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Racial Segregation in the Interwar U.S. Northern Cities: A Dynamic Segregation Approach

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Abstract

Between 1910 and 1950, more than 3.5 million African Americans migrated from the south, largely to northern, urban areas (Collins 1997). Yet when they arrived, they found themselves often limited in their choice of neighbourhoods via racially restrictive covenants (Brooks 2011). Following the literature of Schelling (1971) and Card et al. (2008), we propose an alternative framework based on a random utility approach to theoretically model the dynamic of racial segregation and the "tipping behavior", showing that the tipping point might change over time as a result of changes in racial prejudice or other preference parameters. We also empirically test these predictions by examining whether neighbourhoods in interwar cities in the United States demonstrated tipping behavior. Using census-tract data from both the 1930 and 1940 U.S. Census as well as the 1934 Real Property Inventory, our results suggest that tipping behavior did occur although the tipping points are typically lower than those found in the modern era. Unlike the modern era in which the white population fell around 12 percent, our results suggest that growth of white households in neighbourhoods largely stopped compared to the growth of the white population in the cities as a whole.

Keywords: Racial Segregation, Tipping, Structural Break, Random Utility

J.E.L. reference codes: C23, D19, N92, R23

1. Introduction

Racial segregation across neighborhoods is a salient characteristic of urban areas in the United States. Despite the Constitution of the United States and federal law declaring that everyone is equal, racial segregation in housing has not only persisted in many cities, it has become more extreme over the last century (Massey, 2001). The interwar period in the United States is associated with a time when racial segregation takes on a different dynamic. Blacks in America who were living in difficult conditions during the Great Depression were drawn to the north, mainly motivated by the benefits of the New Deal programs that were distributed more effectively in the north than in the south. The availability of jobs with the arrival of World War II (1939-45) also provided an impetus that witnessed millions of blacks moving from the rural south to the north (Wright, 1986). It has been estimated that between 1910 and 1950, more than 3.5 million African Americans migrated from the south, largely to northern, urban areas (Collins, 1997). Yet when they arrived, African Americans found themselves often limited in their choice of neighborhoods via racially restrictive covenants (Brooks, 2011).

This paper examines the dynamics of racial segregation that took place in six cities of the United States between 1930 and 1940. There are two schools of thought that rationalize racial segregation. On the one hand, the classic models of Tiebout (1956) and Rosen (1974) attribute urban segregation to households' differences in incomes and preferences, which determine their willingness to pay for location characteristics. Given that blacks had restricted access to education, this leads black households towards those neighborhoods with lower levels of amenities commensurate with their income. On the other hand, the models of Schelling (1971) and Becker and Murphy (2000) attribute racial segregation to households' concerns about the demography of their neighbors. The seminal work of Card et al. (2008), which examines the process by which a neighborhood can polarize towards complete segregation – tipping – attributes segregation in urban neighborhoods to white's preference for not residing near non-white minorities. Still there are models that attempt to explain racial segregation as an outcome of interaction between an exogenous location characteristic and demographic segregation (see

Banzhaf and Walsh, 2010).[1] Yet this belief that racial segregation is born out of white's preference for not residing near minorities is not a modern phenomenon. Motivated by the historical background of racial segregation in the interwar period, we provide a theoretical model and empirically test whether tipping was present in some U.S. cities, and if so, did it differ from results based on the modern period.

This paper contributes to the literature of racial segregation by developing a theoretical model, which is based on a random utility approach. The model encompasses both schools of thought on racial segregation as arising from household's preferences for location characteristics and racial prejudice. The model is sufficiently general and it is able to predict the dynamics of tipping in which the minority itself becomes more segregated from the majority as its relative size diminishes. The model also explains the factors that can give rise to variation in the tipping threshold, which is driven by the household's preferences for location characteristics and for not residing near minorities due to racial prejudice. The theoretical model explains the tipping phenomena and identifies a tipping point. Additionally, it provides predicted outcomes of the effect of control covariates like population density, homeownership rate and the median rent which are determinants of the change in the U.S. neighborhood's white population in the regression. Given that our interest is in studying the dynamics of racial segregation in U.S. cities during the interwar period and to compare it with the 1990s data, we rely on the methodology of Card et al. (2008) to test for and determine the tipping point.

Following the regression discontinuity approach of Card et al. (2008), we test for tipping points in the United States for six cities and estimate the "tipping point" at which previously predominantly white neighborhoods see large increases in the share of minority households. Our results are then compared to that of Card et al. (2008) to inform the change in the dynamics of

[1] Banzhaf and Walsh (2010) develop a general equilibrium model that captures the behavior of households when choosing the neighborhood they want to live in based on its endogenous demographics and its exogenous public good. Several interesting findings emerge from the model. When sorting arises from tastes for the exogenous public good rather than demographic tastes, some racial segregation can occur with richer households benefiting from higher levels of the public good. However, when tastes for endogenous demographic composition are incorporated in the model, further segregation occurs consistently with the prediction of Schelling's "tipping model". More importantly, policy that improves the public good in a low-quality but high minority neighborhood may lead to an increase in group segregation, as richer minorities move into the neighborhood due to the improvement in the public good. In neighborhoods where differences in public goods are less important, sorting is dominated by tastes of demographic preferences over income-based sorting on the public good.

tipping that occurred in the interwar years. Our results, using a structural-break procedure, suggest that tipping in cities occurred and appear to have been lower than those found in the modern era with the exception of Washington, DC and Chicago. A possible reason for this outcome is that a city like Washington, DC had the largest share of growth in white households as a share of total population in 1934 and there was strong employment growth of the government sector around the nation's capital.

Our paper proceeds as follows. Section 2 describes our theoretical model for tipping and briefly compares it with other established models, namely Card et al.'s (2008). Section 3 discusses the empirical methodology which to a large extent follows Card et al. (2008). Section 4 reports the data source and descriptive statistics, while Section 5 presents our empirical results which are consistent and support the predictions of our theoretical framework. Section 6 concludes and lays out some direction for future research.

2. The Theoretical Model

We present a simple theoretical model to explain how tipping may be a dynamic outcome of social interactions and choices. To this end we employ a random utility model as outlined in Brock and Durlauf (2001) and Blume and Durlauf (2003) to describe the evolution of the share of the white population in a neighborhood in which individuals are heterogeneous in their degree of racial prejudice. The paper most closely related to ours is Card et al.'s (2008) which develops a simple approach to explain the dynamics of racial segregation[2]. To same extent also in Card et al. (2008) social interactions between whites and blacks are the driver of tipping but the

[2] Apart from our theoretical model in which tipping is driven by social interactions and externalities at neighborhood level, there are alternative theoretical explanations of why dynamic segregation may arise. Heal and Kunreuther (2010) model the effect of social reinforcement in game-theoretic terms that result in tipping, cascading and entrapment, which emerge as properties of the Nash equilibria of games. Specifically, they show that a subset of the participants can shift the system from one equilibrium to another just by changing their choices. This result concurs with the point of Schelling's work, even though Schelling discusses it in the context a dynamic process rather than Nash equilibria. Grauwin et al. (2012) use evolutionary game theory to propose an analytical solution to a Schelling segregation model for a relatively broad range of utility functions. Based on different potential function, they analyze the outcome of the model for utility functions corresponding to different degrees of preference for mixed neighborhoods. They show that for Schelling's original utility function segregation occurs at the expense of collective utility and if agents have a strict preference for mixed neighborhoods but in favor of living with the majority, the model converges to perfectly segregated configurations, which diverge from the social optimum.

underlying mechanism is different from ours along two main respects. (i) Card et al. (2008) model tipping by relying on the bid rent function and they take a broad aggregative approach rather than focusing on individual household choices. In our setup we explicitly account for the possibility that heterogeneous households have different preferences for own-race neighbors; individual choices at the micro level determine the outcomes at the macro level through a social externality channel, thus aggregate segregation outcomes are endogenous in our analysis. (ii) While in Card et al. (2008) social interactions are not explained since affecting exogenously the bid-rent function for housing, in our framework they directly affect the utility function through the presence of a social norm determining the extent to which conforming to the behavior of others is desirable at individual level. Thus, while our model is mainly based upon a behavioral argument, theirs is more focused on economic incentives. We believe that the two approaches are to a large extent complementary, since both behavioral and economic factors stress different determinants of the possible drivers of racial segregation.

