to be in equilibrium with $0<m<1$, it must be that $H(a(m))=m$. If $H(a(m))>m$ for all values of m, the only equilibrium has m=1; while if $H(a(m))<m$ for all m, then m=0 in equilibrium.

It is convenient to recast the analysis in terms of q and $m=a^{-1}(q)$. An integrated equilibrium requires that there exist some quality threshold q with $H(q)=a^{-1}(q)$; the neighborhood will then have minority share $m=a^{-1}(q)$. This equilibrium will be stable if $H'(q) < \partial a^{-1}(q)/ \partial q = 1/a'(m)$ and unstable if the reverse is true. Unstable equilibria are more likely when there is limited quality dispersion (so H(q) is relatively steep), and when white bidders are relatively less tolerant of minority neighbors (so a′(m) is large). Figure 3a plots illustrative functions $a^{-1}(q)$ and H(q) under the assumption that they cross once at an unstable equilibrium, point B.[20] The "absorbing" points A (with m=0) and C (with m=1) are stable equilibria. As is common for such models (e.g. Brock and Durlauf, 2001a), there must be an odd number of equilibria —1 or 3 if

[20] In this illustration, q is uniformly distributed on $[q_0, q_1]$, and we have assumed that $a^{-1}(q)$ is concave. Bond and Coulson (1989) present an example with Cobb-Douglas utility in which $a^{-1}(q)$ is concave, but this is not a general property.

a(m) is concave—with any pair of stable equilibria separated by an unstable equilibrium.[21]

Consider the dynamic evolution of a neighborhood that starts with a minority share m. For $0 \leq m \leq m^B$, $H[a(m)] < m$, and minorities outbid whites for less than a fraction m of houses, so the minority share will fall. The opposite is true if $m^B \leq m \leq 1$: in this interval $H[a(m)] > m$, and minorities outbid whites for more than a fraction m of houses, leading to a rise in m. The unstable equilibrium B thus separates the zones of attraction for the two stable equilibria, A and C. While the rate of change of m depends on the degree of "stickiness" in the housing market, in the absence of large external shocks any neighborhood that starts with a minority share less than m^B will eventually become all-white, whereas any neighborhood that starts with a share over m^B will eventually become 100% minority. m_B is therefore a tipping point.

This simple model has an important implication for the location of the tipping point: m_B will be higher when whites are relatively more tolerant of minorities. To see why, note that $a'(m) = -(\partial b^W/\partial m - \partial b^m/\partial m) / (\partial b^W/\partial q - \partial b^m/\partial q)$. Therefore, if $\partial b^W/\partial m$ increases— i.e. white bidders become more tolerant of minority neighbors— $1/a'(m)$ increases, and the tipping point value m_B increases.

The model also has implications for the local housing market. Assuming that the bid functions of whites and minorities are both decreasing in m,[22] at a value for housing prices that clears the market in a neighborhood with $m=m^B$ there will be excess bidders for houses if $m < m^B$ and excess supply if $m > m^B$. If the housing supply in a neighborhood is fixed, rents for a

[21] The stable equilibria need not be at 0 and 1. If $H[a(0)]>0$ and $H[a(1)]<1$, for example, the unique equilibrium is stable and on the interior of (0, 1). If $a^{-1}(q)$ is tangent to H, the point of tangency is an equilibrium that is stable from one side and unstable from the other; only in this situation—known as a "bifurcation" where two equilibria collapse and disappear as a is shifted slightly—can there be an even number of equilibria.

[22] As we discuss below, this assumption can be tested by examining total population growth around the tipping point.

home of fixed quality will therefore fall if $m>m^B$, or rise if $m<m^B$. In this case the present value of future rents will be discontinuous at m^B, and if agents are forward-looking housing prices will also fall discontinuously at m^B. Alternatively, if the supply of housing is elastic, supply will tend to rise in neighborhoods with $m<m^B$ and decline in neighborhoods with $m> m^B$, leading to a discontinuous relationship between the growth rate of the housing stock and the minority share at the tipping point.[23]

IV. Testing for Tipping Behavior

In this section we develop our empirical approach to testing for tipping behavior in neighborhoods. We focus on a key implication of the model illustrated in Figure 3a, which is the existence of a critical value for the minority share below which neighborhoods tend to gain white residents, and above which they tend to lose white residents.

In many contexts it would be difficult to estimate dynamic behavior around an unstable equilibrium, since the observed data will tend to cluster around the stable equilibria. This characterization is partly true in our application as well: 35% of neighborhoods in our sample had minority shares below 5% in 1980, and 9% had minority shares above 80%. Metropolitan housing markets are subject to continuous shocks, however, and the share of minorities in most cities has risen dramatically over the past several decades. Since housing markets adjust relatively slowly, this means that at any point in time substantial numbers of neighborhoods are

[23] New construction and renovation shifts the H curve rightward, raising m^B. This creates the possibility of self-fulfilling prophecies: A neighborhood that is expected not to tip might attract sufficient investment to prevent tipping, while in another neighborhood with the same current m expectations of tipping could lead to lower construction rates that bring this about. As in Krugman (1991), this could produce an indeterminate range around m^B in which the future evolution depends on expectations. Depending on the nature of heterogeneity in expectations across neighborhoods, this could either smooth out discontinuities at m^B or simply shift the discontinuities to the edges of the indeterminate range.

out of equilibrium. Consider the simple model in Figure 3a, and suppose that every tract in a city is initially at one of the stable equilibria, A and C. If there is an injection of minority residents, some neighborhoods must eventually move from A to C. But if new residents are unable to coordinate, one would expect to see positive inflows of minorities to many different all-white tracts, producing positive density around equilibrium B and permitting estimation of the local dynamics.

a. Observable Implications of a "Tipping Point"

Abstracting from shocks, assume that the dynamics of the neighborhood minority share can be formalized as:

(2) $\Delta m_t = m_t - m_{t-1} = \alpha + \beta\ m_{t-1}$, $\alpha < 0$, $\beta > 0$,

This equation implies that the neighborhood minority share is increasing if $m_{t-1} > m^* = -\alpha/\beta$, and decreasing otherwise, with a rate of change that is increasing in the deviation from the tipping point m^*. Since m_t cannot be smaller than 0 or greater than 1, we add these boundary conditions to (2). Figure 3b illustrates the implications of the augmented equation for the evolution of the white neighborhood share over a short time horizon (1 period) and a longer horizon (10 periods), assuming α=-0.08 and β=0.4. (We plot the changes in the white population share since this is the traditional dependent variable used in studies of neighborhood transition). Note that although equation (2) specifies a continuous relationship between Δm_t and m_{t-1}, over a longer time horizon the relationship between the base year minority share and the subsequent change in the white population share exhibits a "near discontinuity" at the tipping point m^*.

Building on this insight, we proceed to test for tipping behavior using a regression-discontinuity approach. Our data come from successive decennial censuses, providing relatively infrequent observations on a neighborhood. We posit that the change in the white population share from one census to the next, $\Delta w_t = w_t - w_{t-10} = -\Delta m_t$, can be approximated as

(3) $$E[\Delta w_t \mid m_{t-10}] = a(m_{t-10}) \times 1[m_{t-10} \leq m^*] + b(m_{t-10}) \times 1[m_{t-10} > m^*],$$

where 1[ ] represents the indicator function, m^* represents a city-specific tipping point (to be defined below), and a(m) and b(m) are smooth functions defined on $[0, m^*]$ and $[m^*, 1]$, respectively.

We focus on estimating $b(m^*) - a(m^*)$, the "jump" (if any) in $E[\Delta w_t \mid m_{t-10}]$ at m^*. The motivation for this focus is simple: if there is indeed a tipping point that is (approximately) the same for all neighborhoods in a given city, then over a reasonably long time frame, like the 10 years between decadal Censuses, tracts with initial minority shares just above or just below the tipping point will diverge. Though strictly speaking the mapping from initial minority shares to the subsequent change in white population shares is continuous if the dynamic process of neighborhood transition is 'smooth', a sufficiently steep local slope is empirically indistinguishable from a discontinuity, and we will estimate an intercept shift at m^* if the functions a(m) and b(m) describing the evolution of the white share on either side of m^* are not too flexible.

Relative to a conventional regression discontinuity analysis, our investigation of tipping therefore has two important differences. First, we do not know the location of the tipping point, and instead have to locate it empirically. Second, we do not necessarily expect that the data will exhibit unambiguous, sharp discontinuities at a tipping point (although as is clear from Figure 1, such a pattern frequently emerges). Instead, we interpret a finding of a "near discontinuity"—a steeply downward-sloping section in the region of m^*—as evidence of tipping behavior.

b. Distinguishing White and Minority Population Changes

Because neighborhoods are not fixed in size, and because a neighborhood's growth rate depends on its desirability to potential residents of all races, it is useful to consider the evolution of white and minority populations separately. To isolate the changes in m deriving from white population flows, we use an alternative measure of neighborhood racial change that holds the denominator fixed:

$$\Delta(W_t/P_t) \quad = \quad 100*(W_t - W_{t-10})/ P_{t-10} \ ,$$

i.e., the change in the number of white residents (or students) as a percentage of the initial population of the neighborhood (or school). We also present analyses of the corresponding changes in the minority population, $(M_t - M_{t-10})/ P_{t-10}$ and the total population, $(P_t - P_{t-10})/P_{t-10}$.

c. Identification of the Tipping Point

As noted, a key difference between (3) and most existing applications of regression discontinuity methods is that in our case m^* is unknown. There is as yet no consensus method for estimating regression discontinuity models with an unknown point of discontinuity. We explore two approaches, one that draws on the time series literature on structural breaks (as reviewed in Hansen, 2001) and another that takes advantage of the specific structure of our problem. We assume for the moment that a tipping point exists (i.e. that there is a single discontinuity in $E[\Delta(W_t/P_t) \mid m_{t-10}]$) and focus on estimation of m^*. We return below to discuss testing for the existence of tipping against the null hypothesis that $E[\Delta(W_t/P_t) \mid m_{t-10}]$ is continuous, in which case m^* is not identified.

Both approaches begin with the observation that the average change in the white population share conditional on the initial minority share exhibits a common shape across cities, although the level varies from city to city.[24] Typically the expectation function is positive and reasonably flat for low values of m_{t-10}, then falls very rapidly to a negative value. Beyond the (relatively narrow) range of transition, it is flat again until finally, beginning around m_{t-10} = 60%, the expectation function begins to trend upward, approaching 0 as $m_{t-10} \rightarrow 1$.[25] For our "time series" approach, we approximate a(m) and b(m) as constants in the range of minority shares between 0 and 60%. Equation (3) then becomes:

(4) $$E[\Delta(W_t/P_t) \mid m_{t-10}] = a + d * 1[m_{t-10} > m^*] \quad \text{for } 0 \leq m_{t-10} < 60\%\ ,$$

where a is a city-specific constant and d = b – a. We use a search procedure like that discussed by Bai (1997), Andrews (1993), and Hansen (2000) to estimate m^*: For each value $m_{i,\,t-10}$ in our data, we set $m^* = m_{i,\,t-10}$ and compute the OLS estimate of (4), using only points with $m_{t-10}<60\%$. Our estimate of m^* is the value for which this regression has the highest explanatory power or, equivalently, that for which the absolute t statistic on d is maximized. Assuming (4) is correctly specified, Hansen (2000) shows that this procedure yields a consistent estimate of the true m^*.

This procedure works well in many larger cities but performs poorly in others, perhaps because of variability in the true evolution of neighborhood minority shares. Our second approach builds on the observation that if there is a city-specific tipping point, then even in the

[24] Many cities experience sharp increases in their minority shares over our sample period, so that even tracts with negative $\Delta(W_t/P_t)$ can be rising in the city's W/P distribution. To abstract from city-wide trends, we focus on $E[\Delta(W_t/P_t) \mid m_{t-10}] - E[\Delta(W_t/P_t)]$, which equals zero when tracts are evolving in step with the city as a whole.

