Tipping and the Dynamics of Segregation

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ABSTRACT

Schelling (1971) showed that extreme segregation can arise from social interactions in white 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 1970 through 2000 to test for discontinuities in the dynamics of neighborhood racial composition. We find strong evidence that white population flows exhibit tipping-like behavior in most cities, with a distribution of tipping points ranging from 5% to 20% minority share. Tipping is prevalent both in the suburbs and near existing minority enclaves. In contrast to white population flows, there is little evidence of non-linearities in rents or housing prices around the tipping point. Tipping points are higher in cities where whites have more tolerant racial attitudes.

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I. INTRODUCTION

Social interaction models have been used to explain segregation (Schelling, 1971, 1978; Becker and Murphy, 2000), collective action (Granovetter, 1978), persistent unemployment (Cooper and John, 1988), and crime (Glaeser, Sacerdote and Scheinkman, 1996). The key feature of these models is that preferences depend on other agents' choices, potentially leading to multiple equilibria and tipping (Brock and Durlauf, 2001b; Glaeser and Scheinkman, 2003). Researchers have attempted to identify preference spillovers by estimating the effect of peer characteristics on individual decisions (e.g. Case and Katz, 1991; Evans, Oates and Schwab, 1992; Kling, Ludwig and Katz, 2005)[1]; and by testing for excess dispersion in choices across social groups (Glaeser, Sacerdote, and Scheinkman, 1996; Graham 2005). To date, however, there is no direct evidence of the tipping behavior predicted by many social interaction models.

In this paper we use regression discontinuity methods (Angrist and Lavy, 1999; Hahn, Todd and van de Klaauw, 2001) to test for race-based tipping in neighborhoods. To illustrate our approach, Figure 1 plots mean percentage changes in the white population of Chicago Census tracts from 1970 to 1980 against the minority share in 1970.[2] The figure also shows predictions from a local linear regression model, estimated with a break at a 5% minority share – the level identified by two alternative procedures as the most likely tipping point. The graph shows clear evidence of tipping, with white population gains to the left of the tipping point and substantial outflows just to the right. We find similar (though less extreme) patterns for a broad sample of U.S. cities in each of the past three decades.

We begin the paper by outlining a simple model of a local housing market in which

[1] See Manski (1993) for a discussion of the difficulties in testing for interaction effects, and Glaeser and Scheinkman (2003) for a review of many existing studies.
[2] We express the change in white population as a fraction of the total tract population in 1970. Here and throughout the paper, minorities are defined as nonwhites and white Hispanics.

whites' willingness to pay for homes depends on the neighborhood minority share. Under certain assumptions, shifts in the relative demand of whites and minorities will lead to smooth changes in the minority share of the neighborhood as long as the minority share remains below a critical threshold. Beyond this threshold all the white households will leave. The location of the tipping point is determined in part by the strength of white preferences for minority contact, and is higher when whites are more tolerant of minority neighbors.

We then set out to test for tipping behavior using decadal changes in neighborhood racial/ethnic composition. A major obstacle is that the location of the tipping point is unknown. We use two approaches to identify city-specific potential tipping points. First, drawing from the literature on structural breaks, we select the point that yields the best fitting model for tract-level white population changes. Second, building on the pattern in Figure 1, we fit a flexible model for tract-level changes in white population shares in each city, and find the minority share with a predicted change equal to the city-wide average change. The methods yield very similar tipping points for most cities. The estimated tipping points are also highly correlated across the three decades in our sample.

As suggested by the pattern in Figure 1, we find large, significant discontinuities in the white population growth rate at the identified tipping points. These are robust to the inclusion of flexible controls for other neighborhood characteristics, including poverty, unemployment, and housing attributes. Similar tipping patterns are present in larger and smaller cities in all regions of the country, and in both suburban and central city neighborhoods.

Neither rents nor housing prices exhibit sharp discontinuities at the tipping point. Nevertheless, tipping has an important effect on the quantity of new housing units, particularly in tracts with remaining open land where new construction is still possible. Rates of population growth and new construction in these tracts fall sharply once the minority share reaches the tipping point.

We conclude by analyzing the location of the tipping point in different cities. Consistent with earlier work by Cutler, Glaeser and Vigdor (1999) on preferences and segregation, tipping points are higher in cities with more tolerant whites. This is robust to the inclusion of controls for racial composition, income differences across racial and ethnic groups, and other historical and structural features, all of which have effects in the expected directions. This finding underscores the role of white preferences in tipping behavior and the dynamics of segregation.

II. Theoretical Framework

A. A Model of Tipping

We present a partial equilibrium model of neighborhood composition that treats local housing demand functions as primitive.[3] Consider a neighborhood with a homogenous housing stock of measure one and two groups of potential buyers: whites (w) and minorities (m). Let $b^g(n^g, m)$ ($g \in \{w, m\}$) denote the inverse demand functions of the two groups for homes in the neighborhood when it has minority share m, so that there are n^g families from group g who are willing to pay at least $b^g(n^g, m)$ to live there. By construction, the partial derivatives $\partial b^w/\partial n^w$ and $\partial b^m/\partial n^m$ are (weakly) negative. The partial derivatives $\partial b^w/\partial m$ and $\partial b^w/\partial m$ represent social interaction effects on the bid-rent functions. We assume that for minority shares beyond some threshold (say m=10%), $\partial b^w(n^w, m)/\partial m<0$.[4]

[3] The literature contains many models of neighborhood choice that yield tipping behavior, including Schelling (1971, 1978), Miyao (1979), and Bond and Coulson (1989). Ours is derived from Becker and Murphy (2000).
[4] Survey evidence suggests that whites prefer a neighborhood with minority share around 10%, and strongly avoid

At an integrated equilibrium with minority share $m \in (0, 1)$, the m^{th} highest minority bidder has the same willingness to pay as the $(1\text{-}m)^{th}$ highest white bidder. That is,

(1) $b^m(m, m) = b^w(1-m, m)$.[5]

The derivative of the white bid function $b^w(1-m, m)$ with respect to the neighborhood minority share is $-\partial b^w/\partial n^w + \partial b^w/\partial m$. The first term in this expression is positive. If the social interaction effect $\partial b^w/\partial m$ is small at m=0 but becomes more negative as m rises, $b^w(1-m, m)$ will have the shape illustrated in Figure 2 – positively sloped at m=0, but eventually downward-sloping. We assume for illustrative purposes that $b^m(m,m)$ is downward-sloping and linear.[6]

In the neighborhood illustrated in Figure 2, there are three equilibria, one all-minority and two mixed. Point A is a locally stable mixed equilibrium. Just to the right of this point, the marginal white family has a higher willingness to pay than the marginal minority family, and transactions will occur to return the system to A. (A parallel argument applies just to the left of A). The other mixed equilibrium, B, is unstable: a positive shock to the minority share here would reduce the marginal white family's bid by more than that of the marginal minority family, and the neighborhood would trend toward the all-minority equilibrium, C.[7]

Now consider an all-white neighborhood that experiences rising relative demand by minorities, driven by growth in the population or relative income of minorities in a city.[8] Figure 3 shows a series of equilibria for the neighborhood, assuming the demand functions have the

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neighborhoods where m>25%. See e.g., Clark (1991) and Farley et al. (1993). Note, however, that unless all whites have similar preferences, the market-level demand function need not reflect any single person's preferences.

[5] Depending on the shapes of the inverse demand functions, this equation may have multiple solutions. There may also be corner solutions, all-white when $b^w(1, 0) \geq b^m(1, 0)$ and all-minority when $b^w(0, 1) \leq b^m(1, 1)$.

[6] The derivative of the minority bid function $b^m(m, m)$ with respect to m is $\partial b^m/\partial n^w + \partial b^m/\partial m$. This could be positive for low m if minorities strongly dislike all-white neighborhoods.

[7] A standard result is that the number of equilibria, e, must be odd, and that (e-1)/2 of these must be unstable.

[8] Most U.S. metropolitan areas have seen rising minority shares in recent decades. An alternative is to assume that houses become relatively less attractive to white buyers as they age, leading to a relative decline in the white bid function over time. This is similar to the filtering model proposed by Bond and Coulson (1989).

shapes illustrated in Figure 2. At low levels of minority demand, m=0 is a stable equilibrium. As b^m shifts upward, prices begin to rise and a few minority families displace whites with the lowest willingness to pay. The neighborhood will then be in a stable mixed equilibrium. Further increases in the relative demand of minorities will cause the minority share at the stable equilibrium to rise gradually until b^m is just tangent to b^w.

The minority share at the tangency, m^*, is a "tipping point": once m reaches this level, any further increase in minority demand causes the integrated equilibria to disappear, leaving only the 100% minority equilibrium.[9] The neighborhood's minority share will then move toward m=1. Once this process begins, even a downward shift in the minority demand function that restores the integrated equilibria will typically not reverse the tipping process, as m will continue converging toward m=1 so long as it lies to the right of the unstable equilibrium.

The location of the tipping point m^* depends on the strength of white distaste for minority neighbors (i.e., on $\partial b^w/\partial m$). If, for example, white demand for a neighborhood falls off sharply once the minority share exceeds 5%, the tipping point will not be much above this level. More tolerant whites will lead to a higher tipping point.[10]

In this model, the rental price of housing evolves smoothly through the tipping point, despite the discontinuity in white outflows. Rents at the long-run m=1 equilibrium can be higher or lower than at the tipping point, depending on the shape of the minority demand function (and on shifts in minority demand once tipping is underway). As house prices depend on expected future rents, price changes as m passes though m^* depend on expectations about the future

[9] An unstable equilibrium (e.g., point B in Figure 2) is often characterized as a tipping point. Our definition of a tipping point as a so-called "bifurcation" has several advantages over this. Most importantly, it provides a simple explanation for the presence of neighborhoods just to the left of the tipping point. Tipping occurs in only one direction from m^*, whereas an unstable equilibrium is unstable in both directions.

[10] For fixed white demand, the tipping point will be lower the stronger are minority tastes for higher m.

evolution of the neighborhood. A useful extension of the model – particularly given the results on neighborhood population growth presented below – would incorporate housing supply, which may also depend on expected future rents. Careful modeling of expectations is complex and beyond the scope of this paper.[11] We merely note that prices and rates of new construction may, but need not, change discontinuously when a neighborhood tips.

B. Empirical Implications

In Figure 3 we assumed steady increases in relative minority demand. On average this is likely to be true, since minority populations have risen in most U.S. cities over the past 50 years. There are also likely to be neighborhood-specific shifts in relative demand (i.e. in $b^m(m,m) - b^w(1-m, m)$). Under standard assumptions on b^w and b^m, small shifts in relative demand will produce small changes in the location of the integrated equilibrium, so long as it remains below m^*, and the neighborhood will move smoothly toward the new equilibrium.[12] For a neighborhood with an initial minority share m_{t-1} somewhat less than m^*, the expected change in the minority share is therefore a smooth function of m_{t-1}. Formally, if $m_{t-1} \in [0, m^*-r)$, where r represents the maximum (scaled) relative demand shock between t−1 and t, $E[\Delta m_t \mid m_{t-1}] = g(m_{t-1})$ for some continuous function g. By contrast, the expected change for tracts that have begun tipping is positive: $E[\Delta m_t \mid m_{t-1}] = h(m_{t-1}) > 0$ for $m_{t-1} > m^*$. The intermediate range is a grey area—tracts with initial minority shares in $[m^*-r, m^*]$ will tip if they experience sufficiently large shocks, but not otherwise. Assuming this range is small:

(2) $$E[\Delta m_t \mid m_{t-1}] \approx \mathbf{1}(m_{t-1} < m^*)g(m_{t-1}) + \mathbf{1}(m_{t-1} \geq m^*)\, h(m_{t-1}).$$

[11] Frankel and Pauzner (2002) present a model of tipping with rational expectations.

[12] The required condition is that $[\, db^w(1\text{-}m, m)/dm - db^m(m, m)/dm\,]^{-1}$ is continuous. This will hold (everywhere below the tipping point) if the two bid functions are continuous and concave.

If $\lim_{\varepsilon \to 0+} h(m^*+\varepsilon)-g(m^*-\varepsilon) > 0$, the right hand side of this expression is discontinuous at m^*. Given the nature of g and h, we expect the jump to be large. We therefore test for tipping by testing for a discontinuity in $E[\Delta m_t \mid m_{t-1}]$ at candidate values of m^*. Note that the derivation of (2) suggests the function $E[\Delta m_t \mid m_{t-1}]$ may not be strictly discontinuous at m^* but only steeply sloped in the $[m^*-r, m^*]$ range.[13] We interpret such a pattern as evidence of tipping.