Consider a neighborhood populated by a large number of white households, indexed by *j=1, …, N*, who attempt to maximize their utility associated with their residential choice. The utility function of any white household j is associated with the choice $\omega_j = \{0,1\}$ such that $\omega_j = 0$ ($\omega_j = 1$) denotes that the household leaves (stays in) the neighborhood. The decision to leave or stay in the neighborhood is determined by the utility and disutility associated with residing in that neighborhood. The utility depends on three elements: a private and a social component as well as an idiosyncratic (dis)utility component. The private component is common to all households and is equal to $h > 0$. The social component is associated with the choice of the other (white) households and is equal to $J(\widetilde{m}_j^e - \frac{1}{2})$, where $\widetilde{m}_j^e$ is defined as the expectation of a household j about others' mean choices so that $\widetilde{m}_j^e = \frac{1}{N-1} E\left[\sum_{j \neq k} \omega_k\right]$. Here, $J > 0$ is a scale factor measuring the magnitude of such an expectation in each household's utility. The disutility is given by $e_j = e + \epsilon_j$ where $e > 0$ is a disutility term common to all households while ϵ_j is a random term independently and identically distributed (i.i.d.) across households. The utility function of each white household is, therefore, given by the following expression:

$$u_j(\omega_j) = \omega_j \left[h - (e + \epsilon_j) + J\left(\widetilde{m}_j^e - \frac{1}{2}\right)\right]. \tag{1}$$

The utility associated with the decision to stay is $u_j(1) = h - (e + \epsilon_j) + J(\widetilde{m}_j^e - \frac{1}{2})$ while the utility to leave is $u_j(0) = 0$. Clearly, as long as the utility associated with staying in the neighborhood is larger than the utility with leaving, the household will continue to stay in the neighborhood. In other words, whenever $u_j(1)$ is larger (smaller) than zero, the white household will stay (leave). Note that the utility level depends on a number of factors.

The private component h measures the private utility associated with residing in a specific neighborhood. This may be thought of as the utility obtained from a wide range of sources related to the amenities of the neighborhood. They may include population density, degree of safety, location, availability of public transport, school, parks or leisure facilities, or typical price of apartments or units. This private factor is akin to the public good in a community in the model of Tiebout (1956), which influences the consumer-voter's choice of picking a community (or neighborhood). We can think of this private component as the price of a representative property in a neighborhood which represents the average quality of accommodation. A higher price positively affects the utility of both homeowners and tenants; the former utility increases due to the potential rising expected profits from future sale while the latter benefit from the increase in perceived social class or status.

Next is the social component $J(\widetilde{m}_j^e - \frac{1}{2})$ which captures the (positive) externality engendered by the decision of other (white) households while J determines the magnitude of such an externality. Specifically, J quantifies the importance of a social norm measuring the extent to which conforming to the behavior of the majority of whites is desirable from the point of view of the single household. Indeed, the second term in the bracket, $\frac{1}{2}$, represents half of the white population in the neighborhood, meaning that each household takes into account whether the majority of whites decides to stay in ($\widetilde{m}_j^e > \frac{1}{2}$) or to leave ($\widetilde{m}_j^e < \frac{1}{2}$) the neighborhood. Thus the size of the social component in the utility function is strictly related to what most white households are doing: the larger the share of whites staying in the neighborhood, the larger the impact of the social term in each household utility. We could think of the utility arising from this social component as the support and benefits of informal networks in the local community shared by people of the same race or ethnic group.[3]

Lastly, the disutility component e_j captures all other factors which are different from those captured by h, but negatively affect the utility from staying in the neighborhood. This disutility includes the racial or ethnic composition of the household's neighborhood as outlined in Becker and Murphy (2000), and Card et al. (2008). However, one important difference in our model is that we assume the degree of racial prejudice is different from household to household, since the disutility component depends on two terms: one that is common to all households (e) and the other that is household-specific (ϵ_j).

One way of interpreting e is that it represents the degree of racial prejudice commonly shared by all whites. Yet, the full extent of disutility e_j is determined by household specific characteristics (ϵ_j) which are the result of random shocks. This suggests that at any point in time the size of the shock might induce a white household to leave the neighborhood. The random utility component, ϵ_j for *j=1, …, N* denotes i.i.d. random shocks that are drawn from a common distribution η. It can be shown that the utility function (1) can be cast into a probabilistic choice model such that:

$$P\left(\omega_j = 1 \middle| \tilde{m}_j^e\right) = \eta\left[h - e + J\left(\tilde{m}_j^e - \frac{1}{2}\right)\right]. \tag{2}$$

According to the social interactions literature (Brock and Durlauf, 2001; Blume and Durlauf, 2003), racial segregation dynamics can be introduced into model (2). Define $m_t^N = \frac{1}{N}\sum_{j=1}^{N}\omega_{j,t}$ as the proportion of white households at time *t* who stay in the neighborhood. Much like the static model, white households decide whether to leave or stay in a neighborhood at any given time *t* with the probability:

$$P\left(\omega_{j,t+\Delta t} = 1 \middle| \omega_{j,t}, m_t^N\right) = \eta\left[h - e + J\left(m_t^N - \frac{1}{2}\right)\right]. \tag{3}$$

[3] Glazer and Moynihan (1963) note that segregation may be beneficial to minority neighborhoods as it promotes the development of minority-owned businesses. Cutler and Glaeser (1997) suggest the argument is similar to arguments to protect infant-industries.

The Markovian dynamics in (3) cannot be analytically analyzed in a finite dimensional population model. However, it is possible to analyze the deterministic dynamics associated with this model asymptotically by allowing the number of households N to go to infinity. Put differently, we can describe the evolution of the fraction of white households staying in the neighborhood over time when $N \to \infty$. As in Blume and Durlauf (2003), suppose that the random utility shock ϵ_j follows a centered logistic distribution with parameter $\beta > 0$, which is able to capture well several patterns underlying several social phenomena including, amongst others, racial segregation (Anderson et al., 1992):

$$\eta(m) = P(\epsilon_j \leq m) = \frac{1}{1+e^{-2\beta m}}. \tag{4}$$

The parameter β measures the dispersion of racial prejudices in the white population; the higher the β the closer is the level of prejudices to the mean value of e_j, which is given by e. By following the same argument as Blume and Durlauf (2003) and Barucci and Tolotti (2012), it is possible to show that given the initial condition m_0 such that $\lim_{N\to\infty} m_0^N = m_0$, the sequence of processes $\{m_t^N\}_{t\geq 0}$ converges almost surely to m_t and solves the differential equation:

$$\dot{m}_t = \frac{1}{2}\tanh\left\{\beta\left[h - e + J\left(m_t - \frac{1}{2}\right)\right]\right\} - m_t + \frac{1}{2} \tag{5}$$

where $\tanh(\mathrm{x}) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ denotes the hyperbolic tangent function.

Within this framework, we can study the dynamics of m_t, which is the fraction of white households who decide to stay in the neighborhood when subject to social externalities and different degrees of racial prejudice. The differential equation (5) can be solved for its steady states depending on the underlying parameter values. It can be shown that there exists a threshold level $J^T(h,e) > 0$ for J such that: *i*) if $J \leq J^T(h,e)$, equation (5) admits a unique stable equilibrium $\overline{m}^*$; *ii*) if $J > J^T(h,e)$, equation (5) admits three equilibria; the middle one, $\overline{m}_M$, is unstable while the other two, $\overline{m}_L$ and $\overline{m}_H$, are locally stable. Since our goal in this paper is to characterize the dynamic behavior of tipping, the latter case is the most relevant for our analysis hence we restrict our discussion to this specific case. In the former case no tipping will ever occur and thus the white and black population will always coexist, which is not of interest given that our focus is on racial segregation.