[25] $\Delta(W_t/P_t)$ can never be lower than $m_{t-10} - 100$, corresponding to total loss of the t−10 white population by year t. Many neighborhoods with m_{t-10} above about 50% approach this limit.

presence of city-wide shocks, neighborhoods that start with minority shares below the tipping point will experience faster-than-average growth in their white population share, whereas those that start above the tipping point will experience slower-than-average white population growth. Specifically, if there is a tipping point at m^*, $a(m) > E[\Delta(W_t/P_t)]$ for all $m<m^*$, and $b(m) < E[\Delta(W_t/P_t)]$ for all $m^*<m<60\%$. Thus, for small $\varepsilon > 0$,

(5) $$E[\Delta(W_t/P_t) \mid m=m^* - \varepsilon] > E[\Delta(W_t/P_t)] > E[\Delta(W_t/P_t) \mid m=m^* + \varepsilon].$$

This equation implies that the city-specific tipping point is the "fixed point" in the relationship between the initial minority share of a neighborhood and the deviation of the expected change in the white population share from the city-wide average change. Note that this definition corresponds exactly to a definition of a tipping point as an unstable equilibrium.

To use equation (5), we first smooth the data to obtain a well-behaved continuous approximation, $R(m_{t-10})$, to $E[\Delta(W_t/P_t) \mid m_{t-10}]$ on the (0%, 60%) range. We then choose as a potential tipping point the level of minority share m' such that $R(m') = E[\Delta(W_t/P_t)]$. In the case of multiple roots, we choose the root for which R' is the most negative.[26] We call this the "fixed-point" procedure.[27]

d. Hypothesis Testing

These two procedures will produce estimates of m^* whether or not a city's neighborhoods

[26] In practice, a two-stage approach to estimating $R(m)$ local to m^* improves precision. First, we fit a city-specific regression of $\Delta(W_t/P_t)$ on a fourth-order polynomial in m_{t-10}, using tracts with initial minority shares below 60%. We identify a candidate m' from the fitted values of this. Then we estimate a second fourth-order polynomial regression on a sample restricted to tracts with m_{t-10} within ten percentage points of the identified point, and use the fitted values from this regression to obtain a more refined estimate of the fixed point.

[27] We have also explored a third procedure, estimating $E[\Delta(W_t/P_t) \mid m_{t-10}]$ with local quadratic regressions and selecting the point where the estimated slope is most negative. Local slope estimates were quite noisy, however, and though this procedure agreed with the other two in many cities, in other cities it was poorly behaved.

are actually tipping. If they are (and our assumptions about $E[\Delta(W_t/P_t) \mid m_{t-10}]$ are correct), either estimate is consistent for m^*.[28] If $E[\Delta(W_t/P_t) \mid m_{t-10}]$ is continuous over the relevant range, however, it is unclear what either procedure will estimate. Moreover, the distribution of d from equation (4) under this null hypothesis is decidedly non-standard, as the value of m^* is not independent of the observations used to estimate (4). Conventional testing procedures (e.g. Andrews, 1993 and Hansen, 1996) use a simulation approach to approximate the distribution of $\hat{d}$ under the null hypothesis of no break in the functional relation, and then compare the estimate to this distribution.

We take a different approach that, to our knowledge, has not previously appeared in the literature. We begin by randomly dividing our sample of neighborhoods in each city into two parts. We reserve one subsample for the estimation of m^*, using the two search procedures described above. We then use the *other* subsample to estimate equation (4). Since the observations in the second subsample are independent of the data used to estimate m^*, estimates of $\hat{d}$ from this sample have a standard distribution, permitting traditional tests.[29]

City-specific tests have low power: We have relatively few tract-level observations from many smaller cities, and we use only a fraction of tracts in each city to estimate the discontinuity models. Across cities, however, a finding that substantially more than 5% of the t-statistics on city-specific discontinuity estimates are larger than 2 (in absolute value) indicates that the null hypothesis fails in at least a significant subset of cities.

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[28] For the "fixed point" procedure, the polynomial approximation R(m) would need to become arbitrarily flexible as the sample size increases.

[29] The procedure can easily be generalized to higher-order approximations to $E[\Delta(W_t/P_t) \mid m_{t-10}]$. Too flexible an approximation, however, risks absorbing any true discontinuity. Given the small number of observations in our sample—70 in our "testing" subsample in the median city—and our investigation of the data, we conclude that our relatively inflexible parameterization is preferable.

Given the possibility that certain cities do not exhibit tipping, we maintain the split sample approach throughout the paper, using our first subsample only to identify candidate tipping points and relying on the second subsample for all further estimation. An appendix, available on request, reports estimates of the various discontinuity models that use the full sample of tracts for each city.[30]

e. Testing other implications of the tipping model

As noted above, the Bond and Coulson model (and other related models) implies that the tipping point will be higher in cities where whites are more tolerant of minority neighbors. We conclude our empirical analysis by relating the estimated tipping points for different cities to measures of the racial tolerance of the city's white population, while controlling for other city characteristics. We also examine changes in tipping patterns over time: There is evidence from public opinion surveys that whites have become increasingly more tolerant of minorities (Schuman et al., 1998). Both our cross-sectional and time-series comparisons indicate a positive relationship between white tolerance and the level of the tipping point.

V. Data and Potential Tipping Points

We use Census tract data for the 1970-2000 Censuses from the Urban Institute's Neighborhood Change Database (NCDB) as our source of data on neighborhoods. We treat metropolitan statistical areas (MSAs) and primary metropolitan statistical areas (PMSAs) as

[30] If different tracts in the same city are not independent—if, e.g., $\Delta(W_t/P_t)$ - $E[\Delta(W_t/P_t) \mid m_{t-10}]$ is spatially correlated—neither are the two subsamples. We expect that the resulting bias in our test statistics will be small. Full sample estimates are appropriate if there is tipping, and generally indicate larger, more precisely estimated effects than do the split-sample estimates. All of our pooled analyses cluster on the city, so standard errors are robust to arbitrary spatial correlation.

defined in 1999 as "cities." Since estimation of $E[\Delta(W_t/P_t) \mid m_{t-10}]$ requires reasonably large samples, we exclude cities with fewer than 100 tracts that can be merged between Censuses. In 1970, only the central areas of many MSAs were assigned to tracts, so our analysis for the 1970-80 period is largely based on central city neighborhoods. Additional areas were assigned to tracts in 1980 and 1990, allowing us to include more suburban tracts (and more cities) in our analyses of the 1980s and 1990s.[31]

Table 1 presents summary statistics for our primary sample of tracts from larger MSAs. The first two rows show the total number of tracts in the U.S. and in metropolitan areas The number of tracts defined by the Census Bureau has risen steadily, from about 46,000 in 1970—nearly all metropolitan—to about 65,000—one fifth non-metropolitan—in 1990. Rows 3 and 4 report the number of MSAs and tracts in our sample. There are 104 MSAs for which we can match at least 100 tracts between 1970 and 1980, 113 for 1980-1990, and 114 for 1990-2000. The next several rows show average (unweighted) demographic characteristics of tracts in our samples.

The remainder of the table shows statistics for four subgroups of tracts, defined by the fraction of minority residents in the base year: 0-5%, 5-20%, 20-70%, and 70% or higher. In 1970, just under half of tracts—both in the nation and in our sample—had minority shares below 5%. By 1990, only a quarter of sample tracts had such low minority shares. This decline was

[31] Although the NCDB attempts to hold tracts constant at their 2000 boundaries, little information is provided about the quality of the matches. To test whether our results are sensitive to mis-matched tracts, we used a block-level crosswalk to construct our own panel of tracts between 1990 and 2000. We also experimented with alternative treatments of multi-race individuals in the 2000 Census (which, unlike earlier censuses, allowed respondents to report more than one race). Our results were robust to the use of the alternative panel, to the use of 1990 rather than 2000 tract boundaries as the basis for the analysis, to a sample restriction that eliminated any tracts for which the 1990-2000 mapping was non-trivially imperfect, and to defining all multi-race individuals as non-white.

offset by growth in the other categories, particularly the 20-70% minority group (which rose from 15% to 27%) and the 70% or higher minority group (which rose from 7% to 16%).

Comparisons across the four groups of tracts show substantial growth in the white population in the two lower minority share subgroups but small or negative growth in the other two subgroups. The difference in growth rates of the white share between tracts with a 5-20% initial minority share and those with a 20-70% initial share was about 40 percentage points in the 1970s, falling to 24 points in 1980-1990 and 20 in 1990-2000. These gaps are consistent with potential tipping behavior around a 20% minority share. However, the table also shows that higher minority share tracts have lower family incomes, higher unemployment, and more multi-unit housing, all factors that may confound the effects of racial composition.

We use the two algorithms described in Section IV(b) to identify city-specific potential tipping points. Figure 4 shows the identified points for several cities, using a solid vertical line to mark the point identified by the "fixed point" method and a dashed line to mark the "time series" method. (Where only one line is shown, the two coincide.) Both methods are applied to a random 2/3 subsample of tracts in each city.[32] We also plot two approximations to $E[\Delta(W_t/P_t) \mid m_{t-10}]$ computed from the remaining 1/3 subsample. First, we group tracts into 2-percentage-point bins for the value of m_{t-10} and construct the mean of $\Delta(W_t/P_t)$ within each bin. These are the "dots" in the figures. (Although a majority of the tracts in most cities are in the first five bins, the dots are not sized to reflect this). Second, we present local linear estimates of $E[\Delta(W_t/P_t) \mid m_{t-10}]$, computed separately on each side of the "fixed point" candidate tipping point.

[32] We use a 2/3 – 1/3 split instead of ½ - ½ because the search procedures for identifying tipping points in each city are quite data intensive. Once these points are identified, we conduct most of our analysis on a sample that pools data from many cities, for which 1/3 subsamples are adequate.

The first panel of the Figure shows Los Angeles in 1970 – 1980. Both search procedures identify a potential tipping point between 15 and 15.5% minority share in 1970. Tracts to the left of this gained white population, on average, between 1970 and 1980, while tracts just to the right of the tipping point lost substantial numbers of whites. Note that the conditional mean of $E[\Delta(W_t/P_t) \mid m_{t-10}]$ is above the unconditional mean (shown as a horizontal line) everywhere to the left of m^* and below it everywhere to the right, consistent with an interpretation of m^* as the dividing line between the attracting zones of stable long-run equilibria at m=0 and m=1.

The remaining panels of Figure 4 show seven other cities: Indianapolis and Portland (Oregon) in 1970-1980, San Antonio and Middlesex-Somerset-Hunterdon (New Jersey) in 1980-1990, Nashville and Toledo in 1990-2000, and finally Pittsburgh in 1980-1990. All but the last of these (to which we return momentarily) shows clear evidence of a discontinuity around the "fixed point" candidate tipping point; in each case the time series method indicates approximately the same tipping point. As noted earlier, the conditional mean functions are relatively flat on either side of the tipping points, generally above the unconditional mean to the left and below it to the right.[33] Tipping behavior is evident in cities from all regions of the country (North versus South, and "sun-belt" versus "rust-belt"), and in cities with larger and smaller minority shares. The final graph in Figure 4 – Pittsburgh in the 1980s – shows a city with no sign of tipping. In particular, the white population growth rate is a relatively smooth, decreasing function of the initial minority share (for minority shares between 0 and 50%) with no indication of a discontinuity.

