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Working Paper

2017-071

09/2017

HUMAN CAPITAL AND
ECONOMIC OPPORTUNITY
GLOBAL WORKING GROUP

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www.hceconomics.org

Outside Options (Now) More Important than Race in Explaining Tipping Points in US Neighborhoods

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September 25, 2017

Abstract

I develop a revealed-preference method for estimating neighborhood tipping points. I find that census tract tipping points have increased from 15% (1970) to 42% (2010). The corresponding MSA tipping points have also increased from 13% (1970) to 35% (2010). While tipping points are traditionally associated with the racial attitudes of white households, I find that cross-sectional differences in MSA tipping points, going from 1970-2010, depend less on differences in the racial attitudes of white households and more on the outside options faced by white households. These results support a continued role for place-based policies in mitigating residential segregation.

JEL Classification: R23, R21, J60

Keywords: preferences, race, Schelling model, tipping points, outside options.

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†I received helpful comments from: Raj Chetty, William Darity Jr., Anthony Defusco, William Dougan, Gilles Duranton, Steven Durlauf, Molly Espey, Fernando Ferreira, Robert Fleck, Edward Glaeser, Joseph Gyourko, Jessie Handbury, Joseph Harrington, Nathaniel Hendren, Damon Jones, Clarence Lee, Glenn Loury, Corinne Low, Michael Makowsky, Conrad Miller, Albert Saiz, Mark Shepard, Curtis Simon, Todd Sinai, Kent Smetters, Robert Tollison, Susan Wachter, Maisy Wong and the seminar participants at MIT, Wharton, Purdue, Swarthmore, Clemson, Emory, the Cleveland Fed, University of Chicago Summer School for Socioeconomic Inequality, the ASSA meetings, and the Southern Economic Association Conference. Mickey Whitzer, Kinde Wubneh, Lynn Selhat, Jennifer Moore, Julian Blair, Judith Blair, Rafael Luna (Luna Scientific Story Telling) and Daniel DeVougas provided excellent help with preparation of the manuscript. All remaining errors are mine.

1 Introduction

A neighborhood tips when a marginal increase in its minority population leads to white flight from the neighborhood. Given the link between racial segregation and adverse outcomes for minorities, it is important to understand the mechanisms that drive neighborhood tipping.[1] Furthermore, neighborhood tipping points can be important parameters for place-based policies like the Moving to Opportunity Experiment (MTO). In place-based programs where the treatment is the destination neighborhood, it may be important to discern whether the act of assigning minority households to a destination might itself result in the neighborhood tipping, thereby undermining the intended treatment (Kling, Liebman, and Katz 2007).

Historically, the debate between economists and other social scientists on tipping centered on whether neighborhood tipping reflects racial animus of non-minorities (whites) toward minorities. In an early essay, "The Metropolitan Areas as Racial Problem," University of Chicago political scientist Morton Grodzins asserted that neighborhood tipping reflects "the unwillingness of white groups to live in proximity to large numbers of [African Americans]." Later work by economists, notably Thomas Schelling (1969, 1971), challenged this view, demonstrating with a set of intuitive and simple models that segregation, at the neighborhood and city levels, could occur even if white households, at the individual level, did not possess a strong aversion to living in communities with minorities. One of the limitations of this model, as Schelling himself noted, was that it did not include a role for outside options: "This is but a small sample of possible results, using straight-line schedules and simple dynamics. There are no expectations in the model, no speculation, no concerted action, no restriction on the alternative localities available" (Schelling 1969).

The focus of this current paper is the role that outside options, i.e. the "alternative localities available," play in neighborhood tipping. The key insight of this paper is that

[1] Segregation impacts the provision of public goods to minorities, particularly if preferences for redistribution are local (Zeckhauser 1993; Bayer, McMillan, and Rueben 2005). Additionally, residential segregation creates spatial mismatches: minorities are disconnected from jobs, role models, and opportunities to interact with non-minorities, which may result in the persistence of racial stereotypes (Kain 1968).

the tipping threshold for a non-minority household depends on its preferences for minority neighbors and on the household's outside options. In some cases, the dearth of preferable outside options will result in a tipping threshold that is high (more racial integration is tolerated) even though non-minority households have a strong relative preference for living with other non-minorities. As an example, consider a city with a choice-set of two census tracts: tract W, which is 100% non-minority, and tract M, which is 100% minority. Suppose further that non-minority households in the city have a relative preference for non-minority neighbors. What would happen if minorities were to integrate tract W? Would non-minority households exit tract W in preference for tract M? Contrary to the intuition that a stronger relative preference for same-race neighbors leads to more white flight, the stronger the white household's preferences for white neighbors, the more likely it will be to remain in tract W even as the neighborhood integrates. In the same way that competition for employees among firms sets the cost of discriminating against minority employees (Becker 1993), the availability of preferable outside options sets the cost of acting on racial preferences in the housing market.

I define a household's *neighborhood* as the census tract where it resides, and its *outside options* as the set of all of the other census tracts in its MSA of residence. I further impose an incentive compatibility constraint on the exit decision of non-minority households. Non-minority households exit their current neighborhood if exercising their outside option delivers more utility than remaining in their current neighborhood. By imposing this constraint, I am able to exploit sorting patterns in the data to estimate static tipping points at the census tract level which are defined within the context of a discrete choice model of housing (McFadden 1978; Berry, Levinsohn, and Pakes 1995; Bayer et al. 2007). The two main contributions of this papers are: (i) I provide a method for computing census tract tipping points (ii) I produce estimates of census tract tipping points for the census tracts of 123 US cities that cover the five most recent censuses (1970-2010).

Computing tipping points for individual census tracts is a methodological contribution to the empirical literature on tipping, which has progressed from the treating tipping as a national phenomenon (Easterly 2009) to estimating tipping points at the MSA level (Card, Mas, and Rothstein, 2008). In some cases, the distribution of census tract tipping points is disperse and an MSA average may mask this heterogeneity. Mobile, AL and New Jersey provide an illustrative case (Figure 1). In 1970, both cities have a mean MSA tipping point of 22%. In Mobile, the dispersion about this mean is large, whereas for New Jersey there is relatively less dispersion about this mean. As such, an MSA-wide place-based policy is more likely to work consistently in New Jersey, whereas Mobile would require more locally targeted policy to account for the heterogeneity in tipping points by census tract.

In computing the tipping points for the 38,466 tracts in my data, I find that the mean neighborhood (tract) tipping point in the United States has increased at a rate of 6 percentage points per decade – from 15% in 1970 to 42% in 2010. To compare these results with the literature, I aggregate my tract tipping points to the city level and find that the mean metropolitan statistical area (MSA) tipping points also increased at an average rate of 5 percentage points per decade from 13% (1970) to 35% (2010). According to other estimates in the literature, the mean tipping point of US cities increased from 12% in (1970) to 14% in (1990), an average of 1 percentage point per decade (Card, Mas, and Rothstein 2008). I show that prior estimates understated city tipping points because they reflected the average tipping points of the marginal census tracts in the city (i.e., those that were close to tipping), whereas my estimates are an average of the tipping points of both the marginal and infra-marginal census tracts in a city. One way to combine these two sets of results is that the tipping point of the marginal census tract has changed gradually over time, whereas the tipping point of the infra-marginal census tracts have increased more rapidly over time.

In the data, I also find evidence that cross-sectional differences in city tipping points depend crucially on the outside options of non-minority households. Moreover, the relative importance of outside options in explaining cross-sectional differences in city tipping points vis-à-vis racial preferences is increasing over time. In 1970, a decrease of one standard deviation in the clustering of minorities was correlated with a 1.1 percentage point increase in the city tipping point. Clustering is measured using a Herfindahl-Hirschman Index (HHI), therefore a reduced level of minority clustering means that the outside option consists of fewer tracts with only non-minority households. In 2010, a similar decrease in the clustering of minorities was correlated with an increase of 14 percentage points in the tipping point. By contrast, in 1970, a one-standard-deviation increase in the relative preference of non-minorities for minority neighbors was correlated with a 6.6 percentage point increase in the mean MSA tipping point; in 2010, however, the effect size was statistically indistinguishable from zero. Since outside options become increasingly relevant over time, and racial preferences become less predictive of cross-sectional differences in tipping points, it is important to model tipping phenomena with outside options playing a key role.[2] This result also accords with Schelling's seminal result on neighborhood tipping phenomenon: it may depend less on racial forces at the individual level, than previously thought, and that other factors, such as "the alternative localities availabile" would be important for modelling neighborhood tipping.

The rest of the paper is organized as follows: In section 2, I model the neighborhood choice of households. In section 3, I define the tipping point. I discuss the data in section 4, followed by a description of the empirical strategy in section 5 and a discussion of the results in section 6. I end with a summary of the key findings.

2 Model

The key goal of my model is to generate a relationship between the neighborhood tipping point and two quantities: (a) the utility wedge between an agent's current neighborhood

[2] Moreover, in many branches of economics, outside options matter for modeling the decision of agents.The canonical principal agent model of contract theory (Jullien 2000) is one example in economics where outside options matter for decision making by individual agents and the firm. In job search models in macroeconomics (McCall 1970; Mortensen and Pissarides 1994), outside options matter for aggregate market outcomes such as mean unemployment duration. Outside options have also been used to illustrate scenarios in which the Coase Conjecture fails (Board and Pycia 2014).

and his/her outside options; and (b) the marginal utility for minority neighbors. The model consists of a demand side, in which households have neighborhood preferences that depend on the endogenous racial mix of the neighborhood and the price of housing services in the neighborhood, as well as other amenities therein. I follow the literature in focusing on the demand side and abstracting from the influence of changes in housing supply on tipping points (Card et. al. 2008, Caetano and Maheshri 2013).