The steady states of (5) are depicted in Figure 1(a), for an arbitrary choice of parameter values which permit case (*ii*) to hold. Note that the figure shows two curves: an S-shaped curve representing the first term on the right hand side (RHS) of (5), $\frac{1}{2}\tanh\left\{\beta\left[h-e+J\left(m_t-\frac{1}{2}\right)\right]\right\}$, and a straight line representing the second term on the RHS of the same equation, $m_t-\frac{1}{2}$. The equilibria are represented by the points where the two curves cross. When the vertical difference between the S-shaped curve and the straight line is positive (negative) the share of white households remaining in the neighborhood will tend to rise (fall) over time.

– Figure 1(a) and (b) about here –

The middle unstable equilibrium $\bar{m}_M$ represents the tipping point. If the initial condition is given by $m_0 < \bar{m}_M$, the share of white population staying in the neighborhood converges to its low equilibrium level $\bar{m}_L$. This suggests that the share of white households leaving the neighborhood will converge to $1-\bar{m}_L$. On the other hand, if $m_0 > \bar{m}_M$ the share of white population staying in the neighborhood will converge to its high equilibrium level, $\bar{m}_H$ and thus the share of white households leaving the neighborhood will converge to $1-\bar{m}_H$. Consequently, tipping causes a neighborhood to polarize in either direction, resulting in an almost complete segregation at equilibria, $\bar{m}_L$ or $\bar{m}_H$. We summarize our conclusion in the following proposition.

Proposition 1: *Consider a neighborhood populated by a large number of white households affected by a social externality and heterogeneous degrees of racial prejudice. When the share of white households staying in the neighborhood, m_t, evolves according to equation (5), given m_0 and $J > J^T(h,e)$, polarization to a situation of high or low share of white households in the neighborhood may occur over time as a dynamic result of tipping.*

Note that the results discussed thus far are based on the assumption that the parameters h and e are fixed parameters and they are not time-varying. However, it is possible that both h and e may vary over time which results in the three equilibria also varying. By performing a simple comparative static exercise, it is straightforward to show that the stable equilibria move in the same direction as the change in the private component h, but in the opposite direction of the change in the average degree of prejudice e. By construction, the tipping point (i.e., the unstable middle equilibrium) moves in the same direction as the change in the average degree of prejudice

e, but in the opposite direction of the change in the private component h. This is illustrated in Figure 1(b) where the light grey, dark grey and black curves represent the S-shaped curves associated with higher values of h (or lower values of e), respectively. It is straightforward to note that as a result of a rise in h or a fall in e (represented by a darker curve) the S-shaped curve changes both its position and its curvature, and as a result the tipping point shifts left. This implies that changes in the level of tipping may be caused by some exogenous factors that affect the value of h and/or e. For example, the improved sentiment towards the residence of minorities (i.e. captured by a decrease in e) or improved positive amenities (i.e. captured by an increase in h) will lead to a leftward shift in the S-shaped curve. In practical terms, this would result in an increasing share of minorities residing in the neighborhood before the remaining white households would choose to leave the neighborhood. However, these results do suggest that higher values of h and lower e will result in better integrated minority neighborhoods and ironically, predominately white neighborhoods will have fewer minorities. This leads to the following proposition about changes in the level of tipping over time.

Proposition 2: *The tipping point may change over time. Specifically, it may rise (fall) due to a fall (rise) in the private component h or a rise (fall) in the average degree of prejudice e.*

The results in Proposition 2 may appear counterintuitive in that the tipping point decreases with a rise in the private component of utility (or with a fall in the average degree of prejudice) since we would reasonably expect exactly the opposite. However, this is simply due to the fact that we are only focusing on the effects of some comparative statics on the tipping point, which represents the unstable equilibrium. However, if we analyze the impact on the other two stable equilibria, we can see that they both behave exactly as we would expect, that is the equilibrium share of white staying increases with a rise in the private component of utility (or with a fall in the average degree of prejudice). This is consistent with white households being able to outbid for higher quality neighborhoods and pushing out minority neighbors. This can be seen in Figure 1(b) by comparing the high and low equilibria associated with darker curves: as h rises (or e falls) both the low and high equilibria shift right.

Finally, note that since in our model the number of equilibria is three for the case which is of interest, there will always be two-sided tipping, suggesting that for some initial level of the share of white households staying, the share of white households in the neighborhood may end up either being the majority or the minority in equilibrium. From a historical perspective, given that racial segregation is an outcome of a large share of white households leaving a neighborhood as a result of a large influx of black households, in the empirical analysis we will only focus on and test for the presence of one-sided tipping dynamic. This is also the case that is examined by Card et al. (2008) allowing us to compare our results with theirs based on interwar data.

3. The Empirical Model

Our empirical model follows the methodology developed first by Schelling (1971) and fleshed out in Becker and Murphy (2000) as well as Card et al. (2008) so that comparison can be made between our results and previous findings. In these models, households segregate as their utility functions are directly dependent on the racial or ethnic composition of their neighborhood. Yet as discussed in Tiebout (1956) and Rosen (1974), segregation may merely be a product of sorting on exogenous location amenities, preferences for which are highly dependent on racial or ethnic characteristics.

Both Banzhaf and Walsh (2010) and Kasy (2015) indicate strategies to econometrically identify these separate effects, yet current data limitations for the interwar period for the United States does not allow us to make such a distinction. Instead, we rely on narrative evidence of the period to guide the modeling.

> An economist for the Federal Housing Administration, Homer Hoyt wrote in 1939: "*It is a mere truism to enunciate that colored people tend to live in segregated districts of American cities. As we have said [earlier], the reflection of adverse housing characteristics should tend to operate in the same manner in areas populated entirely by colored races as in areas populated only by whites. It is in the twilight zone, where members of different races live together that racial mixtures tend to have a depressing effect upon land values -- and therefore, upon rents.*"

Moreover, the existence of racial covenants in housing deeds restricting various racial, ethnic, and religious households from purchasing housing during the period is again suggestive that the white majority had a preference for living with other white households. The enforcement of these covenants would have thus been unnecessary in a model in which blacks self-segregated into neighborhoods with other blacks based on the existing amenities.

Figure 2 provides further evidence of the diffusion of blacks into the well-known black enclaves, Harlem and Bedford-Stuyvesant, between 1910 and 1940. This figure shows a marked spatial diffusion process in which black households are moving into neighborhoods which were either largely black or in which the surrounding neighborhoods already were.

– Figure 2 about here –

The historical narrative of Harlem suggests that it began life as a black enclave in the early 20th century after the advent of a local housing bubble left housing prices at below market. This allowed several black churches from lower Manhattan to begin to purchase properties and either sell or rent out to black households (Kollmann 2012). While this is suggestive that exogenous housing characteristics must be accounted for, the likelihood that the only neighborhoods experiencing intra-city falls in market prices being the only neighborhoods experiencing black in-migration is unlikely.

The premise as pointed out in our theoretical model is that whites have an aversion to residing with minorities and thus their utility from residing in a certain neighborhood is affected by the rising presence of minorities. Once the minority has achieved a certain critical mass (i.e., it has exceeded a certain share in the neighborhood), the neighborhood effectively "tips" and thus will become predominantly black. As suggested in Figure 2, Harlem and Bedford-Stuyvesant appear to be candidates that illustrate this tipping behavior. This *prima facie* evidence suggests that tipping could well have existed in some cities, including that of New York, during the interwar period.

The benchmark for our empirical analysis is the model in Card et al. (2008), who develop a local housing market in which white's willingness to pay for homes is a function of the minority share in the neighborhood. The minority share in the neighborhood will vary according to changes in the relative demand of whites and minorities but the variation is expected to be smooth as long as the minority share remains below a critical threshold level. However, when the minority share exceeds the threshold, all white households will leave. This abrupt change in the dynamic of white share beyond a certain threshold is a salient feature of tipping. The location of the threshold (i.e. tipping point) is determined by the degree of whites' preference for minority contact; the lower the preference for minority contact the lower is the threshold. Even if the argument is slightly different, the outcome is totally consistent with our theoretical model (see Propositions 1 and 2) and thus we can effectively rely on the empirical strategy in Card et al. (2008) to test our theoretical model. Indeed, Card et al. (2008) analyze the change in the share of the white population induced by minority interactions without specifically estimating bid-rent functions. We make clear below that exactly the same approach is applicable to test our model where interactions directly affect households' utility functions. Despite the empirical approach is the same as Card et al.'s (2008), our theoretical framework will play an essential role in explaining the determinants of the variety in tipping points across different cities, which we will present later.