Table 2 presents a more systematic overview of the potential tipping points derived from

[33] The rightmost portions of the graphs are exceptions. In several of the plotted cities, the conditional mean lies quite close to its theoretical minimum of $m_{t-10} - 100$ at the highest m_{t-10} values, indicating that tracts in this range lose nearly all of their white residents over a ten year period.

the "fixed-point" and "time series" procedures. The first rows show the means and standard deviations of the points identified by each method in each decade. Average potential tipping points are in the 10 – 15 percent range, though the time series method tends to select lower values than the fixed point method. Points selected by either method show moderate increases over time. The third row indicates that the "fixed point" method fails to find a candidate point (at a level of $m<50\%$) in only a very few cities. Finally, the lower portion of the Table shows correlations of the identified points for a given city across methods and over time. These correlations are reasonably high (above 0.5) for the same method in different years and for different methods in the same year. In each year, the two methods select points within 1 percentage point of each other in about 1/3 of cities.

The statistics in Table 2 describe all identified candidate tipping points, without regard to the specific dynamics around them. To give an indication of the prevalence of tipping, we estimate city-specific tests of the hypothesis that $d=0$ in our simplest specification, equation (4), using the estimate of m^* identified by the fixed point method. In the 1980s, we reject this hypothesis at a 5% level in 81 of 111 cities. This almost certainly understates the prevalence of tipping, as we have little power in smaller cities. Figure 5 shows the scatterplot of the estimated t statistics against N, the number of tracts in the city (in the 1/3 testing sample). In the smallest cities, the estimated t-statistics are dispersed around -2, and the mean becomes more negative as the city size grows. Assuming that d is non-zero and constant across cities, the absolute value of the mean t statistic would be expected to increase with $\sqrt{N}$, while if d is zero everywhere the t statistics should be centered around zero independent of N. The dashed line in the figure shows fitted values from a regression of the t statistic on $\sqrt{N}$. The coefficient of this regression is negative, large, and highly significant. The evidence thus suggests the existence of a discontinuity in the great majority of the cities in our sample, even if we do not have enough power to detect a discontinuity in every city.

VI. Pooled Analysis

To permit more flexible analyses than are possible with the relatively small sample sizes available in each city, in this section we turn to pooled analyses that use data from all of the cities in our sample. Section VII extends the regression discontinuity analysis to examine the housing market correlates of tipping, and Section VIII tests the theoretical prediction that the tipping point is higher in areas where whites are relatively more tolerant of minorities

a. Graphical Evidence

To pool the data across cities with different potential tipping points, we deviate each tract's minority share in year $t-10$ from the potential tipping point for the corresponding MSA. For our graphical analysis we also deviate the change in the white share in the tract between $t-10$ and t from the corresponding metropolitan-wide mean. (In our regression models we include city dummies so this step is unnecessary). The two panels in the top row of Figure 6 show the relationship between the 1970 minority share in a Census tract (deviated from the city-specific potential tipping point) and the 1970-1980 change in the white share in the tract (deviated from the city-wide average change). We use candidate tipping points from the fixed point method on the left and from the time series method on the right. Dots in the figures plot the average change in white population at each percentage point deviation from the potential tipping point. To illustrate, the first circle in each panel shows the average of the change in white population minus the mean change for the MSA for tracts with initial minority shares between -29 and -30 percentage points from the MSA-specific candidate tipping point.[34]

The solid lines on the figures show local linear regressions fit to the data on each side of the candidate point, while the dashed lines show fitted values from a global specification that includes a 4th-order polynomial in $\delta = m_{t-10} - m^*$ with an intercept shift at $\delta = 0$. In both the unsmoothed data and the smoothed representations, and using either method for choosing candidate points, we find clear evidence of a discontinuity, with a magnitude around 15 – 20 percentage points.

The middle panel of Figure 6 repeats these plots for the 1980-1990 period. As before, tracts with initial minority shares below the potential tipping points exhibit faster growth in their white population shares than do average tracts in their cities. By contrast, tracts with initial minority shares above the potential tipping point exhibit substantial relative declines in the white share. The discontinuities at zero, while clearly evident in 1970, are somewhat harder to see in 1980: while the trends are relatively stable on the left and right, they slope toward each other as δ approaches zero. This is suggestive of a "near" discontinuity in the long-run relationship between the base year minority share and the subsequent change in the white population share, as predicted by the theoretical model. The highly flexible local linear smoother fails to find much of a discontinuity at the "fixed point" potential tipping points. Visual inspection suggests, however, that if the few points closest to δ=0 are excluded there is a substantial jump. The global smoother, which implicitly identifies the jump using a larger bandwidth around m^*, shows

[34] In most cities the potential tipping points are well below 30%, so not all cities are represented at points on the left side of the graphs.

a discontinuity in each panel.

The last panel of Figure 6 repeats the analysis for the 1990-2000 period. The sharp changes in slope around $\delta=0$ seen in 1970-1980 and 1980-1990 diminish, but do not disappear, in 1990-2000. The local linear smoother indicates no discontinuity at $\delta=0$ in either panel, a result that is again driven by the points closest to $\delta=0$. Taking a slightly broader view, the dynamics do appear to change relatively abruptly in a small region around this point, and our polynomial estimator indicates a reasonably large discontinuity. There are several possible explanations for the apparent reduction in tipping behavior in the 1990s. Most obviously, public opinion polls suggest that race-related attitudes of whites towards minorities have improved over time (Schuman et al., 1998). These changes in attitudes may have translated into less extreme tipping patterns by 1990 and into the observed increase in average m^* values over time.

Taken as a whole, the plots presented in Figure 6 suggest that cities tend to have a threshold level of minority share after which growth of the white population share falls dramatically relative to average MSA growth in the white population—by about -20 percentage points in the 1970s, -15 in the 1980s and -10 in the 1990s. These threshold points vary by city and appear to be well-approximated by the candidate tipping points we have identified using "fixed-point" and "time series" methods. The near-discontinuous changes in the growth of white population around the candidate tipping points are strikingly similar to the long-run prediction of the simple theoretical model of tipping. The finding of such a pattern in the data represents initial evidence that social interactions in preferences have important consequences for neighborhood segregation. The evident shrinking of the effect between the 1970s and 1990s is consistent with survey-based evidence that race-related attitudes of whites towards minorities have improved over time, though the figures suggest that tipping has not disappeared.

b. Parametric Models

The results in Figure 6 are visually striking, but do not permit formal hypothesis tests, nor allow for the impact of other neighborhood characteristics that may affect white mobility rates. Table 3 presents regression versions of the graphical analyses in Figure 6. Again, these models are estimated on a 1/3 subsample of tracts for each city, eliminating the other 2/3 of tracts that were used to identify the potential tipping points. We estimate a generalized version of equation (3):

(6) $E[\ \Delta(W_t/P_t) \mid \delta] = f(\delta) + d * 1[\delta > 0] + \gamma * X$,

where $\delta = m_{t-10} - m^*$, $f(\delta)$ is a smooth function of δ, and X is a vector of other predetermined variables. We model $f(\delta)$ as a pair of quadratic functions, one defined over positive values (i.e. over tracts with $m_{t-10}>m^*$) and the other over negative values. This approach allows the first and second derivatives of f() to vary discontinuously around $m_{t-10} - m^* = 0$, and estimates the discontinuity as the difference in intercepts between the two quadratics.[35] Columns 1-2 use the potential tipping points from the "fixed-point" procedure, and columns 3-4 use the potential tipping points from the "time series" approach. In each case we include a full set of MSA fixed effects to capture differences across cities in white population growth rates, and we cluster standard errors at the MSA level.

The estimates in Table 3 confirm that the growth rate of the white population share is discontinuous in the initial minority share around the potential tipping points. When we use the

[35] The estimates are robust to a variety of alternative specifications of f( ), including the global fourth order polynomial used in Figure 6.

potential tipping points from the fixed point procedure, in Column 1, we obtain precisely estimated discontinuities of -19, -18, and -8 percentage points for the 1970-1980, 1980-1990, and 1990-2000 periods, respectively. Estimates that use the "time series" procedure to identify tipping points are comparable (Column 3). Columns 2 and 4 add controls for five tract-level characteristics, measured in the base year: the unemployment rate, the log of mean family income, and the fractions of single-unit, vacant, and renter-occupied housing units. Inclusion of the control variables attenuates the estimated discontinuities somewhat, but they remain large and highly significant.

c. Additional Specifications

It is possible that the discontinuous relationship between the growth in white population and initial minority share is, in fact, due to a relationship between white population growth and some omitted neighborhood characteristic that is discontinuously related with the minority share. To assess this possibility, we have estimated a variety of alternative specifications of our basic model. The estimated discontinuities at the potential tipping points are unaffected by the inclusion of 4^{th} order polynomials in neighborhood characteristics like the neighborhood poverty rate, mean family income, unemployment rate, or renter share.[36] We have found only one neighborhood characteristic whose inclusion as a control affects the estimated discontinuity at the tipping point: Tracts just to the right of the tipping point tend to be somewhat closer to established "minority" neighborhoods—defined as those with minority shares at least 10

[36] Estimates are reported in Appendix Table 1. In Appendix Table 2 we also explore specifications that count only blacks, or only blacks and Hispanics, as "minorities." Estimated tipping effects are essentially invariant to the definition used, and the pattern of results does not offer clear guidance about which racial composition measure is most relevant.

percentage points above m^* in the base period—than are those just to the left (Mobius and Rosenblat, 2001). Controlling flexibly for this distance reduces the estimated discontinuity at m^* by about 30-50%, though it remains large and significant.

As an alternative approach to reducing or eliminating biases in our RD specification, we exploit geographic information, comparing a neighborhood with m_{t-10} just above m^* with another *nearby* neighborhood for which m_{t-10} is just below m^*. This "within-neighbors" analysis eliminates the influence of any omitted variable—including the distance to a "minority" neighborhood—that is smoothly distributed across space. In contrast to standard data configurations (such as the sibling relationship used in twins comparisons of education and earnings, e.g., Ashenfelter and Rouse, 1998), the "nearest neighbor" relationship is not transitive. Our approach is to include in equation (6) averages of the independent variables across the five closest neighboring tracts, measured from centroid to centroid and capping the distance at four miles. Denoting the average of $1[\delta>0]$ across i's neighbors (including neighborhood i in the average) as $\bar{t}_{n(i)}$ and the average of the terms in the polynomial $f(\delta)$ as $\overline{f(\delta)}_{n(i)}$, we estimate:

$$(7) \qquad E[\,\Delta(W_t/P_t) \mid \delta_i, \bar{t}_{n(i)}, \overline{f(\delta)}_{n(i)}\,] = f(\delta_i) + \overline{f(\delta)}_{n(i)} + d * 1[\delta_i>0] + d' * \bar{t}_{n(i)}.$$

In this specification, d is the "within-neighbors" estimate of the tipping discontinuity. An estimate of $d \neq 0$ indicates that even differences within narrowly-defined clusters of adjacent neighborhoods in the beyond-m^* indicator have impacts on the growth in the white population share. The coefficient d' is of independent interest: If the Census tracts that we use to proxy for "neighborhoods" do not correspond perfectly to the areas that enter into residents' preferences, this would produce apparent spillovers.[37] An indication that d' ≠ 0 would suggest that these spillovers are potentially important.

Table 4 reports estimates of equation (7). Although inclusion of the neighborhood minority share variables reduces the magnitude of the "own-tipping" coefficients from those seen in Table 3, they remain large and statistically significant. Over the 1980s, for example, when neighboring tracts' minority shares are held constant, moving a tract beyond the tipping point causes it to lose 14.3 (= 12.3 + 12.2/6, from column 3) percentage points in white share. The group average of the tipping indicator also has a strong negative effect: In the same specification, a tract with all 5 neighboring tracts beyond the tipping point loses 10.1 (=12.2 × 5/6) percentage points in white share relative to one with the same initial minority share but no neighboring tracts beyond the tipping point. This estimated spillover effect is consistent with a simple measurement story in which the relevant neighborhood for a given household is some average of the immediately surrounding tract and other nearby tracts. It is not large enough, however, for our earlier results to be due solely to an association between a tract's minority share and any omitted variables that are smoothly distributed across space.

