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SEGREGATION, SPILLOVERS, AND THE LOCUS OF RACIAL CHANGE

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Segregation, Spillovers, and the Locus of Racial Change
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ABSTRACT

We use a discrete choice framework to provide the first nesting of Thomas C. Schelling's canonical models of racial segregation amenable to empirical examination. Using U.S. Census data from 1970–2000, we demonstrate a central role for spatial racial spillovers in shaping racial clustering, patterns of racial shares and housing prices at the boundary of racial clusters, and the locus of racial change. Our results on the locus of racial change conflict strongly with prominent prior results on racial tipping. Our theory provides a foundation for spatially stratified regressions. The strongest spatial effects in the prior work are not tipping, but the distinct biased White suburbanization. Tipping effects in urban areas remote from Minority clusters are small or insignificant. In urban areas proximate to Minority clusters they average less than half those reported in prior pooled results. Policies promoting racial integration must thus attend to the heterogeneous fragility of neighborhoods.

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1 Introduction

Racial residential segregation is a stubborn feature of American cities. Collective action, government intervention, and White flight all contributed to its rise (Boustan, 2010; Cutler et al., 1999; Rothstein, 2017; Shertzer and Walsh, 2019). While segregation began to decline in the aftermath of the landmark 1968 Fair Housing Act (Glaeser and Vigdor, 2012), discrimination in housing has not disappeared (Christensen and Timmins, 2022, 2023) and segregation persists at high levels (Logan and Stults, 2021).[1]

This racial division of our cities comes at a high social cost. Research underscores the extent to which the neighborhoods we live in shape our life opportunities (Chyn and Katz, 2021). Randomized studies through the Moving to Opportunity program provide credible causal evidence of these effects (Chetty et al., 2016) and may be thought of as zero-measure experiments in which the direction of causality runs from neighborhoods to outcomes for residents. Quasi-experiments extend and validate these results (Chetty and Hendren, 2018).

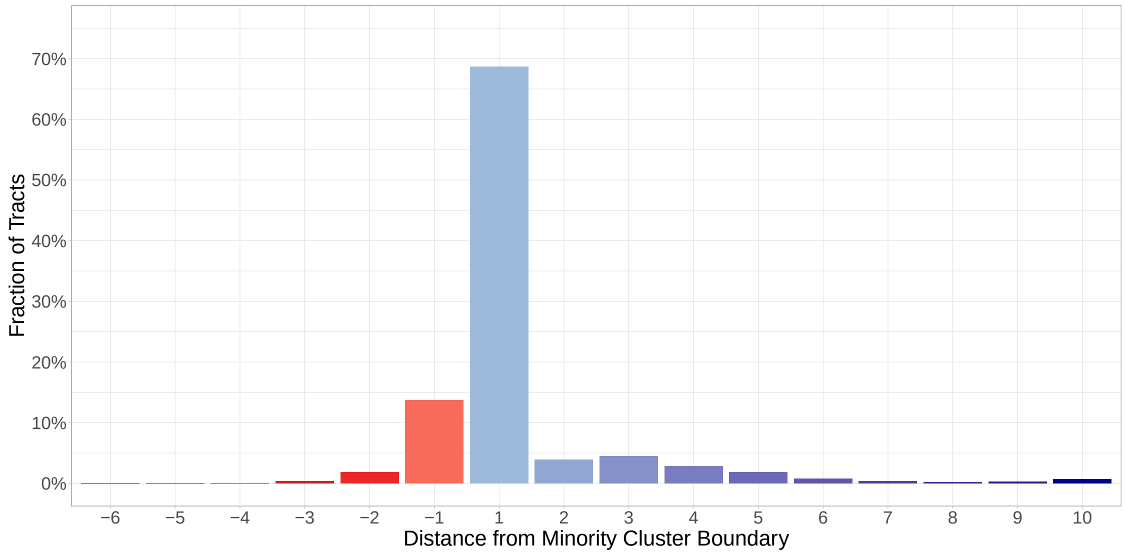
Recent research reveals the specific role of neighborhoods' racial composition. Chyn et al. (2025) provide causal evidence from the Gautreaux program that the racial mix where Black children grow up affects a surprisingly large array of long-run outcomes. These include income and wealth, but also marriage rates, the likelihood of a White marriage partner, and residential choices that may in turn affect the inter-generational transmission of poverty.

The salience of the racial composition of neighborhoods for life outcomes brings to the fore the question of how this composition is determined. If we are to contemplate policy at scale that directly targets neighborhood racial composition, it will also be critical to understand the determinants of neighborhood racial change, especially *drastic change*. The history of White flight in response to inflows of Minorities implies that endogenous responses could entirely undo the racial integration that is the proximate target of policy (Bayer et al., 2024; Boustan, 2010; Derenoncourt, 2022).

The primary empirical approaches in economics to analyzing neighborhood racial change link that change solely to a location's own characteristics. They have no explicit racial links across locations, hence provide no theoretical foundation for predicting the *locus* of neighborhood racial change relative to existing racial clusters. The most prominent study in this genre, Card et al. (2008a), nonetheless does investigate racial tipping in spatially

[1] This is particularly true for the Black-White dissimilarity index, where fifteen of the fifty cities with the largest black populations, including *inter alia* New York, Chicago, Boston, and Philadelphia, remain in the range that Massey and Denton (1988) characterize as a high level of segregation more than a half century after the Fair Housing Act (Logan and Stults, 2021).

Figure I:
Locus of 25 p.p. Decline in White Share, Connected Tracts, All MSAs 1970-1980



The histogram shows for all MSAs in 1970-1980 the frequency of declines of the White share in Census tracts by 25 p.p. or more by location relative to the boundary of racial clusters. Since such drastic change may sprawl from the boundary of the clusters contiguously across more than one tract, location 1 here aggregates such connected changes in initially White mode tracts. More detail appears in Figure VI.

stratified regressions. They conclude that, if anything, tipping is strongest *far* from existing Minority clusters.[2]

We arrive at the opposite conclusion, with Figure I providing the evidence. There we define "drastic racial change" as a decline in a Census tract's White share of 25 p.p. or more in a single decade. The x-axis orders locations according to their distance in units of tracts from the boundary of racial clusters, with negative numbers inside Minority clusters and positive numbers inside White clusters. Location -1 is a Minority mode tract exactly at the boundary with a White cluster. We have aggregated to location 1 here all White mode tracts connected to the racial cluster boundary through an unbroken chain of tracts experiencing a 25 p.p. or more decline in the White share in that decade.

Figure I has a simple, but powerful message. Across all MSAs from 1970-1980, roughly 80% of all drastic declines in the White share are exactly at the boundary of racial clusters or

[2]Card et al. (2008a) (p. 205) write that "Taken together, these results are not consistent with the predictions of the expanding ghetto model. Tipping effects are, if anything, strongest far from the existing ghetto." They cite Möbius and Rosenblat (2001) as representative of the "expanding ghetto model." However, the latter's approach is built on Schelling's spatial proximity model, which we take as the key underlying theoretical foundation. Here we follow Card et al. (2008a) in defining "Whites" as White Non-Hispanics and "Minorities" as the complement.

connected to them by an unbroken spatial chain of such drastic declines. Results for the 1980s and 1990s confirm this pattern.

The extreme concentration of drastic declines in the White share right at the boundary of racial clusters in Figure I stands in strong tension with the results reported by Card et al. (2008a). It cannot be understood within the framework that dominates empirical work in economics, which omits racial spatial spillovers across neighborhoods. In this paper we seek to deepen this critique and then to revisit and reconceptualize highly influential results in the segregation and tipping literatures.

We start with fundamental questions regarding racial segregation in American cities, ones critical to understanding the consequences of policy interventions. What determines patterns of segregation in the cross-section? What role is played by racial clusters? How shall we measure the importance of such clusters? What theory helps us to make sense of these features? What determines the *locus* of neighborhood racial change? Are features of an individual neighborhood alone sufficient to predict its racial evolution? Or do we need to know its location relative to existing racial clusters? How important is the phenomenon of *tipping* in understanding drastic neighborhood racial change? Are these the same thing or different phenomena?[3] Are we measuring the magnitudes and location of tipping appropriately?

Our research proceeds in three steps. Step one shows how to nest Schelling's (1971) bounded neighborhood and spatial proximity models within a discrete choice framework that builds on Bayer et al. (2007). The key link between the models is the absence (bounded neighborhood) or presence (spatial proximity) of racial spillovers *across* neighborhoods. We then simulate the model to identify four fundamental contrasts in predictions about the racial composition of neighborhoods in the cross-section and their dynamics. These concern the salience of racial clusters, the locus of racial neighborhood change, and the behavior of Minority shares and housing prices at the boundary of racial clusters.