In particular, in order to test for this tipping phenomenon, we use inter-war period (i.e. 1930-1934, 1934-1940 and 1930-1940) changes in neighborhood racial composition. Given that the tipping point is unobserved, we use two methods to identify possible city-specific tipping points. The first method relies on structural break tests and chooses the break point associated with the best-fitting model for census tract-level white population changes. The second method uses a nonparametric method that is considered to be more flexible and does not make specific assumptions about the functional form for census tract-level changes in white population shares in each city. However, unlike the methods employed by Card et al. (2008), we undertake further analysis by utilizing different weights and applying them to the data. The basis of this approach is that the six cities we examined vary significantly in terms of their population size. To the extent that the dynamics of tipping may be contingent on the size of the population, we explore both the tipping point without weighting a census tract as well as controlling for the population in the base year to underweight tracts with small populations that may be driving the results.[4]

3.1 Empirical Strategy

Given the period examined is associated with a large influx of black moving from the rural south to the north, we accommodate changes in the population of a neighborhood by expressing

[4] An alternative approach consisting of weighting the census tracts by the inverse z-score of the population was also employed to underweight both the smallest and largest census tracts. However, this approach produced very similar results to when the census tract are unweighted and are thus omitted from further discussion.

changes in the numbers of white and black residents as a fraction of the base year population. The base year is either 1930 or 1934. Following Card et al. (2008), we define $W_{ic,t}$ as the number of whites, $M_{ic,t}$ the number of minorities and $P_{ic,t} = (W_{ic,t} + M_{ic,t})$ the number of total residents of neighborhood *i* in city *c* in year *t* (=1930, 1934, 1940). The dependent variable is the change in the neighborhood's white population, taken as a share of the initial population in the base year, $DW_{ic,t} = (W_{ic,t} - W_{ic,base\ year})/P_{ic,base\ year}$. To establish the dynamic of tipping, the dependent variable is specified as:

$$DW_{ic,t} = p(\delta_{ic,base\ year}) + d\ I(\delta_{ic,base\ year} > 0) + \tau_c + \boldsymbol{X}_{ic,base\ year}\beta + \varepsilon_{ic,t} \tag{6}$$

where $\delta_{ic,base\ year} = m_{ic,base\ year} - m^*_{ic,base\ year}$, such that $m_{ic,base\ year} = \frac{M_{ic,base\ year}}{P_{ic,base\ year}}$. Here, $m^*_{ic,base\ year}$ is the tipping point or threshold. Note that τ_c is a city fixed effect and $\boldsymbol{X}_{ic,base\ year}$ is a vector of neighborhood control variables. Depending on the availability of data for the neighborhood control variables in different periods, we include the homeownership rate in base year, share of multiple dwellings in base year and the median rent in base year in the specification. $p(\delta_{ic,base\ year})$ is a smooth control fourth-order polynomial function. This specification is estimated for the following sample period: 1930-34, 1934-1940 and 1930-1940.

Before estimating equation (6), it is necessary to estimate $m^*_{ic,base\ year}$ from the data. This requires the assumption that there exists a tipping point for which $d \neq 0$. In establishing the location of the tipping point, we employ the structural break test which involves searching over the time series data of $m_{ic,t}$ for a break point satisfying certain condition. Using a simplified version of equation (6) which ignores the covariates and replacing the polynomial function $p(\cdot)$ with a constant, we estimate:

$$DW_{ic,t} = \alpha_c + d_c\ I(m_{ic,base\ year} > m^*_{ic,base\ year}) + \varepsilon_{ic,t} \tag{7}$$

for $0 \leq m_{ic,base\ year} \leq$M where M is set to 60% and the value of $m^*_{ic,base\ year}$ is determined in the [0,50%] interval based on the condition that the R^2 of (7) is maximized for each city and each period. A consistent estimate of the threshold can be obtained following this procedure as long as equation (7) is correctly specified (Hansen, 2000).

The structural break method for determining the tipping point can be unreliable when applied to small cities and it can be heavily influenced by outliers. The second method utilizes the approximation of the smoothed polynomial function for $E(Dw_{ic,t}|c, m_{ic,base\ year})$ for many different cities. To ensure that our results are not biased by city-wide trends of rising minority shares, we subtract $E(Dw_{ic,t}|c)$ from $E(Dw_{ic,t}|c, m_{ic,base\ year})$. Tipping in the second approach is defined by:

$$E\left(Dw_{ic,t}\middle|c, m_{ic,base\ year} = m^{*} - \varepsilon\right) > E\left(Dw_{ic,t}\middle|c\right) > E\left(Dw_{ic,t}\middle|c, m_{ic,base\ year} = m^{*} + \varepsilon\right) \quad (8)$$

for $\varepsilon > 0$. Here, there is a "fixed point" for the city-specific tipping point, that is at m^{*}. This is also the level of minority share at which the neighborhood white population grows at the average rate for the city. In identifying this fixed point, we need to smooth the data to obtain a continuous approximation, $R(m_{base\ year})$, to $E\left(Dw_{ic,t}\middle|c, m_{ic,base\ year}\right) - E\left(Dw_{ic,t}\middle|c\right)$. We then choose the root of this function. The steps involve first fitting $Dw_{ic,t} - E\left(Dw_{ic,t}\middle|c\right)$ to a quartic polynomial in $m_{ic,base\ year}$ for neighborhoods with $m_{ic,base\ year}$< 60% which yields $R(m_{base\ year})$. Using a root of this polynomial, m', we exclude all neighborhoods with $abs(m_{ic,base\ year} - m') > 10$ before fitting a second quartic polynomial to the remaining sample. The "fixed point", m^{*}, is the root of this second polynomial. For the purpose of consistency with the first method, we only consider minority shares below 50% as fixed points. When multiple roots are present in this range, we choose the one at which the slope of $R(m)$, is most negative.

Our results suggest that the use of weights in determining the threshold is important for some cities. There is significant variation in the threshold with and without the use of weights. Weighting the data by population size gives rise to an increase (decrease) in the threshold for cities such as Washington, DC and New York (Boston and Louisville).

We undertake further robustness analysis by focusing on census tract samples which have the share of non-white lesser than 60%. The intuition is that city specific analysis involving tracts with a high proportion of non-white is prone to overestimate the threshold. Our results indicate that, by and large, the tipping point is robust to the inclusion of tracts that contain a high share of non-white (i.e. greater than 60%). These results are not reported here for brevity, but are available from the authors upon request.

3.2 Statistical Inference

Inference under the null of no discontinuity (i.e. d=0) is not straightforward in the threshold regressions (6) and (7). At the point of structural break, the estimate of d has a non-standard distribution. This arises from the specification search bias (Leamer, 1978), that is conventional test statistics have a tendency to reject the null hypothesis of d=0 given that the same data are used both for the identification of the location of a structural break and for estimating the magnitude of the break. Inference in threshold models usually relies on simulating the distribution of the $\hat{d}$ estimate under the null and the test statistic is compared to the simulated critical values at the appropriate significance level to determine whether the null fails to be rejected (Andrews, 1993 and Hansen, 2000). This method is cumbersome. Card et al. (2008) use a different approach for statistical inference of the null of no discontinuity following the method of Angrist et al. (1999). They use a randomly selected subset of their sample for the search of a structural break point followed by the use of the remaining subsample for other analyses. Given that the two subsamples are independent, estimates of $\hat{d}$ from the second sample have a standard distribution under the null hypothesis that permits the use of conventional tests. Our smaller sample does not permit the adoption of the Card et al. (2008) split-sample procedure for inference.