A final specification test explores the possibility that what looks like tipping in the minority share of a neighborhood is actually driven by non-linear dynamics in the share of low-income neighbors. To implement this test, we identified potential tipping points in the neighborhood poverty rate (using the fixed point and time series procedures) for each city. We then estimated models for the change in the white population share that include polynomials and

[37] This might be a particular issue in the later years of our tract-based analysis. Although Census tracts—geographic units of approximately 4,000 people—were initially drawn with the goal of corresponding to socially-understood neighborhoods, their boundaries may not have changed to keep up with shifts in true neighborhood boundaries. Thus, by 1990 there could be substantial slippage between the units used in our analysis and those that enter into residents' preferences.

potential discontinuities in the deviation of a tract's minority share from the city-wide racial tipping point, and in the deviation of the tract's poverty rate from the associated poverty tipping point. Table 5 reports the resulting estimates. There is some evidence of a discontinuity in white mobility rates at the poverty rate tipping point, at least in the 1970s and 1980s. This does not account for our earlier results, however: The estimated discontinuities at the racial tipping point are only slightly diminished by inclusion of the additional controls, and remain large and highly significant.

Our analysis so far suggests that integrated neighborhoods in most cities are dynamically unstable, with a clear demarcation point between the range of minority shares that lead to increases in the white population share, and the range that lead to systematic decreases. Movements toward a nearly all-white or nearly all-minority state are rapid enough to produce an apparent discontinuity in decadal changes in white population shares at this point. The presence of tipping behavior is robust to a variety of alternative specifications, and in particular cannot be attributed to other tract-level variables that co-vary with the minority share. A neighborhood's racial composition itself appears to be the key determinant of subsequent white population flows, as the discontinuity in the base-year minority share remains even when we introduce the possibility of non-linear dynamics in the local poverty rate. Finally, the magnitude of the discontinuity at the tipping point—the degree of instability—is large in the 1970s and diminishes slightly in the 1980s and somewhat more in the 1990s.

Taken together, these results provide strong evidence of social interactions in families' preferences. The highly nonlinear dynamics identified in Tables 3-5 would not arise if preferences depended only on neighborhoods' exogenous characteristics. The remainder of our analysis attempts to flesh out this result. We first examine the effects of the minority share of neighborhoods on local housing markets, focusing on the growth rate of the local population and the timing of housing price changes. We then consider changes in the white enrollment shares at elementary schools over the 1990s, to test whether tipping is evident in schools as well as neighborhoods. Finally, in Section IX, we relate the *location* of the tipping point—theoretically a function of the degree of white intolerance for integrated neighborhoods—with survey-based measures of white racial attitudes.

VII. Housing Markets

The models presented earlier predict that the market-clearing price of a constant-quality house will be lower if the neighborhood's minority share is above the tipping point—and so is likely to end up with m=1 in the long run—than if it is below that point. This prediction derives from our assumption that *white* preferences over neighborhood minority shares drive tipping; if instead minority families have a positive willingness-to-pay for a neighborhoods with a high minority share, the predicted price effects are reversed.[38]

Theoretical models of tipping generally treat the number of houses in each neighborhood as fixed. This is empirically inaccurate, raising the possibility that the discontinuity in anticipated long-run housing demand at the tipping point m^* can be accommodated through quantity adjustments. To set the stage for our analysis of housing markets, we therefore begin by looking at the presence of tipping behavior in total population, and in the minority population share. Table 6 presents models for the neighborhood minority population and total population,

[38] Note that a model with positive preferences among minorities for high-minority-share neighborhoods would generate tipping behavior in the white population share.

each measured as the change between t−10 and t, as a percentage of the total population in t−10. Specifications are otherwise identical to those in even-numbered columns in Table 3. In each decade, tracts just beyond the tipping point saw small increases in their non-white populations relative to the metropolitan area average, though not nearly enough to offset the white population losses.[39] Total populations shrank substantially for tracts beyond the tipping point relative to those just to the left. Tipping is therefore more about changes in the total population than it is about replacing the existing white population with non-whites. Consistent with this, in supplementary analyses, reported in Appendix Table 3, we see a sharp dropoff in the rate of new housing construction during the t−10 – 10 decade at $m_{t-10} = m^*$.[40]

Prices represent the other side of the market. The Census data report homeowners' assessments of their houses' values, though this is measured with substantial error (Bayer, Ferreira, and MacMillan, 2003). Table 7 presents analyses of log mean housing values in 1970, 1980, 1990, and 2000 as a function of a tract's distance from the 1970-1980 or the 1990-2000 tipping point. The final three columns show estimates for changes in log mean housing values over various periods. Tracts that were beyond the 1970-1980 tipping point had substantially (8.2%) lower values in 1970 – prior to the onset of tipping – than did those just to the left of the tipping point. This gap grew slightly over the next decade, but closed somewhat thereafter. This pattern is consistent with market anticipation of the difference in long-run trajectories, and with

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[39] The *proportional* changes in the minority population approach those for whites, since around a 15% tipping point, the base minority population is about 1/6 as large as the base white population.

[40] These results suggest that availability of developable land might be an important determinant of the character of tipping. To examine this, we used data on tract-level land use patterns generously provided by Albert Saiz and Susan Wachter (2006) to divide our sample into quartiles based on the fraction of land that is undeveloped. Tipping appears to be most prominent in the middle quartiles, where density is high enough to make "neighborhood" a meaningful concept but low enough to allow room for further development. An important caveat to this analysis is that the land use data pertains only to 1992; by 1990, most central-city tracts have minority shares well in excess of the tipping point, so tipping can only be reliably estimated for the suburbs in any case.

little additional information being revealed during a decade in which tipping actually occurred.

Price effects around the 1990 tipping point, in the second row, are smaller, perhaps reflecting the diminished degree of tipping in 1990 relative to 1970, and few are significant. The change in values between 1970 and 1990 was lower for tracts to the right of the 1990 tipping point by 2.5% (nearly significant), and imprecise point estimates suggest that this effect arrived primarily between 1970 and 1980. There is no further decline in prices after 1990. Again, the results seem to suggest that the housing market anticipated the sharp changes in neighborhoods' fates associated with tipping.

Overall, we conclude that the housing price reactions to tipping behavior are relatively modest, and tend to pre-date the white flight that occurs once a neighborhood passes the tipping point. The quantity side of the housing market is more affected: the white outflows associated are offset only slightly by minority inflows, leading to net declines in population in neighborhoods that have passed the tipping point, relative to neighborhoods with minority shares just below the tipping point.

VIII. Schools

A natural hypothesis about the apparent importance of neighborhood racial composition to residential choices is that families are motivated by the racial composition of children's schools, which frequently depends on that of the surrounding neighborhoods.[41] Table 8 reports estimates of specifications similar to those in Tables 3 and 6, focusing on changes in school racial composition between 1990 and 2000. We re-estimate the city-specific tipping points for

[41] In future work, we hope to disentangle the separate roles of schools and neighborhoods by studying cities where school assignment policies change dramatically on the lifting of school desegregation remedies (Lutz, 2005).

this analysis, again dividing the sample of schools into two random subsamples and using the "fixed point" method to find the racial tipping points for elementary schools. The correlation between estimated school and neighborhood-level tipping points is 0.4.

Dynamics in schools are similar to those in neighborhoods. White enrollment growth drops off substantially in schools that are just beyond the tipping point, though the effect is somewhat smaller than in neighborhoods. Interestingly, total enrollment falls as much as does white enrollment, suggesting that, unlike neighborhoods, schools beyond the tipping point do not see offsetting inflows of minority students. Overall, however, we conclude that patterns of white mobility at the school level are quite similar to the patterns at the neighborhood level, and point to non-linear tipping-like responses once the minority share exceeds a critical threshold.

IX. Attitudes of Whites and the Location of the Tipping Point

The results from our analyses of white and overall population changes are consistent with a model in which tipping derives from white families' distaste for neighborhoods with high minority shares. If so, the model presented above indicates that the location of the tipping point should be higher in cities with more racially tolerant whites. To examine this, we use information on the racial attitudes of white residents in different cities from the General Social Survey (GSS).[42]

The annual GSS samples are small, and the survey instrument changes substantially from year to year. To develop a reasonably reliable index of white attitudes, we pooled GSS data

[42] Cutler, Glaeser, and Vigdor (1999) also use the GSS data in their examination of the relationship between white attitudes and residential segregation. It is important to note that causation—in both our own analysis and that of Cutler, Glaeser, and Vigdor—could run in either direction: Intolerant whites could lead to lower tipping points (and higher segregation), but similarly a lower tipping point could lead to greater levels of segregation, less inter-racial contact, and more intolerant attitudes.

from 1975 to 1998 and selected white respondents who could be matched to MSAs.[43] We used four questions that have been asked relatively frequently and that elicit direct information on preferences regarding contact between races:

I: Do you think there should be laws against marriages between blacks and whites?

II: In general, do you favor or oppose the busing of black and white school children from one school district to another?

III: How strongly do you agree or disagree with the statement: "White people have a right to keep blacks out of their neighborhoods if they want to, and blacks should respect that right"?

IV: Suppose there is a community wide vote on the general housing issue. Which (of the following two) laws would you vote for:

A. One law says that a homeowner can decide for himself whom to sell his house to, even if he prefers not to sell to blacks.
B. The second law says that a homeowner cannot refuse to sell to someone because of their race or color.

To form an index of racial attitudes, we estimated linear regressions for each question of the binary responses on year dummies, MSA dummies, and a set of controls for the characteristics of the respondent (age, gender, and education). We then standardized the estimated MSA effects to have mean 0 and standard deviation 1. As reported in Appendix Table 4, the MSA effects are reasonably highly correlated across questions. Our racial attitudes index is the average of the standardized MSA effects from the four questions.[44] This index has standard deviation 0.72.

We were able to construct a value of the index for 70 cities in our tipping sample, with an average of approximately 177 GSS responses to question I and 105 responses per question on questions II-IV. City-specific values of the index are reported in Appendix Table 5. The cities

[43] The GSS uses a geographically stratified sample, with changes in the sampling frame in 1983 and 1993. The mapping from Primary Sampling Units to MSAs is necessarily approximate; in many cases only a subset of an MSA is in the GSS sample. Because PMSAs are inconsistently identified in the GSS codings, we assign all GSS respondents to the CMSA and use a single CMSA-level value of the racism index for all of the constituent PMSAs. Our analyses with the GSS data are clustered on the CMSA.

[44] We also explored using the principal component of the four sets of MSA effects. This puts approximately equal weight on each factor, and yields similar results.

in our sample with the highest values of the index (indicating more strongly held views *against* racial contact) are Memphis (value=1.44), Birmingham (1.31), and Knoxville (1.28). The cities with lowest values of the index are San Diego (-1.06), Rochester (-1.05), and Tucson (-0.95)

Table 9 reports a series of models that take as the dependent variable the average of our estimated tipping points in 1970-80, 1980-90, and 1990-2000. For reference, the first column shows the mean and standard deviation of each of the independent variables. Our first specification includes only the attitudes index. The second adds controls for the fractions of blacks and Hispanics in the city. These have coefficients around 0.4 – 0.5, suggesting that tipping points are higher (though not proportionately so) in cities with higher minority shares. The coefficient on the attitudes index in this specification is negative, but small and insignificant. Column 3 adds region controls, identifying the attitudes effect solely from contrasts between cities in the same geographic region. This produces a more negative and more precisely estimated coefficient on the attitudes index. Column 4 adds the log mean incomes of blacks, Hispanics, and whites in the city, since prior research has suggested that income differences are an important determinant of segregation (Bayer, Fang, and McMillan, 2005). Higher white incomes are associated with lower tipping points, and higher black and Hispanic incomes with lower tipping points. The magnitudes are similar, so an overall increase in incomes has little effect on the tipping point. The inclusion of income controls considerably strengthens the attitude effect.