Step two is to take these contrasting predictions to the data for over 100 American MSAs in the period 1970-2000. The results strongly endorse the predictions of the spatial proximity model over those of the bounded neighborhood model. This matters because virtually all empirical work in economics takes some variant of the bounded neighborhood model as its foundation. Our conclusion is supported by the degree of racial clustering and patterns of racial shares and housing prices near the boundaries of these clusters. As observed in

[3] This ambiguity about the distinction between drastic racial change and tipping is evident in the Nobel citation of Schelling's work. See Aumann and Schelling (2005), p. 11. Drastic racial change should be the primary phenomenon of interest, with tipping one approach to understanding it, focused on bifurcations at a specific neighborhood Minority share.

Figure I, the strongest contrast with prior empirical work concerns the locus of drastic racial change.

Step three reconciles these conflicting views on the locus of racial change. We re-examine the powerful visual evidence of tipping in Chicago 1970-1980 presented by Card et al. (2008a) in Figure 1 of their paper and use the insights from this to motivate our examination of the data for all MSAs and periods in our data. Two results are key. The first is that the headline results of Card et al. (2008a) conflate two quite distinct social processes. In urban areas, there is massive White *exit* and this might properly be thought of as tipping. In suburban areas, there is massive White *entry* and so it is simply not tipping. One cannot just pool these distinct processes and declare that they jointly measure tipping. The resulting second key insight, then, is that the focus must be on spatially stratified regressions. In urban areas remote from existing Minority clusters, tipping effects are zero or negligible. In urban areas close to the boundary of racial clusters, tipping effects are measurable but far smaller than the headline pooled results previously reported. This contrast *within* the urban areas is exactly as one would expect based on the spatial proximity but not bounded neighborhood models. Rather than measuring tipping, the suburban results reveal large impacts on what we term "biased White suburbanization," i.e. White entry that avoids existing Minority areas. These changes in suburban areas nonetheless have zero or negligible effects on racial *composition* in any period.

Our results thus contribute to an understanding of segregation, neighborhood racial spillovers, tipping, and drastic racial change. We provide the first nesting of Schelling's (1971) bounded neighborhood and spatial proximity models in a form amenable to empirical examination. We show how to measure the importance of racial clusters, how to use these as a way to visualize the data and to formulate contrasting empirical implications of the models. We use a rich data set to show that the contrasts between the models strongly support the spatial proximity model, with its mechanism of cross-neighborhood racial spillovers. Our analysis highlights the importance of the adding up constraints of general equilibrium in interpreting the empirics of tipping. This allows us to distinguish tipping in urban areas from the conceptually distinct biased White suburbanization in initially lower density areas. It also leads us to strongly revise downward the magnitude of measured tipping in locations where tipping is correctly interpreted. Our approach provides an appropriate spatial analysis of locations prone to drastic racial change, helping to focus attention on where policy directed at racial integration should have greater concern regarding potential neighborhood instability.

Relation to the literature

Our work contributes to several strands of literature addressing racial segregation, neighborhood sorting, and the broader dynamics of urban change.

Foundational theoretical works are Schelling (1969, 1971); Becker and Murphy (2000); Brock and Durlauf (2001); Sethi and Somanathan (2004). A significant strand of the literature consists of simulated agent-based models, including Zhang (2011) and Axtell and Farmer (2022). We add to this literature by providing the first nesting of Schelling's bounded neighborhood (including tipping) and spatial proximity (checkerboard) models in a framework amenable to empirical investigation via a discrete choice model without or with spatial racial spillovers.

Card et al. (2008a) is a landmark in the economic study of the dynamics of racial segregation in American cities. Building on Schelling (1971) and Becker and Murphy (2000), they develop a rich partial equilibrium model of tipping. They also make great advances in taking the model's predictions to the data to search for tipping as a bifurcation in U.S. MSAs. Our work relies strongly on the foundation they built. Our general equilibrium spatial proximity approach revises both the conceptual foundations of their approach as well as the resulting empirical magnitudes for tipping one draws from such a study.

Massey and Denton (1988) provide an overview of measures to quantify segregation, including the dissimilarity and isolation indices. Echenique and Fryer Jr (2007) and Harari (2024) refine these measures to account in different ways for space, although without the focus on racial clusters and the boundaries between them central to our work. Dai and Schiff (2023) provide a way to operationalize the idea of ethnic clusters, but not in a way appropriate to our efforts. We instead partition tracts into clusters defined as groups of contiguous tracts with the same racial mode, allowing us to focus on how neighborhood racial change occurs distinctly according to a location's distance to the boundaries of these racial clusters.

An additional branch of the literature that likewise is fundamental to our approach is the discrete choice models that make explicit the general equilibrium dimensions of the problem. These have become highly influential for recent empirical investigations into neighborhood sorting by race and class. This literature includes Bayer and Timmins (2005, 2007); Bayer et al. (2007, 2014); Caetano and Maheshri (2017); Almagro et al. (2023); Tsivanidis (2023); Blair (2023); Weiwu (2023); Couture et al. (2023); Li (2023); Couture et al. (2024) using static models and Bayer et al. (2016); Caetano and Maheshri (2023); Davis et al. (2023) using dynamic models. We extend this literature by incorporating spatial racial preferences and studying their consequences on the city-level. The papers most similar to ours in the focus on social spillovers across space are Redding and Sturm (2024) and Bagagli (2023). The former focuses on sorting by socioeconomic status in London and the latter estimates spatial racial preferences in the context of expressway construction in Chicago. We investigate the implications of spatial racial spillovers for racial clustering and the locus of drastic racial change in all US metros from 1970 to 2000.

Further empirical investigations into the patterns and causes of racial residential segregation in the U.S. can be found in Cutler et al. (1999); Ellen (2000); Card et al. (2008b); Glaeser and Vigdor (2012); Boustan (2016); Logan and Parman (2017); Shertzer and Walsh (2019); Logan and Stults (2021); Bayer et al. (2024). Work with a focus variously on the interplay between segregation, the great migration, and suburbanization appears in Baum-Snow (2007); Boustan (2010); Weiwu (2023); Bagagli (2023); Neubauer and Fabian (2024). There is a focus on neighborhood racial tipping in Easterly (2009) and Card et al. (2008a,b). We add to this literature by introducing a theoretically well-grounded approach to empirically examine the role of the spatial proximity of racial groups in neighborhood evolution.

Outline

The remainder of the paper is structured as follows. Section 2 introduces our model of discrete neighborhood choice with spatial spillovers. It also examines how the model nests Schelling's ideas of tipping, explains our simulation procedure, and introduces our main empirical hypotheses. Section 3 evaluates these hypotheses empirically. In light of our theory and empirical findings, Section 4 revisits and re-conceives results on tipping, drastic racial change, and location by Card et al. (2008a). Section 5 concludes.

2 A Model of Neighborhood Choice and Spatial Spillovers

The theoretical ideas of Schelling (1971) are transparent, enormously influential, and yet difficult to take to data. For this reason, formal empirical work in economics based on his models ranges from sparse (bounded neighborhood and tipping models) to non-existent (spatial proximity and checkerboard model).[4] In this section, we will show that Schelling's main ideas can be introduced into a common framework that nests them in a discrete choice model, which allows us to articulate contrasting predictions we can investigate with data.

[4]Schelling (1971) is considered a founder of agent-based modeling and there is a large literature based on this foundation (Axtell and Farmer, 2022). The only formal empirical work in economics on segregation we are aware of that explicitly takes as its setting the spatial proximity model is the very interesting, but apparently abandoned, project by Möbius and Rosenblat (2001).

2.1 A Discrete Choice Model with Spatial Spillovers

We start by describing the overarching model and its general parametrization before contrasting the main predictions of its bounded neighborhood and spatial proximity versions in the next section. The model has the following components.

Geography Space consists of a discrete set of locations $j \in J$ endowed with a distance metric d_{jk} that describes the distance between two locations j and k. In our empirical analyses we will focus on census tracts.