C. Empirical Specification

While the model presented above assumes a fixed supply of housing in each neighborhood, most neighborhoods in our sample experience significant growth in their housing stocks and populations. To allow for shifts in the population of a neighborhood, we focus on changes in the numbers of white and minority residents, each expressed as a fraction of the base-period population. Specifically, let $W_{ic,t}$, $M_{ic,t}$, and $P_{ic,t}$ ($=W_{ic,t}+M_{ic,t}$) represent the numbers of whites, minorities, and total residents of neighborhood i in city c in year t (=1980, 1990, 2000). Our main dependent variable is the ten-year change in the neighborhood's white population, taken as a share of the initial population, $Dw_{ic,t} = (W_{ic,t} - W_{ic,t-10}) / P_{ic,t-10}$. We also examine analogous measures for minorities and the total population, $Dm_{ic,t}$ and $Dp_{ic,t} = Dw_{ic,t} + Dm_{ic,t}$, respectively. Our key explanatory variable is the base-year minority share in the neighborhood, $m_{ic,t-10} = M_{ic,t-10}/P_{ic,t-10}$.

Equation (2) asserts that $E[Dw_{ic,t} \mid m_{ic,t-10}]$ is a smooth function of $m_{it-10,}$ except perhaps at the tipping point m^*. We assume that a tipping point, if it exists, is specific to a given city (i.e. metropolitan area) and decade, and we define $\delta_{ic,t-10} = m_{ic,t-10} - m^*_{c,t-10}$. Our basic empirical specification is:

[13] Any heterogeneity in the location of the tipping point across a city's neighborhoods or imperfect alignment between actual neighborhood boundaries and those that we use for measurement of m will lead us to smooth away true discontinuities and will produce a similar pattern of a steep slope in a range around m^*.

(3) $Dw_{ic,,t} = p(\delta_{ic,t-10}) + d\, \mathbf{1}[\delta_{ic,t-10} > 0] + \tau_c + X_{ic,t-10}\beta + \varepsilon_{ic,t}$,

where τ_c represents a city fixed effect, $X_{ic,t-10}$ is a vector of neighborhood-level control variables, and $p(\delta_{ic,t-10})$ is a smooth control function, which we model as a 4^{th}-order polynomial.[14] We estimate (3) separately by decade. In some specifications we also allow the discontinuity d and the parameters of the p( ) function to vary across cities.

D. Identification of the Tipping Point

A key problem in estimating a model like (3) is that the discontinuity point $m^*_{c,t-10}$ must be estimated from the data. We assume for the moment that a tipping point exists (i.e. $d \neq 0$), and focus on estimating its location. We discuss the possibility that d=0 in the next subsection.

We use two methods to obtain candidate values of $m^*_{c,t-10}$. The first is a search technique similar to that used to identify structural breaks in time series data. Ignoring covariates and approximating p() by a constant function in the [0, M] range, equation (3) becomes:

(4) $Dw_{ic,t} = a_c + d_c \mathbf{1}[m_{ic,t-10} > m^*_{c,t-10}] + \varepsilon_{ic,t}$, for $0 \leq m_{ic,t-10} \leq M$,

We set M=60% and select the value of $m^*_{c,t-10}$ in the [0, 50%] interval that maximizes the R^2 of (4), separately for each city and decade. Hansen (2000) shows that if (4) is correctly specified this procedure yields a consistent estimate of the true change point $m^*_{c,t-10}$.[15]

This procedure works well for larger cities but performs poorly in a few smaller cities, sometimes choosing a value for m^* that reflects obvious outliers. Our second, preferred approach builds on the consistent shape of smoothed approximations to $E[Dw_{ic,t} \mid c, m_{ic,t-10}]$ for

[14] In principle p() should be flexible enough to allow (for example) $h'(m^*) \neq g'(m^*)$. Specifications using separate quadratics for $\delta<0$ and $\delta>0$ yield estimates very similar to those presented below.
[15] Loader (1996) shows that the location of change points can be estimated non-parametrically using local linear regression methods. These methods would be appropriate for the largest cities in our sample.

many different cities.[16] Typically, this function is positive but relatively flat for low values of m_{t-10}, then declines sharply. Beyond the range of transition, $E[Dw_{ic,t} \mid c, m_{ic,t-10}]$ is again relatively flat until, at a minority share of about 60%, it begins to trend upward, approaching 0 as $m_{ic,t-10} \rightarrow 1$.[17] Interpreting the sharp decline as tipping, this pattern implies that neighborhoods with minority shares below the tipping point experience faster-than-average growth in white population, whereas those above it experience a relative decline. If there is a tipping point at m^*, then:

(5) $E[Dw_{ic,t} \mid c, m_{ic,t-10} = m^* - \varepsilon] > E[Dw_{ic,t} \mid c] > E[Dw_{ic,t} \mid c, m_{c,t-10} = m^* + \varepsilon]$ for $\varepsilon > 0$.

The city-specific tipping point is a "fixed point": the minority share at which the neighborhood white population grows at the average rate for the city. To identify this fixed point, we smooth the data to obtain a continuous approximation, $R(m_{t-10})$, to $E[Dw_{ic,t} \mid c, m_{ic,t-10}] - E[Dw_{ic,t} \mid c]$, then select the root of this function.[18] We refer to this as our "fixed-point" procedure.[19]

E. Hypothesis Testing

If our functional form assumptions are correct, both procedures will yield consistent estimates of the location of any true discontinuity. A standard result in the structural break literature (see, e.g., Bai, 1997) is that sampling error in the location of a change point (m^*) can be

[16] Many cities experience rising minority shares over our sample period. To abstract from city-wide trends, we focus on $E[Dw_{ic,t} \mid c, m_{ic,t-10}] - E[Dw_{ic,t} \mid c]$, which equals zero when neighborhoods are evolving in step with the city.
[17] $Dw_{ic,t}$ can never be lower than $m_{ic,t-10} - 100$, corresponding to total loss of the t−10 white population by year t. Many neighborhoods with $m_{ic,t-10}$ above 60% approach this limit.
[18] We use a two-step procedure to improve precision. We first fit $Dw_{ic,t} - E[Dw_{ic,t} \mid c]$ to a quartic polynomial in $m_{ic,t-10}$, using only neighborhoods with $m_{ic,t-10} < 60\%$, to obtain $R(m_{t-10})$. After identifying a root of this polynomial, m', we discard all neighborhoods with $abs(m_{ic,t-10} - m') > 10$ and fit a second quartic polynomial to the remaining neighborhoods. Our candidate point, m^*, is a root of this second polynomial. We consider only minority shares below 50% as candidate points. When there are multiple roots in this range, we select the one at which the slope of R(m) is smallest (most negative). In a few cities, R(m) has no roots below 50%. These cities are excluded from the fixed-point analysis. The Data Appendix discusses the details of the algorithm in greater detail.
[19] We also explored a third procedure, selecting values for which a smoothed approximation to $E[Dw \mid c, m]$ is most negatively sloped. Though this procedure agreed with the other two in many cities, in others it was poorly behaved.

ignored in estimation of the magnitude of the break (d). We rely on this result, and do not adjust our standard errors for the estimation of m^*.[20]

Under the null hypothesis that there is no discontinuity, however, the estimate of d has a non-standard distribution. The problem is essentially one of specification search bias (Leamer, 1978): When the same data are used to identify the location of structural break and to estimate its magnitude, conventional test statistics will reject the null hypothesis d=0 too often. The usual solution (Hansen, 2000; Andrews, 1993) is to simulate the distribution of $\hat{d}$ under the null, then compare the estimate to this distribution. We use a different approach that permits conventional tests. We use a randomly selected subset of our sample for our search procedures and use the remaining subsample for all further analyses. Because the two subsamples are independent, estimates of $\hat{d}$ from the second sample have a standard distribution, even under the null.[21]

F. Testing other implications of the tipping model

The model in Section II predicts that rents will evolve smoothly through any tipping point, though it has no clear prediction for housing prices. To explore tipping effects on rents and prices, we estimate models similar to (3), but with the change in average rents or in the average value of owner-occupied homes as the dependent variable. We also explore the prediction that the tipping point will be higher in cities where whites are more tolerant of minority neighbors by relating the estimated tipping point for a city to survey-based measures of the racial tolerance of the city's white population, controlling for many other city characteristics.

[20] We have also explored bootstrap estimators. Our most conservative approach (which re-samples both cities and tracts within cities) yields slightly larger standard errors than those reported in Table 3, but the differences are not large enough to qualitatively affect the interpretation of the estimates. Moreover, a Monte Carlo exercise indicates that the size of tests based on our analytic standard errors is reasonable. See Card, Mas, and Rothstein (2007).

[21] Angrist, Imbens, and Krueger (1999) proposed an analogous split sample approach for IV estimation with weak instruments. Estimates based on the full sample show somewhat larger, more precisely estimated discontinuities than our split-sample estimates.

III. Data and Potential Tipping Points

A. Tract Level Data

Our primary data source is the Neighborhood Change Database (NCDB), a panel of Census tracts matched from 1970 to 2000. Tracts are areas of about 4,000 people, drawn to represent demographically homogenous neighborhoods. The NCDB provides tabulations from each Census year for each year-2000 tract, mapping the earlier data onto the current boundaries.[22] We do not exploit the full panel structure of the NCDB, but focus only on changes over three ten-year inter-censal windows: 1970 to 1980, 1980 to 1990, and 1990 to 2000.

Our "cities" are metropolitan statistical areas (MSAs) and primary metropolitan statistical areas (PMSAs), as defined in 1999. In 1970, tract-level data were collected only for the central areas of many MSAs, so our 1970-80 analysis is based largely on central city neighborhoods. We are able to include more suburban areas in analyses of the 1980s and 1990s. We exclude from each ten-year sample tracts that were largely undeveloped (had very few residents) in the base year. We also exclude cities with fewer than 100 sample tracts, effectively limiting our analysis to larger metropolitan areas. The Data Appendix describes our sample in detail.

Table 1 presents summary statistics for the tract-level data. The NCDB has 1970 data on about 46,000 tracts, increasing to 65,000 in 1990. After dropping undeveloped tracts, those that cannot be matched over time, and all tracts from smaller cities, our sample includes roughly 40,000 tracts from 114 metropolitan areas. The white populations of the cities in our sample have grown over time, but because minority (i.e., non-white and Hispanic) populations have

[22] Ideally, we would hold tracts fixed at their initial boundaries, as later boundaries may be endogenous. We were able to construct our own panel of tracts for our 1990-2000 analyses using 1990 boundaries. Results on this panel were very similar to those from the NCDB data, and were unchanged by dropping tracts with boundary changes.

grown faster, the average minority share has risen steadily, from 16% in 1970 to 29% in 1990.

The remainder of Table 1 compares four subgroups of tracts, defined by the fraction of minority residents in the base year. In 1970, nearly one-half of tracts in our sample had minority shares below 5%. By 1990, only a quarter had such a low minority share. This decline was offset by growth in the 20-40% minority group (which rose from 10% to 35% of all tracts) and the 40% or higher group (which rose from 13% to 27%). The growth rate of the white population is strikingly different across subgroups, averaging +19% in the two lower-minority-share groups and negative or close to zero in the higher-minority-share groups.

B. Estimated Tipping Points

Figure 4 presents data similar to that in Figure 1 for a selection of cities in our sample. The vertical lines in each panel represent the estimated tipping points – solid for the point selected by the "fixed point" method and dashed for the point selected by the "structural break" method. (Where only one line is shown, the two coincide.) Both points are identified from a randomly-selected 2/3 subsample of tracts in each city.[23] We also plot two approximations to $E[Dw_{ic,t} \mid c, m_{ic,t-10}]$, computed on the remaining 1/3 subsample of tracts. The dots represent the means of $Dw_{ic,t}$ among all tracts with $m_{ic,t-10}$ in each 2-percentage-point bin. The solid lines represent a local linear regression fit to the underlying data, allowing a break at the estimate of m^* from the fixed point method. Finally, the horizontal line in each figure shows the city-wide average change in the white population share, $E[Dw_{ic,t} \mid c]$.

The upper left panel shows Los Angeles in 1970-80. Both search procedures identify a potential tipping point at a 1970 minority share of around 15%. Tracts with $m_{ic,1970} < 15\%$

[23] We use a 2/3 – 1/3 split because the search procedures for identifying tipping points in each city are quite data intensive. Most of the remainder of our analysis pools data across cities, and 1/3 subsamples are adequate for this.

gained white residents between 1970 and 1980, on average, while those with $m_{ic,1970} > 15\%$ lost substantial numbers of whites. There is a clear separation between the two groups: the average in every bin in the first group lies above $E[Dw_{ic,1980} \mid c]$, while the average for bins in the second group (excepting a few with minority shares close to 100%) lie below.