A household's choice-set consists of all of the census tracts in its MSA. Accordingly, its outside option consists of all of the tracts in its MSA excluding its current tract of residence. In cities where there are many minority tracts, the outside option will impact the ability of non-minorities to exit their neighborhoods of residence. With this definition of households choice-set, I use a discrete choice model to exploit within-MSA sorting patterns in the data to obtain tipping points for each census tract-year observation (McFadden 1978; Berry, Levinsohn, and Pakes 1995; Bayer et al. 2007). I use data from N census tracts in an MSA from two consecutive census periods to estimate 2N tipping points – one for each census-tract-year observation. Using the approach in Card et. al. (2008) and similar data generates a single tipping point – the MSA tipping point.

In the model, I construct the tipping point in two steps. First, I use the estimates of the sorting model to compute an exit function of white households from the neighborhood. For a given exogenous change in the mean utility of whites in neighborhood, τ, the exit function measures the probability that a white household exits its current neighborhood for its best alternative in its choice-set. I refer to τ as the utility tolerance of white households since it parametrizes the exit probability as a function of changes in the mean utility of whites. At the tipping point, the first derivative of the exit function, the exit rate, equals zero, and the tolerance equals τ^*. This definition of tipping is similar to the approach in Card et al. (2008), which associates the tipping point with the share of minorities for which the rate of decline in white population is maximal. I get the tipping point by converting the utility tolerance into a percent minority by using an empirical relationship between the percent minority and the mean utility.

2.1 Demand Side

In the model, there are C cities indexed $c \in \{1, 2, ..., C\}$, and two types of households that are differentiated by a type index, $r \in \{w, m\}$. The type index $r = w$ references white households, while the type index $r = m$ references minority households. Each city is exogenously assigned a total of Q^w_{tot} white households and total of Q^m_{tot} minority households. Each household, in turn, endogenously sorts into one of the N neighborhoods in that city, indexed by $n \in \{1, 2, ..., N\}$. The sorting of households to neighborhoods depends on the household income, the price of housing in equilibrium, and the equilibrium level of amenities in each of the N neighborhoods.

A household's problem is to choose the neighborhood that delivers the maximum utility. Solving the household's problem requires first solving for the indirect utility for each of the N possible neighborhoods, and then choosing the neighborhood that delivers the maximum indirect utility. Households h of type r have utility over neighborhood amenities, consumption, and housing services in each neighborhood n. The utility function takes the form:

$$U_{hnr} = \underbrace{\log(A_{hnr})}_{\text{Amenities}} + \underbrace{\alpha \log(C_{hnr})}_{\text{Consumption}} + \underbrace{\beta \log(H_{hnr})}_{\text{Housing}}, \text{ for r} \in \{w, m\}. \tag{1}$$

The parameters α and β are the consumption and housing shares. The neighborhood amenity, A_{hnr}, consists of an endogenous component and an exogenous component in addition to an idiosyncratic taste shock:

$$\log(A_{hnr}) = \underbrace{\gamma_r f_n}_{\text{Endog. Amenity}} + \underbrace{\theta X}_{\text{Exog. Amenities}} + \underbrace{\xi_n}_{\text{Unobs. Quality}} + \underbrace{\epsilon_{hnr}}_{\text{Taste Shocks}}. \tag{2}$$

The endogenous amenity is the racial composition of neighborhood, $f^m_n = \frac{Q^m_n}{Q^m_n + Q^w_n}$, which is the percent minority in the neighborhood. The value of the endogenous amenity varies by agent type, with whites valuing a one percentage point increase in the minority share by an amount γ_w, and minorities valuing a one percentage point increase in the minority share by an amount γ_m. The X's represent observable characteristics of the neighborhood, which also capture the overall quality of the neighborhood and the ξ_{nr} unobservable measures of neighborhood quality, which may vary by race. I assume that the taste shocks are i.i.d. and follow a type 1 extreme value distribution. This assumption makes it convenient to obtain closed-form solutions without compromising the key insight of the model – which is that the choice-set of white agents impacts the neighborhood tipping points – and allows for the estimation of sub-MSA tipping points.

2.1.1 Solving for the Indirect Utility of a Neighborhood

For each neighborhood n households choose a bundle of consumption C_{hnr} and housing H_{hnr} to maximize utility, subject to the household's budget constraint:

$$C_{hnr} + p_n H_{hnr} \leq I_h. \tag{3}$$

Consumption is the numeraire good, and housing price p_n is in terms of units of consumption. The household's income I_h is exogenously determined and independent of the household's choice of a neighborhood n. For neighborhood n, the optimal bundle (C^*_{hnr}, H^*_{hnr}) is:

$$C^*_{hnr} = \left(\frac{\alpha_r}{\alpha_r + \beta_r}\right) I_h \tag{4}$$

$$H^*_{hnr} = \left(\frac{\beta_r}{\alpha_r + \beta_r}\right)\left(\frac{I_h}{p_n}\right), \tag{5}$$

and the associated indirect utility is:

$$\tilde{V}_{hnr} = \gamma_r \left(\frac{Q^m_n}{Q^m_n + Q^w_n}\right) + (\alpha_r + \beta_r)\log(I_h) - \beta_r \log(p_n) + X\theta + \xi_n + \epsilon_{hnr}. \tag{6}$$

To simplify notation, I define V_{hnr}, the deterministic part of the indirect utility, using the following relation:

$$\tilde{V}_{hnr} = V_{hnr} + \epsilon_{hnr}. \tag{7}$$

2.1.2 Solving for Neighborhood Demand

After having solved for the indirect utility for each neighborhood, each household of income I_h and type r chooses the neighborhood, n^*_{hr}, that delivers the highest indirect utility:

$$n^*_{hr} = \text{arg max}\{V_{hnr}\} \tag{8}$$

The household's utility-maximizing behavior across the N neighborhoods in the city generates a conditional demand function, $Q^r_n\left(\vec{p}\middle| I_h\right)$, for each neighborhood by both household type and household income category I_h. The conditional demand functions take the form:

$$Q^r_n\left(\vec{p}|I_h\right) = Q^r_{tot}\left(\frac{\exp(V_{hnr})}{\sum\limits_{n'=1}^{N}\exp(V_{hn'r})}\right), \quad \text{for } r \in \{w, m\}, \tag{9}$$

where $\vec{p_n} = \{p_1, p_2, ..., p_N\}$ is the vector of house prices for all neighborhoods in the city. The unconditional demand for neighborhood n by households of type r equals the sum of the conditional demand functions over the income categories:

$$Q^r_n\left(\vec{p_n}\right) = \sum_h Q^r_n\left(\vec{p}|I_h\right), \quad \text{for } r \in \{w, m\} \tag{10}$$

3 Tipping Point

In the empirical literature on tipping, the tipping point of a neighborhood n is defined by a threshold minority fraction, f^*_n. When the minority fraction of the neighborhood exceeds this threshold, whites exit the neighborhood at a rapid rate. Below this threshold, changes in the white population of the neighborhood are less stark. In the context of this model, I define the tipping point of a neighborhood as corresponding to the minority fraction for which the exit rate of whites from the neighborhood is maximal.

In order to compute the tipping point, I first construct the exit function for each neighborhood. This exit function traces out the probability of white flight from the neighborhood n as a function of the decrease in utility experienced by whites in the neighborhood due to the arrival of minorities. I adopt a similar approach to Caetano and Maheshri (2013) by using counter-factual decreases in the utility of whites to construct the exit function. The exit function also depends on the utility wedge between the households inside option, V_{hnw}, and the household's next best alternative, $V_{ha(n)w}$, where the notation $a(n)$ is the neighborhood that is the households best alternative, should it choose to relocate to another census tract in the same MSA.

After constructing the exit probability as a function of the counter-factual decrease in utility, I will solve for the utility of whites in the neighborhood at the tipping point by solving for the inflection point of the exit function: the level of utility for which the second derivative of the exit function is zero. The first derivative of the exit function is the exit rate. The second derivative, which is required to solve for the inflection point, captures the marginal exit rate. When the marginal exit rate equals zero, the exit rate is maximal.