Given the small set of cities for which the attitudes index is available, we explore additional control variables in several sets. Measures of the growth rate of the city and of the minority share between 1980 and 2000 (Column 5) have no relationship with tipping, nor do two "structural" characteristics of the local school system (Column 6) that may influence residential location decisions: the fraction of 5-12 year olds in private school and a Herfindahl index measuring the concentration of students across school districts (Hoxby 2000; Rothstein, forthcoming). Column 7 controls for the city size (in 1990), density, and housing construction between 1980 and 1990. None of the additional variables has significant explanatory power for the tipping point, and none impacts the attitudes index coefficient. Finally, we consider an index of the severity of riots experienced in the city during the late 1960s, which might be expected to predict white concerns about the stability of integrated neighborhoods (Collins and Margo, 2004).[45] When included in our basic specification (Column 8), the riots measure has the expected negative effect, and is nearly significant. Its inclusion has no effect on the attitudes index coefficient, however. Column 9 presents a final specification that excludes the attitudes index, permitting use of a larger sample of cities. Coefficients are generally similar, though the riots index coefficient is notably smaller.

To understand the magnitude of the coefficients on the white attitudes index in columns 1-8, consider the difference between a city in which whites have strong views against inter-racial contact (e.g. Memphis) and one where whites are relatively tolerant (e.g., San Diego). The difference in the attitudes index between these cities is 2.5. Multiplying this by a coefficient of −4 implies that the tipping point is shifted to the right by about 10 percentage points in San Diego relative to Memphis. Compared to a mean tipping point (averaged over three decades) of 12.7% and a standard deviation of 7.1%, this is a large effect. Assuming the same -4 coefficient, a standard deviation change in the value of the attitudes index implies a 2.4 percentage point rise

[45] Our index is drawn from Collins and Margo (2004). We are grateful to Gregg Carter (1986) and Bill Collins for compiling and providing the data used for its construction.

in the tipping point, or a 0.34 “effect size.”

X. Conclusions

One longstanding explanation for the prevalence and persistence of racial segregation is that white families are unwilling to live in neighborhoods with high minority shares. Schelling (1971) demonstrated that such preferences can give rise to “tipping points” beyond which neighborhoods experience rapid outflows of whites. Tipping arises from social interactions among the location choices of individual families, and can arise even with smooth, well behaved preferences. Modern regression discontinuity techniques are well suited for estimation of tipping behavior. Applying them, we find strong evidence of tipping. Although the extent of tipping declined between the 1970s and 1990s, it remains statistically and practically significant.

A variety of specifications indicate that tipping behavior reflects the influence of neighborhood racial composition per se rather than the effect of other neighborhood characteristics like income. Only a portion of the white population outflow from tipping neighborhoods is offset by minority inflow, suggesting that whites’ distaste for high-minority-share neighborhoods is the key determinant of tipping dynamics. The longer run changes in housing demand associated with tipping appear to be absorbed mainly through quantity responses, rather than through prices: our point estimates indicate relatively small price declines when a neighborhood passes the tipping point. Finally, the location of the city-specific tipping point is robustly correlated with survey-based estimates of white attitudes about integration, reinforcing the inference that tipping reflects white families’ preferences over the racial composition of their neighbors.

This is, to our knowledge, the first direct evidence of the highly nonlinear responses that are predicted by many theoretical models of social interactions. Our analysis confirms that phase transitions are an important feature of the dynamics of neighborhood change. These complex dynamics are unlikely to arise in the absence of social interactions, so our findings support the view that location choices depend at least in part on the (endogenous) composition of neighborhoods.

Data Appendix

The sample that is used to identify the candidate tipping points for neighborhoods is from the Urban Institute's Neighborhood Change Database (NCDB). We assign each tract to the 1999 MSA in which it lies. We exclude tracts where the population growth rate exceeds five standard deviations from the MSA mean growth rate, tracts with fewer than 200 residents in the base year, and tracts where the ten-year growth in the white population exceeds 500% of the base-year total population. We focus on MSAs for which we still have 100 matched tracts after these exclusions. We then divide the sample in each city into two random subsamples, one containing 2/3 of the tracts and the other containing 1/3.

We define the white population as the number of non-Hispanic whites, and minorities as all other residents. Because the 1970 data do not separately identify white Hispanics and non-Hispanics, we impute the number of white/non-Hispanics in each tract using information on the share of black, white and Hispanic household heads. Specifically, we use 1980 data to estimate a regression of white/non-Hispanic share in a tract on the black share, white share, and Hispanic share. The R-squared of this regression is 0.99. Using the coefficient estimates from this regression and 1970 data on the tract's white share, black share, and Hispanic share in 1970, we predict the 1970 non-Hispanic white share, censoring predicted values at 0 and 1. When we compute changes in the non-Hispanic white population between 1970 and 1980, we use fitted values in both years. We use a similar imputation procedure to identify the number of non-Hispanic blacks in each tract in 1970 for our analysis of alternative tipping points in Table 8.

We use the procedures identified in the text to identify candidate tipping points in the 2/3 subsample. The "time series" procedure always identifies a point, while the "fixed point" procedure fails to find a candidate point in a few cities where a polynomial fit to $E[\Delta(W_t/P_t) \mid m_{t-10}]$ never equals $E[\Delta(W_t/P_t)]$ at any m_{t-10} value below 50%. Once candidate tipping points are identified, we use the 1/3 sample for all further analyses.

Our analysis of schools parallels that of neighborhoods, but relies on the Common Core of Data to measure public elementary schools' racial compositions in 1990 and 2000.

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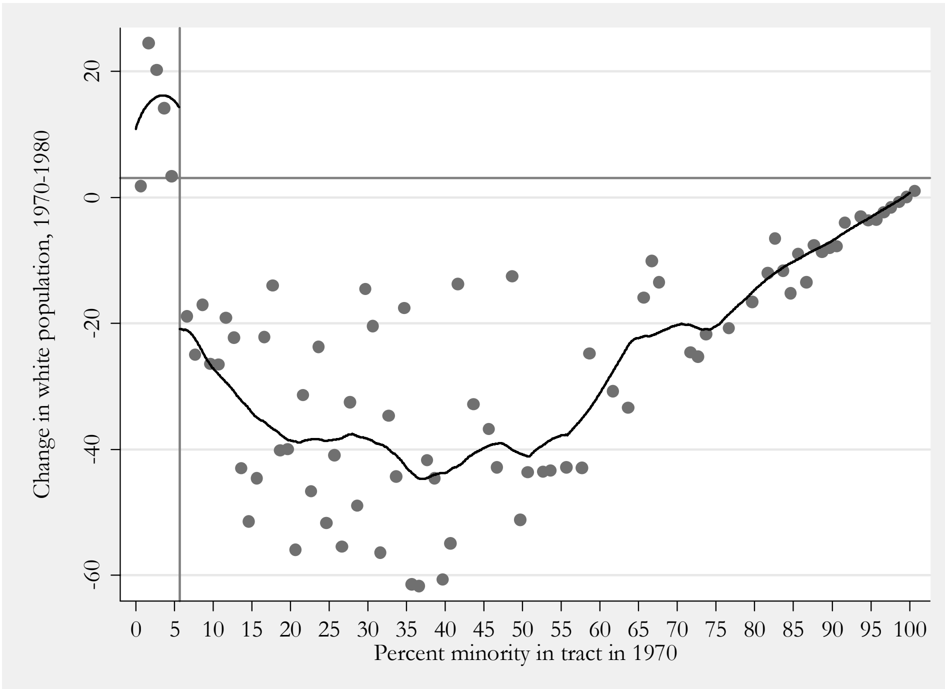
Figure 1. Neighborhood change in Chicago, 1970-1980



Notes: Dots show mean of the change in the tract-level white population between 1970 and 1980 as a percentage of the total tract population in 1970, grouping tracts into cells of width 1% by the 1970 minority share. The horizontal line depicts the unconditional mean. Fitted series is a local linear regression fit to the underlying data, using an Epanechnikov kernel and a bandwidth of 3.5 and allowing for a discontinuity at 5.7%. This point is chosen using a search procedure and a 2/3 sample of Chicago tracts. Only the remaining 1/3 subsample is used for the series depicted here. See text for details.

Figure 2. A Tipping Point in the Schelling Model

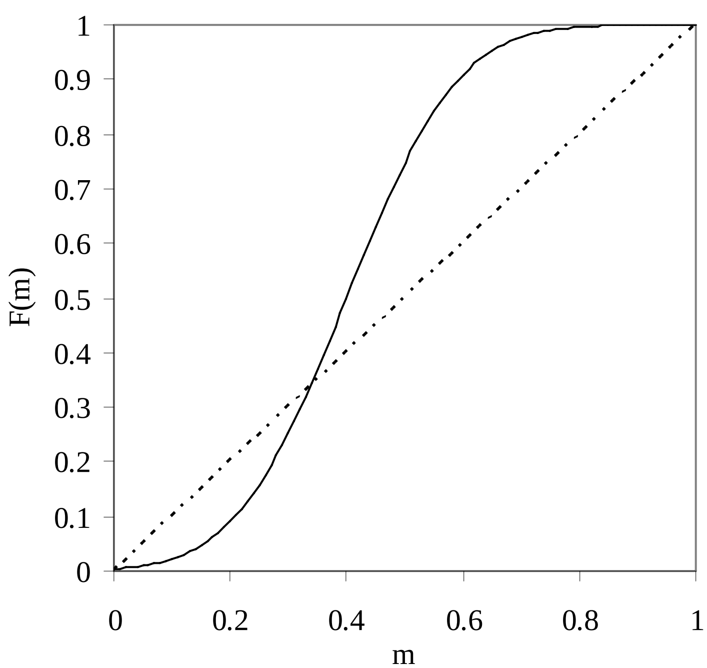


Figure 3A: Three equilibria in the Bond & Coulson tipping model

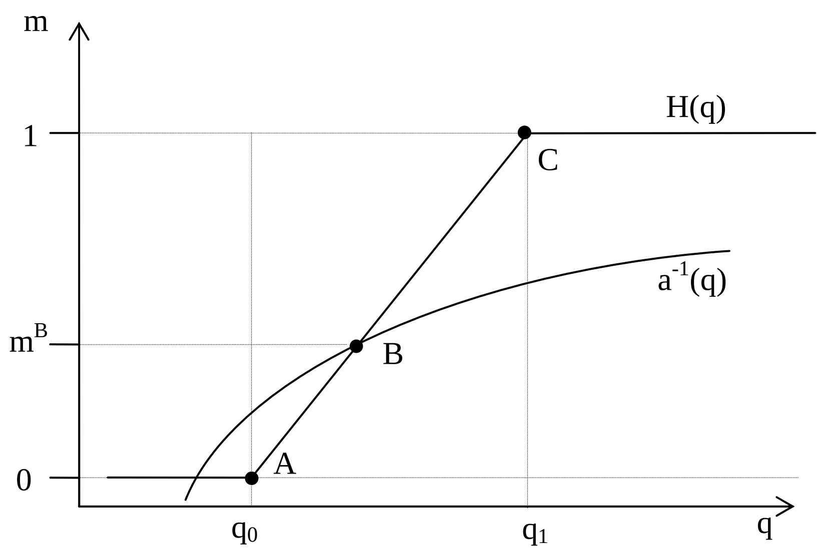


Figure 3B: Illustrative dynamics of neighborhood transition in the short and long run