Demand There are different population groups $r \in R$ living in the city each having an exogenous total size of N_r. The total population inhabiting the city is thus $N = \sum_{r \in R} N_r$. Following a simple logit specification, households i of group $r(i)$ derive the following indirect utility from living in j

$$v_{ij} = u_{r(i)j} + \epsilon_{ji} \tag{1}$$

where ϵ_{ji} is a household- and location-specific i.i.d. Gumbel shock with unit scale. The location-specific mean utility is common across groups and takes the following form

$$u_{r(i)j} = -\alpha_{r(i)} \log(p_j) + \beta'_{r(i)} \sum_{k \in J} w_{jk} s_k + \eta_{r(i)j}. \tag{2}$$

Here, p_j is the average rental price of housing at location j and $s'_k = (s_{1k}, \ldots, s_{Rk})$ is a vector of neighborhood group shares at location k. Neighborhood fundamentals and amenities which do not endogenously respond to racial sorting but which can be group-specific are captured through η_{rj}. The scalar α_r describes the price sensitivity and the vector $\beta'_r = (\beta_{r1}, \ldots, \beta_{rR})$ captures the racial preferences of group r for all other racial groups.[5] To gain intuition, the baseline formulation of our model features racial preferences that enter indirect utility linearly but the setup can in principle be extended to more complex cases.[6]

The key distinction between our model and most existing discrete choice models of segregation is the incorporation of spatial spillovers in racial preferences through the origin-destination-specific weights w_{jk}. The inclusion of these weights allows us to bridge the gap

[5]Racial preferences here should be interpreted broadly. The parameter vector β_r captures direct preferences for the race of neighbors, but also captures preferences for other neighborhood attributes that vary endogenously as the racial composition of the neighborhood changes.

[6]Note that this indirect utility formulation can also be derived by assuming a Cobb Douglas utility function with a housing share of $\tilde{\alpha}_r$ and a multiplicative taste draw that is i.i.d. Fréchet distributed across locations with shape parameter $1/\sigma_r$, location parameter 0, and scale parameter 1. The log indirect utility in this formulation would be equivalent to our additive formulation in Equations (1) and (2) with our price sensitivity α_r corresponding to the housing share multiplied with the shape parameter $\alpha_r = \tilde{\alpha}_r/\sigma_r$.

between Schelling's spatial proximity and bounded neighborhood models. The weights describe the degree to which households living at j care about the racial composition in location k. In principle, the distance decay could have an arbitrary form varying by race and depending on population density or the local transportation network. In our simulations, we assume that w_{jk} decays exponentially with distance, where the decay rate is determined by κ, and weights satisfy the normalization $\sum_k w_{jk} = 1$:

$$w_{jk}(\kappa) = \frac{e^{-\kappa d_{jk}}}{\sum_{k' \in J} e^{-\kappa d_{jk'}}}$$

Using this formulation, racial preferences are very localized if $\kappa \to \infty$, meaning that households only care about the racial composition at location j itself. By contrast, only the city-wide racial composition plays a role if $\kappa = 0$.

Households choose where to live by maximizing their utility. This yields the following aggregate demand of group r for location j depending on the vector of all prices, neighborhood racial shares, and exogenous demand shifters:

$$D_{rj}(\{p_k\}, \{s_k\}, \{\eta_{rk}\}) = N_r \frac{\exp(u_{rj})}{\sum_{k \in J} \exp(u_{rk})} \tag{3}$$

Supply In the baseline version of our model, supply for housing is fixed and exogenous. Each location is endowed with a fixed housing stock H_j and total housing units available equal the total population: $\sum_{j \in J} H_j = N$.[7]

Equilibrium The share s_{rj} of group r at location j is given by

$$s_{rj} = \frac{D_{rj}(\{p_k\}, \{s_k\}, \{\eta_{rk}\})}{\sum_{r'} D_{r'j}(\{p_k\}, \{s_k\}, \{\eta_{rk}\})} \tag{4}$$

An equilibrium is then defined by a vector of prices $\{p_k\}$ and a matrix of racial shares $\{s_{rk}\}$ such that Equation 4 is satisfied and housing supply equals total demand at each location

$$H_j = \sum_r D_{rj}(\{p_k\}, \{s_k\}, \{\eta_{rk}\}). \tag{5}$$

The existence of an equilibrium can be shown through Brouwer's fixed point theorem but uniqueness is not guaranteed (Bayer and Timmins, 2005). In fact, multiple equilibria are a

[7]The model can be extended to allow for endogenous supply by specifying a simple reduced form housing supply curve such as $H_j = \bar{H}_j p_j^{\theta_j}$ where $\bar{H}_j$ is a supply shifter and θ_j is the local supply elasticity.

key feature of the model and arise if agglomeration forces in the form of racial preferences and spillovers are sufficiently strong.

Simplifying assumptions In all of the following we will focus on two racial groups $R = \{w, m\}$ where w indicates White and m indicates Minority households.[8] Since racial preferences enter linearly in the baseline version of our model and there are only two racial groups, we can describe the racial composition of location k by its scalar Minority share s_{mk}. This also implies that racial preferences of each group can be fully described by the scalars β_{ww} and β_{mm} i.e. the preference of Whites for living with Whites (and thus not with Minorities) and the preference of Minorities to colocate with other Minorities (and thus not with Whites). For ease of notation, we will refer to these simply as β_w and β_m, respectively. We limit ourselves to this simplified two-group analysis, as much of the existing literature on segregation and tipping is written in a two-group context and this simplified setting allows us to gain intuition more easily.[9] As the general model foreshadows, most of what follows can be extended to a multi-group setting.

2.2 Nesting Schelling's Models

The theoretical model outlined above can nest the key aspects of the existing literature on racial neighborhood tipping. To see this more clearly we will consider three versions of our model: (1) a partial equilibrium version; (2) a general equilibrium version without spatial spillovers; and (3) a general equilibrium version with spatial spillovers.

The foundational theoretical work on neighborhood tipping is by Schelling (1969, 1971). Becker and Murphy (2000) show how to convert this to a more conventional economic partial equilibrium setting. Card et al. (2008a) introduce tipping in the latter framework and, along with Easterly (2009), develop related empirical work. Focusing on a discrete location, a bid-rent function describes the maximum willingness to pay of a marginal household to move into the location given a certain Minority share at that location. Our model allows for the derivation of graphical bid-rent functions that focus on a single location, assume that housing supply is inelastic, and abstract from general equilibrium.[10]

Two cases of bid-rent functions are provided in Figure II, which we will use to illustrate

[8]We take non-Hispanic White individuals to be "White", and all other races and ethnicities to be "Minority". The two groups defined here, in our theoretical portion, align with definitions of racial groups we use for analysis in our empirical section.

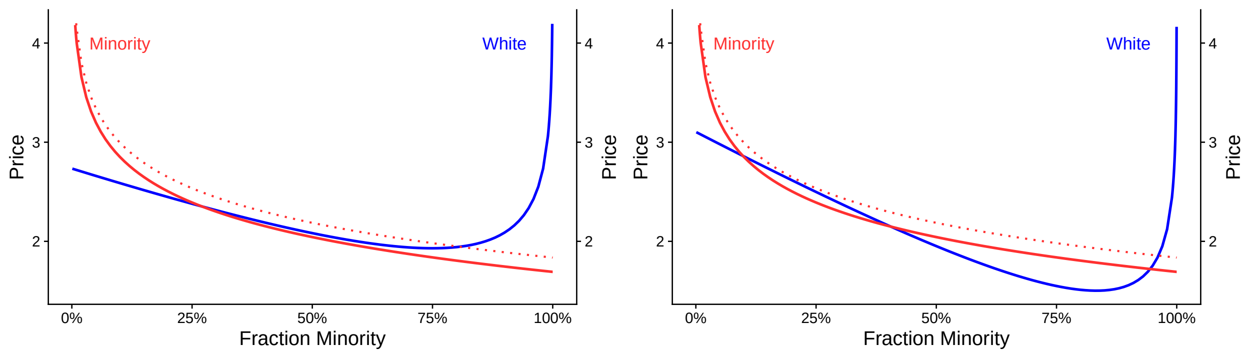
[9]For example Schelling (1969, 1971); Becker and Murphy (2000); Card et al. (2008a) and Easterly (2009) all consider a two group context. Recently Caetano and Maheshri (2017) have explored multi-group tipping in a school choice setting.