For the purpose of inference we employ the method proposed by Gonzalo and Pitarakis (2002) which does not require any simulations but view the problem as one of model selection. The problem of detecting the presence of threshold effects is perceived as a model selection problem among two competing models given by the linear specification:

$$DW_{ic,t} = \tau_c + \boldsymbol{X}_{ic,base\ year}\beta + \varepsilon_{ic,t} \tag{9}$$

versus its threshold counterpart given by equation (6). The decision rule is based on the theoretic criterion $IC_T(\gamma) = lnS_T(\gamma) + \frac{m}{T}$ where $\frac{1}{T}$ is the reciprocal of the sample size that is in turn multiplied by the number of parameters, m. Here, S_T is the residual sum of squares. Intuitively, an increase in m arising from the threshold nonlinearity will lead to a reduction in $S_T(\gamma)$ but this reduction is penalized by the $\frac{m}{T}$ term due to the resulting increase in the number of estimated parameters. The optimal model is then selected as the model that leads to the smallest value of the IC criterion. In other words, the linear specification (9) is preferred if $IC_T < \min_{\gamma \in T} IC_T(\gamma)$, and opt for the threshold model otherwise. In their Monte Carlo experiments, Gonzalo and Pitarakis (2002) demonstrate that amongst the three types of widely used model selection criteria, namely AIC, HQ and the BIC, the best performance is displayed by the BIC in that it does not lead to spurious parsimonious choices even for finite sample sizes. For the purpose of inference, we use the BIC to determine the adequacy of the threshold model.

4. Data and Descriptive Statistics

The primary data comes from various 1934 Real Property Inventories for seven cities: Boston, Chicago, Cleveland, Louisville, New York, Philadelphia, and Washington, DC.[5] This dataset contains census-tract level information detailing the condition of residential structures, racial and demographic distribution of the population, contract rents, and property values for a subset of cities. This data is then matched to the census-tract level data from both the 1930 and 1940 United States Census available from the National Historical Geographic Information System (Minnesota Population Center, 2011). Descriptions of the variables available are found in Table 1.

– Tables 1 and 2 about here –

Table 2 describes the racial composition of black and white households in 1934 by city. To minimize the distortion of the small tracts on the outskirts of the city, we have weighted the means by the tract-level population in 1934. We see substantial differences in the racial composition across cities, Louisville and Washington, DC having the largest average shares of blacks at 15.85 and 25.07 percent in a census tract, respectively. Interestingly, these two cities had the largest share of growth in white households as a share of the total population in 1934. The growth in Washington, DC is obvious due to the substantial expansion of the federal government via the creation of various New Deal programs during the Great Depression.

Blacks were also moving into the cities in our sample, but much more modestly than whites at this time. New York is an interesting case. It had established black enclaves during the period, yet the overall black population was small. However, Table 2 suggests strong growth,

[5] Data from Chicago was obtained via the National Historical Geographic Information System (NHGIS) as it was part of a special Census taken in 1934.

tracts on average saw 2.5 percent growth of blacks from 1934-40 as a share of the total 1934 population. Washington, DC saw the strongest growth among the sample of cities. Similar to the growth of the white population in DC, it is likely a reflection of the strong employment growth of the government sector around the nation's capital.

Yet before we explore the dynamic tipping model discussed above, it is a useful exercise to explore whether we see evidence of tipping in the summary statistics. Table 3 breaks down the growth in the white population from 1934-40 as a share of the total population in 1934 by the distribution of share of blacks in a tract in 1934. The summary statistics are again weighted by 1934 population in order to minimize the effects of small tracts distorting the means.

– Tables 3 about here –

What we see from the summary statistics is evidence that as the share of blacks in a census tract increases, there is a clear trend towards a reduction in the growth rate of whites from 1934 to 1940. Moreover, the growth rate becomes negative once a census tract has become at least 20 percent black. While the results are not as stark as those in the 1970s through 1990s presented in Card et al. (2008), they reflect evidence that there are disincentives for whites living in increasingly black neighborhoods.

5. Empirical Results

5.1 Tipping Point Estimates

The results for the estimates of the tipping points for each city using the structural break method are found in Figure 3. This figure includes several scatter plots where we plot the share of the black population from 1934 on the x-axis with the percent change in the white population from 1934 through 1940 on the y-axis. The vertical red line indicates the estimated tipping point constructed from the full sample of census tracts as found in Table 4. As we can see from the results, the tipping points for Louisville, Boston, New York, and Philadelphia are under four percent. In particular, the estimates for Philadelphia at 0.1 percent suggest that the preferences for segregation are extreme as compared to the other cities in the sample.

– Figure 3 about here –

On the other end of the spectrum we have Washington, DC and Chicago with predicted tipping points of 10.1 percent and 23.3 percent respectively. In the case of Washington, DC, this should be expected given that the physical composition of the city during the period resulted in many African Americans living in the alleyways behind housing that was reserved for white families. However, the results for Chicago are striking given that Chicago more recently has had severe conflicts of segregation in the southern portion of the city.

Yet these estimates of tipping points appear to be sensitive to the specification for Boston and Chicago. If we again estimate the tipping points, but restrict the sample to only tracts with a share of less than 60 percent black, the estimated tipping point for Boston in the 1934-40 period (Table 4) rises from 0.6 percent to 50 percent. Chicago estimates fall from 23.9 percent to 0.2 percent. Yet the estimates for the other cities as well as the other time frames found in Table 4 and Table 6 remain largely consistent.

– Tables 4 to 6 about here –

The remaining estimates for the cities have been estimated to be quite small and in the case of restricted specification, under one percent for Chicago and Philadelphia. The results from the tipping points, however, are smaller than those that are found in Card et al. (2008) which typically found estimates of tipping points to be between 5 and 20 percent. While it is plausible and likely that racial attitudes have improved from the 1930s through to the 1990s leading to an increase in the tipping points (see Proposition 2), the methodology currently employed in this paper as well as Card et al. (2008) suggest that households in a census tract are making decisions to remain or move into a neighborhood completely independent of what is occurring in the surrounding census tracts. Given that a census tract is at best an imperfect definition of a neighborhood, it is plausible that white households begin moving out of a tract once surrounding neighborhoods reach a particular threshold. This could lead to an underestimate of the true tipping point. Such a caveat is left for future research to address.

5.2 Model Estimates

Table 7 presents the estimation results of Equation 6 in which we regress the change in the share of the white population as a share of the base year population on an indicator variable describing whether a tract is above the estimated tipping point, a quartic polynomial of the difference between the share of blacks in a tract and the tipping point, a set of neighborhood control variables and city fixed effects.

– Table 7 about here –

Our main coefficient of interest is “Beyond Tipping Point”. As we can see across the two different weighting schemes, the models suggest substantially different effects of a tract being beyond the estimated tipping point. For example, from 1930-34, the unweighted model suggests that tracts above the tipping point experience a fall of 38.6 percent of the white population as a share of the 1930 total population. Yet if we weight the data by the 1930 population, this decrease is estimated to be only 6.92 percent. It becomes quickly evident when viewing the unweighted summary statistics that these results are being driven by small tracts on the outskirts of the cities in the sample, primarily New York. Yet it would be incorrect to omit these tracts as they suggest an interesting dynamic between tracts on the outskirts of the city and those within the heart. These results suggest that white households living in underdeveloped portions of the city are much more likely to leave a tract in the presence of blacks than those living elsewhere.

Referring to the control covariates of population density, homeownership rate in base year and the median rent in base year, which are all statistically significant at some conventional levels of significance, we can infer that the sign of their coefficients is largely consistent with the predictions of the theoretical model. These estimates predict the adjustments of the (stable) equilibrium share of whites when there are changes in the preference for positive location or neighborhood characteristics (h) and/or preference for living with neighbors of a different race as determined by the level of household’s prejudice (e). Population density in base year measures the neighborhood characteristics and to the extent that population density is higher, the lower is the utility of staying in the neighborhood by a white household (i.e. h is lower) and the bigger is the fall in the share of white population as a share of base year total population. This prediction is correctly depicted by the negative coefficient in all regressions for different data period. Homeownership rate in base year refers to the percentage of homes owned by black households. It can be used as a proxy for the presence of a different racial household living in the neighborhood. The higher the homeownership rate, the higher is the level of e which is associated with the level of prejudice towards a different race living in the neighborhood, and the lower is the utility thus leading to a fall in the share of white population. This prediction is depicted by the negative sign of the coefficient of homeownership rate. Finally, the effect of a rising median rent on the share of white population can be interpreted in two ways. If the increase in median rent is driven by an influx of black households then the increase in median rent is deemed to represent a strong presence of different racial/ethnic group in the neighborhood, which will reduce the share of white population. This is a possible explanation for the observed negative sign for the unweighted regression for 1934-40 data period. On the other hand, if rising median rent was caused by an increase in the underlying value of housing property in the neighborhood, then this is viewed as a positive location characteristic that will increase the share of white population, in which case this view supports the observed positive sign of the median rent coefficient for the population weighted regression.