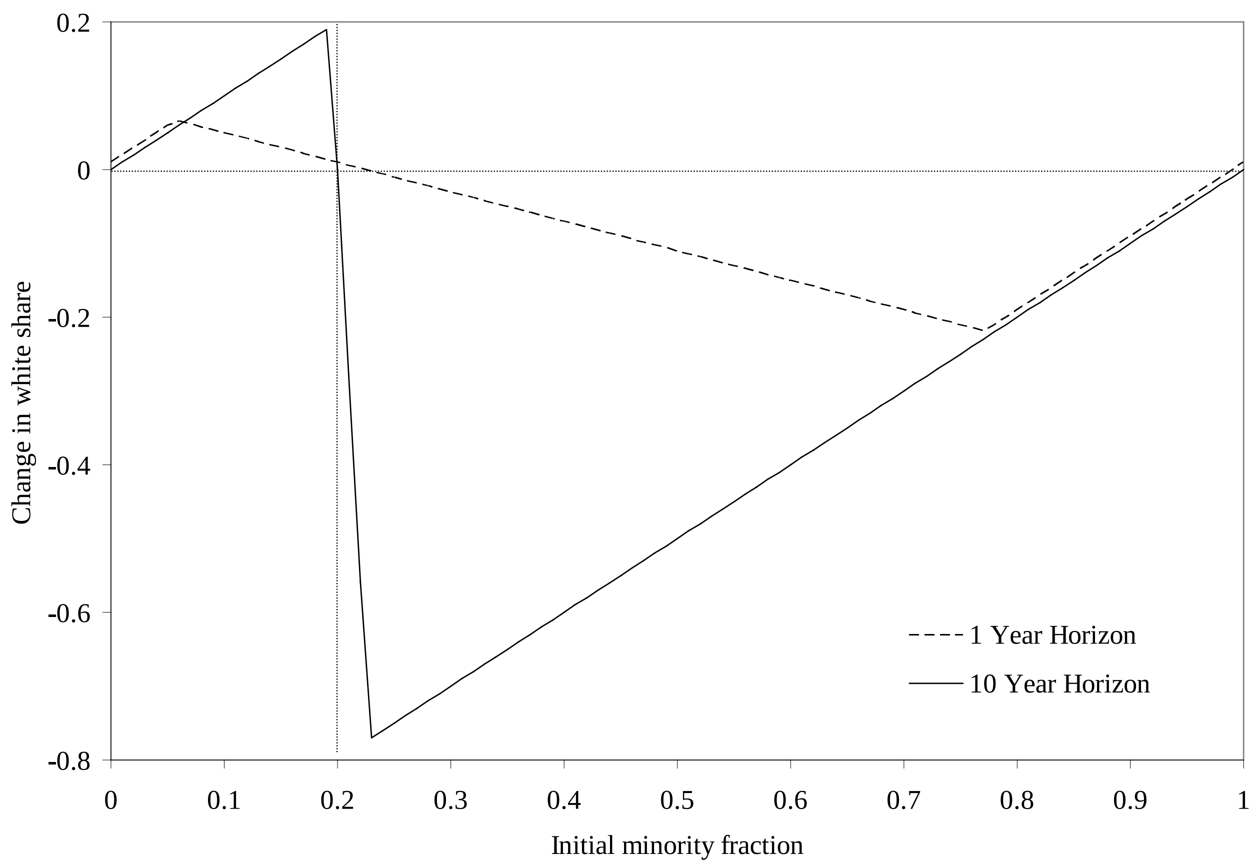
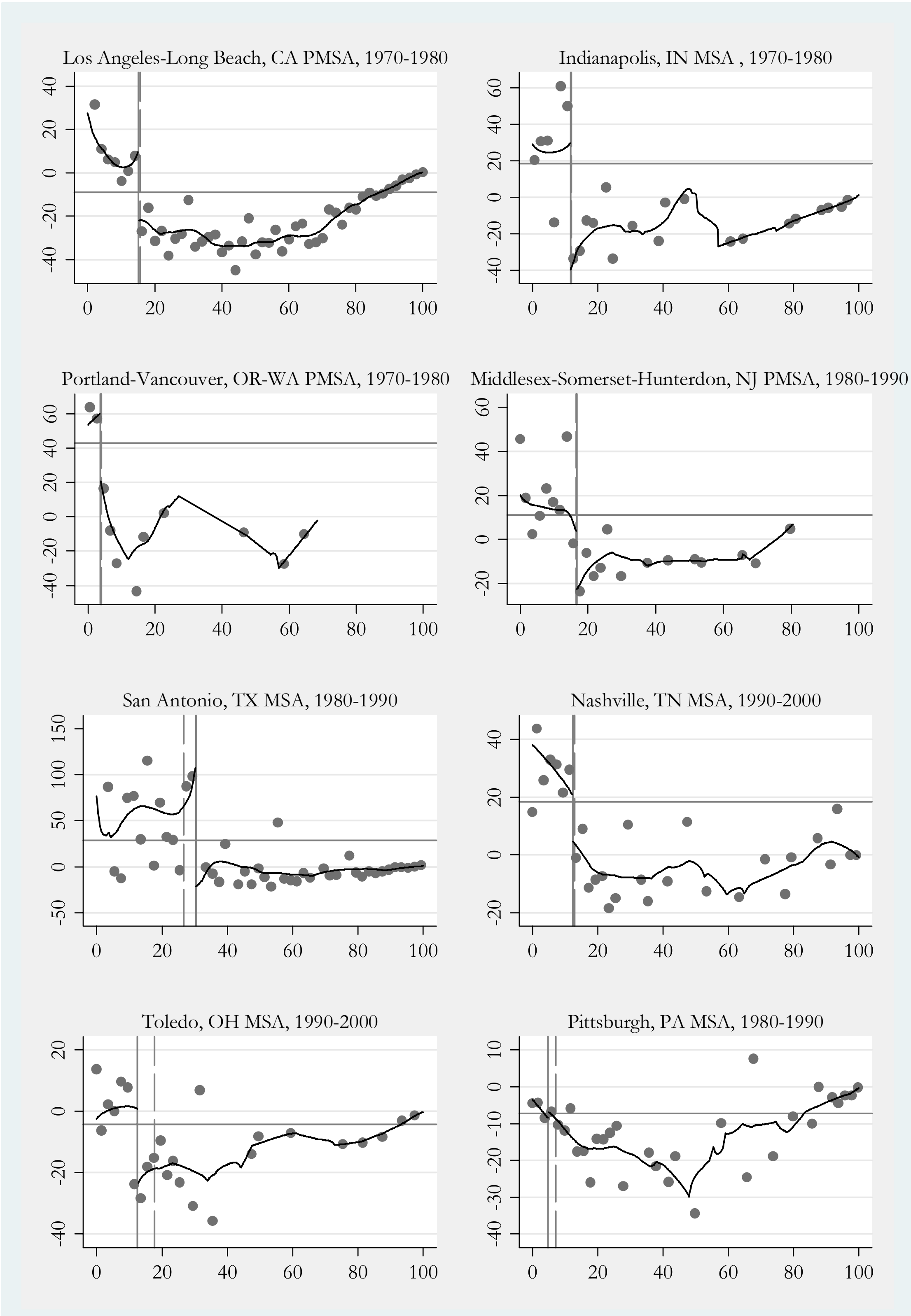
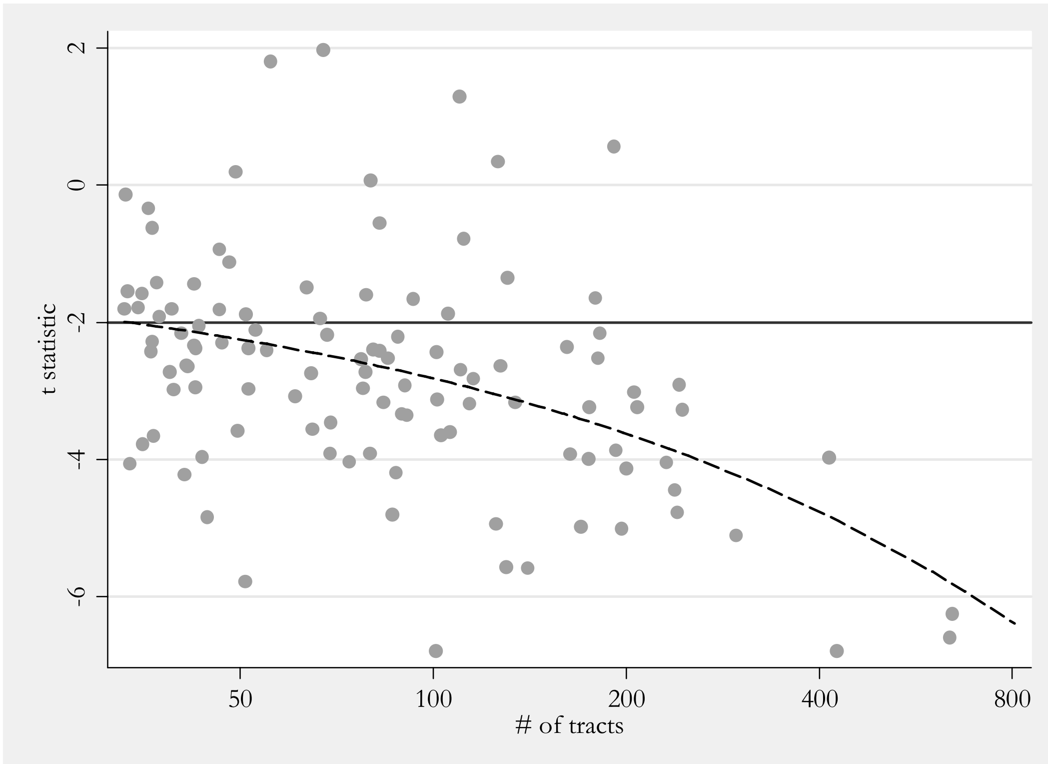