[10]Details on the derivation appear in Appendix B

Figure II:
Bid-Rent Curves for Different Homophily Preferences

(a) Moderate homophily with unique equilibrium

(b) Strong homophily with multiple equilibria, tipping



The partial equilibrium bid-rent curves determine equilibrium housing prices and fraction Minority. Homophily in the diagrams is asymmetric, zero for Minorities and higher for Whites. Panel (a) features moderate White homophily and a unique equilibrium. Panel (b) features stronger White homophily, multiple equilibria, and the possibility of tipping. The dashed red curve represents a shift of the Minority bid-rent curve, showing drastic racial change (a) without or (b) with tipping.

the central insights derived from the partial equilibrium approach. The bid-rent curves for Whites are colored blue, while those for Minorities are colored red. The dotted lines show how the Minority bid-rent curve shifts outward in response to an increased Minority demand for the location, for example due to an aggregate inflow of Minorities into the city. Panel (a) illustrates a setting with moderate homophily preferences of Whites, zero racial preferences of Minorities, and a unique partial equilibrium. Panel (b) shows a setting with strong homophily preferences of Whites in which multiple equilibria exist. The difference in shape of the bid-rent functions across the two panels emphasizes a characteristic feature of homophily in the model. For Minority households, who are assumed to have zero homophily preference here, the bid-rent function has the conventional downward sloping shape. For White households, the bid-rent function first becomes more elastic and later upward sloping relative to their own axis as the local Minority share varies.

In both Panels (a) and (b), upward shifts of the Minority bid-rent function can lead to drastic changes in equilibrium Minority shares, and in both panels these changes are associated with reductions in neighborhood prices. With moderate homophily preferences, adjustments occur without involving a bifurcation or crossing of a proper tipping point. In Panel (b), an upward shift of the Minority bid-rent curve can render the low Minority share equilibrium unstable. It is the existence of such bifurcations that is commonly understood as a central element in the theory of tipping. However the fact that drastic racial change in the partial equilibrium framework is possible both when a formal bifurcation exists (Panel b) and when it does not (Panel a) is a caution that drastic change alone is not evidence of such bifurcations. It also suggests the potential value of considering such drastic change directly as tipping without only or necessarily focusing on a search for bifurcations.[11]

The partial equilibrium model provides a rich setting for contemplating the fate of a single neighborhood in response to shocks. However, the shortcomings of the framework are clear, particularly when we consider the evolution of all census tracts within a city. The aggregate shock contemplated, that of an upward movement in the Minority bid-rent curve, leads to White *exit* from the neighborhood. This is true whether or not tipping in the form of a bifurcation is formally present. When we try to apply this to understanding what happens for all tracts in an MSA, it is clear that one must move to general equilibrium in order to understand the adding-up constraints that affect White *entry* to other neighborhoods. Everyone must go somewhere.[12] In addition, the partial equilibrium approach has no clear predictions about the spatial location of neighborhood racial change. It does not provide a setting that allows us to understand how shifts in bid-rent functions will differ by location and whether we should expect the importance of tipping to vary across space.

To move beyond partial equilibrium and a single neighborhood, we can invoke the full equilibrium structure of our model. With $\kappa \to \infty$ we abstract from spatial spillovers in racial preferences and move to the general equilibrium bounded neighborhood model. This version alleviates concerns about adding-up constraints, which will be met when satisfying the general equilibrium conditions in Equations (4) and (5). The flexible structure of the demand function with exogenous location- and race-specific demand shifters η_{rj} allows the model to be taken to the data and can match observed heterogeneity in prices as well as the distribution of racial groups across locations in a city. Due to this flexibility, the recent quantitative urban literature on racial sorting works with a model conceptually close to our bounded neighborhood formulation (Bayer et al., 2007; Almagro et al., 2023; Weiwu, 2023).

An important tension remains in both the partial and general equilibrium bounded neighborhood model. The central point of these models is that households have strong preferences about the racial composition of their neighborhood. For this reason, it seems implausible

[11]Our approach to the bounded neighborhood model has similarities and contrasts with the model developed by Card et al. (2008a). The model does admit the possibility of a tipping point at a critical Minority share s^*_{mj}. However one feature of the logit demand model relevant here is that the bid-rent curve of group r will always tend to infinity for low values of s_{rj}. This ensures that in every location households from every group are represented in expectation. In the post-tipping equilibrium, the Minority share won't be strictly $s_{mj} = 1$, which is in any case rare in the data.

[12]This will prove important when we seek to understand the roles, respectively, of White exit and White entry in driving prominent empirical results in the partial equilibrium model in Card et al. (2008a).

that preferences stop at the often arbitrary boundaries of the census tracts used to examine these models empirically. The bounded neighborhood model does not allow for these spillovers across neighborhoods, while the spatial proximity model with $\kappa < \infty$ makes them a key element of analysis.

A central insight of Schelling is that micro-motives responding to localized spatial spillovers can have important macro consequences. This speaks to two questions regarding the choice of spatial aggregation. The first is that Schelling's work implies that it would be incorrect to assume that if spillovers are highly localized that one can just work with larger spatial units to eliminate this problem. The second is that to verify some of the effects of micro-motives, it will be valuable to work with more granular geographies where feasible (Bayer et al., 2024).

As central as spatial racial spillovers are to the theory of segregation, few empirical papers model them, as estimation can be challenging and standards in the literature for unconfounded identification are high. Bagagli (2023) is to our knowledge the first empirical paper in economics focusing on these cross-location racial spillovers in her study of the sorting consequences of expressway construction in Chicago. Redding and Sturm (2024) also estimate a spatial proximity model in London, though focused on spillovers due to socioeconomic status rather than race. They use exogenous variation due to the bombings of London in World War II for identification. Aliprantis and Lin (2025) examine the role of spatial spillovers in neighborhood income sorting.

In what follows, we take a distinct approach. Instead of focusing on a single city and leveraging a distinct policy or event to identify the parameters of the bounded neighborhood and spatial proximity model, we present evidence from a broad range of cities across multiple decades. To this end we first simulate the two models to articulate key differences in their predictions. In Section 3, we then turn to data from a panel of more than 100 US cities from 1970 to 2000 to examine the key patterns of racial sorting, house prices and rents across space, and the locus of racial change that help us to distinguish the two models.

2.3 Simulating the Bounded Neighborhood and Spatial Proximity Models

In this section we simulate the bounded neighborhood and spatial proximity models to develop a set of empirical features we can examine with data. We have to make a range of decisions regarding parameters, spatial resolution, and initializations to simulate the models. In the following, we focus on simple cases illustrating the key predictions that the spatial proximity model makes but that the bounded neighborhood model cannot explain endogenously. To solve for the equilibrium in each simulation, we implement a fixed point algorithm closely resembling the solver outlined in Almagro et al. (2023).

We simulate rectangular cities with 400 locations arranged on a 20×20 unit grid. Each location has fixed and identical housing supply. Demand comes from a unit mass of households. At baseline, 80% of households are White and 20% of households belong to the Minority group. Each group has equal price sensitivity $\alpha_m = \alpha_w = 10$ and Whites have strong homophily preferences ($\beta_w = 8$) while Minorities are indifferent about the racial composition of their neighborhood ($\beta_m = 0$).[13] The chosen parameters imply a semi-elasticity of $\beta_w/\alpha_w = 0.8$, i.e. if the average Minority share in the neighborhood increases by 1 percentage point, prices must decrease by 0.8% to keep White households indifferent.

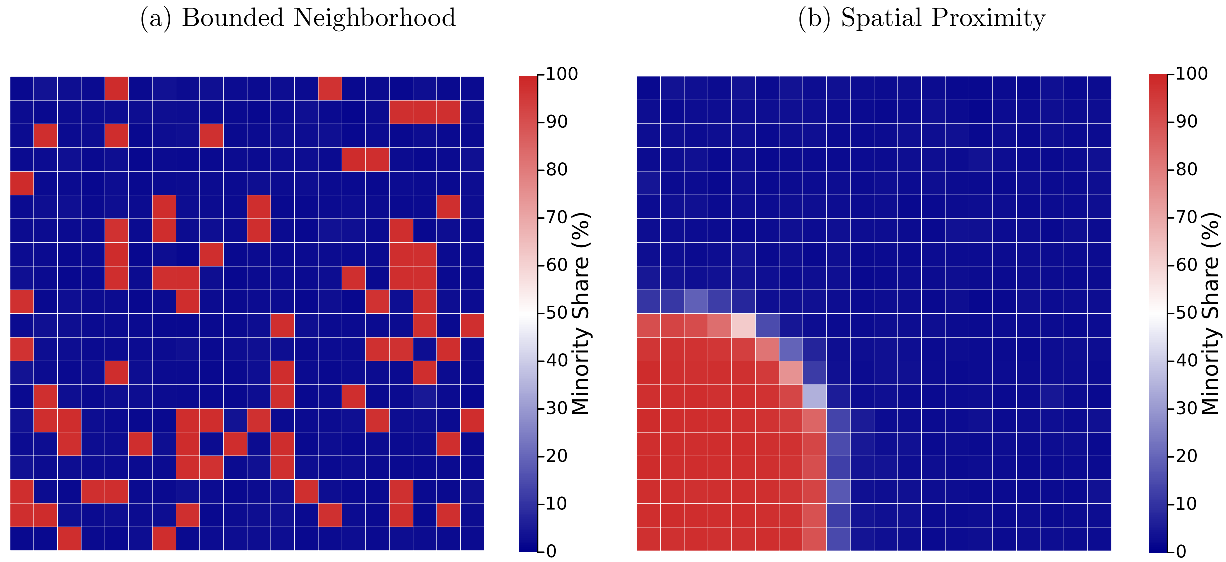
We set fundamentals η_{rj} close to zero in all simulations so there are no important exogenous reasons why demand of each racial group should vary across locations. This allows us to focus on the endogenous patterns that each model generates.[14] To find an equilibrium, we initialize each location with a Minority share s_j^0 that is independently drawn from a uniform distribution. Given the initial Minority shares $\{s_j^0\}$ we find the price vector $\{p_j^0\}$ that equates supply and demand at each location. Since we assume constant housing supply, only relative prices matter to determine the equilibrium and we set the average log price as the numeraire. Given the price vector, we can compute demand of each racial group for each location and update Minority shares respectively. We then iterate between updating prices and Minority shares until we converge to an equilibrium satisfying Equations 4 and 5.