– Figure 4 about here –

Figure 4 plots the coefficient estimates from the “beyond the candidate tipping point” as well as the quartic polynomial coefficients in the 1930-40 specification found in Table 6. The x-axis is the share of blacks in a tract while the y-axis plots the percent change in the white population from 1930 to 1940. The figure is shown assuming a hypothetical tipping point of 10 percent.

The results are again interesting as they show the substantially different response found in the unweighted and weighted coefficient estimates. We see in the unweighted results, a large increase in the white population before the tipping point, yet a large decline after the threshold. This is contrasted to the results where we weight for the population. This suggests that while the white population growth shows a decline after the candidate tipping point, whites are still moving into these neighborhoods, albeit at a reduced rate.

6. Conclusion

This paper contributes to the literature on racial segregation both from a theoretical and an empirical point of view. We use a random utility approach to model the dynamic of racial segregation as a result of household’s preferences for location characteristics and towards the races of neighbors. The decision to reside in a particular neighborhood hinges on social interactions, and therefore there is plenty of room for discriminatory beliefs and preferences to play a role. An important prediction of the model is that as a result of a whole set of social attitudes and other preferences that are directly linked to the neighborhood attributes, there exists a critical threshold for the minority share in a neighborhood beyond which a specific race of households will leave. This threshold level is known as the tipping point.

Using a regression discontinuity approach, we test for tipping in the racial composition of Census tracts in seven U.S. cities for interwar data from 1930 to 1940. We find the level of tipping point across the seven cities shows significant variation; Philadelphia exhibits the strongest preferences for segregation given its lowest estimate at 0.1%. The low level of tipping estimates compared with the higher estimates based on 1970-2000 Census tracts data reported by Card et al. (2008) suggest that racial attitudes have improved from the 1930s through to the 1990s.[6] We also find evidence suggesting that white households living in underdeveloped portions of the city are prone to leaving a tract in the presence of blacks than those living elsewhere. There is also empirical evidence supporting the predictions of the theoretical model that both location characteristics and social prejudice are determinants of a household's decision to remain or leave a neighborhood.

One possible extension of the theoretical and empirical models is to incorporate the notion that households may choose to move in or out of a census tract based not only on the composition of the tract, but those surrounding it. It is clear from Figure 1 that there is an element of spatial diffusion occurring as we can visually see blacks moving into census tracts near those that are already primarily black. Failure to capture this effect is likely to underestimate the tipping points. While this is not suggesting that we suspect white households to be more tolerant, it is more of a reflection that a census tract is not fully capturing the definition of a neighborhood. This issue is outside of the scope of this paper and is best left for future research.

References

Anderson, S., De Palma, A., Thisse, J.-F. (1992). Discrete choice theory of product differentiation (Cambridge: MIT Press)

Andrews, Donald W.K. (1993). "Test for Parameter Instability and Structural Change with Unknown Change Point", *Econometrica*, 61, 821-856.

[6] Improvement in racial attitudes has manifested in whites becoming more tolerant and accepting of non-whites.

Angrist, Joshua D., Guido Imbens, and Alan B. Krueger (1999). "Jackknife Instrumental Variables Estimation", *Journal of Applied Econometrics*. 14: 57-67.

Banzhaf, Spencer H. and Randall P. Walsh (2010). "Segregation and Tiebout Sorting: Investigating the Link between Investments in Public Goods and Neighborhood Tipping." NBER Working Paper 16057.

Barucci, Emilio and Marco Tolotti (2012). "Social interaction and conformism in a random utility model", *Journal of Economics Dynamics & Control*, 36, 1855-1866

Becker, Gary S. and Kevin M. Murphy (2000). *Social Economics: Market Behavior in a Social Environment*. Harvard University Press.

Blume, Lawrence and Steven Durlauf (2003). "Equilibrium concepts for social interaction models", *International Game Theory Review* 5, 193-209

Brock, William and Steven Durlauf (2001). "Discrete choice with social interactions", *Review of Economic Studies* 68, 235-260

Brooks, Richard R.W. (2011). "Covenants without Courts: Enforcing Residential Segregation with Legally Unenforceable Agreements." *American Economic Review*. 101(3): 360-365.

Card, David, Alexandre Mas, and Jesse Rothstein (2008). "Tipping and the Dynamics of Segregation." *Quarterly Journal of Economics*. 123(1): 177-218.

Collins, William J. (1997). "When the tide turned: Immigration and the Delay of the Great Black Migration." *Journal of Economic History*. 57(3): 607-632.

Cutler, David and Edward L. Glaeser (1997). "Are Ghettos Good or Bad?" *Quarterly Journal of Economics*. 112(3): 827-872.

Glazer, N., and D. Moynihan (1963). *Beyond the Melting Pot*. MIT Press.

Gonzalo, Jesús and Jean-Yves Pitarakis (2002). "Estimation and Model Selection Based Inference in Single and Multiple Threshold Models", *Journal of Econometrics*. 110: 319-352.

Grauwin, Sebastian, Florence Goffette-Nagot, and Pablo Jensen (2012). "Dynamic models of residential segregation: An analytical solution." *Journal of Public Economics*, 96(1): 124-141.

Hansen, Bruce (2000). "Sample Splitting and Threshold Estimation." *Econometrica*. 68(2): 575-603.

Heal, Geoffrey and Howard Kunreuther (2010). "Social reinforcement: cascades, entrapment, and tipping." *American Economic Journal: Microeconomics*, 2(1): 86-99.

Hoyt, Homer (1939). *The Structure and Growth of Residential Neighborhoods in American Cities*. Washington, DC: Federal Housing Administration.

Kasy, Maximilian (2015). "Identification in a model of sorting with social externalities and the causes of urban segregation." *Journal of Urban Economics*. 85(1): 16-33.

Leamer, Edward. *Specification Searches: Ad Hoc Inference with Non Experimental Data* (New York: Wiley, 1978).

Massey, Douglas and Nancy Denton (1988). "The Dimensions of Residential Segregation." *Social Forces*. 67(2): 281-315.

Massey, Douglas (2001). "Residential Segregation and Neighborhood Conditions in US Metropolitan Areas." In *America Becoming: Racial Trends and their Consequences*, Volume 1. Editors Smelser, Neil J, William Wilson and Faith Mitchell. Washington, DC: National Academy Press.

Minnesota Population Center. *National Historical Geographic Information System: Version 2.0*. Minneapolis, MN: University of Minnesota 2011.

Rosen, Sherwin. (1974). "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy*. 82:34-55.

Schelling, Thomas C. (1971). "Dynamic Models of Segregation." *Journal of Mathematical Sociology*. 1(2): 143-186.

Tiebout, Charles (1956). "A Pure Theory of Local Expenditures." *Journal of Political Economy*. 64: 416-424.