Figure 4: Neighborhood change and tipping points in several illustrative cities



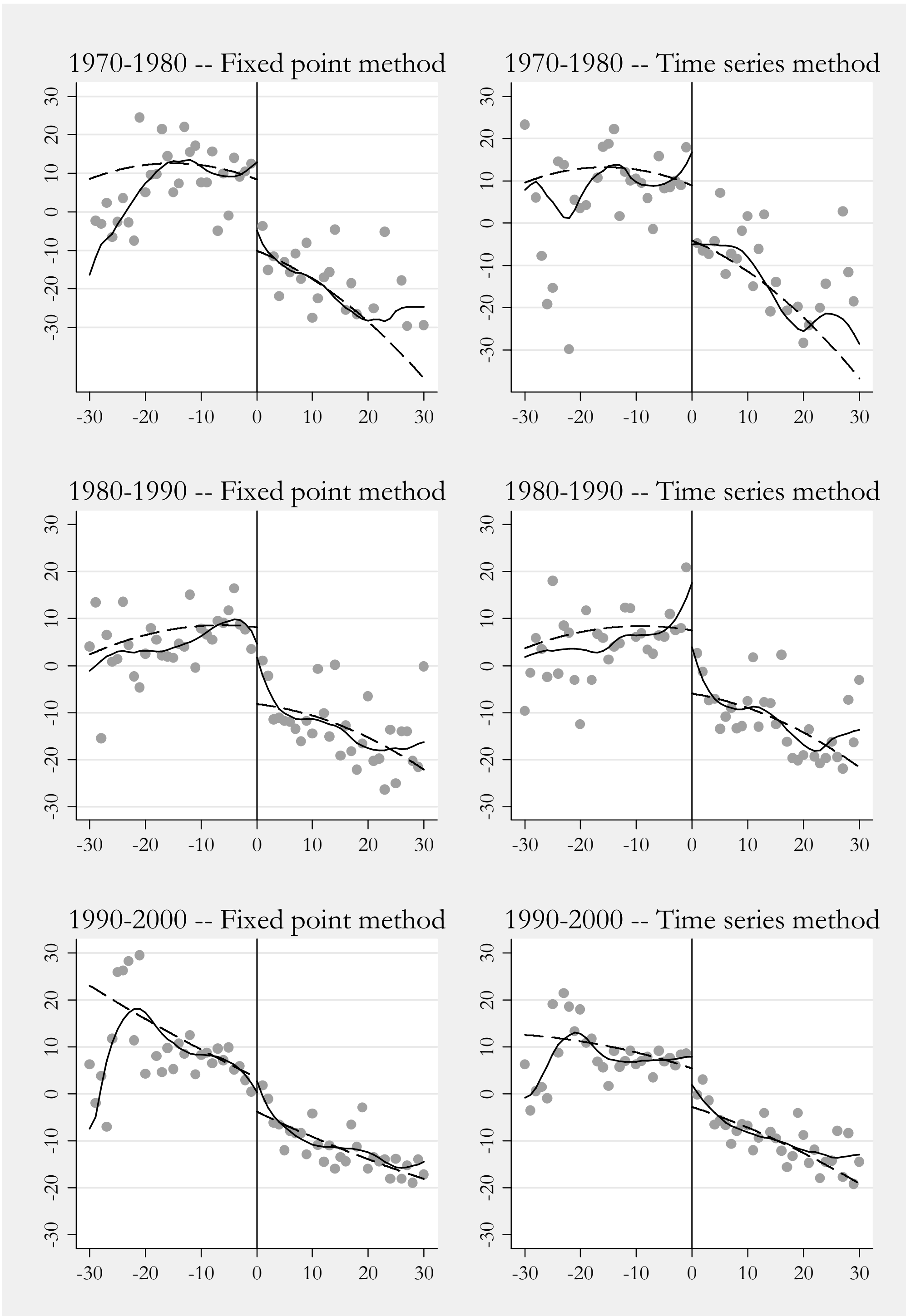
Note: See notes to Figure 1.

Figure 5: City-by-city tests (t statistics) for a discontinuity at the estimated tipping point



Notes: X axis is the size of the 1/3 subsample of tracts in the city used for testing. Y axis is the t statistic on the intercept shift at the estimated tipping point, computed from city-specific regressions without additional controls. The "fixed point" method candidate tipping points are used. Dashed line is the OLS fit of the t statistic on the square root of the size of the subsample.

Figure 6: Neighborhood change in a pooled sample of metropolitan tracts, by relationship to candidate tipping point



Notes: X axis is minority share in tract minus the estimated tipping point in the city. Y axis is the change in the white population over 10 years, expressed as a percentage of the total base year population and deviated from the mean of this in the city. Dots depict averages in 1-percentage-point bins. Solid line is a local linear regression fit separately on either side of zero. Dashed line is a global 4th order polynomial with an intercept shift at zero.

Table 1. Summary statistics for metropolitan census tracts

	1970	1980	1990
# of tracts (nationwide)	46,334	51,857	64,891
# of tracts (MSAs as defined in 1999)	45,636	49,896	51,037
# of tracts in sample for 10-year comparisons	36,114	39,442	40,439
# of MSAs in sample	104	113	114
Mean % minority	16.4	23.4	29.0
Mean family income (nominal)	$12,148	$24,666	$47,209
Unemployment rate	4.3	6.6	6.8
% single family homes	68.1	64.9	64.0
Growth in total population, t to t+10 (%)	39.4	23.4	21.7
Growth in white population (as % of base year population), t to t+10	27.1	15.2	8.1
0-5% minority in base year:			
# of tracts (in MSAs, in sample)	17,285	13,062	9,468
Mean family income (nominal)	$13,478	$27,627	$52,257
Unemployment rate	3.5	5.5	4.6
% single family homes	75.2	75.8	77.7
Growth in total population	39.3	22.3	21.7
Growth in white population	32.6	18.4	16.7
5-20% minority:			
# of tracts (in MSAs, in sample)	10,942	13,378	13,793
Mean family income	$12,282	$27,179	$55.908
Unemployment rate	4.4	5.1	4.6
% single family homes	66.8	66.6	67.8
Growth in total population	58.4	40.4	31.0
Growth in white population	39.6	26.4	16.4
20-70% minority:			
# of tracts (in MSAs, in sample)	5,281	8,109	10,784
Mean family income	$9,689	$21,193	$42,505
Unemployment rate	5.6	7.2	7.1
% single family homes	58.4	55.2	55.4
Growth in total population	28.3	26.7	21.0
Growth in white population	-0.95	2.4	-3.8
70-100% minority:			
# of tracts (in MSAs, in sample)	2,606	4,893	6,394
Mean family income	$7,753	15,646	28,905
Unemployment rate	7.2	12.4	14.6
% single family homes	46.0	47.2	49.9
Growth in total population	-17.6	-0.6	2.5
Growth in white population	-5.8	-2.5	-2.1

Table 2: Overview of candidate tipping points

	1970 – 1980		1980 – 1990		1990 – 2000	
	Fixed point method	Time series method	Fixed point	Time series	Fixed point	Time series
Mean	11.9	9.0	13.6	12.2	14.1	13.9
SD	9.4	8.8	9.6	8.4	8.2	9.7
# of MSAs without identified points	4	0	2	0	2	0
Correlations						
1970-1980, fixed point	1.00					
1970-1980, time series	0.54	1.00				
1980-1990, fixed point	0.47	0.49	1.00			
1980-1990, time series	0.37	0.40	0.64	1.00		
1990-2000, fixed point	0.50	0.34	0.59	0.51	1.00	
1990-2000, time series	0.48	0.60	0.60	0.70	0.71	1.00

Note: Tipping points describe the minority share in the census tract, measured in percentage points. Summary statistics are unweighted. All candidate points are estimated using a 2/3 subsample of the original data.

Table 3. Basic regression discontinuity models for the change in white share around the candidate tipping point

	Fixed point method		Time series method	
	(1)	(2)	(3)	(4)
1970 – 1980				
Beyond candidate tipping point (Yes = 1)	-18.7	-12.1	-19.3	-12.4
	(3.3)	(3.1)	(4.1)	(3.7)
Two quadratics in deviation from candidate tipping point (one on each side)	X	X	X	X
Baseline demographic / housing characteristic controls		X		X
Observations	11,631	11,611	11,906	11,886
R^2	0.18	0.24	0.17	0.25
1980 – 1990				
Beyond candidate tipping point (Yes = 1)	-18.1	-14.5	-19.4	-14.6
	(2.7)	(2.5)	(4.0)	(3.9)
Observations	12,244	12,217	13,102	13,071
R^2	0.21	0.30	0.21	0.30
1990 – 2000				
Beyond candidate tipping point (Yes = 1)	-8.0	-7.1	-10.8	-9.7
	(1.7)	(1.6)	(1.9)	(1.9)
Observations	13,285	13,261	13,393	13,369
R^2	0.13	0.15	0.12	0.14

Notes: Dependent variable is the change in white population in the tract over 10 years, expressed as a percentage (0 – 100) of the base-year total tract population. Demographic and housing characteristic controls are the base-year unemployment rate, log(mean family income), housing vacancy rate, renter share, and fraction of homes in single-unit buildings. All specifications include MSA fixed effects, and standard errors are clustered on the MSA. Candidate tipping points are computed from 2/3 subsamples of the tracts in each MSA, and the remaining 1/3 subsample is used for estimation of the specifications presented here.

Table 4: Models with average minority share in neighboring tracts

	1970-1980		1980-1990		1990-2000	
	Fixed point	Time series	Fixed point	Time series	Fixed point	Time series
	(1)	(2)	(3)	(4)	(5)	(6)
Beyond potential tipping point	-14.4	-7.3	-12.3	-9.4	-3.8	-5.0
for minority share	(2.7)	(2.5)	(2.3)	(3.1)	(1.5)	(1.5)
Fraction of neighbor group	-12.8	-12.5	-12.2	-12.1	-7.4	-6.8
beyond the potential tipping point	(3.0)	(2.8)	(2.5)	(3.0)	(1.6)	(1.8)
R^2	0.19	0.19	0.23	0.22	0.11	0.12

Notes: The "neighbor group" is the tract itself plus the five closest tracts within four miles, measuring distances from tract centroids. All specifications include MSA fixed effects, a fourth-order polynomial in the tract's deviation from the estimated tipping point, and the average across the neighboring group of this fourth order polynomial. Standard errors are clustered on the MSA.

Table 5: Tipping in racial composition and poverty rate

	1970-1980				1980-1990				1990-2000			
	Fixed point		Time series		Fixed point		Time series		Fixed point		Time series	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Beyond potential tipping point for minority share	-17.8	-17.1	-17.7	-18.2	-17.1	-15.4	-17.2	-17.1	-7.7	-6.5	-12.5	-12.9
	(2.9)	(3.1)	(3.8)	(3.9)	(3.2)	(3.3)	(4.8)	(5.1)	(1.5)	(1.5)	(2.3)	(2.4)
Beyond potential tipping point for poverty	-7.6	-7.3	-13.6	-15.9	-9.5	-7.5	-15.8	-18.1	-3.8	-3.0	-1.9	-1.2
	(2.9)	(3.1)	(4.6)	(5.1)	(1.6)	(1.8)	(2.5)	(2.9)	(1.5)	(1.8)	(1.4)	(1.5)
Global 4-th order polynomials in deviations from tipping points	X		X		X		X		X		X	
Quadratics in deviations from tipping points (one on each side of each tipping point)		X		X		X		X		X		X
R^2	0.26	0.26	0.26	0.26	0.24	0.24	0.25	0.25	0.14	0.14	0.14	0.14

Notes: Dependent variable is the change in the white population in a single tract, expressed as a percentage (0 – 100) of the base-year total tract population. All specifications include MSA fixed effects, and standard errors are clustered on the MSA.

Table 6: Basic regression discontinuity models for the change in minority and total population around the candidate tipping point

	Change in Minority Population		Change in Total Population	
	Fixed point	Time series	Fixed point	Time series
	(1)	(2)	(3)	(4)
1970 – 1980				
Beyond candidate tipping point	3.1	1.0	-9.0	-11.4
	(1.5)	(1.4)	(3.8)	(4.0)
Observations	11,611	11,886	11,611	11,886
R^2	0.21	0.22	0.23	0.23
1980 – 1990				
Beyond candidate tipping point	-0.3	0.6	-14.8	-14.0
	(0.9)	(1.6)	(2.8)	(4.8)
Observations	12,217	13,071	12,217	13,071
R^2	0.26	0.26	0.29	0.29
1990 – 2000				
Beyond candidate tipping point	2.4	3.1	-4.7	-6.6
	(0.9)	(0.9)	(2.2)	(2.3)
Observations	13,261	13,369	13,261	13,369
R^2	0.20	0.19	0.13	0.13

Notes: Dependent variable in columns 1-2 is the change in the non-white population in the tract over 10 years, expressed as a percentage (0 – 100) of the base-year total tract population. In columns 3-4, dependent variable is the percentage change in the total tract population over 10 years. All specifications include MSA fixed effects, a pair of quadratics in the deviation from the candidate tipping point, and the demographic/housing characteristics listed in the notes to Table 3. Standard errors are clustered on the MSA.