Figure III contrasts equilibrium Minority shares arising after the *same* random initialization of the model in the bounded neighborhood version (Panel a) and in the spatial proximity version (Panel b). The bounded neighborhood version assumes $\kappa \to \infty$, so spatial racial spillovers are zero. The spatial proximity version features spillovers with $\kappa = 35$. Together with our assumption of locations on a unit square, this implies that in the spatial proximity version the racial composition of a location itself contributes on average about 45%, the 8 neighboring tracts together contribute 28%, and all other tracts combined contribute the

[13]The asymmetry in homophily preferences is implicit in the model of Card et al. (2008a), Figure II, which explains why the Minority bid-rent function is strictly downward sloping while the White bid-rent function is backward bending. Weiwu (2023) provides empirical support for the contrast of strong homophily preferences for Whites and (in her data and our simulations) zero homophily preferences for Blacks.

[14]Across racial groups and locations, we do allow for a negligible shock on η_{rj} that is drawn independently and identically from a Normal distribution with a standard deviation of 0.1. These small shocks help in breaking ties in our convergence routine. Ties can occur when the numerical equilibrium solver converges towards an unstable equilibrium. In these situations a random neighborhood needs to tip and the algorithm cannot determine which location this should be as all neighborhoods appear identical in fundamentals. In such cases, the small i.i.d. shocks on η_{rj} help to determine which neighborhood will tip.

Figure III:
Racial Clustering in General Equilibrium Simulations



The bounded neighborhood setting in Panel (a) exhibits a random distribution of Minority and White tracts, whereas the spatial proximity setting in Panel (b) exhibits strong clustering of Whites and Minorities. High White-share tracts are shaded blue, high Minority-share tracts are shaded red, and mixed-share regions are colored white. Parameters for the simulation are provided in the text.

remaining 27% to the experienced racial composition at a location. The equilibrium Minority shares in Panel (a) directly reflect the random initialization of the model. By contrast, Panel (b) shows a remarkable amount of clustering, even though it derives from exactly the same initialization. This highlights the first key feature, that the spatial proximity model endogenously delivers the formation of Minority clusters.

The extent of clustering depends on the spatial decay of the racial preference spillovers. For the chosen parameter of $\kappa = 35$, multiple clusters arise only rarely in equilibrium. When racial preferences are more localized (larger κ), multiple smaller clusters become stable equilibria. Multiple employment centers can also be incorporated into the model, and in combination with racial preference spillovers, they can similarly lead to multiple racial clusters in equilibrium. We show this in appendix C. In short, the spatial proximity model gives rise to clustering that is above random, but need not lead to a single cluster.

While one can easily spot the stark difference in the amount of clustering between the bounded neighborhood and spatial proximity models in Figure III, we require a quantitative measure of clustering when running repeated simulations and when turning to census data in the next section. We define a racial cluster as a set of N or more contiguous locations with the same modal race.[15]

Having defined clusters, we need to resolve another issue for visualizing repeated simulations and census data: Due to strong homophily preferences, multiple equilibria are a common feature of this setting. To visualize the key spatial patterns in a manner that is robust to the existence of multiple equilibria and comparable across geographies, we proceed in the following way: We assign an integer distance l to each location that reflects the minimum number of tracts one has to traverse to reach the border between clusters of opposite mode. Thinking of the boundary itself as location 0, we assign negative integers to locations that are inside of a Minority cluster and positive integers to locations inside a White cluster. For example, a White-mode tract bordering a Minority tract is assigned the location 1. As we move from the boundary further into the White cluster, these are then locations $\{1, 2, 3, \dots\}$. We then provide diagrams that show average characteristics of neighborhoods by distance from a cluster boundary.[16]

Figure IV shows the mean fraction Minority in this space for the simulated bounded neighborhood and spatial proximity models. Instead of displaying a single realization of the simulation as in Figure III, the bar plot shows averages across 1,000 random initializations of the models and focus on tracts in proximity to a cluster boundary. As there are no racial preference spillovers across locations in the bounded neighborhood model, Minority shares are predicted to drop precipitously when moving across the boundary of a cluster (Panel a). By contrast, Minority shares are changing more smoothly when crossing a cluster boundary in the spatial proximity model (Panel b) reflecting White preferences for market access to other White households. Similar precipitous (bounded neighborhood) or smooth (spatial proximity) changes are predicted for neighborhood prices, where in both models households with strong homophily preferences pay a price for self-segregation (see appendix Figure A.I for predicted patterns).

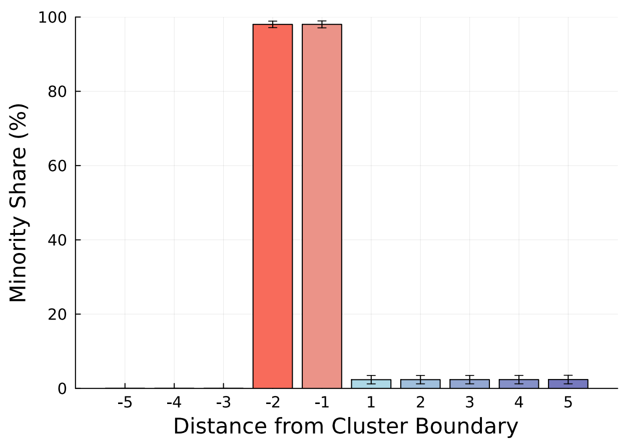
A critical question in the segregation literature is how city neighborhoods evolve in response to a shock to the aggregate city Minority share. Much of this is motivated by the shocks

[15]There is a considerable amount of work on clustering across many fields. Much of this focuses on the construction of scalar measures of the degree of clustering. This is not adequate to our needs, since we need to be able to locate clusters in geographical space and to measure the location of tracts relative to the boundaries of these clusters. We thus take the definition of clusters as primary and then measure the degree of clustering according to the fractions of group populations living in same-mode clusters. In related work, Dai and Schiff (2023) provide an interesting method for constructing ethnic clusters using US census data. Our approach, based on the modal race, is better suited to our problem since it provides a unique mapping of every census tract to one of our two groups.

[16]In Figure A.II, we illustrate, using Census data for tracts from the South Side of Chicago, how to move from tract populations to racial clusters, how to index the locations within clusters, and then how to form histograms to represent this information.