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 Pittsburgh in 1980-1990. These cities are drawn from all regions of the country, and vary widely in their overall minority shares. In each city, our two search methods yield similar candidate tipping points. In all but one, there is clear evidence of a discontinuity around the candidate tipping points. The exception is Pittsburgh in the 1980s, which shows a smooth V-shaped relationship between the white population growth rate and the initial minority share that does not appear to reflect discontinuous tipping.

Table 2 summarizes the estimated tipping points for all the cities in our sample. The fixed point method tends to identify higher tipping points than the structural break method, though both methods show an upward trend over time.[24] This increase accords with the predictions of our model and evidence from public opinion surveys that whites have become more tolerant of minorities (Schuman et al., 1998). The lower portion of the Table shows the correlations of the candidate tipping points for a city identified by the alternative methods in a given year, or over time. These correlations are all reasonably high. The two methods select candidate tipping points within one percentage point of each other in about one third of cities.

IV. POOLED ANALYSIS OF WHITE POPULATION CHANGES

[24] The fixed point method fails to find a tipping point in 4 cities in 1970 and 3 cities in 1980. By construction, the structural break method always identifies a point.

A. Graphical Overview

We now turn to pooled specifications that combine the data from all of the cities in our sample. The six panels in Figure 5 show the relationship between the base year minority share in a Census tract, deviated from the city-specific potential tipping point, and the subsequent change in the white share in the tract, deviated from the city-wide mean. We use candidate tipping points from the fixed point method on the left and from the structural break method on the right, with 1970-80 data at the top, 1980-90 data in the middle, and 1990-2000 data in the lower panels. The dots in each figure represent mean changes for one-percentage-point bins of $\delta_{ic} = m_{ic} - m^*_c$, while the solid lines show local linear regressions fit to the data on each side of the candidate point. Finally, the dashed lines show fitted values from a 4th-order polynomial in δ_{ic}, allowing an intercept shift at $\delta_{ic} = 0$. We limit attention to $\delta_{ic} \in [-30, 30]$. Note that relatively few cities are represented in the lower range of this interval, since most cities have $m^*_c < 20$.

The 1970-80 and 1980-1990 data show very clear evidence that the pattern seen in Figure 4 is a general phenomenon. We see a 15 percentage point drop in the mean change in the white population share when we compare tracts just below and just above the tipping point. In 1990-2000, the discontinuity is still evident but is somewhat less sharply defined, as a few tracts near the tipping point smooth away some of the difference between the trends on either side. Overall, however, we believe the plots provide strong evidence of tipping behaviour. In each year, using either set of candidate tipping points, tracts just beyond the tipping point experience substantial relative outflows of white families.

B. RD Models

The results in Figure 5 are visually striking but do not permit formal hypothesis tests nor do they control for other neighborhood characteristics that may affect white mobility. Table 3 presents decade-specific estimates of equation (3), fit to the subsample of tracts from each city not used to identify m^*. All the models in the table include city fixed effects and a quartic polynomial in the deviation of the tract minority share from the city-specific tipping point.[25] The models in columns 1 and 2 – using candidate tipping points from each of our search procedures – also include controls for six tract-level characteristics in the base year: the unemployment rate, the log of mean family income, the fractions of single-unit, vacant, and renter-occupied housing units in the tract, and the fraction of workers who use public transport to travel to work.

The estimated coefficients for the models in columns 1 and 2 confirm that the growth rate of the white population share is discontinuous in the initial minority share around the candidate tipping points. When we use the points from the fixed point procedure (column 1), we obtain precisely estimated, statistically significant discontinuities of -12, -14, and -7 percentage points for the 1970-1980, 1980-1990, and 1990-2000 periods, respectively. Specifications that use the "structural break" tipping points (column 2) are comparable, though marginally less precise.

A potential concern with these models is that we have constrained the polynomial $p(\delta)$ and discontinuity coefficient d to be the same for all cities in a given decade. The specifications in columns 3 and 4 relax these assumptions by including city-specific quartic polynomials and discontinuities (but excluding the tract-level covariates). We report the average discontinuities across cities, weighting each city by the number of tracts it provides to the sample. We see relatively large, statistically significant average discontinuities in all but one case (1990-2000 with fixed point estimates of m^*).

[25] The standard errors in Table 3 (and in all remaining tables) are clustered by city. We have also estimated models with several alternative specifications for p( ), including quadratics with separate first and second order coefficients on each side of the candidate tipping point. These yield very similar estimates of the discontinuities.

Columns 5-8 of Table 3 present models for the growth rates in the neighborhood minority population and total population, each measured as a percentage of the total base-year population. The specifications are otherwise identical to those in columns 1 and 2. Columns 5 and 6 show that the upward jump in minority inflows at the city-specific tipping point is quite small. As shown in the last two columns, the outflow of whites at the tipping point coincides with a discontinuous drop in the growth rate of the tract's population (relative to the city as a whole).

Across specifications in Table 3, the estimated discontinuities around the candidate tipping points derived from the "fixed-point" and "structural break" procedures are relatively similar in magnitude and precision. For simplicity, we hereafter restrict attention to the tipping points derived from the "fixed-point" procedure. In the remainder of this section, we explore the robustness of the results in Table 3 and test alternative explanations for them.

C. Full Tracts versus Tracts with Open Space

The models in Table 3 show that tipping is associated with a discontinuous drop in overall population growth, but little change in minority inflows. Similarly, in Table 1 we found that tracts with initial minority shares below 20% experienced substantial population growth over the next ten years, while those with higher initial shares did not. These observations underscore an important factor that is missing from our model: housing supply. In further (unreported) analyses, we use our basic specification to model the change in the neighborhood housing stock. There are large discontinuities – comparable to the estimates in columns 7 and 8 of Table 3 – in the rate of new construction once a tract exceeds the tipping point, but we find no evidence of discontinuities in the disappearance of existing units.

With a fixed housing stock, as in the model in Section II, any decline in white demand is mechanically offset by minority inflows. To approximate a fixed-supply environment, we identified a subset of tracts where new construction is constrained by the availability of open land. Specifically, we used data from satellite images to estimate the fraction of open space in each Census tract in 1992.[26] We then split tracts into two groups: those in the lowest quartile of open space (9% or less); and all other tracts. Because comparable land use data are unavailable for earlier years, our analysis here is restricted to changes between 1990 and 2000.

For reference, the first row of Table 4 reproduces estimates of white, minority, and total population changes at the tipping point from our baseline sample (as in Table 3). The remaining rows present estimates fit separately to the more- and less-developed subsets of tracts. In the most intensively developed tracts (row 2), the estimated discontinuity in white population growth at the tipping point is -4.7%. This is somewhat smaller than the corresponding estimate from the full sample, but is still highly significant. In these highly developed tracts the estimated discontinuity in minority population growth is equal and opposite to the jump in white population growth, while total population growth shows no discontinuity. Thus, mobility patterns in these supply-constrained tracts closely match the predictions from a model with fixed housing supply.

The patterns are quite different for tracts with substantial undeveloped land (row 3). Although we still see a discontinuous drop in white population growth (-6.1%) at the tipping point, there is only a modest increase in minority inflows at this point. As in the overall sample,

[26] We define open space as the fraction of the developable land area that is not occupied by residential, commercial, industrial, or transportation uses. We use the National Land Cover Data, produced from satellite photos taken in and around 1992 (see Vogelmann et al., 2001). We are extremely grateful to Albert Saiz and Susan Wachter for providing a tract-level version of these data, also used in Saiz and Wachter (2006).

most of the drop in white population growth appears as a decline in total population growth.

Column 4 of Table 4 presents estimates where the dependent variable is the change in the tract's minority share, $m_{ic,t} – m_{ic,t-10}$. The estimated tipping effect on this variable – the traditional focus of tipping models – is apparent in all three rows, though it is largest in the tracts with constrained supply where the denominator of the minority share is essentially fixed. In tracts with available open land there are competing changes in the numerator and denominator around the tipping point, leading to a relatively small discontinuity in the minority share.

The estimates in Table 4 suggest that in neighborhoods with available land and minority shares below the tipping point, new housing is built that is primarily occupied by whites. In neighborhoods that tip, however, inflows of white families fall off and new construction ceases. We return to these results below, in our discussion of the housing market effects of tipping.

D. Minority Definition

So far we have defined minorities as all non-whites plus white Hispanics. Table 5 presents a series of models in which we vary the definition of "minority." We explore alternatives that count only blacks, or only blacks and Hispanics, as minorities. We also present a composite model that includes indicators for being beyond the tipping point for all three minority definitions.[27] As in earlier tables, our dependent variable in each specification is the change in the white non-Hispanic population.

The estimates offer no clear guidance about which definition to use. In the 1970s, tipping behavior seems to have been driven more by the black share than by the presence of other groups. In the 1980s and 1990s, however, estimates are similar across all three definitions.

[27] Each model includes a quartic polynomial in the deviation of the tract's minority share from the tipping point, measuring both the same way. The composite model includes all three quartics. Candidate tipping points are estimated separately for each definition of minorities, using the fixed point procedure discussed above.

In the composite models, in columns 3, 6, and 9, none of the measures consistently dominates. In the remainder of the paper we continue with our original measure, counting all non-whites and Hispanics as minorities.

E. Geography

One concern with our models so far is that the discontinuous relationship between white mobility flows and the initial minority share may be due to omitted neighborhood characteristics that happen to be discontinuously related to the minority share. Our main specifications include a vector of neighborhood demographic and housing characteristics, but these linear controls may not be sufficiently flexible to absorb their effects. To assess this possibility, in Table 6 we present a series of extended specifications that add quartic polynomials in these variables. Our estimates are robust to the inclusion of these polynomials, suggesting that omitted variables of this sort are unlikely to account for our results.

Another possible explanation for apparent tipping behavior is suburbanization and white exodus from the central city, driven by changing preferences of whites and/or an expansion in the traditional minority ghetto areas of the inner city.[28] Consider first the hypothesis that white families have developed an increasing preference for lower density neighborhoods. If integrated tracts are systematically denser than nearly all-white tracts, and the latter are mainly concentrated in the suburbs, one might observe a discontinuous relationship between white population changes and the initial minority share, even though whites do not care about the minority share of a neighborhood. A similar but distinct explanation invokes politics: white families may have fled central city neighborhoods to avoid living in majority-black cities

[28] There is a large literature examining the rapid suburbanization of the post-war era. See, for example, Baum-Snow (2007), Boustan (2006), Mieszkowski and Mills (1993), and Margo (1992). Bajari and Kahn (2005) consider the role of racial preferences and other factors that explain suburbanization.

(Glaeser, Kahn and Rappaport 2000; Boustan, 2006). Either channel predicts that tipping effects should be concentrated in the relatively dense central city tracts.

To evaluate these explanations we extend our baseline model to allow different discontinuities (and different city fixed effects, polynomials p(δ), and control variable coefficients) for tracts within and outside the central city. Columns 1 through 3 of Table 7 report the results. There are no systematic differences in the magnitude of the tipping discontinuity between central-city and suburban tracts. For all three decades of our sample the estimated discontinuities in the white population growth rate are negative and statistically significant for both central city and non-central city tracts, and in the 1980s and 1990s the discontinuity is larger for the latter group.[29]

A related explanation for apparent tipping behavior is an expanding ghetto (Mobius and Rosenblat, 2002). Specifically, consider a circular city, with a minority ghetto at the center that is surrounded by a ring of integrated neighborhoods and an outer ring of nearly all-white suburbs. As the minority population of the city grows, the ghetto expands and the integrated ring moves outward. Outer tracts remain predominantly white, but integrated tracts near the boundary of the ghetto experience significant white flight.[30] Such a process could yield tipping-like patterns.

Several analyses suggest that an expanding ghetto cannot account for the tipping behavior we have documented, however. First, contrary to the pattern predicted by an expanding ghetto, tracts with minority shares near the tipping point tend to be relatively far from the existing ghetto, and show no tendency to be farther away in later decades. In each decade of our

[29] We have also fit a model that allows different tipping effects in tracts with high and low rates of public transport usage. We found no systematic differences along this dimension either.
[30] A model along these lines is developed in Rose-Ackerman (1975).

sample, tracts with minority shares near the city-specific tipping point lie at an average distance of 13 miles from the center of the historical ghetto.[31]

Second, tipping is not confined to tracts that are close to existing high minority areas. Columns 4-6 of Table 7 present models that are fully interacted with indicators for being 2-5 miles from any other tract with at least a 60% minority share in the base year and for being more than 5 miles from any such tracts. In 1970-80 and 1980-90, the tipping effect is larger in magnitude in tracts that are farthest from a high-minority tract than in those near such a tract. In 1990-2000, the estimated discontinuities are very similar for all three groups of tracts.