Figure 1a Steady states of m_t – the fraction of white households staying in a neighborhood

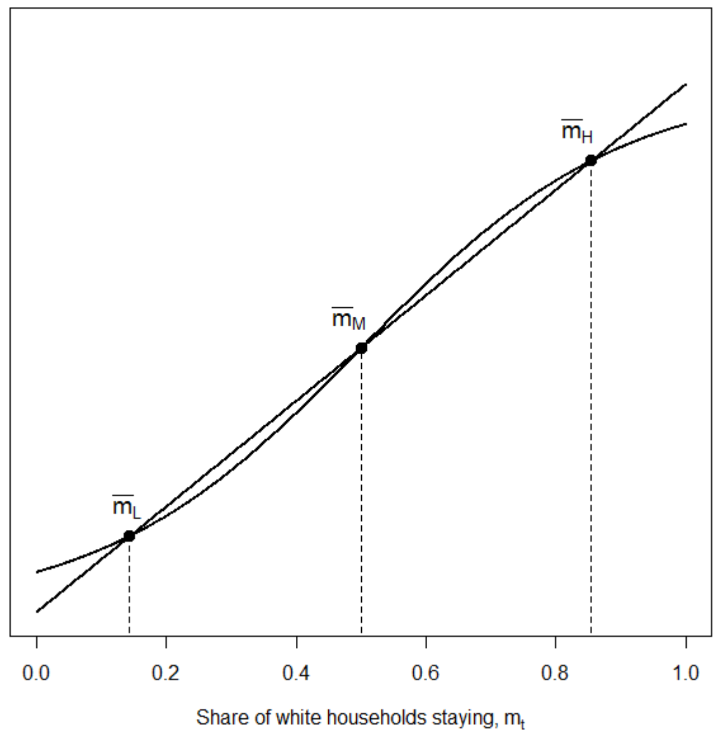


Figure 1b Variation in the tipping point as result of variation in *h* and *e*

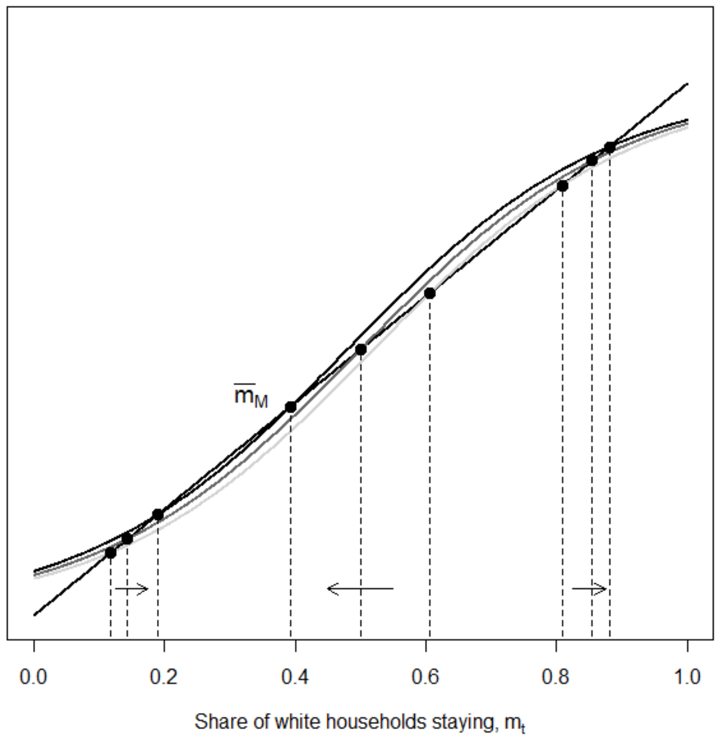
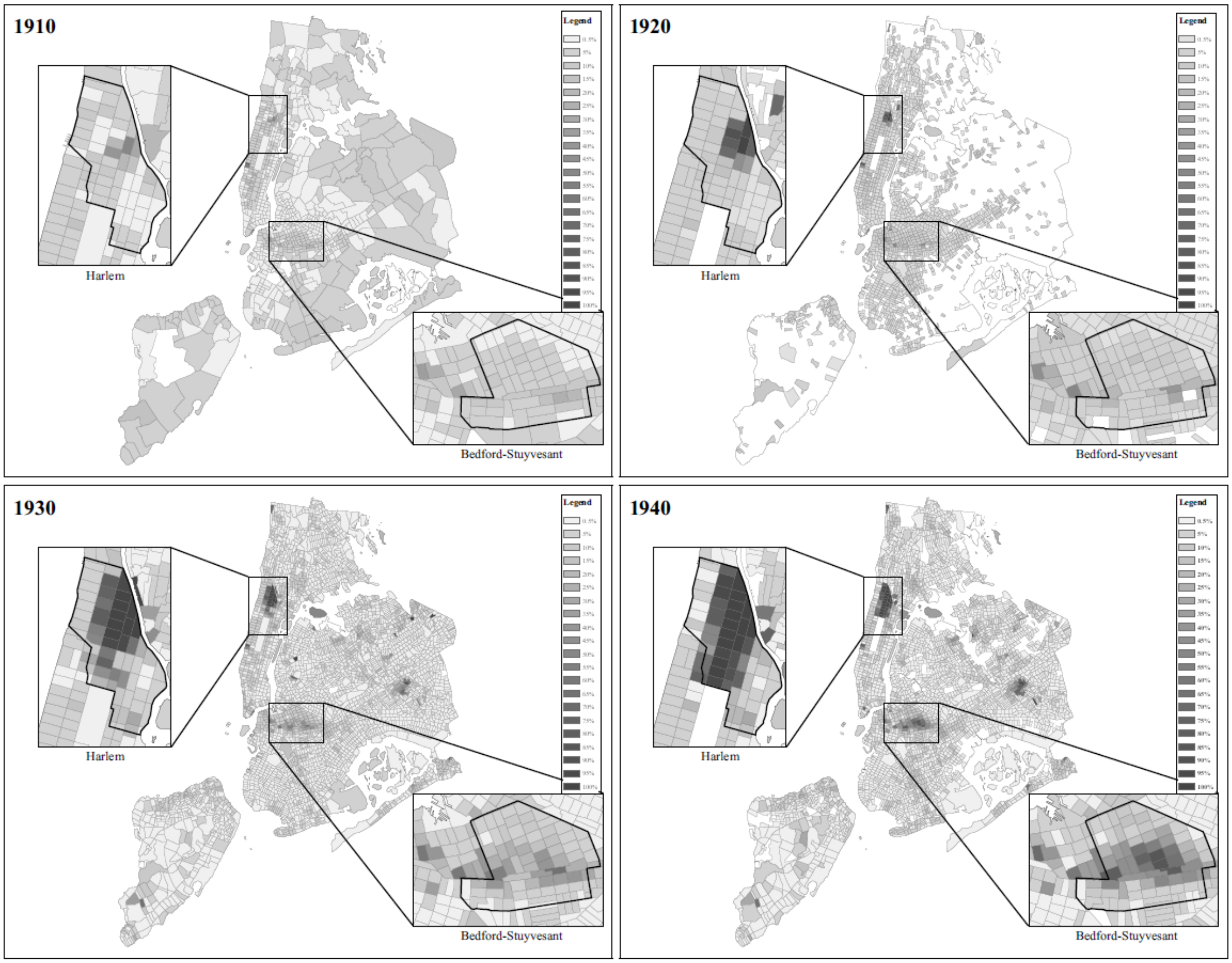


Figure 2 Share of Non-White Population in New York by Census Tract



Note: The darker shaded areas refer to the share black in a census tract.

Source: NHGIS

Figure 3 Scatterplot of black population versus the percent change in white population from 1934-40 by city.