Figure IV:
Mean Minority Shares by Distance from the Cluster Boundary in Simulations

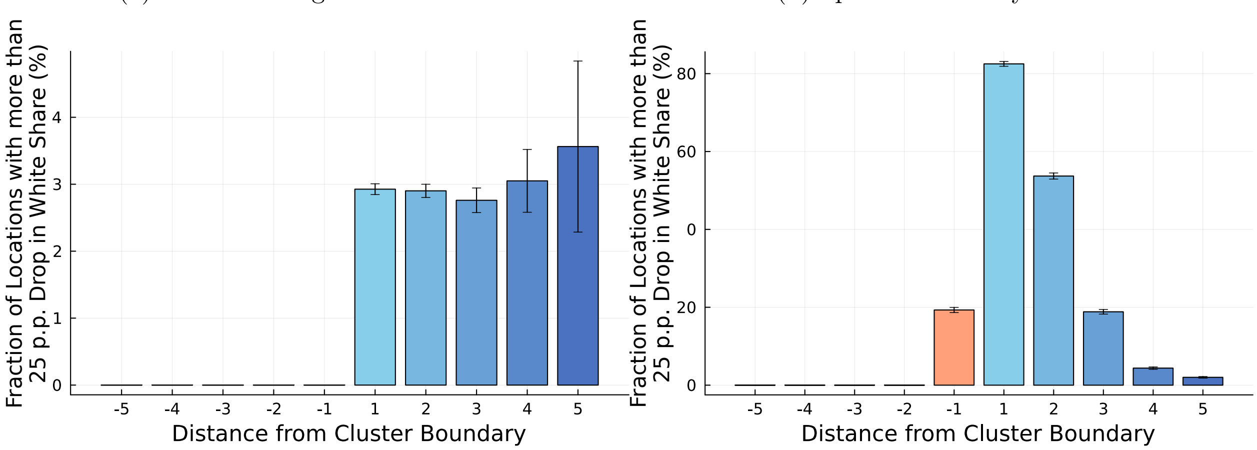
(a) Bounded Neighborhood (b) Spatial Proximity



Bar plots show averages across 1000 initializations. Observations with an absolute distance from the cluster boundary larger than 5 are dropped to focus on patterns close to the cluster boundary.

Figure V:
Locus of Racial Change, Increase in Minority Share from 20 to 25% in Simulations

(a) Bounded Neighborhood Model (b) Spatial Proximity Model



Bar plots show averages across 1000 initializations. Observations with an absolute distance from the cluster boundary larger than 5 are dropped to focus on patterns close to the cluster boundary.

of the two great migrations of Blacks to northern cities. Since our model features multiple equilibria, one needs to start with an initial equilibrium and then consider what happens relative to this baseline as we progressively raise the Minority share. We initialize the city with the original equilibrium Minority shares and then increase the citywide Minority share from 20% to 25% while reducing the White share from 80% to 75%.[17] Figure V displays the resulting probability for experiencing drastic Minority share changes of 25 percentage points or more by distance from the Minority cluster boundary. In our bounded neighborhood simulations, the locus of such drastic changes is independent of the distance to any existing racial cluster. In our spatial proximity model, by contrast, the increasing Minority share is reflected in large changes in the locations adjacent to the existing Minority cluster.

3 Evidence from a Panel of Cities

Our theory and simulations highlight four key contrasts between the bounded neighborhood and spatial proximity models. The first concerns the salience of racial clusters. The bounded neighborhood model has no intrinsic link across tracts and so no mechanism to generate clusters beyond chance. The spatial proximity model provides strong reasons to expect racial clustering to be important, as the same forces that lead to segregation within tracts also lead to clustering of same-group tracts.

A second key contrast concerns the locus of racial change in the face of shocks to aggregate levels of the groups. Just as the bounded neighborhood model has no mechanism to generate racial clusters, it likewise has no mechanism to explain how aggregate shocks translate to the *locus* for entry of new tracts by mode. The spatial proximity model, by contrast, says that change will be such as to preserve the clustering that exists, hence change will be concentrated at the boundaries of clusters.

A third key contrast concerns how the Minority share changes at the boundary of clusters. The bounded neighborhood model has a bang-bang prediction in which racial composition of tracts is unaffected by whether we are near or far from the boundary of clusters. By contrast, in the spatial proximity model, boundary and interior tracts are quite different due to the spillovers. As we demonstrated, this leads to a strong but not precipitous gradient in the Minority share at the boundary of clusters.

Our fourth key contrast applies related logic to housing prices interior to and at the boundary of clusters. We assume an asymmetry in the strength of racial homophily, greater for Whites

[17] These changes are roughly in line with the average change in the Minority share observed in US cities between 1970 and 1980. See Section 3 for details.

Table I: Predictions of the Model

	Bounded Neighborhood	Spatial Proximity
Racial Clusters	Random	Strong Clustering
Locus of Racial Change	Random	At Boundaries of Clusters
Price gradients at cluster boundaries	Precipitous Jump	Smooth Increase Into White Cluster
Racial composition at cluster boundaries	Precipitous Jump	Smooth Decrease

than for Minorities.[18] As with Minority shares, the bounded neighborhood model provides a bang-bang prediction about price differences between Minority and White mode locations. There is no role for the location of the tract relative to the boundary of clusters. Both models predict that Minorities will pay lower prices and that there will be little variation of price within the Minority cluster. Where they differ is how prices change as we move from the boundary to the interior of the White cluster. The bounded neighborhood model predicts the rise in prices will be precipitous, whereas the spatial proximity model predicts prices will show a potentially strong, but non-precipitous increase. As we move further in, Whites will pay more to be in tracts remote from Minorities.

Table I summarizes the contrasting predictions of the models. These highlight that the bounded neighborhood model makes quite sharp predictions. Clustering and racial neighborhood change arise in space only randomly. Changes in Minority share and housing prices are precipitous at the boundary of clusters. One can reasonably ask why one may want to examine such sharp hypotheses with data. We believe there are two good reasons. The first is that the bounded neighborhood model, with its sharp predictions, explicitly or implicitly is the foundation for nearly all formal empirical work on segregation in economics. The second is that we would like to establish magnitudes for the features that separate the models. Our hope is that highlighting the strong contrasts between the models and documenting their empirical importance will stimulate future work to assess how important the spillovers at the heart of the model are in specific experimental and policy contexts.

[18]Evidence for this asymmetry in the period of interest comes from experiments that elicit preferences by race for the racial composition of one's neighborhood, as discussed in Charles (2003).

3.1 The Data

We examine these contrasts using U.S. Census data from 1970 to 2000. For these four censuses we have detailed information on the racial composition of census tracts as well as a rich set of covariates. Our panel data of cities derives from the replication data of Card et al. (2008a). We do not go beyond the year 2000 as we want to compare the results that we will show to their prominent investigation of tipping points. All data is harmonized to 2000 census tract geometries and, similarly to Card et al. (2008a), we focus on tracts that are located within 1999 MSA definitions.[19] We also supplement the racial composition data with tract-level housing price data from the Longitudinal Tract Database (LTDB) and add information on tract-level family incomes for the 2000 census.[20] Additionally, we include information on the geometry and land area of each 2000 census tract, which we use to visualize the data through maps and to compute population densities. Stratifying the analysis by location and the initial population density of a tract will be a key departure relative to Card et al. (2008a). The details matter, as discussed further in Footnote 36. For the 1990 census, information on house prices, rents, and racial composition is also available on the more granular block-level. We use this data to investigate if our cross-section results are robust to changes in the spatial resolution of the data. As in the preceding theory section, we focus on a dichotomous classification of race comparing non-Hispanic White households and Minority households, understood to be the complement. For simplicity and following the literature, we refer to the two groups as White and Minority households respectively.[21]

3.2 Racial Clusters in the Data

Casual inspection of maps for American cities with significant Minority populations suggests that ethnic and racial clustering of tracts is quite powerful. We would like to go beyond this by providing quantitative measures of the importance of this clustering to shed light on the social processes at work.

[19] Our regressions follow the sample selection methods of Card et al. (2008a), so exclude all tracts in which (1) the decadal population growth rate exceeds the MSA mean by more than five standard deviations, (2) the ten-year growth in the White population exceeds 500% of the base-year total population, or (3) the MSA contains fewer than 100 tracts (after applying the previous criteria).

[20] The LTDB is available at `https://s4.ad.brown.edu/projects/diversity/Researcher/Bridging.htm`. The replication data of Card et al. (2008a) only contains family income information for 1970-1990 so we add 2000 information from census table P07.

[21] Non-Hispanic White households constituted the majority of the population throughout this period. We do robustness checks that split the sample by Black versus non-Black, with broadly similar results. The year 2000 also provides a useful break in another sense. In 1970, non-Hispanic Whites and Blacks jointly constituted nearly 95% of the US population and this fell steadily to a bit more than 80% in 2000. Moving beyond this in time invites consideration of a framework designed for more than two groups, which is of great interest but beyond the scope of our study.