Columns 7-9 present specifications using a different measure of proximity, based on the presence of at least one neighboring tract with a minority share above the tipping point. We fully interact our model with an indicator for having no such tracts nearby. During the 1970s and 1980s, tipping was concentrated in tracts with no neighbors that had tipped; in the 1990s, it is strongest in such tracts but also appears in tracts with neighbors that have tipped.

We have also experimented with more flexible models that include controls for the average minority share of nearby tracts and that allow the tipping effect to vary with the fraction of neighboring tracts that are themselves beyond the tipping point. Consistent with the results in columns 7-9 of Table 7, these specifications suggest that the tipping effect is relatively large for tracts with no neighboring tracts that have tipped, and much smaller when the neighbors all have high minority shares. They also show clear spillover effects: White population inflows are strongly decreasing in the fraction of nearby tracts with $m>m^*$. Our interpretation of these extended models is that the "own tract" minority share is an imperfect measure of the minority

[31] This statistic is based on tracts with $m_{ic,t-10}$ within two percentage points of $m^*_{c,t-10}$. The center of the ghetto is defined as the tract in the MSA with the highest minority fraction in 1970. Other definitions yield similar results.

share variable driving neighborhood choice. If, for example, residents near the boundary of a tract see their neighborhood as including homes in neighboring tracts, we would expect to see significant spillover effects. The "own-tract" tipping indicator would then be an unreliable measure of whether the relevant area has a minority share above the tipping point, with particularly little signal when neighboring tracts have high minority shares.

Taken together, these results are not consistent with the predictions of the expanding ghetto model. Tipping effects are if anything strongest far from the existing ghetto. We conclude that this model cannot account for the non-linear dynamics we see in Figures 4 and 5.

V. HOUSING MARKETS

The model presented in Section II predicts that rents will evolve relatively smoothly as a neighborhood exceeds the tipping point, despite a discontinuity in the racial composition of the neighborhood. As we noted earlier, implications for home values are less clear, since the price of an asset like housing will be sensitive to long-term expectations about future rents and prices.

Figure 6 presents graphs of the relationship between $\delta_{ic,t-10}$ (the deviation of the minority share in a tract from the appropriate tipping point) and the intercensal changes in the log average monthly rent paid by renters in the tract and the log average housing values reported by homeowners in the tract.[32] As in Figure 5, we show dots representing means for percentage-point bins of $\delta_{ic,t-10}$ in the interval [-30,30], as well as fitted values from our fourth-order polynomial model (dashed lines) and the predictions from local linear regression models (solid lines). Looking first at the pattern for rents, on the left, there is no indication of substantial drops

[32] Census housing value data have been used to measure the market valuation of locational amenities (e.g., Chay and Greenstone, 2005; Gyourko, Mayer and Sinai, 2006) and the effect of inter-city variation in supply restrictions (Glaeser, Gyourko, and Saks, 2005). Values are self-reported, and frequently incorporate long lags (Bayer, Ferreira, and MacMillan, 2003). This may make it difficult to observe sharp changes when a neighborhood tips.

as the minority share in a tract moves from below the tipping point to well above it. Indeed, the estimated discontinuities in the change in rents are small (-1.5% in 1970-80 and -0.6% in 1980-90 and 1990-2000) and statistically insignificant. Housing value changes (plotted in the right hand column) show a negative relationship with $\delta_{ic,t-10}$ in 1970-80 and 1990-2000 periods, but not between 1980 and 1990. Again, there is modest evidence for a discontinuous reaction at the tipping point. The estimated discontinuities in values are -3.6% in 1970-80, -0.4% in 1980-90, and -2.2% in 1990-2000. The first and last of these are significantly different from zero, though the former is not robust to the inclusion of additional controls.

Theoretical predictions for the effect of demand shifts on home values depend importantly on the elasticity of local supply. A decline in total (white plus minority) demand will lower prices if supply is inelastic, but will only reduce quantities if supply is perfectly elastic. We have estimated separate models for the change in housing values over the 1990s for the subset of highly developed tracts (as in row 2 of Table 4) and those with remaining room to build. As expected, the estimated discontinuity in home values is larger in the former group of tracts. It is also less precisely estimated, however, and is insignificantly different from zero.

Overall, we conclude that housing price reactions to tipping are relatively modest. This is consistent with the findings from a long literature (mainly in sociology) that studies the effects of the initial entry of minorities to previously all-white Census tracts.[33] Our results indicate that the primary housing market effect of tipping is in the quantity domain: neighborhoods that tip grow more slowly than other tracts in the same city. This may be consistent with a highly elastic supply of new housing units, coupled with a fear among builders that neighborhoods that have

[33] See, e.g., Myrdal (1944), Rapkin and Grigsby (1960), and Laurenti (1960). Boston, Rigsby and Zald (1972) review the literature on this question up to the early 1970s.

tipped will experience long run housing value declines.[34] While we find a larger reaction of housing prices in areas where supply responses are constrained, the magnitude of the effect remains modest and is relatively imprecisely estimated.

VI. SCHOOLS

One explanation for the importance of neighborhood racial composition is that families are concerned about the racial composition of schools.[35] An advantage of a schools-based analysis is that the peer group is clearly defined, so there are less likely to be spillovers among nearby schools. Table 8 reports estimates of specifications similar to those in the top row of Table 4, focusing on changes in the racial composition of elementary schools between 1990 and 2000. As in our neighborhood analysis, we use 2/3 of the schools in each MSA to search for a candidate tipping point (using the "fixed point" method) and the remaining 1/3 of schools to study dynamic behavior around these points.[36] The correlation between school and neighborhood-level tipping points for the same MSA is 0.4.

Enrollment dynamics at elementary schools are remarkably similar to dynamics in neighborhoods. White enrollment growth drops off substantially in schools that are just beyond the tipping point. The magnitude of the discontinuity (-7.4) is very close to that observed in neighborhoods over the same period (-7.3). As in the neighborhood analysis, relatively little of the outflow of white students is offset by inflows of minority students. Instead, enrollment growth drops discontinuously in schools that tip. Overall, the similarity of the dynamic behavior

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[34] Another possibility is that the housing market anticipates tipping, and that its effect on prices is fully realized even before the base year (that is, that prices fall between 1960 and 1970 for neighborhoods that tip between 1970 and 1980). Estimated price changes in the decade before tipping are negative, but are as imprecise as those in Figure 6.

[35] There is a substantial literature on white flight from high-minority school districts, including Coleman Kelly and Moore (1975), Clotfelter (1979, 2001), Farley, Richards, and Wurdoch (1980), and Reber (2005).

[36] The school data are drawn from the Common Core. Our sample includes 5,641 schools (in 72 MSA's) that can be matched between 1990 and 2000. See the Data Appendix for more information.

of schools and neighborhoods suggests that similar forces are driving the two processes.

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

The model presented in Section II suggests that the location of the tipping point will be higher in cities with more racially tolerant whites. Our final analysis focuses on testing this insight, using information on the attitudes of white residents in different cities constructed from the General Social Survey (GSS).[37] To develop a reliable index of white attitudes, we pool GSS data from 1975 to 1998 and average the responses to four questions that elicit direct information about attitudes regarding contact between races. Specifically, for each question we fit a model for the likelihood of a "racist" response, including characteristics of the respondent, year dummies, and MSA dummies.[38] We then standardize the MSA effects for each question to have a mean of 0 and standard deviation of 1, and form a simple average of the standardized MSA effects for each city. We are able to construct a value of the index for 81 cities in our tipping sample, with 100 to 175 responses per city on each GSS question. The cities with the highest index values (indicating more strongly held views *against* racial contact) are Memphis (1.44) and Birmingham (1.31). The cities with the lowest values are San Diego (-1.06) and Rochester (-1.05).

Table 9 reports a series of models that take the tipping point ($m^{*}_{c,t-10}$) as the dependent variable.[39] We pool the 1970, 1980, and 1990 points together in one sample, and include dummy variables for each period. For reference, the first column shows the mean and standard deviation of each of the independent variables. Unless otherwise noted, the independent variables

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[37] We follow here Cutler, Glaeser, and Vigdor (1999), who use the GSS attitudinal data for a similar investigation of cross-city variation in residential segregation. Details of our attitudes index construction are in the Data Appendix; city-specific values are available on request.
[38] The mapping to MSAs is necessarily approximate. Details are available on request.
[39] For greater precision, we use estimated tipping points obtained from the full sample of tracts in each city.

correspond to the base year. Standard errors for the regressions are clustered on the CMSA.

Our first specification includes the attitudes index, four region dummies, the black and Hispanic shares in the city, the density of the average resident's census tract, and the log of the city's population. The racial share variables have coefficients of 0.53 and 0.65, suggesting that tipping points are higher – but less than proportionately so – in cities with higher minority shares. More densely populated cities have lower tipping points, consistent with Cutler, Glaeser and Vigdor's (1999) finding of a positive relationship between density and segregation. The attitudes index also has a significant negative coefficient, indicating, as predicted, that tipping points are lower in areas where whites have stronger preferences against minority contact.

Research by Bayer, Fang, and McMillan (2005) suggests that income differences are an important determinant of segregation. Column 3 adds the log mean incomes of blacks, Hispanics, and whites in the city. Higher white incomes are associated with lower tipping points, while higher black and Hispanic incomes lead to higher tipping points. The magnitudes are comparable, suggesting that an increase in income that is distributed evenly across races has little effect. Note that the inclusion of income controls slightly strengthens the attitude effect.

Finally, the model in column 4 adds four additional variables. The first is the rate of new housing construction in the city over the decade. The second is an index of the cumulative severity of riots experienced in the city during the late 1960s (Collins and Margo, 2004).[40] The last two are crime rates: the number of murders per 100,000 residents and the number of all other "index crimes" per capita. The riot measure and the murder rate have negative and significant effects, but their addition has little impact on the coefficient of the attitudes index.

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[40] We are grateful to Gregg Carter (1986) and Bill Collins for compiling and providing the data used for the construction of this index, which is drawn from Collins and Margo (2004).

To interpret the effect of the attitudes index, 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. A coefficient of -3 implies that the tipping point will be about 7.5 percentage points higher in San Diego than in Memphis, other factors equal. Compared to a mean tipping point (over three decades) of 13.3 and a standard deviation of 9.6, this is a reasonably large effect, confirming the important link between tipping and white preferences.

VII. Conclusions

Social interactions in the preferences of white families can lead to a tipping point, a critical threshold for the minority share in a neighborhood beyond which all the white families will leave. We use a regression discontinuity approach to test for tipping in the racial and ethnic composition of Census tracts in major cities between 1970 and 2000. We find strong evidence of discontinuities in white mobility flows around city- and decade-specific tipping points.

An earlier literature in sociology (e.g., Duncan and Duncan, 1957; Tauber and Tauber, 1965) documented that in the 1940s and 1950s, neighborhoods with more than a handful of black residents experienced rapid white outflows and transitioned to a nearly 100% black population within a decade. Such behavior can be interpreted as tipping with a very low tipping point. Other work suggested that property values would not necessarily collapse when neighborhood tipped. Indeed, a comprehensive survey (Boston et al., 1972) found little evidence that the onset of racial transition reduced prices.

Our results indicate important differences, but also similarities, in recent decades. Integrated neighborhoods with non-trivial minority shares can be stable: our estimated tipping points range from 5 to over 20 percent in some cities. But once the minority share exceeds the tipping point, the neighborhood transitions rapidly to a very high minority share. As in the older literature, we find little effect of tipping on rental prices or home values, though tipping is associated with a sharp drop in new construction in tracts with available open land.

Our analysis provides some of the first direct evidence of the nonlinear dynamic behavior predicted by social interaction models. We conclude that such behavior is an important feature of neighborhood-level data, providing further support for the view that segregation is driven at least in part by preferences of white families over the (endogenous) racial and ethnic composition of neighborhoods.