3.1 Conditional Exit Functions

Following the arrival of new minority households to a neighborhood n, some white households may find it preferable to exit the neighborhood and relocate to the best alternative among the other N-1 neighborhoods in its city, neighborhood $a(n)$, instead of remaining in neighborhood n. I use τ_{nw} to represent the loss in indirect utility that white households of income category h experience due to the arrival of new minority households to their host neighborhood n. The conditional exit function of whites, which represents the exit probability of whites of a given income category, is given by:

$$E(\tau_{nw};\vec{V}|I_h) = \sum_{a(n)} \left[\underbrace{\text{Prob}(V_{hnw} - \tau_{nw} + \epsilon^{n}_{hnw} < V_{ha(n)w} + \epsilon_{ha(n)w})}_{\text{Prob. exit n for a(n)}} \times \underbrace{\omega_{a(n)}}_{\text{Prob. a(n) is best opt.}} \right] \quad (11)$$

$$= \sum_{a(n)} \left(\left[\int_{-\infty}^{\infty} F(V_{ha(n)w} - V_{hnw} + \tau_{nw} + \epsilon_{ha(n)w}) f(\epsilon_{ha(n)w}) d\epsilon_{ha(n)w} \right] \omega_{ha(n)w} \right), \quad (12)$$

where $\omega_{ha(n)w}$ is the probability that neighborhood $a(n) \in \{1, 2, ..n-1, n+1, ...N\}$ is the best alternative among the N-1 options in the household's choice-set, and $F(\cdot)$ is the cumulative distribution function for the taste shocks, which I assume follow a type 1 extreme value distribution. The probability weight $\omega_{ha(n)w}$ is assumed to be the share of whites in the alternative neighborhood $a(n)$ relative to the total number of whites in the MSA excluding the current tract n:

$$\omega_{ha(n)w} = \frac{\exp(V_{ha(n)w})}{\sum\limits_{a \in \{a(n)\}} \exp(V_{haw})}. \quad (13)$$

Each non-minority household living in a given tract will have a single best alternative. However, since I do not observe all of the covariates of an individual non-minority household, I average over all the non-minority households in a neighborhood to obtain a probability than a given tract in the MSA is best alternative for non-minority households in this tract. The probability weights in equation (13) are type of counter-factual market shares for utility maximizing non-minority households who face a choice-set of the N-1 census tracts in the MSA, where census tract n has been excluded from consideration. As such these weights present the probability that a tract $a(n)$ is the best option of the N-1 tracts for non-minority households. Since I have assumed that preferences are homogeneous with-in racial group, but heterogeneous across racial group, these probability weights are natural measures of the probability that tract $a(n)$ is the best alternative for a moving agent.[3]

[3]This assumption is particularly reliable for cases where there are a large number of census tracts in the MSA. In these cases, the removal a single census tract has a diminishing effect on the overall sorting in the

3.2 Unconditional Exit Function

The unconditional exit probability of whites from neighborhood n is the sum of the conditional exit functions weighted by the number of households in the income category that corresponds to the individual conditional demand functions, Q^w_{hn}, as a fraction of the total number of whites in neighborhood n, Q^w_n:

$$E(\tau_{nw};\vec{V}) = \sum_{h=1}^{15}\left(E(\tau_{nw};\vec{V}|I_h)\cdot\frac{Q^w_{hn}}{Q^w_n}\right) \tag{14}$$

The unconditional exit function will be dominated by the behavior of whites in the most highly represented income categories in the neighborhood. This is captured in the weighting. As the utility drop becomes large and positive, due to the arrival of minorities, the exit probability goes to one, and all whites exit the neighborhood. In the opposite limit, as τ_{nw} gets arbitrarily large and negative, which corresponds to whites moving into the neighborhood, the probability of white residents exiting the neighborhood converges to zero. In general, the exit function will resemble an S-curve with τ_{nw} on the horizontal axis and the associated conditional exit probability on the vertical axis.

3.3 Tipping Point

The tipping point of the neighborhood is the percent minority at the inflection point of the exit function. This is the point at which the exit function changes concavity and the exit rate (the derivative of the exit function with respect to τ_{nw}) is maximal:

$$\frac{d^2E(\tau^*_{nw};\vec{V})}{d\tau_{nw}{}^2} = 0. \tag{15}$$

At the tipping point, the mean utility of white households in neighborhood n has decreased by an amount $-\tau^*_n$. I use the the relative marginal utility for minority neighbors to

MSA as the number of tracts in the MSA increases. In the paper, we follow the literature and restrict our analysis to MSAs with at least 100 census tracts (Card et. al. 2008).

convert this decrement in mean utility into a change in the percent minority. Accordingly, the percent minority at the tipping point is given by:

$$\boxed{f_n^* = f_n - \frac{\tau_n^*}{\gamma_w - \gamma_m}} \tag{16}$$

The first piece of the tipping point is the initial percent minority in the census tract, $f_n = \frac{Q_n^m}{Q_n^m + Q_n^w}$. The second part of the tipping point is the change in the percent minority that takes the neighborhood to the critical point of the exit function. The key take-away from equation (16) is that the tipping point is directly proportional to the utility tolerance of non-minorities for minorities, τ, and inversely proportional to the relative preference of non-minority households for minority neighbors, $\gamma_w - \gamma_m$, which in the data is negative. If $\tau_n^* > 0$, then the neighborhood n is a more desirable neighborhood than the alternatives in the choice-set. In order for this neighborhood to tip, minorities must move in to lower the utility of non-minorities to the point where the neighborhood tips. If $\tau < 0$, the opposite is true, and the tipping point is lower than the current fraction of minorities. One merit of estimating tipping points in this manner is that it allows researchers to estimate the tipping point of census tracts that have tipped, that have yet to tip ($\tau > 0$), and that are beyond their tipping points ($\tau < 0$).

3.3.1 Estimating Preferences

This preference parameter, $\gamma_w - \gamma_m$, is identified from the differential sorting of non-minorities into neighborhoods as a function of the fraction of minorities in the neighborhood. From equation (6), we relate the ratio of the non-minority to minority market share of a neighborhood to the percent minority in the neighborhood and the relative preference parameter $\gamma_w - \gamma_m$:

$$\log\left(\frac{Q_n^w}{Q_{tot,c}^w}\right) - \log\left(\frac{Q_n^m}{Q_{tot,c}^m}\right) = (\gamma_w - \gamma_m)\left(\frac{Q_n^m}{Q_n^m + Q_n^w}\right) + e_{n,m} \tag{17}$$

The term on the left-hand side is the relative market share of whites to minorities in neighborhood n. The market share of a neighborhood is the fraction of households in the MSA of a given type that reside in the neighborhood. Moreover, the log of the market share is mean utility of an household of the given racial type. The regressor on the right-hand side is the percent minority in the census tract. By taking the relative market share, I can difference out characteristics of the neighborhood that are valued equally by minorities and non-minorities. Here I make the assumption that white and minority households value everything similarly except the percent minority in the tract.

3.4 Semi-Parametric Estimate of Tipping Point

I also use the relative market shares to develop a semi-parametric estimator of the tipping point, which is non-linear parallel to equation (16). In equation (17), the relative market shares are a linear function of the fraction of minorities, f_n. One limitation of this specification is that it can produce tipping points that lie outside of the interval $[0,1]$. I relax this assumption by allowing the percent minority in a neighborhood to depend flexibly on the relative market shares. I obtain this relationship, empirically, by regressing the percent minority in the census tract on powers of the log of the relative market shares:

$$\frac{Q_n^m}{Q_n^m + Q_n^w} = \alpha_0 + \sum_{j=1}^{5} \alpha_j \underbrace{\left[\log\left(\frac{Q_n^w}{Q_{tot,c}^w}\right) - \log\left(\frac{Q_n^m}{Q_{tot,c}^m}\right)\right]^j}_{\text{ratio of white:minority market share}} \tag{18}$$

The coefficients of this regression define the inverse mapping from the ratio of the non-minority to minority market shares to the percent minority in the tract. This inverse mapping is important because I have calculated the mean utility of white households at the tipping point, but the ultimate quantity of interest is the percent minority, which defines the tipping point; therefore we need the inverse mapping of the relative utility to percent minority. I use the estimated parameters to obtain the percent minority at the tipping point by inserting a value of $V_{nw} - \tau_{nw}^* - V_{nm} = \log\left(\frac{Q_n^w}{Q_{tot,c}^w}\right) - \log\left(\frac{Q_n^m}{Q_{tot,c}^m}\right) - \tau_{nw}^*$ for the relative market share at the tipping point.

4 Data

To estimate the model, I use data from the U.S. census covering five decades: 1970, 1980, 1990, 2000, and 2010. This data consists of the demographic characteristics of the households living in each of the census tracts, as well tract-level measures of the local housing stock and local economic conditions. The key variables of interest for this study are the population shares of each census tract broken down by race. Prior work has used similar data from the 1970-2000 extracts of the census data to compute MSA tipping points (Card et al. 2008). I build on this work by updating the previous results to include estimates of tipping points from the 2000 and 2010 censuses. With these five decades of tipping points, I trace the time evolution of tipping points to show that, over time, tipping points in the United States have increased. In addition to this empirical contribution, my paper also makes a methodological contribution. Whereas these data have been used in Card et. al. (2008) to compute MSA tipping points, I use these data to compute census tract tipping points. These tract-level estimates capture the distribution of neighborhood tipping points within an MSA.

I follow Card et al. (2008) in making the following cuts in the data. First, I eliminate any tracts whose population growth between consecutive census years surpasses average population growth in the MSA by more than five standard deviations. Second, I drop all tracts that experience an increase of more than 500% in their white population between consecutive census years. These first two cuts reduce the effect of outliers on the results of this study. For the final cut, I focus my analysis on MSAs that have 100 census tracts or more, also following Card et al. (2008). There are 123 MSAs that satisfy these criteria, and these MSAs cover the 38,489 census tracts that comprise my final data set.

5 Results

5.1 Descriptive Statistics: Racial Preferences

In Table 1, I report the mean, median, and standard deviation of these relative preference estimates from the "diff-in-diff" procedure of equation (17). To compute standard errors on the point estimate and preference parameters, I use an N=1000 bootstrap. The estimates for $\gamma_w - \gamma_m$ range from -8.84 in 1970 to -6.11 in 2010. For 1970, the diff-in-diff point estimate of -8.84 means that a 7.8 percentage point increase in the fraction of minorities was associated with a 50% reduction in the non-minority population of the average neighborhood. The diff-in-diff point estimate of -6.11 for 2010 indicates that an 11.3 percentage point increase in the fraction of minorities was needed for the non-minority population in a neighborhood to halve.