As detailed in Section 2.3, we can characterize clusters by first classifying census tracts according to their racial mode. We then define a racial cluster as a set of N or more contiguous tracts within an MSA with the same modal race that surpasses a minimum tract count. One can vary the choice of the minimum number of contiguous tracts that will constitute a cluster. When we want to include all tracts in our calculations, we consider the special case of $N = 1$. We then measure the distance from the cluster boundary l as the minimum number of contiguous tracts traversed to reach a tract of opposite racial mode. Negative numbers indicate tracts inside of a Minority cluster and positive numbers indicate tracts inside of a White cluster.[22]

A first important indicator of the degree of racial clustering is the fraction of the Minority population living in own-race racial clusters. The logic is simple. If we had perfect racial integration, so a dissimilarity index of zero, then the entire metro area would have a single unified White cluster; there would be no Minority clusters. In this case, the fraction of the White population living in own-race clusters would be unity and that for the Minority population would be zero. To be inclusive of all tracts, we first report this for cluster size $N = 1$ and then for other minimum cluster sizes in the Appendix. The first line of Table II shows that throughout our period in excess of 60% of Minorities live in own-race tracts. This is only modestly reduced if we instead use a minimum cluster size $N = 10$, so roughly 40,000 people (see Appendix Table A.I). In short, the visual impression from racial share maps of the importance of Minority clustering is strongly validated by this measure.[23]

Table I notes that in the general equilibrium bounded neighborhood model, even absent racial spillovers across tracts, racial clusters can arise from simple random processes. We can examine that. Assume that the actual racial composition of individual tracts is explained *exactly* per the bounded neighborhood model. On this premise we can construct three versions of each MSA. The first is the actual MSA in the data. The second is the MSA if the *location* of specific tracts is purely random, with 1,000 randomizations of the geography. The third is where we constrain the randomization of the location of tracts to be *within a fixed set of income bins* (either 5 or 20). This last version responds to a potential concern that important racial clustering may arise due to income sorting.

The contrast across these cases is examined in Table II with a measure of how *deep* inside clusters the Minority population resides. In the data for all MSAs between 1970 and 2000,

[22]The classification procedure is illustrated in Panels (a) and (b) of appendix Figure A.II for selected census tracts in Chicago's South Side.

[23]In all years, the share of Whites living in own-race racial clusters greatly exceeds that of Minorities. This contrast is an illustration of the maxim by Anderson (2015) that many Minorities as a condition of their existence must live in "white space."

Table II: Clustering Measures and Related Tract Summary Statistics

	1970	1980	1990	2000
Fraction Minority at Cluster Distance ≤ -1	60.4	62.4	61.8	65.6
Fraction Minority at Cluster Distance ≤ -2				
Observed	21.5	28.1	31.0	35.6
Simulated Random	0.1	0.8	2.0	4.4
	(0.05)	(0.11)	(0.15)	(0.18)
Simulated Random within 5 Income Quantiles	1.1	5.5	9.4	12.3
	(0.2)	(0.3)	(0.3)	(0.3)
Simulated Random within 20 Income Quantiles	3.1	8.1	11.5	14.2
	(0.3)	(0.3)	(0.3)	(0.3)
# Tracts	35,725	39,283	40,187	40,187
# MSAs	104	113	114	114
Population (millions)	119.1	137.6	157.3	177.2
Minority Share in MSAs (%)	18.5	24.1	28.8	36.1
Average Dissimilarity Index	61.7	59.5	54.9	52.1

Notes: The Average Dissimilarity Index is computed as the total population weighted average of all MSA-level White / Minority Dissimilarity Indices in the sample.

the fraction of the Minority population that lives at locations *strictly interior to the Minority cluster*, i.e. at $l \leq -2$ relative to the cluster boundary, ranges from 22% to 36%. In the simple randomization over the same periods, the counterpart is only 0% to 4%; and when constraining randomization to be within five income bins, this remains only 1% to 12%. Even if we strongly constrain randomization to be within 20 income bins over these decades, this rises only to 3% to 14%. Randomization implied by the bounded neighborhood model simply does not generate sufficient clustering of the Minority population to lead to the observed fraction living strictly interior to Minority clusters.[24]

3.3 The Locus of Racial Change in All MSAs

An aggregate shock that increases the Minority share of a city will also change the allocation of space between neighborhoods for each group. The bounded neighborhood model, by the very nature of being *bounded*, provides no prediction about *where* the new Minority neighborhoods will arise. It suggests that the likelihood of change solely is a function of the initial Minority share of a tract. By contrast, a central prediction of the spatial proximity model is that change is concentrated at the boundaries of racial clusters.

[24] Figure A.IV illustrates the associated histograms of the Minority population for all MSAs. Figure A.III shows illustrative maps contrasting the actual and randomized geographies for Chicago in 1990. One cannot possibly mistake which is data and which randomization.

We examine this for the three decades in our sample in Figure VI. The first row of histograms shows the location of drastic racial change ($>$ 25 p.p. decline in the White share) for all MSAs relative to the boundary of racial clusters. In each decade, this is strongly centered at that boundary. More than half of all instances of such drastic change are exactly at tracts $l \in \{-1, 1\}$ at the boundary.[25]

This actually understates the extent to which change happens at the boundary of clusters. Many tracts experiencing drastic change lie outside this range in tracts along an unbroken path of contiguous change to the cluster boundary. We have already seen this for all MSAs in the 1970s in Figure I, where we aggregated into location 1 the tracts connected to location 1 that also experience such a drastic change. The second row of Figure VI implements this for all decades in our sample. We see that in each case, approximately 80% of all drastic change occurs at the boundary of racial clusters or in an unbroken chain of such changes connected to that boundary. The lesson of Figure I of extreme concentration of these changes at the boundary of racial clusters is strongly confirmed for the entire period 1970-2000.

We examine how this varies if we alter the cutoffs that define drastic racial change from 10 p.p. to 25 p.p. or 50 p.p. in Appendix Figure A.IX. We see that in each case change is centered on the tracts at the boundary of the Minority cluster and that the more drastic the change considered, the greater the concentration near the boundary of clusters.

For the pooled MSAs, all thresholds for drastic change, and all periods, a simple message emerges: drastic racial change is powerfully concentrated at the boundary of racial clusters. This is exactly as one would expect in the spatial proximity model and wholly unexplained by the bounded neighborhood model.

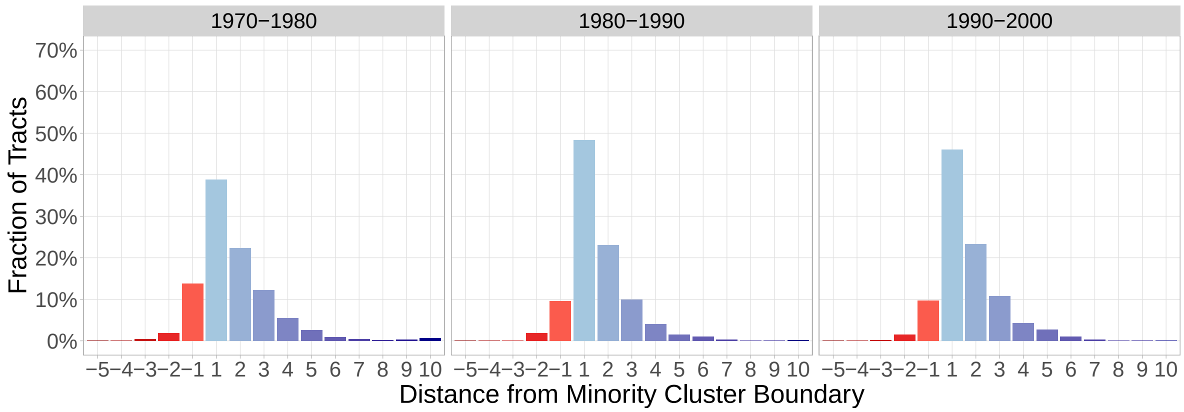
3.4 Clusters, Location, and Patterns of Segregation in the Data

Our models have distinct predictions about how the Minority share will vary at the boundary of clusters. The very nature that the bounded neighborhood model is *bounded* means that the *boundary between clusters* has no special character. There should be a discrete jump of the Minority share when moving across tracts between a Minority versus White cluster. By contrast, our variant of the spatial proximity model predicts that the Minority share may vary strongly as we move across the boundary of clusters, but that the gradient will not be precipitous.