Appendices

Appendix A: Data

Most of our data are taken from tract-level tabulations of decennial Census data, mapped to the boundaries of year-2000 tracts and reported in the Neighborhood Change Database (NCDB). We assign each tract to the 1999 MSA in which it lies. Our sample for each decade excludes tracts meeting any of the following criteria:

- The decadal population growth rate exceeds the MSA mean by more than five standard deviations
- The ten-year growth in the white population exceeds 500% of the base-year total population.
- The MSA contains fewer than 100 tracts (after applying the previous criteria).

We divide the remaining sample in each city into two random subsamples, one containing 2/3 of the tracts and the other containing 1/3.

Throughout the paper, the "white" population consists of white, non-Hispanics. All other residents are "minorities" (except in Table 4, where we consider other definitions). Because the 1970 data do not separately identify white and non-white Hispanics, we impute the white non-Hispanic share. We use 1980 data to estimate a regression of the white, non-Hispanic share in a tract on the black share, white share, and Hispanic share. We use the coefficient estimates from this regression and the black, white, and Hispanic shares in 1970 to predict the 1970 white non-Hispanic share in the tract, censoring predicted values at 0 and 1. When we compute changes in the non-Hispanic white population between 1970 and 1980, we use imputed values in both years. For our analysis of alternative tipping points Table 4, we use a similar imputation procedure to identify the number of non-Hispanic blacks in each tract in 1970.

We use the procedures identified in the text to identify candidate tipping points in the 2/3 subsample. We use a two-step procedure to identify the roots of $E[Dw_{ic,t} \mid c, m_{ic,t-10}] - E[Dw_{ic,t} \mid c]$ for the "fixed point" procedure. We first fit $Dw_{ic,t} - E[Dw_{ic,t} \mid c]$ to a quartic polynomial in $m_{ic,t-10}$, using only tracts with minority shares below 60%. We identify a root of this polynomial, excluding those above 50% minority share and, in cases where there are multiple roots, selecting the one at which the polynomial has the most negative slope. We then fit a second quartic polynomial, using only tracts with $m_{ic,t-10}$ within ten percentage points of this root, and select a root of this second polynomial as our candidate point. There are a few cities where these polynomials have no roots; in these cases, we do not identify a tipping point.

Once candidate tipping points are identified, we discard the 2/3 sample used to identify them and use the 1/3 sample for all further analyses.

The tract-level covariates used in Tables 3-7 are also drawn from the NCDB, using data from the base year (i.e. 1970 for the 1970-1980 analysis). These are:

- The proportion of persons 16+ years old who are in the civilian labor force and unemployed.
- Natural logarithm of mean family income.
- The fraction of workers who use public transport to travel to work (aged 16+ in 1980 and 1990; 14+ in 1970).
- The fraction of homes in a tract that are vacant, renter-occupied, and single-unit.

Land-use data

In Table 4, we distinguish between tracts in which more or less than 91% of the developable land is developed. We use the National Land Cover Database, created by the USGS. These data are derived from satellite photographs taken in 1992, machine-coded to describe land use. We use a version of the data that reports the fraction of each census tract devoted to each of 21 uses (e.g., water, low-intensity residential, row crops, deciduous forest). This was created by Albert Saiz and Susan Wachter, and we are grateful to them for making it available to us. We exclude several categories (water, perennial ice/snow, bare rock, quarries) as undevelopable, and compute the fraction of the remainder that is devoted to residential or commercial/industrial/transport uses.

Schools

Our analysis of schools parallels that of neighborhoods, but relies on the Common Core of Data (CCD) to measure public elementary schools' racial compositions in 1990 and 2000. The only available control variable is the fraction of students qualifying for free school lunches. This is missing for many schools in 1990; we impute values from 1995 or 2000 where necessary.

Metropolitan-level variables

In Table 9, we examine the correlates of the metropolitan-level tipping point. The demographic variables used here—the racial composition, population, and income variables, as well as the housing development measure, are drawn from summary tape files of the 1970, 1980, and 1990 Censuses. We use county-level records (towns in New England), matched to 1999 MSA boundaries and then aggregated to the MSA level. We were unable to match the 1970 town records to the current town codes, so the New England observations are constructed as averages of the counties that overlap each MSA, weighted by the fraction of the county population in the MSA.

The density measure used in Table 9 is constructed from the NCDB tract-level data. We compute the population density of each tract in the base year, then compute a metropolitan-level average weighting tracts by their populations.

The crime variables were computed from Uniform Crime Reports data for 1970, 1980, and 1990, obtained from the Inter-University Consortium for Political and Social Research (ICPSR). In 1980 and 1990, the underlying data are at the county level. In 1970, the underlying data are at the agency level. We used the Law Enforcement Agency Identifiers Crosswalk (2005), also from ICPSR, to aggregate to the county-level. We then aggregate county-level data to the level of the MSA, weighting New England counties by the fraction of their population in each relevant MSA.

The riots index is constructed from data from Carter (1986), following the definition proposed by Collins and Margo (2004). For each riot, we compute $S_j = \sum_i \left(X_{ji} / X_{iT} \right)$, where X_{ji} is a component of severity (deaths, injuries, arsons, and days of rioting) and X_{iT} is the sum of components X_{ji} across all riots. We created a crosswalk between the cities reported in the Carter data and our MSAs. We add across the severity measure for all riots within each MSA to form the MSA-level index.

The final metropolitan-level variable is the racial attitudes index. We use four questions from the General Social Survey:

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.

For each question, we compute an indicator for an intolerant response. We estimate a linear probability model for each indicator, using only white GSS respondents who can be assigned to an MSA or CMSA. The models include MSA/CMSA fixed effects and controls for gender, age, education, a socioeconomic status index, and survey year dummies. We extract the MSA effects and standardize each set to have mean zero and standard deviation one. Our attitudes index is the simple average of these standardized MSA effects.

The dependent variable in Table 9 is the MSA/PMSA-level candidate tipping point, from the fixed point procedure. In this table, we use points identified from the full sample of tracts in each MSA rather than the 2/3 sample used elsewhere.

Appendix B: Falsification Exercise

Our estimation procedure is not part of the econometrician's standard toolbox, and the possibility exists that it might be biased toward finding evidence of a discontinuous tipping effect even if the true relationship between the base-year minority share and the change in the white population over ten years is smooth. To assess the size of our test, we estimated our model using simulated data with a smooth data generating process. Specifically, using the observed distribution of tract minority shares in two cities, we generated simulated data using two DGPs. The first assumes that $E[Dw_t \mid m_{t-10}]$ matches the estimates we obtain by fitting the following model to the true data:

$$(B1)\ Dw_t = \alpha + m_{t-10}\,\beta_1 + m_{t-10}^2\,\beta_2 + m_{t-10}^3\,\beta_3 + m_{t-10}^4\,\beta_4 + 1(m_{t-10} > m^*)\,\gamma + \varepsilon_t.$$

Our second DGP assumes that

$$(B2)\ Dw_t = \alpha + m_{t-10}\,\beta_1 + m_{t-10}^2\,\beta_2 + m_{t-10}^3\,\beta_3 + m_{t-10}^4\,\beta_4 + \varepsilon_t.$$

We again obtain the coefficients by fitting this model to the true data, not allowing a discontinuity. This yields a polynomial that is much steeper than that indicated by equation (B1).

For each tract, we draw ε_t from a normal distribution with variance equal to the observed residual variance, then add it to the fitted values from (B1) or (B2). We then apply our estimation procedure to this simulated sample, first dividing it into subsamples, identifying the tipping point from one subsample, and finally estimating model (B1) using the other subsample.

We use two cities as the basis for these simulations. In Appendix Figure 1, the DGPs are estimated using data from Chicago in 1970-1980, and each of the simulation samples is the same size and has the same 1970 minority share distribution as the Chicago data. In Appendix Figure 2, we use a smaller city, Portland, Oregon, in 1970-1980. In each Figure, the solid line shows the distribution when the DGP is (B1), while the dashed line shows the distribution for DGP (B2). The solid vertical line in each figure shows the threshold for rejection of the hypothesis that the true effect equals zero, using a 5% one-sided test and the mean standard error across simulation draws.

In Appendix Figure 1, the bulk of the estimates from the first DGP are to the left of the average rejection threshold, while nearly all of those from the second are to the right. We reject the null hypothesis of no effect (using a 1-sided 5% test) in 6.0% of the simulations from the second DGP and in 90.2% of those from the first. The figure thus indicates that the size of our test is 6% when the true DGP is a continuous 4^{th}-order polynomial, and that we have 90% power against the null hypothesis when the sample size and discontinuity are as large as in Chicago.

Appendix Figure 2 repeats the exercise using Portland data. We again see that DGP 1 yields consistently lower estimates than DGP 2, though because the sample size is much smaller both sets of estimates are more widely dispersed than in Figure A1 and they overlap substantially. This simulation indicates that the size of our test is 6.6%, but because the Portland sample size (387 tracts) is much smaller than that in Chicago (1,803 tracts), we reject the null hypothesis of no discontinuity in Portland in only 26.4% of the replications.

Appendix C: Bootstrap Standard Errors

A second concern with the estimates in the main text is that our standard errors do not take account of the fact that m^* is estimated. The change point literature (e.g., Bai 1997) indicates that if there is in fact a change point, m^* is super-consistent and that variance estimators that treat it as known are consistent. However, because some of the cities in our sample may not have a change point, this result may not hold in our application.

Appendix Table 1 presents several alternative estimates of the standard errors for the estimates in Column 1 of Table 3. The first two rows repeat the estimates and standard errors from Table 3. Row 3 presents classical standard errors that treat the data as independent and homoskedastic. These are somewhat smaller than those in Table 3. Row 4 presents heteroskedastic-robust standard errors that maintain the independence assumption. These are nearly identical to those in row 3.

The remaining rows present standard errors from the (nonparametric) bootstrap. Implementing the bootstrap is somewhat complex—an individual bootstrap ignores the possible clustering, while a block bootstrap allows for non-independence within MSAs but cannot account for sampling variation in the estimated m^* for each city. We take three approaches. The first approach ignores the clustering of the data and draws bootstrap samples (with replacement) from the full sample, independent of city. The second is a block bootstrap, drawing a sample of the same number of cities as in our original sample. (The number of tracts in the bootstrap samples varies somewhat here, as in some draws larger cities are overrepresented and in other draws the smaller cities are.)

The final bootstrap approach is the most sophisticated. We first stratify cities into three groups: Those with fewer than 225 tracts in the sample, those with 225-999 tracts, and those with 1000 or more tracts. We perform a block bootstrap, stratifying on the city strata. This ensures a sample of the same number of cities with approximately the same size distribution as in our original sample. For each city in the bootstrap sample – treating multiple draws of the same original city as distinct – we draw with replacement from the tracts in that city to obtain a sample matching the original size. This block-and-individual bootstrap allows for both sampling variation in city-level statistics and non-independence of observations within cities.

For each bootstrap strategy, on each draw we repeat our full estimation procedure. We randomly divide each city (or, in the case of the block bootstraps, city replicate) into subsamples, and use a 2/3 sample to select candidate tipping points. We then use the remaining 1/3 subsample to estimate the coefficients of our model. Rows 5-7 of Appendix Table 1 present average point estimates across 200 replications for each of the three bootstrap strategies. Those in rows 5 and 6 are comparable to those in Table 3. Those in row 7 are slightly larger than our clustered standard errors, but not enough so to change any of our qualitative conclusions.