In Figure 2, I graph decadal changes in the distribution of the relative racial preferences. Each of the kernel density plots uses data from the 5th to 95th percentile to limit the effect of outliers on the shape of the graphs. In each ten-year period, the distribution of preferences shifts to the right, indicating that the mean is decreasing over time. A decreasing mean over time is consistent with white households becoming more tolerant of living with minorities. Over time, the distribution of preferences also narrows. This suggests that, on average, white households increase in tolerance is occurring across all levels of the preference distribution. The compression in the distribution of racial preferences across cities, over time, is responsible for the declining importance of racial preferences as an explanatory factor in cross-sectional differences in tipping points across cities.

5.2 Descriptive Statistics: Tipping Points

By applying the model to the data, I obtain two sets of census tract tipping points. The first set comes from the the linear model in equation (16), and the second set comes from the semi-parametric estimator of equation (18). Since the predicted outcome of both approaches is a tipping point that lies in the interval [0,1], an apt analogy for describing the two methods is that the linear (diff-in-diff method) is analogous to a linear probability model, while the semi-parametric method is analogous to a non-linear, e.g. probit model, which produces estimates that lie in the interval [0,1].

5.2.1 Tract Tipping Points

In Table 2, I report summary statistics for the census tract tipping points from the diff-in-diff method of equation (16). The table is divided into three panels. In the first panel I report the mean, median, and standard deviation of the census tract tipping points for the full sample in each of the census years. In the second panel I report the identical statistics for the census tract tipping points that are in the allowable [0,1] range for the given census year. In the third panel, I report the identical statistics for each census tract that is in range in 2010. This restriction gives a consistent set of tracts across all census years. Because some of the tipping points are not "in range," I use the results from these three panels as checks that the time trends in the tipping points that I observe are consistent under the three sample restrictions: the full sample, the sample of tracts that are in range in the census year, and a consistent set of tracts that are required to be in range in the 2010 census year. In Table 3, I present results from the semi-parametric (inverse) method of equation (18).

The mean and median of the census tract tipping points increase monotonically over time for both the diff-in-diff and the semi-parametric (inverse) mapping methods. Moreover, the mean tipping point is greater than the median tipping point for all years. The magnitudes of the estimates are also comparable in both methods. I focus my discussion on the estimates from the inverse mapping method, because between 98% and 99.6% of the tipping points for this method are in the allowable [0,1] range.[4] For this method the tipping points have a mean of 15% in 1970, 22% in 1980, 28% in 1990, 36% in 2000, and 41% in 2010. The median-tract tipping point also monotonically increased from 1970 to 2010. In 1970, the

[4]By comparison, only 57%-84% of the diff-in-diff linear estimates are in range. Nevertheless, the results in the second panel of Table 2 agree with the results in the inverse mapping method for all years.

median-tract tipping point was 13% and by 2010 it was 34%. The inter-censal correlation between the tract tipping points is between 0.71 and 0.78, as reported in Table 4. This demonstrates that while the mean tipping points of the tracts has increased over time, there has been strong persistence in the ranking of tracts across time.

In Figure 3, I report kernel density plots of the tract tipping points in each census year. The distribution for each year is a single peaked distribution that is left skewed. Over time the peak pushes out the right, and the distribution flattens and gains more mass in the right tail. With each succeeding census year the curve shifts out by less, indicating that the tipping point is increasing at a decreasing rate.

5.2.2 MSA Tipping Points

Using the census tract tipping points, I construct two measures of MSA tipping points. The first is a mean MSA tipping point and the second is a median MSA tipping point. The mean MSA tipping point is the average tipping point of the census tracts in the MSA. The median MSA tipping point is the median census tract tipping point in the MSA. In Table 5, I report the mean, median, 25th percentile, 50th percentile, and 75th percentile of the mean MSA tipping points for all MSAs and also broken down by geographic region – Northeast, Midwest, South, and West. The results in Table 6 are for the median MSA tipping points.

From 1970 to 2010, both MSA tipping points increased monotonically over time. In 1970 the mean MSA tipping point was 11%; by 2010 it rose to 33%. This increase in the MSA tipping points over time was undergirded by an increasing time trend in tipping points in all regions of the US. MSA tipping points in the West increased fastest, at a rate of 7.5 percentage points per decade, while MSA tipping points increased slowest in the Midwest - 3.25 percentage points per decade. The distribution of tipping points in the Northeast parallels the distribution of MSA tipping points in the Midwest. The mean tipping points in both regions over time were (9%/9%) (12%/12%), (15%/14%), (22%/19%), (26%/22%) in 1970, 1980, 1990, 2000, and 2010, respectively. Likewise, the MSA tipping points in the

South mirrored those in the West.

The MSA tipping points exhibited a high degree of correlation across consecutive census periods, notwithstanding the fact that they increased substantially across time (Table 7). One striking fact about the MSA tipping points is that the mean MSA tipping points and the median MSA tipping points had very similar distributions. For example, in the full sample the mean of the mean MSA tipping points and the mean of the median MSA tipping points were (13%/11%), (18%/16%), (22%/21%), (30%/28%), and (35%/33%) in 1970, 1980, 1990, 2000, and 2010, respectively. For each year the difference between the mean and the median MSA tipping points was between 1 and 2 percentage points.[5] Moreover, the mean of the mean MSA tipping points is similar to the median of the census tract tipping points. I exploit this fact in the next section, where I show that the tipping points estimated by Card et al. (2008) are similar to the local mean and the local median of the tipping points of the marginal census tracts in the MSA.

5.3 Comparison with Prior Estimates of Tipping Points

The Card et al. 2008 (CMR) tipping points cover three decades – 1970, 1980, and 1990. On average, the tipping points that I get are 3 percentage points higher in 1970, 9 percentage points higher in 1980, and 12 percentage points higher in 1990 than CMR. This difference occurs because the two tipping points capture different aspects of the underlying distribution of census tract tipping points. The MSA tipping points that I report are an average of the underlying census tract tipping points, which I am able to estimate because I model the location decision of households within the MSA and use the counter-factual exercise to obtain census tract tipping points. The CMR approach accurately measures a local average of the marginal census tracts (i.e., tracts that are close to the tipping threshold). This distinction between the two MSA tipping points is evident from the theories guiding their

[5] By comparison, the mean and median of the census tract tipping points were more dissimilar (15%/13%), (22%/16%), (28%/21%), (36%/28%), and (41%/34%) in the respective census years. For each year the difference between the mean and the median tract tipping points is between 2 and 8 percentage points.

construction.

The CMR tipping points are the result of a fixed-point procedure. To obtain the MSA tipping point, the CMR fits a polynomial of the change in the percent of whites between census years (above the MSA average) as a function of the fraction of minorities in the base census year. Each observation used to fit this function is a census tract in the MSA which is appears into consecutive periods. The first method for determining the tipping point is to solve for the zeros of this polynomial. The key point is that tracts below the tipping point experience above-average growth in their non-minority (white) populations, whereas tracts beyond the tipping point experience below average growth in their non-minority populations. The minority fraction at the zero of this polynomial is taken to be the MSA tipping point.

In cases where there are multiple zeros, the authors took the zero that delivered the most negative first derivative. This equilibrium selection procedure parallels the approach that I take in this paper, where for each tract I stipulate that the tipping point occurs at the level of utility for which the exit rate of non-minorities is maximal (and the marginal exit rate equals zero). Since the CMR tipping point is the zero of a fitted polynomial, it depends crucially on the behavior of the census tracts in the vicinity of this zero. I call these census tracts the "marginal census tracts." These are tracts that are close to their tipping points. I call tracts that are farther away from the zero of the polynomial "infra-marginal census tracts" because changes in the behavior the infra-marginal tracts have less bearing on the estimated value of the CMR MSA tipping points.The setup of the CMR procedure suggests that the CMR tipping points are local averages of the tipping points of the marginal tracts, or perhaps the median of the tipping points of the marginal census tracts in the MSA. Since I have estimates of tipping points for each census tract in an MSA, I can test the hypothesis that the CMR tipping points are local averages of the tipping points of marginal census tracts or the median of the tipping points of the marginal tracts.

In Table 8, I present results from a regression of the difference between the CMR and

Revealed-Preference (PR) MSA tipping points, which I call the *tipping difference*,[6] and the fraction of marginal census tracts in the MSA. Here, a marginal census tract is a tract whose percent minority is within 5 percentage points of its estimated tract tipping point. For example, if a tract has a tipping point of 35% and a current percent minority of 32% it is considered a marginal tract. Likewise, if another tract in the same MSA has a tipping point of 7% and a current percent minority of 11%, I also consider it a marginal tract. To allow for asymmetry in the impact of marginal tracts that lie to the left and to the right of their respective tipping points, I include separate explanatory variables for (a) the fraction of tracts in the MSA that are marginal and have minority fractions below their tipping points; and (b) the fraction of tracts in the MSA that are marginal and have minority fractions greater than their tipping points.

The constant terms from the regressions in Table 8 capture the mean *tipping difference*. In 1990, the tipping difference was -15%. It was -10% in 1980 and -8% in 1970. These regression results accord with the -13%, -9%, and -3% tipping differences from the raw data. Based on the regression results, the marginal tracts that were below the tipping point drove the tipping difference in 1990 and 1980. In 1970, the marginal tracts that were above the tipping point (i.e., those that had already tipped), drove the tipping difference. One reason there is a tipping difference at all is that there were few marginal tracts, and so an average of the marginal tracts is different from an average of all tracts. To illustrate this point, I combine the constant term from the regression and the significant coefficient on the marginal tracts to compute the threshold fraction of marginal tracts, $\tilde{f}$ required for there to be no tipping difference in each year:

$$\tilde{f} = \frac{\#\text{ marginal tracts in MSA}}{\text{Total }\#\text{ tracts in MSA}}. \tag{19}$$

To solve for $\tilde{f}$, I set the sum the constant term from the regression and the product of the

[6] I do not call this quantity a bias because my hypothesis is that the CMR tipping points measure the distribution of the marginal census tracts, which in and of itself is an important quantity. We care about which tracts are marginal and how the distribution of marginal tracts varies across time and across space.