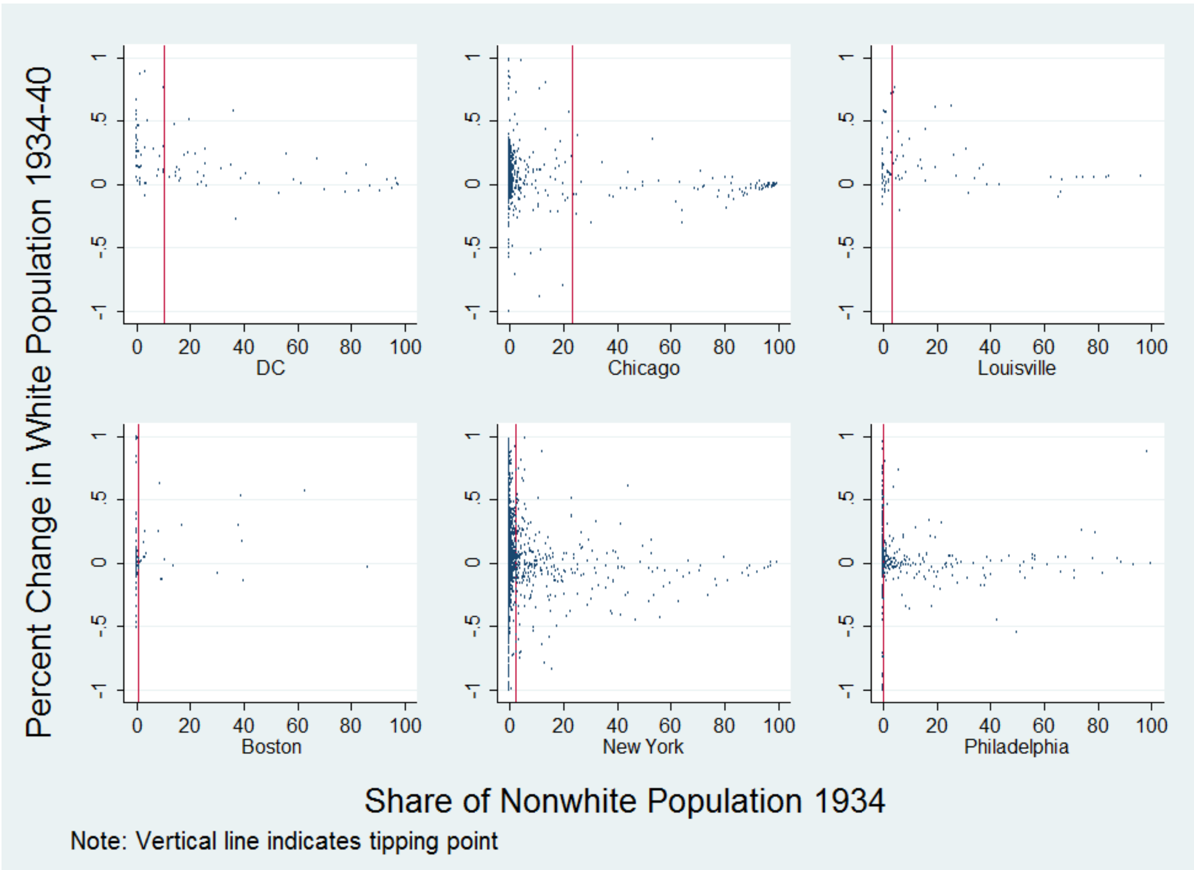


Figure 4

Note: Graph constructed from coefficient estimates found in Table 6 from the 1930-40 specifications. This graph assumes a hypothetical tipping point of 10 percent.

Table 1 Variable Definitions

Variable	**Definition**
Share Black	In 1934, Share of families that are non-white in a census tract. Family generally follows the 1930 US Census definition: “a group of persons, related by either blood or by marriage or adoption, who live together as one household.” The 1930 and 1940 definition is the share of non-white people residing in a census tract.
Median Contract Rent	Median contract rents per month for rental-occupied dwellings within a census tract
Homeownership Rate	Ratio of owner-occupied to occupied dwellings in a census tract.
Share of Multifamily Units	Share of occupied dwellings in structures exceeding three dwellings per structure or two dwellings per structure in Louisville or New York City
Population Density	Total population in thousands residing in a census tract per square mile.

Table 2 **Weighted Summary Statistics by City**

Means	Share Black 34	$\Delta White_{34-40}$	$\Delta \text{Black}_{34-40}$	N
Boston	2.75	0.051	0.0073	127
Chicago	7.78	0.034	0.0088	916
Louisville	15.85	0.12	0.0079	89
New York	4.44	0.057	0.025	2862
Philadelphia	11.46	0.023	0.022	396
Washington DC	25.07	0.21	0.13	95

Note: $\Delta White_{34-40}$ indicates the change in the white population from 1934-40 as a share of the total population in 1934. Summary statistics weighted by 1934 tract-level population.

Table 3 **Percent change in white population 1934-40 from total population in 1934 over the distribution of share black in 1934.**

Share Black in 1934	Mean (Pct Change White Pop 34-40)	SD	N
0-1	0.069	0.76	3462
1-5	0.044	0.31	433
5-10	0.032	0.34	146
10-20	0.020	0.39	134
20-30	-0.011	0.18	70
30-40	-0.025	0.21	47
40-50	-0.087	0.19	28
50-100	-0.018	0.24	165

Note: Summary statistics weighted by 1934 population.

Table 4 Estimates of Tipping Points (1930-34)

	Full Sample		Share Black < 60	
	Unweighted	**Population**	**Unweighted**	**Population**
Boston	0.5	0.5	0.5	0.5
Chicago	0.1	0.4	2.7	0.4
Louisville	---	---	---	---
New York	0.1	0.9	0.1	0.9
Philadelphia	---	---	---	---
Washington DC	4.3	4.3	4.3	4.3

Note: Estimation of Tipping Point constructed using the Structural Break Method

Table 5 Estimates of Tipping Points (1934-40)

	Full Sample		Share Black < 60	
	Unweighted	**Population**	**Unweighted**	**Population**
Boston	5.8	0.6	5.8	50
Chicago	23.9	23.9	13	0.2
Louisville	43.5	3.1	3.1	3.1
New York	0.1	2.4	0.1	2.4
Philadelphia	0.1	0.1	0.1	0.1
Washington DC	7.9	10.1	7.9	10.1

Note: Estimation of Tipping Point constructed using the Structural Break Method

Table 6 Estimates of Tipping Points (1930-40)

	Full Sample		Share Black < 60	
	Unweighted	**Population**	**Unweighted**	**Population**
Boston	0.6	0.6	0.6	0.6
Chicago	1.1	2.7	1.1	2.7
Louisville	---	---	---	---
New York	0.1	1.5	0.1	1.5
Philadelphia	---	---	---	---
Washington DC	15.4	15.4	15.4	15.4

Note: Estimation of Tipping Point constructed using the Structural Break Method

Table 7 Results for the Change in Share of White Population as a share of base year total population

	1930-34		1934-40		1930-40	
	Unweight b/(se)	Pop Weight b/(se)	Unweight b/(se)	Pop Weight b/(se)	Unweight b/(se)	Pop Weight b/(se)
Beyond Tipping Point	-0.386***	-0.0692***	-0.888**	-0.00909	-1.619	-0.0786
	(0.0794)	(0.00979)	(0.356)	(0.0272)	(0.429)	(0.0304
Difference in Share	0.0106	-0.00659***	-0.00252	-0.00366	0.0429	-0.00778
Nonwhite and Tipping Point	(0.0206)	(0.00256)	(0.0402)	(0.0024)	(0.0799)	(0.00365)
Difference Squared	-0.000391	0.000448***	-0.000284	-0.0000339	-0.0018	0.000285
	(0.00129)	(0.000148)	(0.00218)	(0.0000392)	(0.00494)	(0.000204)
Difference Cubed	0.00000469	-0.00000836***	0.00000494	0.00000155*	0.0000292	-0.00000498
	(0.0000241)	(0.00000265)	(0.0000497)	(0.000000915)	(0.0000971)	(0.00000408)
Difference 4th	-1.20E-08	4.76e-08***	-9.00E-09	-8.66E-09	-0.000000139	3.14E-08
	(0.000000136)	(1.45E-08)	(0.00000034)	(8.55E-09)	(0.000000569)	(2.44E-08)
Population Density 000s	-0.00372***	-0.000826***	-0.0198***	-0.00141***	-0.0151***	-0.00157***
per Sq Mi in Base Year	(0.000793)	(0.0000649)	(0.00492)	(0.000273)	(0.00468)	(0.000164)
Homeownership Rate			-0.0365***	-0.00115*		
in Base Year			(0.00733)	(0.000684)		
Share of Multi-Fam			-0.0159*	0.000327		
Dwellings in Base Year			(0.00864)	(0.00056)		
Median Rent in Base Year			-0.0131*	0.00282***		
			(0.00796)	(0.000628)		
Constant	0.21	-0.00112	2.803***	0.19	1.24	0.0873
	(0.167)	(0.0132)	(0.859)	(0.175)	(0.986)	(0.034)
City Fixed Effects	Included	Included	Included	Included	Included	Included

Note: Tipping points estimated using tracts where the share of non-white families < 60%. Regressions are run on full sample. The dependent variable is the change in share of white population as a share of based year total population.