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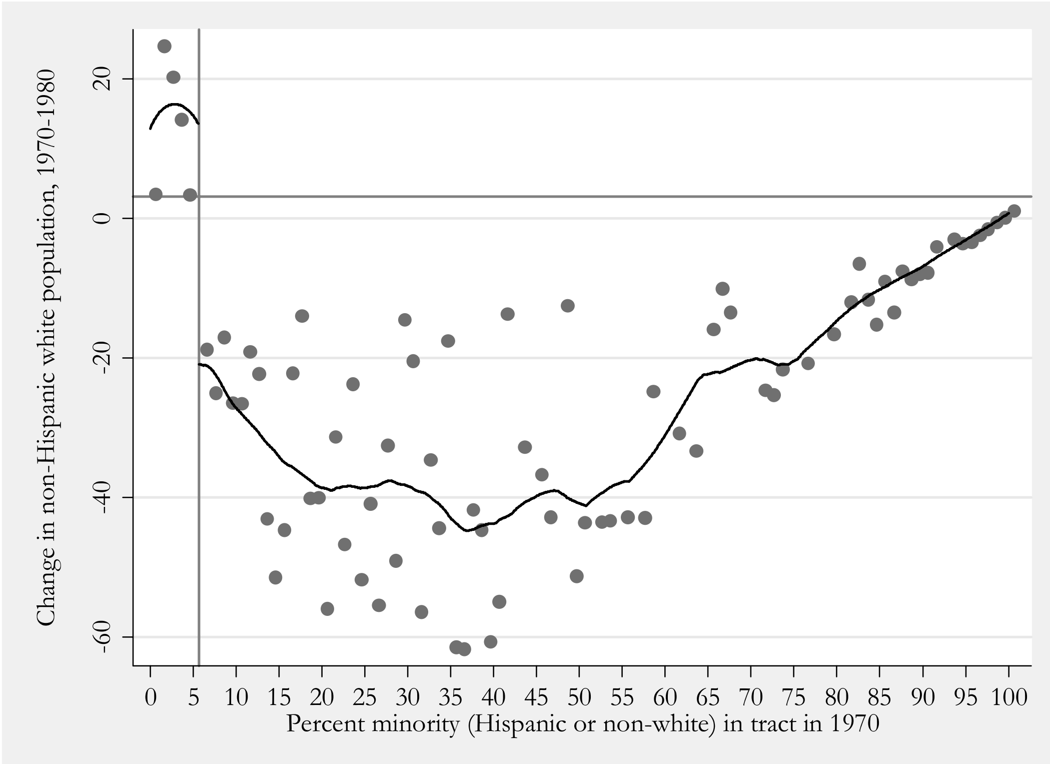
Figure 1: Neighborhood change in Chicago, 1970-1980



Notes: Dots show mean of the change in the tract-level non-Hispanic 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 (Hispanic and/or non-white) share. The horizontal line depicts the unconditional mean. Also shown is a local linear regression fit to the tract-level data, using an Epanechnikov kernel and a bandwidth of 3.5 and estimated separately on each side of 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: Three equilibria

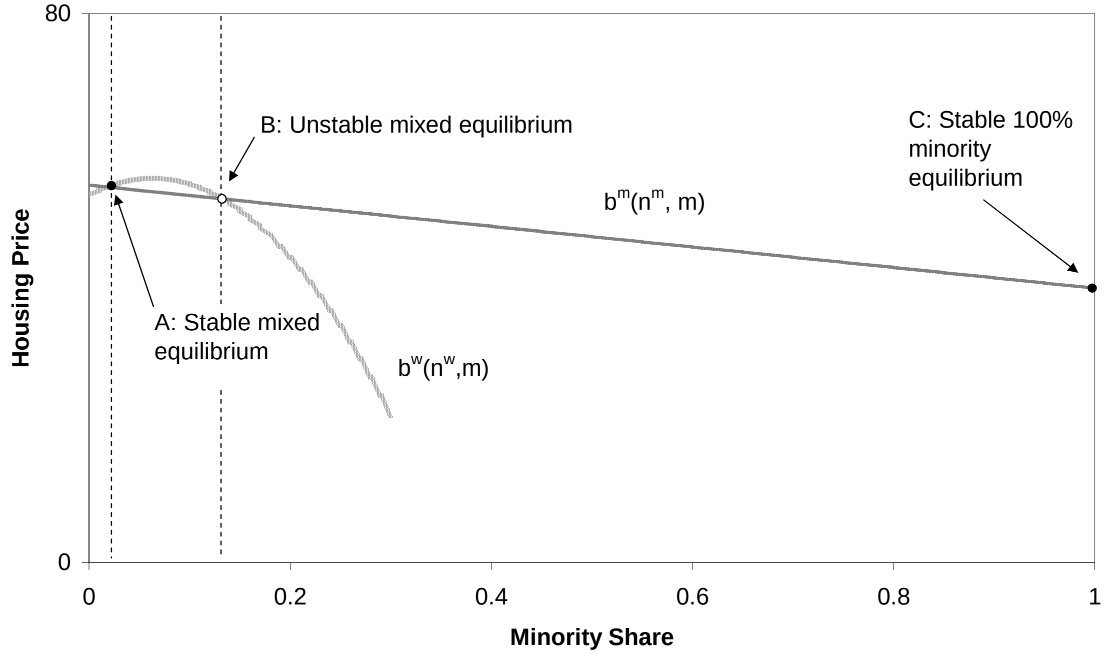


Figure 3: Rising minority demand leads to a tipping point

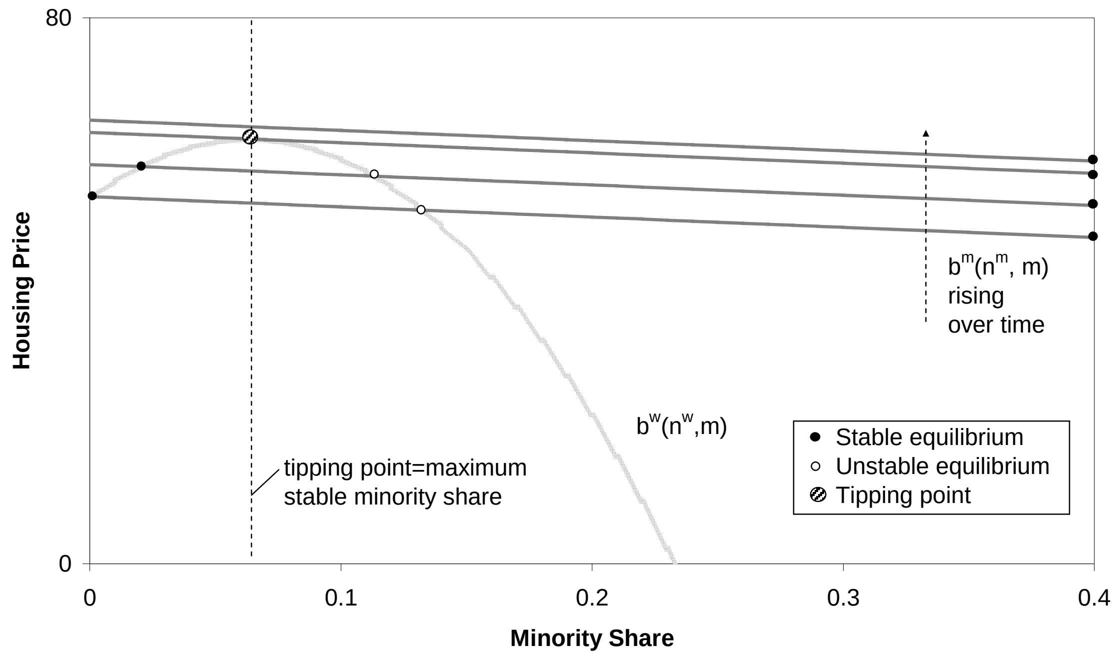
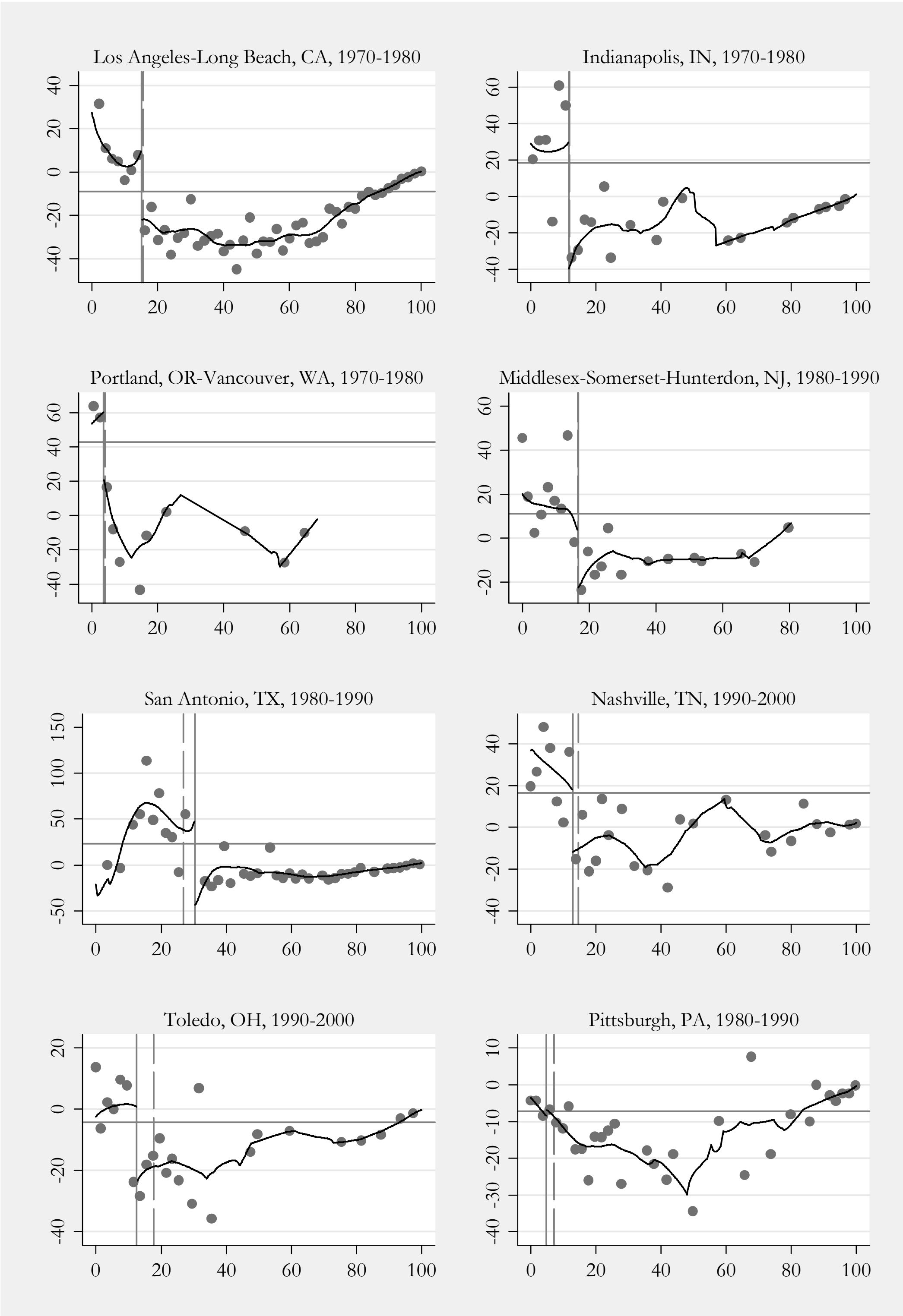
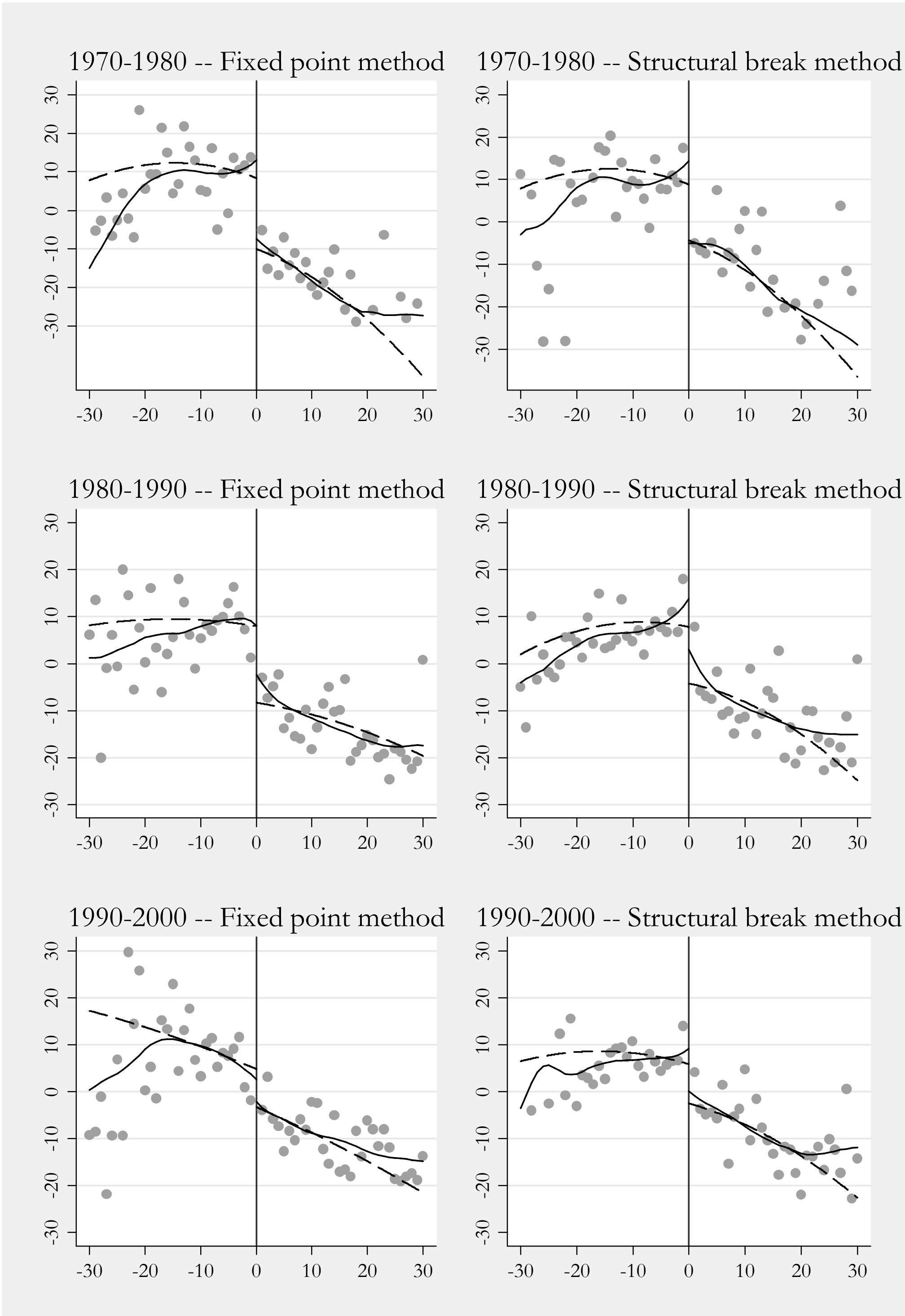