(significant) coefficient on the marginal tracts times $\tilde{f}$ equal to zero. At this value of $\tilde{f}$, the tipping difference is zero, and the CMR tipping points and the tipping points that I obtain are equal. In 1990, 72% of the tracts would have to be marginal for there to be no tipping difference. In 1980, 53% of the tracts would have to be marginal; and in 1970, 13% of tracts would have to be marginal. In the reality, the average MSA consisted of 14% of marginal tracts (below) in 1990, 13% of marginal tracts (below) in 1980, and 11% of marginal tracts (above) in 1970. Since the mean number of marginal tracts was closest to the required level in 1970, it is not surprising that the tipping difference was smallest in 1970. The opposite is true for 1990, the year when the difference between the required threshold and the fraction of tracts that were marginal was largest.

To verify this, I perform a similar exercise, this time changing the definition of the tipping difference to be the difference between the CMR tipping point and the tipping point of the median census tract in each MSA. When I restrict the sample to only the marginal tracts, the tipping difference equals the difference between the CMR tipping point and the median tipping point of the marginal census tracts. Apart from this change in the definition of the tipping difference, Figure 6 is laid out identically to Figure 5. The dashed lines peak to the left of zero, reflecting the fact that the CMR tipping points are smaller, on average, than the MSA tipping points that I compute from the median. The solid lines, however, peak even more sharply around zero than the solid lines using the mean. This reflects the fact that the tipping difference also disappears when I compute MSA tipping points using only the marginal tracts. With this sample restriction, the tipping difference of the median MSA is reduced from -11.2% to -1.7% in 1990, from -7.8% to 0.1% in 1980, and does not substantively change in magnitude in 1970 (from -3.7% to 4%). Taking the best of the local mean and median results, the tipping difference of the median MSA is bounded above by 1.9% and bounded below by -0.1%. These results provide further support for the hypothesis that the CMR tipping points capture the shape of the distribution of marginal census tracts in an MSA.

From this comparison of marginal and infra-marginal tracts, we learn that the tipping points of the marginal census tracts evolve more slowly over time than those of the infra-marginal tracts. The CMR tipping points, which were shown to be an average of the marginal tipping points, increased an average of 1 percentage point per decade (1970–1990). We also learn that the infra-marginal tracts play an important role in the secular time trend of tipping points. The MSA tipping points using all tracts (both marginal and infra-marginal) increased at an average rate of 5.5 percentage points per decade (1970–2010), which is substantially higher than the growth rate of the tipping points of infra-marginal tracts. An important contribution of the method in this paper is that it enables researchers to compute the tipping points of all census tracts and derived MSA tipping points, which are aggregates of the underlying census tract tipping points. The dynamics of these MSA tipping points better reflect the dynamics of the underlying census tracts.[7]

5.4 Results: Preferences versus Outside Options

The motivating insight of this paper is that outside options affect the ability of households to act on their preferences for neighborhood racial composition. A household may remain in a neighborhood despite its racial composition if the outside options do not offer higher utility. The reverse is also true – a household may exit its current neighborhood because of the availability of desirable alternative neighborhoods in its city. For each census year, I decompose the mean MSA tipping point into a component due to the mean preferences of the households and a measure of their outside options, which depends on the extent of clustering in the city by race.

To measure minority clustering, I use a Herfindahl-Hirschman Index (HHI) that is standardized to have a mean of zero and standard deviation of one. To compute the index, I construct the minority market share of each census tract n in a given census year y by dividing the number of minorities in the tract by the total number of minorities in its MSA

[7] The mean tipping point of census tracts in the data increased by 6.75 percentage points per decade (19702010)

c: $s^c_{n,m,y} = \frac{Q^c_{n,m,y}}{Q^c_{tot,m,y}}$. I then square the minority market shares, $s_{n,m,y}$ and sum over them for each MSA, c, to get the MSA HHI^c :

$$HHI_c = \sum_n (s^c_{n,m,y})^2. \tag{20}$$

Finally, I de-mean the Minority HHI and normalize it to have variance 1 in each year. This yields a minority HHI z-score,($HHI^c_{m,z,y}$) for each MSA for each census year from 1970 to 2010. I construct a standardized non-minority HHI using an identical procedure ($HHI^c_{w,z,y}$). To construct the standardized measure of racial preferences, ($\Delta\gamma^c_{z,y}$), I de-mean the relative marginal utility for minority neighbors from the diff-in-diff procedure of equation (17) and normalize it to have standard deviation 1.

A one standard deviation *decrease* in the minority HHI corresponds to less clustering of minorities in the MSA, or more census tracts in the MSA having some minority households. Less clustering of minorities creates a choice-set in which many census tracts are sprinkled with at least some minorities, making it difficult for non-minority households to sort into all-white neighborhoods. A one standard deviation *increase* in the non-minority HHI corresponds to more clustering of non-minorities into fewer census tracts within an MSA. Greater clustering of non-minorities creates a choice-set that is potentially bimodal, with some tracts having many non-minorities and others having few non-minorities. A one standard deviation *increase* in the race preferences is associated with non-minorities having preferences for minority neighbors that is more similar to the preferences that minorities have for minority neighbors.

In Table 9, I report the results of a regression of mean MSA tipping points (T^c_y) on the minority HHI ($HHI^c_{m,z,y}$), the non-minority HHI ($HHI^c_{w,z,y}$), and the standardized race preferences ($\Delta\gamma^c_{z,y}$):

$$T^c_y = \eta^y_1 HHI^c_{m,z,y} + \eta^y_2 HHI^c_{w,z,y} + \phi^y \Delta\gamma^c_{z,y}. \tag{21}$$

Since the tipping points were constructed using the choice-set faced by households and the estimated preferences, I read this regression as providing a decomposition of the MSA tipping points into a component due to the configuration of the outside option and the mean preferences in the MSA. The results of this regression are summarized in Figure 7. The first result is that less minority clustering, or having the presence of a more diverse choice-set, is associated with a higher tipping point. In 1970, for example, a one standard deviation decrease in the minority HHI results in a $\eta_1^{1970} = 1.1$ percentage point increase in the tipping point. From 1970 to 2010, this effect of a reduction in minority clustering on mean MSA tipping points strengthens monotonically. By 2010, a one standard deviation decrease in minority clustering increases the mean tipping point by 14 percentage points, which is roughly 50% of the base tipping point of 30% in 2010. Since reductions in the clustering of minorities result in many tracts having at least some minorities, this reduces the number of all-white tracts, which in turn creates a barrier to neighborhood exit by non-minorities.

Increasing the clustering of non-minorities has no statistically significant effect on MSA tipping points in 1970. In 1980, however, a one standard deviation increase the non-minority HHI increases the tipping point by 2.6 percentage points or 15%. By 2010, a one standard deviation increase in the non-minority HHI is associated with a 11.2 percentage point increase in the tipping point. When the non-minority HHI increases, non-minorities are clustered in fewer census tracts. This creates a bimodal distribution of tracts by racial composition. There are fewer tracts with some non-minorities because of the increased clustering of minorities; and there are more tracts with higher minority fractions also because of the clustering. Both of these factors act as barriers to the exit of non-minorities from neighborhoods, resulting in an increasing tipping point. Hence both the diffusion of minorities through the MSA by a decrease in the minority HHI and an increase in the clustering of non-minorities by an increase in the non-minority HHI are associated with greater tipping points in the cross-section. This effect also strengthens over time, as illustrated by the non-zero slope of the HHI coefficients over time in Figure 7.

While the role of outside options becomes increasingly important over time, the role of racial preferences diminishes. This is illustrated by the negative downward slope of the racial preferences coefficients. In 1970, a one standard deviation increase in racial preferences was associated with a $\phi^{1970} = 6.6$ percentage point increase in the tipping point, which equals a more than 50% increase in the tipping point. In 2010, a one standard deviation increase in racial preferences had no effect on the tipping point. The decline in the effect of racial preferences on the tipping point is nearly monotonic over time. Interestingly, 1970 and 2010 are opposite sides of the coin when it comes to the respective roles of racial preferences and outside options in MSA tipping points. In 1970, the clustering of minorities and non-minorities had a small effect on tipping points, whereas racial preferences were at the zenith of their importance. In 2010, the opposite was true – the configuration of the outside options was paramount, and racial preferences appear to have played no role in explaining cross-sectional differences in MSA tipping points. With the configuration of a households choice-set mattering more now than in the past, modeling the tipping with outside options, as I do here, is of principal importance in understanding the future evolution of city tipping points.

6 Conclusion

A neighborhood tips when non-minorities exit in response to integration. Prior literature has focused on racial preferences as a key driver for tipping. I show that in addition, the outside options of households also matter. To incorporate outside options into a model of tipping, I start with the assumption that a household's outside options are the other neighborhoods in its city of residence. I further require that a household's response to integration is incentive compatible – the household only exits its current neighborhood if relocating delivers higher utility than staying. I pair this assumption about the choice-set and the incentive compatibility constraint with a discrete choice model in order to exploit the sub-MSA sorting patterns in the data to estimate census tract tipping points.