Table 7: Regression discontinuity models for housing prices before and after tipping

	Log(mean value)*100				Change in log(mean value)*100		
	1970	1980	1990	2000	1970-80	1980-2000	1970-2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Beyond tipping point in 1970	-8.2	-12.3	-9.3	-6.4	-3.7	2.6	0.6
	(2.3)	(3.1)	(3.0)	(3.3)	(1.6)	(1.6)	(2.2)
	Log(mean value)*100				Change in log(mean value)*100		
	1970	1980	1990	2000	1970-90	1990-2000	1970-2000
Beyond tipping point in 1990	1.7	-2.1	-2.2	-1.8	-2.5	0.7	-1.1
	(1.8)	(2.2)	(2.0)	(2.4)	(1.3)	(1.1)	(1.6)

Note: Tipping points from the "fixed point" method are used. All specifications include MSA fixed effects, a quadratic in the minority share minus the tipping point (in 1970 in the first row and in 1990 in the second row), and the interaction of this quadratic with the "beyond tipping point" indicator. Standard errors are clustered on the MSA.

Table 8. School-level tipping between 1990 and 2000

	Change in white enrollment, 1990-2000			Change in total enrollment, 1990-2000		
	(1)	(2)	(3)	(4)	(5)	(6)
Beyond tipping point (1=yes)	-5.3	-4.6	-3.7	-4.9	-4.6	-4.3
	(1.7)	(1.8)	(1.9)	(1.7)	(1.9)	(2.1)
4th order polynomial in deviation from fixed point	X			X		
Two quadratics in deviation from fixed point		X	X		X	X
Fraction free lunch			X			X
N	5,273	5,273	4,734	5,273	5,273	4,734
R2	0.13	0.13	0.15	0.10	0.10	0.10

Note: The "fixed point" method is used to find the candidate tipping points. All specifications include MSA fixed effects, and standard errors are clustered on the MSA. Free lunch variable is unavailable for most schools in 1990. 1995 or 2000 values are assigned when the 1990 value is missing.

Table 9. Relation of residential tipping points with attitudes

Dependent variable is the average of the 1970-1980, 1980-1990 and 1990-2000 tipping points (in percentage points)

	Mean [SD]	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Race attitudes index	-0.1	-0.5	-1.2	-2.7	-3.7	-3.9	-3.8	-4.1	-4.1	
	[0.6]	(1.8)	(1.6)	(1.2)	(1.5)	(1.5)	(1.6)	(1.6)	(1.5)	
% Black	12.8		0.4	0.3	0.4	0.4	0.4	0.4	0.4	0.4
	[8.2]		(0.2)	(0.1)	(0.1)	(0.2)	(0.1)	(0.2)	(0.1)	(0.1)
% Hispanic	7.4		0.5	0.3	0.5	0.5	0.5	0.6	0.6	0.4
	[8.3]		(0.1)	(0.1)	(0.1)	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)
Log(per capita	10.0				-14.9	-16.0	-12.2	-8.7	-11.3	-7.0
income), whites	[0.1]				(5.2)	(6.5)	(6.7)	(5.2)	(5.2)	(5.9)
Log(per capita	9.5				9.5	10.8	6.2	15.4	7.5	10.0
income), blacks	[0.2]				(7.0)	(7.9)	(7.6)	(4.4)	(8.0)	(5.6)
Log(per capita	9.6				13.1	12.3	13.6	15.4	14.3	7.0
income), Hispanics	[0.2]				(4.7)	(5.1)	(5.0)	(4.4)	(4.6)	(3.8)
Population growth	0.3					1.8				
rate (1980-2000)	[0.3]					(3.4)				
Change in % black,	1.1					-0.5				
1980-2000	[1.8]					(0.4)				
Change in % Hisp.	5.3					-0.2				
1980-2000	[4.4]					(0.3)				
% 5-12 year olds in	13.8						-0.1			
private school	[4.6]						(0.2)			
Herfindahl index	0.2						-2.8			
(school districts)	[0.2]						(5.1)			
Population density	1.2							-0.4		
	[1.2]							(0.8)		
% 1990 houses built	20.5							0.1		
in the 1980's	[9.4]							(0.1)		
Log(1990 MSA	14.1							-1.5	-0.8	-0.8
population)	[0.7]							(0.9)	(1.0)	(0.9)
Cumulative riots	0.05								-10.1	-8.5
index	[0.1]								(5.4)	(6.4)
Region dummies (4)				X	X	X	X	X	X	X
R^2		0.00	0.39	0.61	0.68	0.70	0.69	0.70	0.71	0.67

Notes: N=70 in columns (1)-(8) and N=98 in column (9). The racism index is derived from responses to the General Social Survey, and pools data for the entire CMSA over all available GSS years; see text for details. Other explanatory variables are measured at the MSA/PMSA level in 1990. Standard errors are clustered at the MSA/CMSA level.

Appendix Table 1. Sensitivity of 1990-2000 regression discontinuity results to additional baseline controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fixed point	-7.1	-6.5	-6.8	-7.2	-6.4	-3.3	-2.7
	(1.6)	(1.6)	(1.6)	(1.6)	(1.7)	(1.6)	(1.6)
Time series	-9.7	-9.3	-9.4	-9.7	-9.1	-6.5	-5.8
	(1.9)	(1.8)	(1.8)	(1.9)	(1.8)	(1.7)	(1.7)
Two quadratics in deviation from candidate tipping point (one on each side)	X	X	X	X	X	X	X
Baseline demographic / housing characteristic controls	X	X	X	X	X	X	X
4th order polynomial in:							
Poverty rate		X					X
log(mean family income)			X				X
Unemployment rate				X			X
Renter share					X		X
Distance to nearest "minority" tract						X	X

Notes: See notes to table 3.

Appendix Table 2. Tipping in minority share, black share, and black/Hispanic share

	1970-1980				1980-1990				1990-2000			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Beyond minority share tipping point	-12.1 (3.1)			-2.5 (4.5)	-14.5 (2.5)			-7.2 (2.3)	-7.1 (1.6)			-2.7 (1.7)
Beyond black share tipping point		-17.3 (2.5)		-12.2 (2.9)		-14.8 (2.3)		-8.1 (2.3)		-8.4 (1.7)		-3.1 (1.6)
Beyond black/Hispanic share tipping point			-13.3 (3.6)	-6.7 (4.7)			-15.4 (2.7)	-7.6 (2.8)			-10.2 (1.6)	-6.3 (1.8)
Two quadratics in minority share deviation from tipping point	X			X	X			X	X			X
Two quadratics in black share deviation from tipping point		X		X		X		X		X		X
Two quadratics in black/Hisp share dev. from tipping point			X	X			X	X			X	X
Tract chars from Table 3, column 3	X	X	X	X	X	X	X	X	X	X	X	X

Note: Non-Hispanic blacks are not separately identified in 1970 data, so must be imputed. All specifications include MSA fixed effects, and standard errors are clustered on the MSA.

Appendix Table 3. Regression discontinuity models for new housing unit construction before and after tipping

	Percentage of homes less than 10 years old in			
	1970	1980	1990	2000
	(1)	(2)	(3)	(4)
Beyond tipping point in 1970	-5.6	-6.5	-3.3	-3.5
	(1.5)	(1.2)	(0.8)	(1.0)
Beyond tipping point in 1990	-1.5	-1.8	-2.2	-3.5
	(1.3)	(1.3)	(1.0)	(1.2)

Note: Tipping points from the "fixed point" method are used. All specifications include MSA fixed effects, a quadratic in the minority share minus the tipping point (in 1970 in the first row and in 1990 in the second row), and the interaction of this quadratic with the "beyond tipping point" indicator. Standard errors are clustered on the MSA.

Appendix Table 4. Correlations of MSA effects on responses to GSS questions about racial attitudes

	Individual mean	Correlations of MSA effects on question:			
		I.	II.	III.	IV.
I.	0.13	1.00			
II.	0.71	0.43	1.00		
III.	0.17	0.44	0.34	1.00	
IV.	0.37	0.57	0.38	0.35	1.00
Average		0.80	0.74	0.68	0.77

Note: Questions are:

I: Do you think there should be laws against marriages between blacks and whites?
Coded as "Yes"=1, "No"=0, "Don't know"=missing.
II: In general, do you favor or oppose the busing of black and white school children from one school district to another?
"Oppose"=1, "Favor"=0.
III. How strongly do you agree or disagree with the statement: "White people have a right to keep blacks out of their neighborhoods if they want to, and blacks should respect that right"? (1 = "agree strongly" or "agree slightly")
"Agree strongly" and "agree slightly" = 1, "disagree strongly and "disagree slightly" = 0.
IV. Suppose there is a community wide vote on the general housing issue. Which (of the following two) laws would you vote for:
A. One law says that a homeowner can decide for himself whom to sell his house to, even if he prefers not to sell to blacks.
B. The second law says that a homeowner cannot refuse to sell to someone because of their race or color.
A = 1, B=0.

Appendix Table 5. City values of the racism index

MSA	Racism index value	MSA	Racism index value
San Diego, CA	-1.06	Austin-San Marcos, TX	-0.04
Rochester, NY	-1.05	Lansing-East Lansing, MI	-0.04
Tucson, AZ	-0.95	Richmond-Petersburg, VA	-0.01
San Francisco-Oakland-San Jose, CA	-0.92	Columbus, OH	-0.01
Boston-Worcester-Lawrence, MA-NH-ME-CT	-0.87	Fort Myers-Cape Coral, FL	0.07
Minneapolis-St., Paul, MN-WI	-0.85	Cincinnati, OH-KY-IN	0.10
Phoenix-Mesa, AZ	-0.84	Fort Lauderdale, FL	0.10
Grand Rapids-Muskegon-Holland, MI	-0.76	St. Louis, MO-IL	0.11
Washington, DC-MD-VA-WV	-0.76	Baltimore, MD	0.11
Seattle-Bellevue-Everett, WA	-0.71	Pittsburgh, PA	0.18
Portland-Vancouver, OR-WA	-0.69	Kansas City, MO-KS	0.20
Des Moines, IA	-0.68	Chicago-Gary-Kenosha, IL-IN-WI	0.24
Allentown-Bethlehem-Easton, PA	-0.65	Tampa-St. Petersburg-Clearwater, FL	0.26
Denver, CO	-0.64	Dallas-Fort Worth, TX	0.34
Tacoma, WA	-0.63	Buffalo-Niagara Falls, NY	0.36
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	-0.57	Dayton-Springfield, OH	0.38
Sacramento, CA	-0.55	Detroit-Ann Arbor-Flint, MI	0.40
Saginaw-Bay City-Midland, MI	-0.52	Indianapolis, IN	0.51
Providence-Fall River-Warwick, RI-MA	-0.52	Atlanta, GA	0.55
Fresno, CA	-0.47	Oklahoma City, OK	0.57
Los Angeles-Riverside-Orange County, CA	-0.42	Lakeland-Winter Haven, FL	0.74
Syracuse, NY	-0.40	West Palm Beach-Boca Raton, FL	0.75
New York-Northern New Jersey-Long Island, NY-NJ-CT-PA	-0.19	Jackson, MS	0.79
Fort Wayne, IN	-0.19	Charleston-North Charleston, SC	0.82
Harrisburg-Lebanon-Carlisle, PA	-0.18	Nashville, TN	0.87
Cleveland-Lorain-Elyria, OH	-0.13	Jacksonville, FL	0.93
Norfolk-Virginia Beach-Newport News, VA-NC	-0.10	Charlotte-Gastonia-Rock Hill, NC-SC	1.07
Milwaukee-Waukesha, WI	-0.10	New Orleans, LA	1.17
Houston, TX	-0.06	Johnson City-Kingsport-Bristol, TN-VA	1.23
		Knoxville, TN	1.28
		Birmingham, AL	1.31
		Memphis, TN-AR-MS	1.44