Figure 4: Neighborhood change and tipping points in several illustrative cities



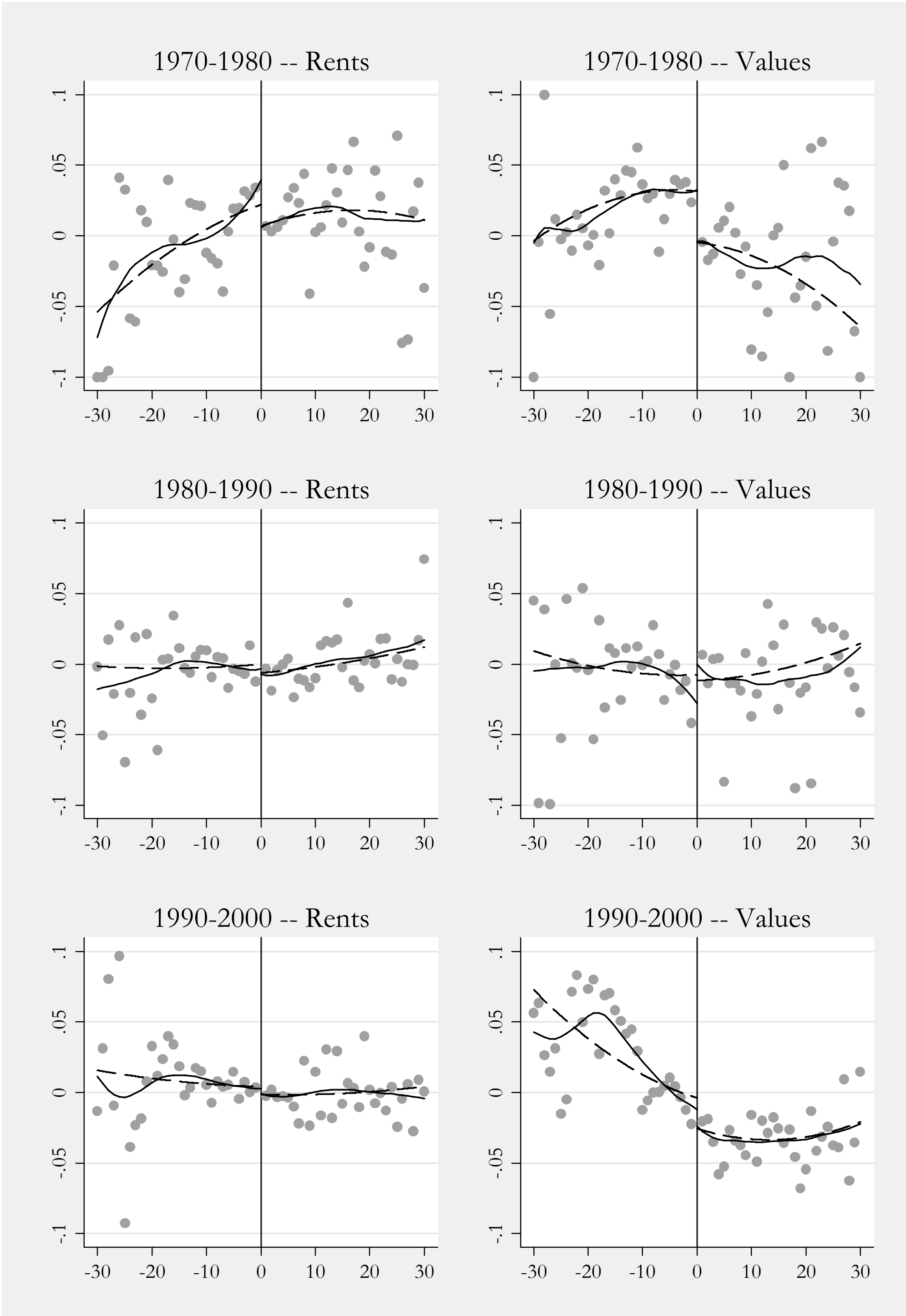
Note: See notes to Figure 1. Solid vertical line represents the point identified by the "fixed point" method and dashed for that selected by the "structural break" method. Where only one line is shown, the two coincide.

Figure 5: 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 using an Epanechnikov kernel and a bandwidth of 5. Dashed line is a global 4^{th} order polynomial with an intercept shift at zero. All series use only the 1/3 of tracts not used to identify the tipping points.

Figure 6: Change in log mean housing rents and values, 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 log change in mean rents or values over 10 years, computed over renter- and owner- occupied homes, respectively, and deviated from the mean of this logged change 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
	(1)	(2)	(3)
# of tracts in NCDB data (with pop>0)	46,334	51,857	64,891
# of tracts in MSAs	45,636	49,896	51,037
# of tracts in sample	35,725	39,283	40,187
# of MSAs in sample	104	113	114
Mean % minority, t-10	16.4	23.5	29.0
Growth in total population, t-10 to t (%)	31.0	24.0	16.6
Growth in white population, t-10 to t			
as % of t-10 population	19.5	13.2	4.2
0-5% minority in base year:			
# of tracts in sample	17,097	13,001	9,394
Growth in total population	31.3	19.4	16.2
Growth in white population	25.2	15.7	11.8
5-20% minority in base year:			
# of tracts in sample	10,770	13,301	13,666
Growth in total population	45.6	36.8	22.8
Growth in white population	28.2	23.4	9.7
20-40% minority in base year:			
# of tracts in sample	3,131	4,870	6,325
Growth in total population	30.5	30.2	19.8
Growth in white population	0.7	6.6	-3.5
40-100% minority in base year:			
# of tracts in sample	4,727	8,111	10,802
Growth in total population	-3.2	6.7	7.2
Growth in white population	-8.5	-3.9	-5.0

Notes: Year at top of column is base year, t-10.

Table 2: Overview of candidate tipping points

	1970-1980		1980-1990		1990-2000	
	Fixed point method	**Structural break method**	**Fixed point**	**Struct. break**	**Fixed point**	**Struct. break**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Mean	11.87	8.98	13.53	11.69	14.46	13.96
SD	9.51	8.78	10.19	8.23	9.00	9.68
# of MSAs in sample	104	104	113	113	114	114
# without identified points	4	--	3	--	0	--
Correlations						
1970-1980, fixed point	1.00					
1970-1980, structural break	0.55	1.00				
1980-1990, fixed point	0.46	0.45	1.00			
1980-1990, structural break	0.45	0.39	0.64	1.00		
1990-2000, fixed point	0.50	0.44	0.59	0.68	1.00	
1990-2000, structural break	0.45	0.61	0.58	0.73	0.73	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 original data.

Table 3: Basic regression discontinuity models for population changes around the candidate tipping point

	Change in white population				Change in minority pop.		Change in total population	
	Pooled		Fully interacted		Pooled		Pooled	
	Fixed point	Structural break	Fixed point	Struct. break	Fixed point	Struct. break	Fixed point	Struct. break
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1970-1980								
Beyond candidate tipping point in 1970	-12.1	-10.4	-14.2	-16.4	2.0	-0.1	-10.1	-10.4
	(2.7)	(3.4)	(3.1)	(4.3)	(1.0)	(1.2)	(3.0)	(3.5)
Demographic/housing controls	y	y	n	n	y	y	y	y
N	11,611	11,886			11,611	11,886	11,611	11,886
R^2	0.25	0.25			0.22	0.22	0.23	0.24
1980-1990								
Beyond candidate tipping point in 1980	-13.6	-11.4	-17.0	-18.6	-1.1	0.3	-14.7	-11.1
	(2.0)	(3.5)	(3.1)	(3.5)	(1.1)	(1.1)	(2.6)	(4.1)
N	12,151	13,067			12,151	13,067	12,151	13,067
R^2	0.30	0.30			0.26	0.26	0.29	0.29
1990-2000								
Beyond candidate tipping point in 1990	-7.3	-9.3	-3.6	-6.6	2.9	1.4	-4.3	-7.9
	(1.5)	(1.8)	(2.1)	(2.0)	(1.1)	(0.8)	(2.1)	(2.2)
N	13,371	13,371			13,371	13,371	13,371	13,371
R^2	0.15	0.14			0.18	0.19	0.13	0.13

Notes: The unit of observation is a tract in the indicated decade. Dependent variables are the change in the relevant population (white in columns 1-4, minority in 5-6, or total in 7-8) as a percentage (0-100) of the tract's total base-year population. Pooled specifications (columns 1-2 and 5-8) include MSA fixed effects, a quartic polynomial in the deviation in the tract's minority share from the candidate tipping point, the unemployment rate, log(mean family income), housing vacancy rate, renter share, fraction of homes in single-unit buildings, and fraction of workers who commute using public transit, all measured in the base year at the tract-level. Standard errors are clustered on the MSA. Fully interacted specifications (columns 3-4) report average tipping coefficients from city-by-city regressions with quartics in the tract minority share. The coefficient on the "beyond tipping point" indicator is averaged across cities, weighing cities by their numbers of tracts. Standard errors in these columns are robust to heteroskedasticity. All specifications are estimated using only the 1/3 of tracts not used to identify the tipping points.

Table 4: Tipping in the 1990s, by amount of remaining undeveloped land

	# of tracts	Tipping discontinuity, 1990-2000			
		Change in white population	Change in minority population	Change in total population	Change in minority share
	(1)	(2)	(3)	(4)	(5)
Full sample	13,371	-7.3	2.9	-4.3	3.4
		(1.5)	(1.1)	(2.1)	(0.4)
>91% developed	3,368	-4.7	4.7	0.0	4.6
		(1.1)	(1.1)	(1.3)	(1.0)
<91% developed	9,875	-6.1	2.4	-3.7	2.5
		(1.8)	(1.3)	(2.6)	(0.4)

Note: See notes to Table 3 (columns 1, 5, and 7) for details on sample and specifications. Fixed point candidate tipping points are used. Column 5 takes as the dependent variable the minority share in 2000 minus the minority share in 1990, but is otherwise identical. Developed land measure is computed from the National Land Cover Data; 91% is the 75th percentile of this measure. See text for details.

Table 5. 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 fixed point	-12.1			-6.4	-13.6			-12.6	-7.3			-3.9
	(2.7)			(3.1)	(2.0)			(2.1)	(1.5)			(1.4)
Beyond black share fixed point		-22.0		-16.2		-10.3		-3.0		-11.7		-4.3
		(2.5)		(3.3)		(2.9)		(3.2)		(1.8)		(1.6)
Beyond black/Hispanic share fixed point			-13.2	0.0			-11.0	0.0			-10.3	-3.2
			(2.9)	(3.7)			(1.8)	(2.6)			(1.6)	(1.7)
Quartic in min. share minus TP	y			y	y			y	y			y
Quartic in black share minus		y		y		y		y		y		y
Quartic in bl/hi share minus TP			y	y			y	y			y	y
Demographic/housing controls	y	y	y	y	y	y	y	y	y	y	y	y

Notes: See Table 3 footnote for a description of demographic/housing controls. Specifications in columns 1, 5, and 7 are identical to those in Table 3, column 1. Other columns explore candidate tipping points in the tract black share or combined black and Hispanic share. In each case, the dependent variable is the change in the tract's non-Hispanic white population, expressed as a percentage of the base-year total population. All specifications include MSA fixed effects, and are estimated using only the 1/3 of tracts not used to identify the tipping points. Standard errors are clustered on the MSA.