The census tract tipping points that I estimate reveal two key findings. First, tipping points we learn that tipping points have increased over time by more than previously thought. This result also holds when I aggregate the tract tipping points at the MSA level. Prior estimates in the literature pegged the growth in city tipping points at an average of 1 percentage point per decade, whereas I find that city tipping points have grown by an average rate of 5 percentage points per decade. I show that my estimates of city tipping points are different from the prior literature because the city tipping points that I estimate are an average of the underlying distribution of tract tipping points. The CMR tipping points appear to be local averages of the tipping points of census tracts that are close to tipping.

The second key finding of this paper is that outside options are increasingly important for explaining cross-sectional variation in tipping points. In 1970, a one standard deviation increase in the diffusion of minorities across a city was associated with a 1 percent increase in the tipping point. By 2010, a similar change in the outside option was associated with a 14 percentage point increase in the tipping point. By contrast, differences in racial preferences have become less important for explaining cross-sectional differences in city tipping points.

From a policy standpoint, the distinction between preferences and outside options is important. If heterogeneity in tipping points were driven primarily by racial preferences, then the government would require policy levers that change preferences in order to mitigate neighborhood tipping. If, on the other hand, heterogeneity in tipping points were due to differences in the outside options of households, then this would provide more scope for place-based policies to promote integration. The results of this study suggest that the latter is the case, since the effect of outside options has become larger over time, while the effect of racial preferences on tipping points has diminished in significance.

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8 Figures and Tables

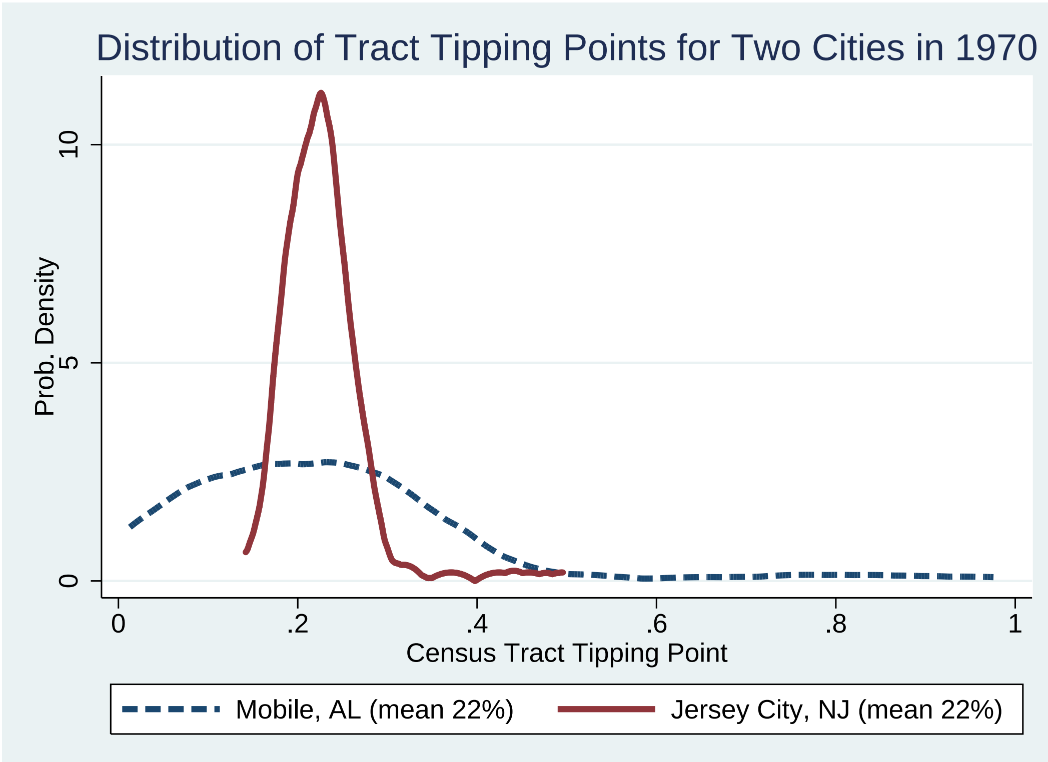

Figure 1: Kernel density plot of estimated census tract tipping points of Jersey City, NJ and Mobile, AL in 1970.

Table 1: **Relative Marginal Utility of Minority Neighbors (Diff-in-Diff)**

stats	**1970**	**1980**	**1990**	**2000**	**2010**
mean	-8.84	-7.29	-6.82	-6.41	-6.11
	(0.79)	(0.57)	(0.10)	(0.14)	(0.10)
p50	-8.75	-7.10	-6.72	-6.48	-6.06
	(0.18)	(0.10)	(0.29)	(0.10)	(0.10)
N	124	124	124	124	124

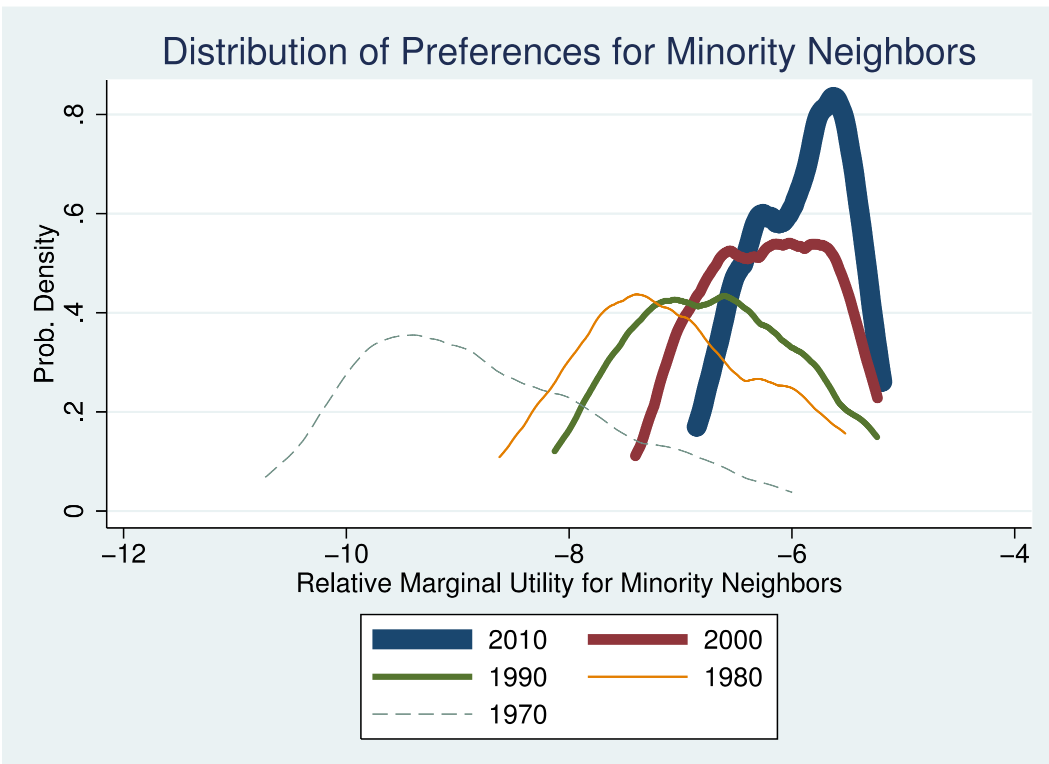

Figure 2: Kernel density plot of the racial preference parameter for each MSA from 1970 to 2010, using the diff-in-diff estimates.

Table 2: **Census Tract Tipping Points (Diff-in-Diff)**

All	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.06	0.15	0.21	0.29	0.34
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
p50	0.02	0.07	0.11	0.21	0.29
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
N	38,489	38,489	38,489	38,489	38,489

In Range (Current Year)[†]	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.18	0.26	0.30	0.36	0.41
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
p50	0.09	0.14	0.19	0.28	0.35
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
N	22,391	26,399	29,039	31,504	32,447

In Range (Census 2010)[†]	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.07	0.17	0.25	0.35	0.41
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
p50	0.03	0.09	0.15	0.27	0.35
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
N	32,447	32,447	32,447	32,447	32,447

[†] A tract is in range if its tipping point $\in [0, 1]$.

Table 3: **Census Tract Tipping Point (Semi-Parametric)**

All	**1970**	**1980**	**1990**	**2000**	**2010***
mean	0.15	0.22	0.28	0.36	0.42
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p50	0.13	0.16	0.20	0.28	0.34
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
N	38,489	38,489	38,489	38,489	38,466

In Range (Current Year)	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.15	0.22	0.28	0.36	0.41
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p50	0.13	0.16	0.21	0.28	0.34
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	38,333	38,085	37,941	37,803	37,694

In Range (Census 2010)	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.16	0.23	0.28	0.36	0.41
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p50	0.13	0.16	0.21	0.29	0.34
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	37,694	37,694	37,694	37,694	37,694

* I dropped 23 extreme outliers in 2010.