Table 6. Sensitivity to flexible controls for neighborhood demographics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1970-1980	-12.1	-12.2	-12.2	-12.7	-11.3	-12.7	-12.1
	(2.7)	(2.7)	(2.7)	(2.7)	(2.6)	(2.7)	(2.6)
4th order polynomial in:							
Unemployment rate		y					y
log(mean family income)			y				y
Vacancy rate				y			y
Renter share					y		y
Fraction single-unit buildings						y	y
1980-1990	-13.6	-13.3	-13.3	-13.6	-12.6	-13.6	-11.8
	(2.0)	(2.0)	(2.0)	(2.0)	(2.0)	(2.0)	(2.0)
1990-2000	-7.3	-7.0	-7.1	-7.5	-6.0	-6.9	-5.5
	(1.5)	(1.5)	(1.5)	(1.5)	(1.5)	(1.5)	(1.5)

Notes: Specification in column 1 is that from column 1 of Table 3. Remaining specifications add quartic polynomials in the listed control variables.

Table 7. Variation in discontinuity at the tipping point by measures of distance to the existing ghetto

	By central city / remainder of MSA			By distance to nearest high-minority share			By indicator for having a neighbor with m>m*		
	1970-1980	1980-1990	1990-2000	1970-1980	1980-1990	1990-2000	1970-1980	1980-1990	1990-2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Main effect: Beyond tipping point	-10.7	-10.6	-4.9	-7.6	-4.7	-3.4	-0.6	-2.7	-3.4
	(3.5)	(2.5)	(2.2)	(2.2)	(2.7)	(1.2)	(3.0)	(2.2)	(1.4)
Interaction: Beyond TP x outside of central city	3.0	-5.9	-2.5						
	(5.1)	(4.6)	(2.8)						
Total tipping effect when outside of central city	-7.7	-16.5	-7.3						
	(3.4)	(3.8)	(2.1)						
Interaction: Beyond TP x nearest high-minority-share tract is 2-5 miles away				-3.9	5.1	0.1			
				(5.3)	(5.3)	(2.3)			
Interaction: Beyond TP x nearest high-minority-share tract is >5 miles away				-2.6	-15.9	0.6			
				(4.4)	(4.8)	(2.9)			
Total tipping effect when distance is 2-5 miles				-11.5	0.5	-3.3			
				(5.1)	(4.1)	(1.9)			
Total tipping effect when distance is >5 miles				-10.3	-20.6	-2.8			
				(3.8)	(3.7)	(2.6)			
Interaction: Beyond TP x none of neighbors have m>m*							-30.3	-31.8	-2.1
							(7.0)	(4.7)	(5.4)
Total tipping effect when none of neighbors have m>m*							-30.9	-34.5	-5.4
							(6.3)	(4.6)	(5.2)

Notes: Specifications are identical to those in Table 3, Column 1, but are fully interacted with the indicated tract characteristics. Reported here are the beyond-tipping-point main effects, interaction coefficients, and the net effect of being beyond the tipping point for tracts in each category. The nearest high-minority-tract is the closest tract (measuring distances between tract centroids) with a minority share above 60%. "Neighbors" in columns 7-9 are the five closest tracts within five miles.

Table 8: Tipping in elementary schools

	Tipping discontinuity, 1990-2000			
	Change in white population	**Change in minority population**	**Change in total population**	**Change in minority share**
	(2)	**(3)**	**(4)**	**(5)**
Beyond candidate	-7.4	0.9	-6.5	2.3
tipping point	(2.3)	(0.9)	(2.3)	(0.8)
N	5,641	5,641	5,641	5,641

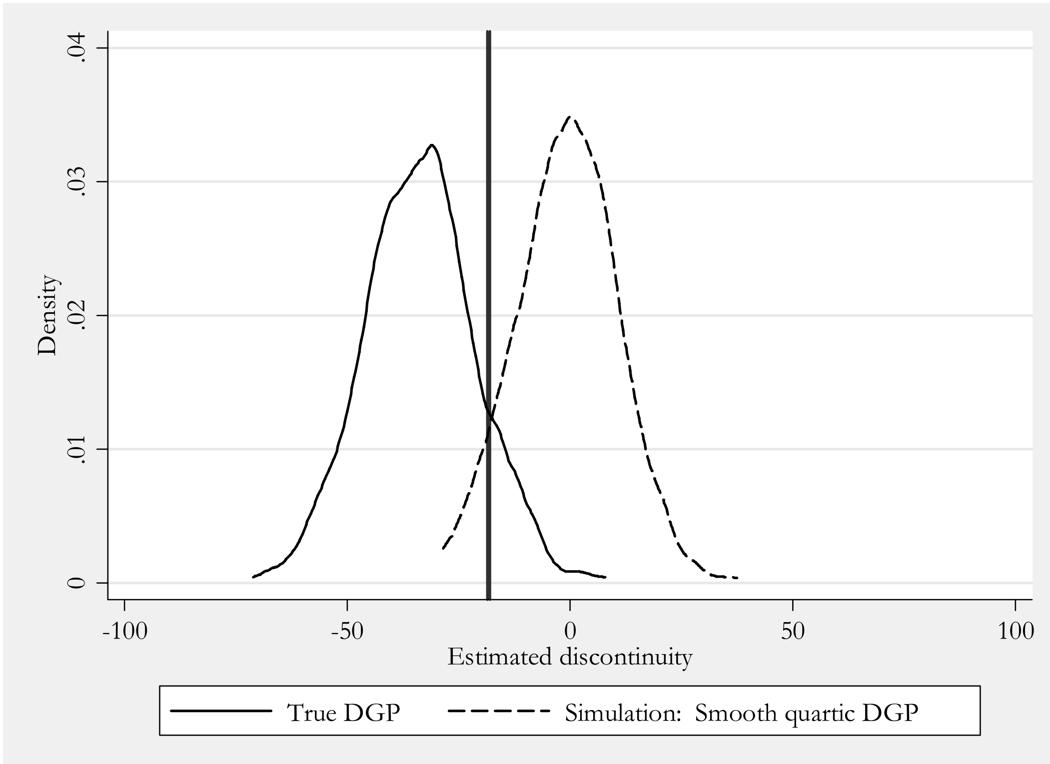
Note: Sample consists of elementary schools in the MSA. Tipping points are estimated using the fixed point method over a 2/3 subsample; the remaining 1/3 subsample is used to estimate the specifications shown here. Each includes a quartic polynomial in the minority share relative to the candidate tipping point, MSA fixed effects, and a control for the school free lunch share. Standard errors are clustered on the MSA.

Table 9. Models for the location of the tipping point

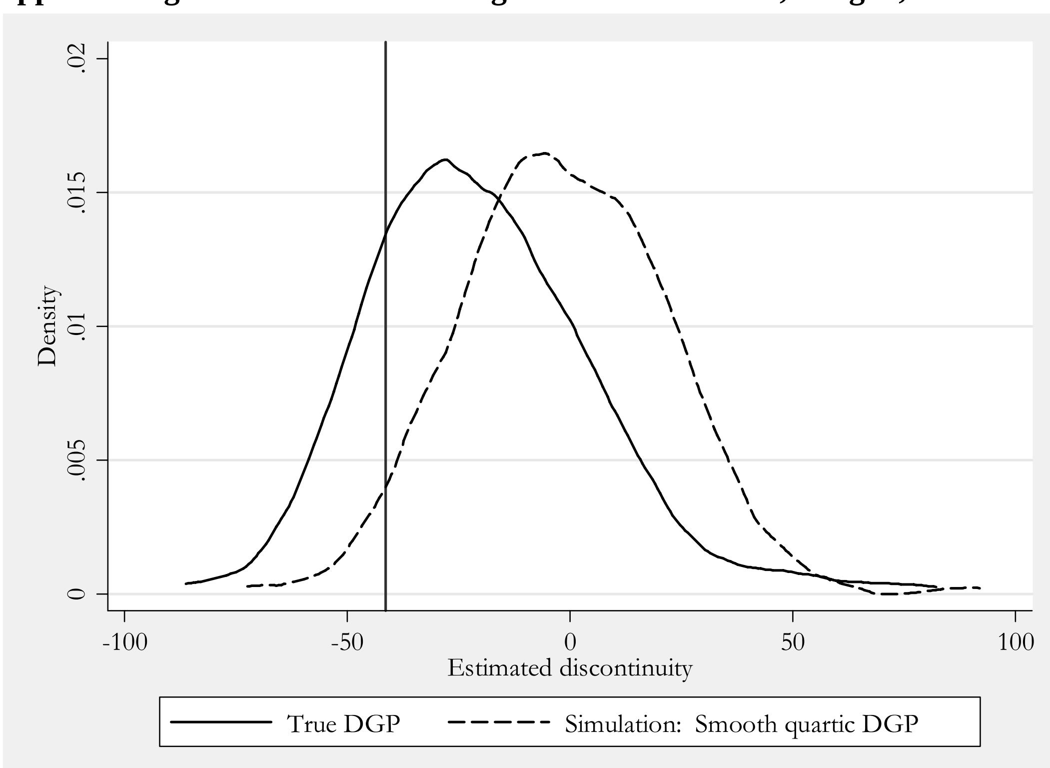
	Mean [SD] (1)	(2)	(3)	(4)
Race attitudes index	-0.1	-2.77	-2.98	-2.66
(positive = less tolerant)	[0.6]	(1.16)	(1.08)	(0.94)
% Black	11.4	0.53	0.59	0.81
	[8.6]	(0.10)	(0.10)	(0.10)
% Hispanic	6.7	0.65	0.75	0.94
	[9.9]	(0.07)	(0.07)	(0.09)
Population density (10,000s/sq mile)	0.50	-1.81	-1.80	-1.42
	[0.60]	(0.45)	(0.39)	(0.39)
Log (MSA population)	13.7	-0.89	-1.15	0.70
	[0.8]	(0.60)	(0.63)	(0.69)
Log(per capita income), whites	9.0		-11.77	-9.34
	[0.7]		(5.38)	(3.99)
Log(per capita income), blacks	8.5		9.26	6.83
	[0.8]		(5.62)	(4.68)
Log(per capita income), Hispanics	8.6		7.08	7.17
	[0.8]		(2.92)	(2.34)
Fraction of houses built in last decade	0.26			1.90
	[0.11]			(6.26)
Cumulative riots index	0.04			-14.33
	[0.09]			(6.57)
Murders per 100,000 population	8.9			-0.50
	[5.5]			(0.18)
Other index crimes per 100 population	5.9			-0.59
	[1.9]			(0.36)
1980		-0.97	-4.66	-2.96
		(1.26)	(3.45)	(2.68)
1990		-0.98	-10.40	-9.69
		(1.02)	(6.54)	(5.04)
N		234	234	234
R2		0.52	0.54	0.60

Notes: Unit of observation is an MSA/PMSA-decade (1970, 1980, and 1990). All specifications include three Census region dummies. Standard errors are clustered at the MSA/CMSA level. Tipping points are estimated from the full sample of tracts in each city. Explanatory variables correspond to the base year and MSA/PMSA, unless otherwise noted. The race attitudes index is derived from responses to the General Social Survey, and is constant for the entire CMSA over all years. The cumulative riots index is derived from the riot severity dataset from Carter (1986) and is constant for the MSA/PMSA over all years. Murder and other index crime rates are derived from the Uniform Crime Reports. See appendix for details on the construction of the variables.

Appendix Figure 1: Simulation of tipping estimates when true data generating process is discontinuous and when it is continuous, using data from Chicago, 1970-1980.



Appendix Figure 2: Simulation using data from Portland, Oregon, 1970-1980.



Appendix Table 1: Bootstrap vs. regular SEs

		1970s	1980s	1990s
(1)	Coefficient estimate	-12.15	-13.63	-7.26
(2)	SE: Cluster	2.73	2.02	1.53
(3)	SE: Classical	2.21	1.63	1.22
(4)	SE: Robust	2.15	1.67	1.23
(5)	SE: Bootstrap	2.27	1.49	1.09
(6)	SE: Block bootstrap	2.51	2.22	1.52
(7)	SE: Block and individual bootstrap	2.99	2.29	1.72

Notes: Point estimates in row 1 and standard errors in row 2 are from Column 1 of Table 3. Remaining rows report standard errors from various alternative estimators.