Table 4: **Correlation Tract Tipping Points (Semi-Parametric)**

Year	**2010**	**2000**	**1990**	**1980**	**1970**
2010	1.00				
2000	0.71	1.00			
1990	0.58	0.78	1.00		
1980	0.39	0.53	0.73	1.00	
1970	0.18	0.25	0.40	0.77	1.00
# Observations	38,466	38,466	38,466	38,466	38,466

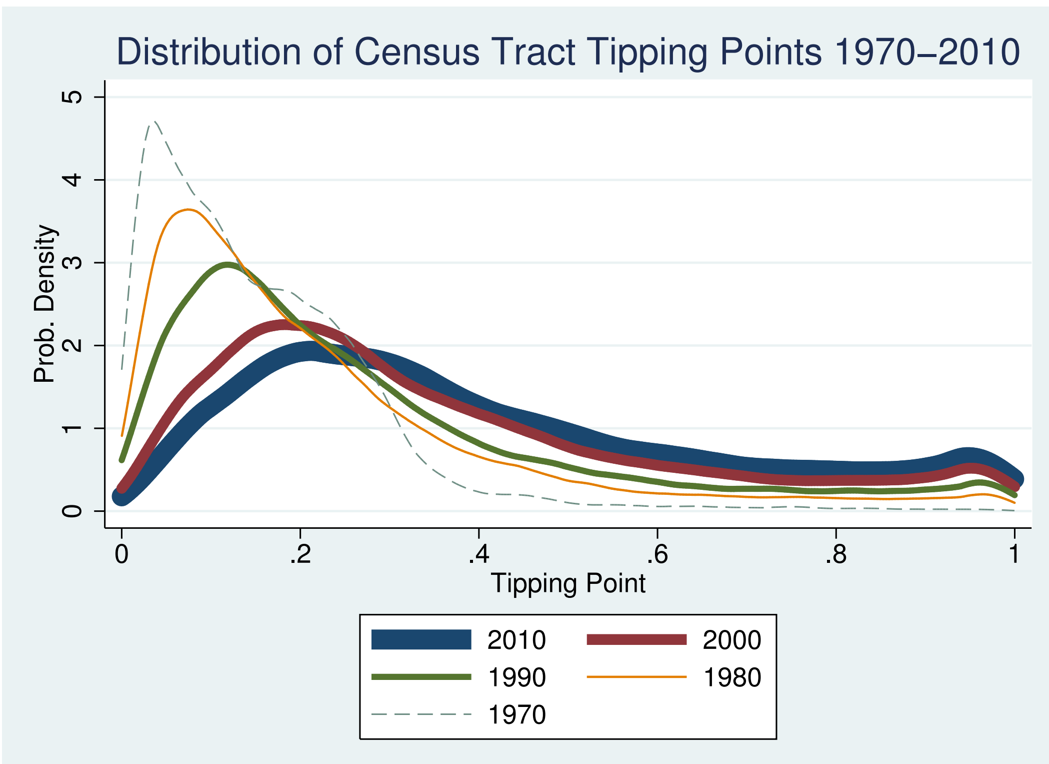

Figure 3: Distribution of census tract tipping points for each census year using the tipping points from the semi-parametric (inverse) method.

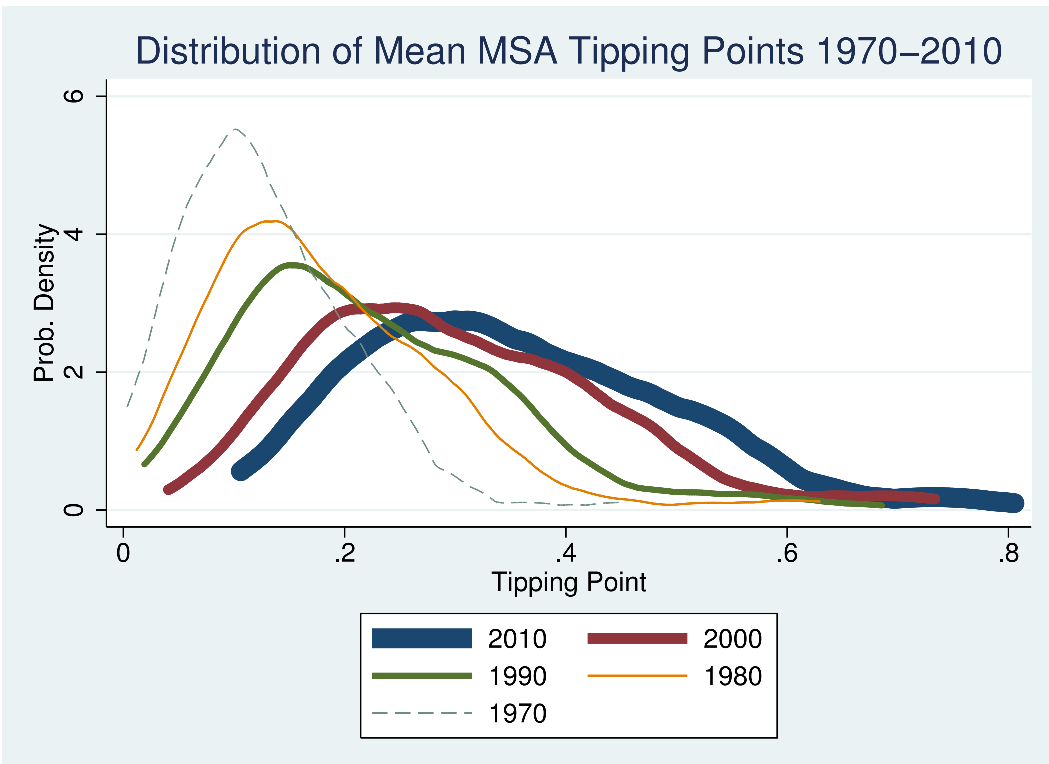

Figure 4: Distribution of mean MSA tipping points for each census year using the tipping points from the semi-parametric (inverse) method.

Table 5: **Average MSA Tipping Points**

All	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.13	0.18	0.22	0.30	0.35
	(0.007)	(0.010)	(0.011)	(0.012)	(0.013)
p25	0.07	0.11	0.13	0.19	0.22
p50	0.12	0.16	0.19	0.26	0.32
p75	0.17	0.24	0.29	0.39	0.46
N	123	123	123	123	123

Northeast	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.09	0.13	0.17	0.24	0.28
	(0.014)	(0.019)	(0.022)	(0.026)	(0.028)
p25	0.03	0.06	0.10	0.15	0.18
p50	0.07	0.11	0.15	0.20	0.24
p75	0.11	0.17	0.24	0.30	0.36
N	23	23	23	23	23

Midwest	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.10	0.14	0.16	0.21	0.24
	(0.010)	(0.011)	(0.012)	(0.012)	(0.012)
p25	0.07	0.10	0.12	0.17	0.19
p50	0.09	0.14	0.16	0.20	0.22
p75	0.13	0.16	0.19	0.23	0.26
N	27	27	27	27	27

South	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.17	0.22	0.26	0.34	0.41
	(0.012)	(0.017)	(0.020)	(0.020)	(0.020)
p25	0.11	0.14	0.18	0.26	0.29
p50	0.15	0.20	0.25	0.32	0.37
p75	0.21	0.27	0.30	0.40	0.49
N	45	45	45	45	45

West	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.12	0.20	0.26	0.36	0.43
	(0.013)	(0.021)	(0.025)	(0.027)	(0.028)
p25	0.06	0.10	0.15	0.24	0.32
p50	0.12	0.19	0.28	0.38	0.46
p75	0.17	0.26	0.35	0.45	0.52
N	28	28	28	28	28

Table 6: **Median MSA Tipping Points**

All	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.11	0.16	0.21	0.28	0.33
	(0.007)	(0.010)	(0.010)	(0.013)	(0.013)
p25	0.06	0.10	0.12	0.17	0.22
p50	0.10	0.13	0.17	0.24	0.31
p75	0.16	0.22	0.27	0.37	0.43
N	123	123	123	123	123

Northeast	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.09	0.12	0.15	0.22	0.26
	(0.013)	(0.017)	(0.019)	(0.025)	(0.025)
p25	0.03	0.06	0.09	0.14	0.18
p50	0.07	0.10	0.14	0.18	0.23
p75	0.10	0.14	0.21	0.28	0.31
N	23	23	23	23	23

Midwest	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.09	0.12	0.14	0.19	0.22
	(0.009)	(0.009)	(0.09)	(0.010)	(0.010)
p25	0.06	0.09	0.11	0.17	0.18
p50	0.08	0.12	0.14	0.17	0.22
p75	0.11	0.14	0.16	0.21	0.24
N	27	27	27	27	27

South	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.14	0.20	0.25	0.32	0.38
	(0.013)	(0.017)	(0.020)	(0.022)	(0.022)
p25	0.09	0.13	0.17	0.24	0.30
p50	0.11	0.17	0.22	0.29	0.35
p75	0.19	0.24	0.29	0.37	0.43
N	45	45	45	45	45

West	**1970**	**1980**	**1990**	**2000**	**2010**
mean	0.11	0.19	0.25	0.36	0.42
	(0.013)	(0.021)	(0.025)	(0.027)	(0.028)
p25	0.05	0.10	0.14	0.24	0.31
p50	0.12	0.17	0.26	0.38	0.43
p75	0.17	0.25	0.34	0.44	0.53
N	28	28	28	28	28

Table 7: **Correlation in Mean MSA Tipping Points**

Year	**2010**	**2000**	**1990**	**1980**	**1970**
2010	1.00				
2000	0.88	1.00			
1990	0.85	0.97	1.00		
1980	0.81	0.93	0.98	1.00	
1970	0.65	0.79	0.84	0.88	1.00
# MSA	123	123	123	123	123

Table 8: **Comparison of CMR and Revealed Preference Tipping Points**

	1990	1980	1970
% Marginal Tracts in MSA (below TP)	0.212	0.193	-0.015
	(0.069)**	(0.067)**	(0.055)
% Marginal Tracts in MSA (above TP)	0.311	0.121	0.603
	(0.169)	(0.157)	(0.123)**
Constant (Avg. Diff in CMR & RP MSA TP)	-0.153	-0.102	-0.077
	(0.021)**	(0.020)**	(0.017)**
R^2	0.17	0.12	0.26
N	101	100	93

Table 9: **Effect of Preferences and Options on Tipping Points**

	1970	1980	1990	2000	2010
Minority HHI	-0.011	-0.034	-0.070	-0.097	-0.144
	(0.005)*	(0.007)**	(0.009)**	(0.012)**	(0.015)**
Non-minority HHI	0.006	0.026	0.055	0.066	0.112
	(0.005)	(0.007)**	(0.009)**	(0.012)**	(0.015)**
Race Prefs.	0.066	0.076	0.058	0.032	-0.005
	(0.007)**	(0.012)**	(0.012)**	(0.011)**	(0.008)
Constant	0.128	0.169	0.218	0.293	0.300
	(0.012)**	(0.016)**	(0.018)**	(0.020)**	(0.020)**
Region Fixed Effects	Y	Y	Y	Y	Y
R^2	0.55	0.52	0.57	0.55	0.58
N	116	116	118	118	119

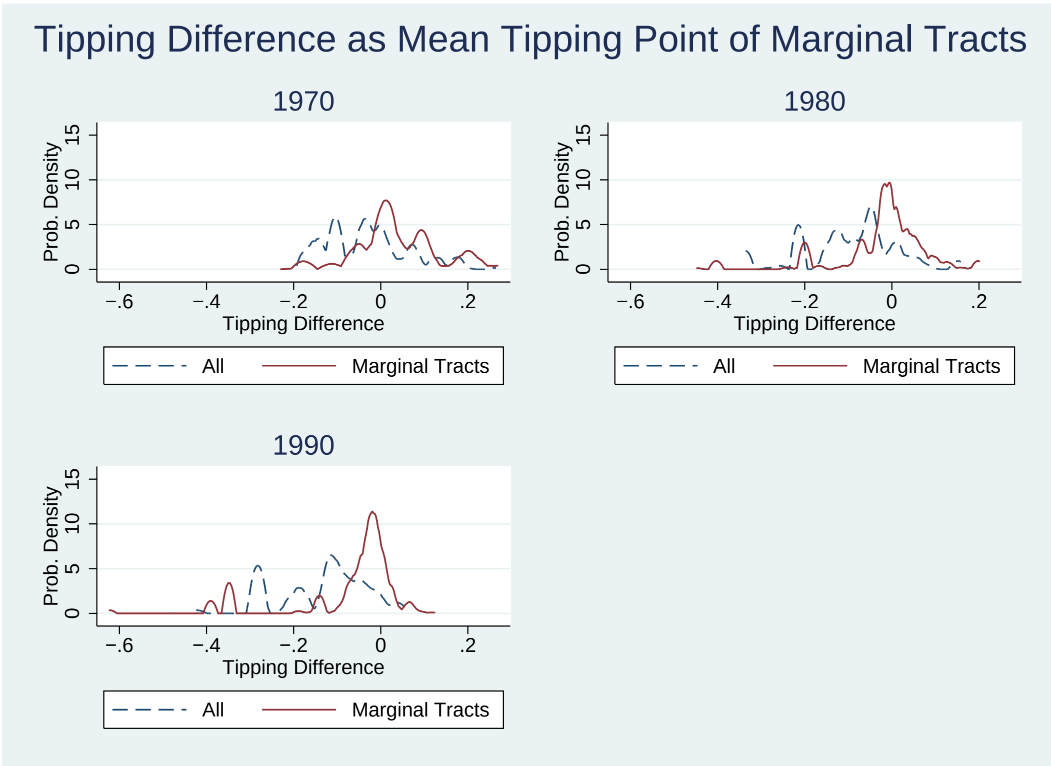

Figure 5: Kernel density plot of the difference between the CMR tipping points and mean MSA tipping points using all tracts, and using the marginal census tracts that are within 5 percentage points of their tipping point.

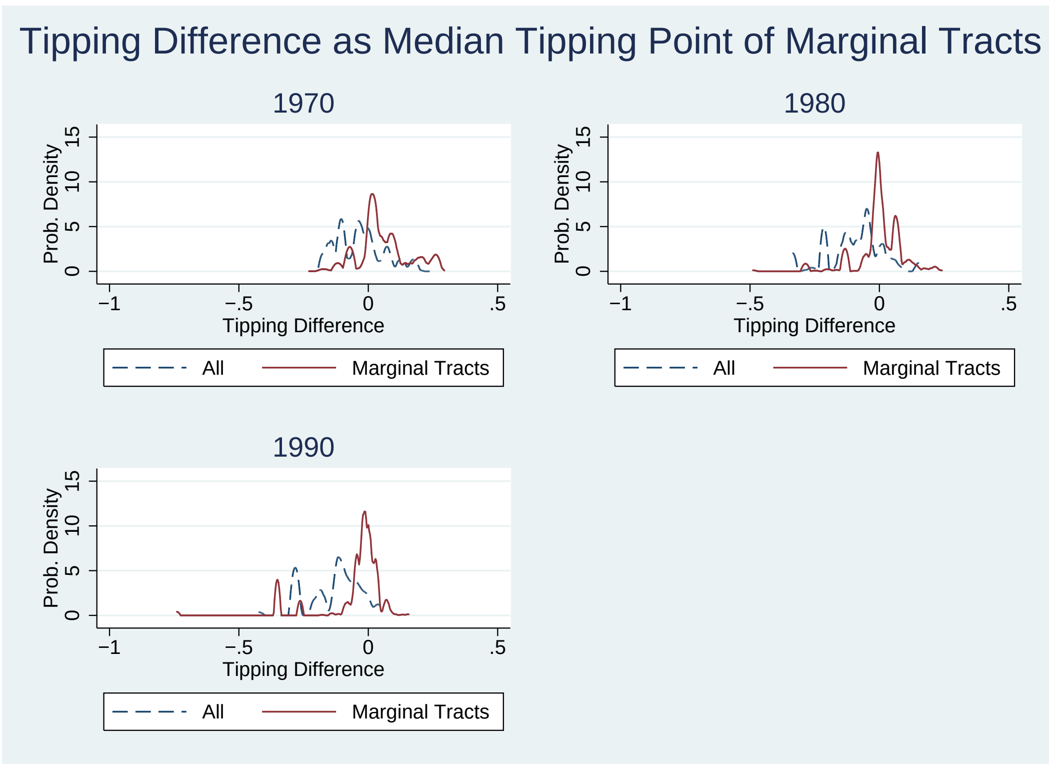

Figure 6: Kernel density plot of the difference between the CMR tipping points and median MSA tipping points using all tracts, and using just the marginal census tracts that are within 5 percentage points of their tipping point.

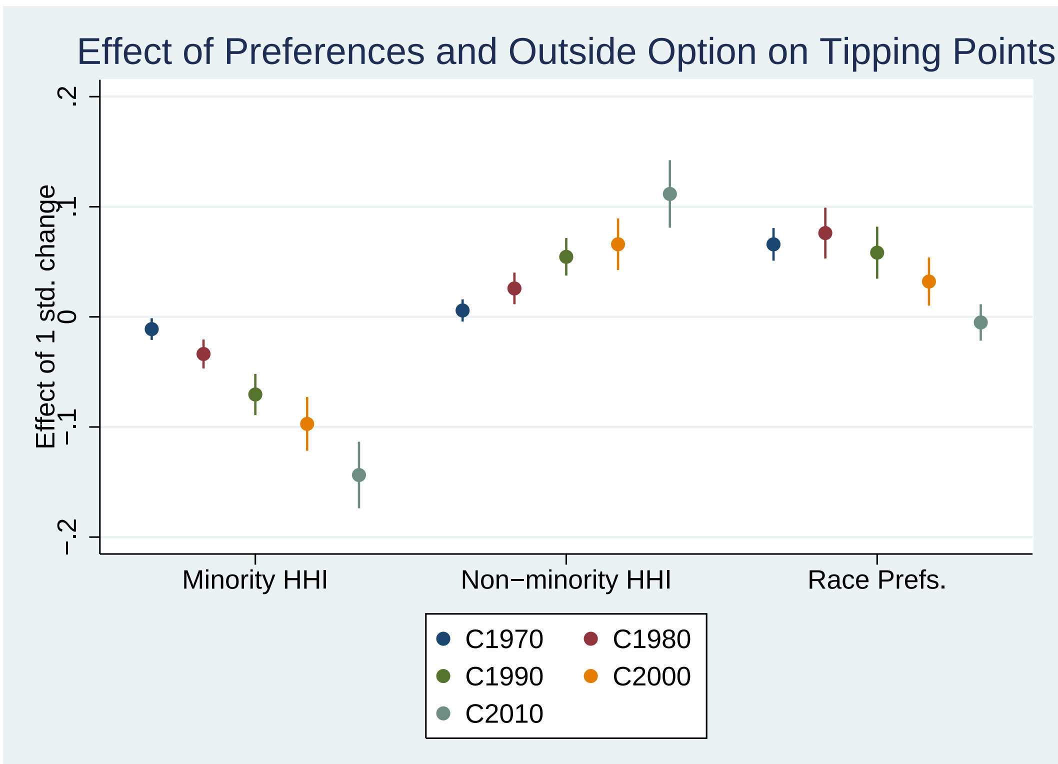

Figure 7: A plot of coefficient estimates from a regression of MSA tipping points on standardized measures of racial preferences and Herfindahl-Hirschman Indices (HHI) of the minority and non-minority concentration of the MSA in census years C1970-C2010.