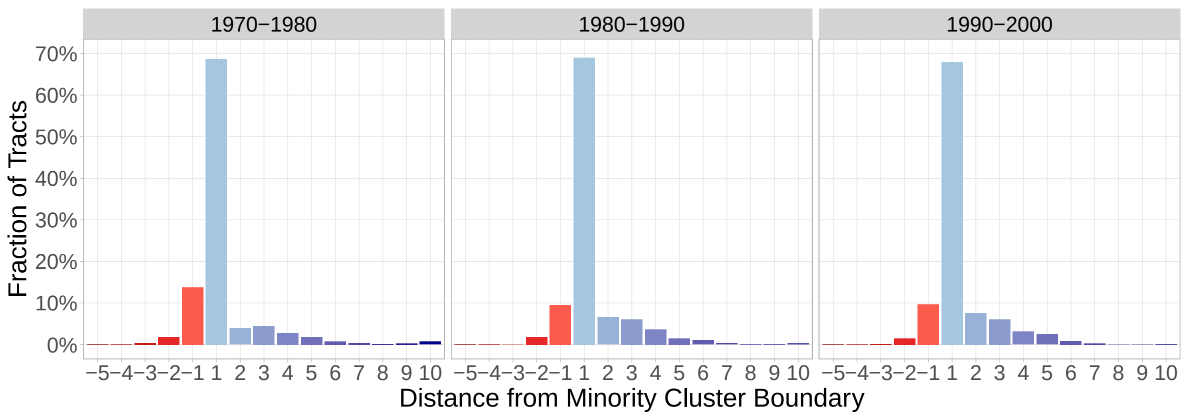
[25] A possible concern when investigating the location of all tracts experiencing drastic change is that differences in the number of tracts at each distance bin could drive results. As a robustness check appendix Figure A.VIII shows the fraction of tracts at each distance bin experiencing drastic racial change. The dominant pattern of racial change at the boundaries of clusters is equally salient in this figure.

Figure VI:
Decline in White Share of 25 p.p. or More, All MSAs 1970-2000

(a) By Location



(b) Contiguous Tracts to Boundary



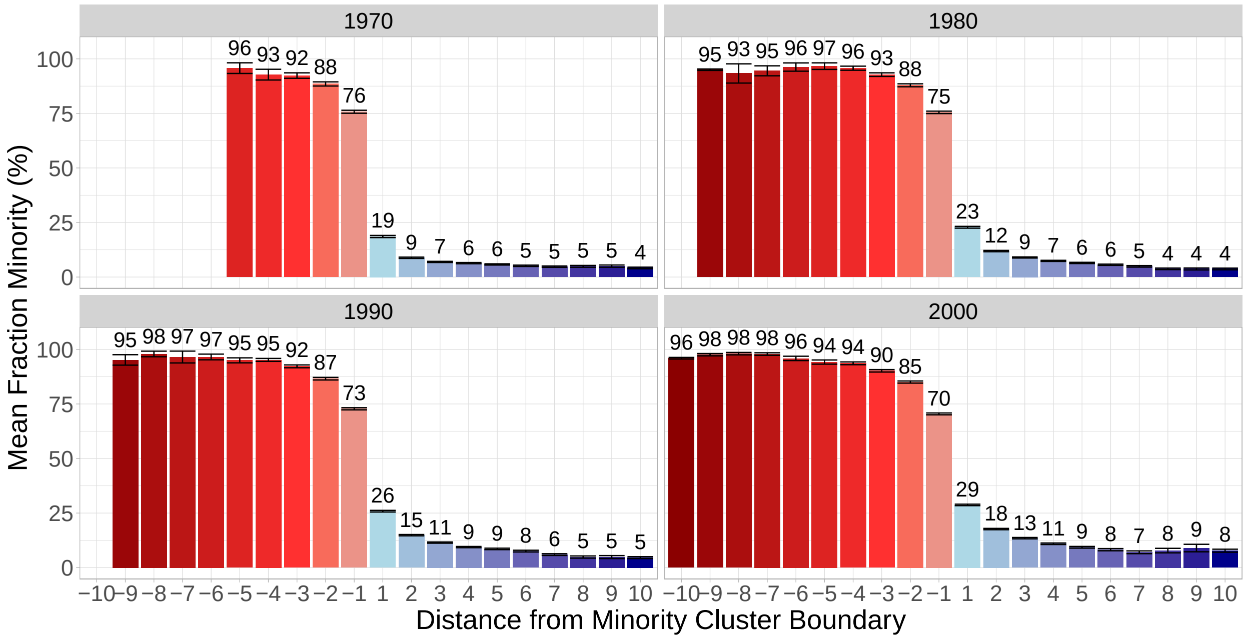
The locus of racial change occurs predominantly at tracts near and connected to cluster boundaries across decades for all MSAs. Each bar shows P(Cluster Distance $= l \mid$ Decline in White Share of 25 p.p. or more) so probabilities sum to 100%. In Panel (b), any tracts which experienced 25 p.p. or greater decline in White share and are contiguous with a cluster boundary are allocated to distance bin 1.

Evidence from all MSAs appears in Figure VII. An examination of the gradient at the boundary for all decades reveals that it is steep, but non-precipitous. This favors the spatial proximity approach. Within this approach, the mixed neighborhoods at the boundary reflect the willingness of Whites with particularly strong Gumbel draws for those boundary neighborhoods to live in racially mixed neighborhoods that also feature lower prices.[26]

A natural concern is whether some of this non-precipitous gradient arises due to the boundaries of census tracts not coinciding exactly with the actual racial boundaries of the neigh-

[26]The results are broadly similar if we instead divide the groups into Black and non-Black. We see this for all MSAs in Figure A.VI.

Figure VII:
Mean Minority Share by Location, All MSAs, 1970-2000



95% confidence bands are provided for each mean. The numbers at the top of each bar are the point estimates.

borhood. We offer two pieces of evidence that this is not the dominant factor. The first is that the gradient becomes notably less steep in later decades, when racial attitudes of Whites became more tolerant, suggesting that aggregation issues are not the only force at work.[27] Second, the Census data for 1990 permits us to examine Minority shares at the block level. Disaggregating the data from the tract to the block level does not change this conclusion (see Appendix Figure A.V).[28]

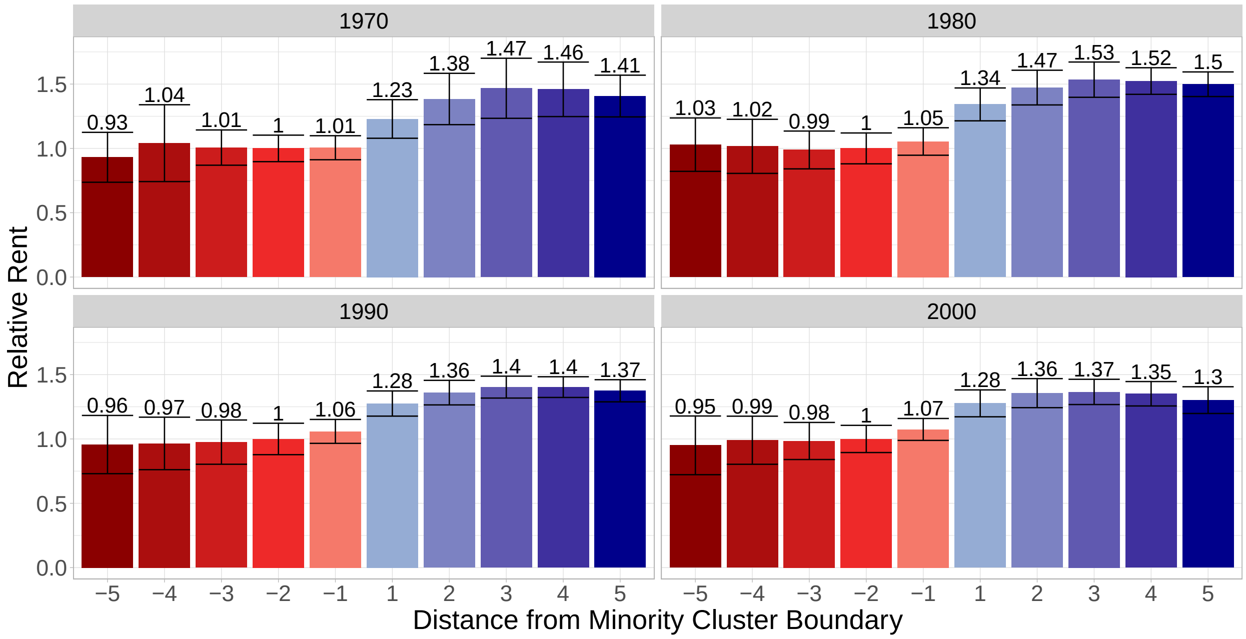
3.5 Price Gradients by Distance from Cluster Boundaries

Our two models provide distinct predictions about how housing prices should behave inside and at the boundary of the respective clusters. Both models predict that since Whites

[27] As Glaeser and Vigdor (2012) document, 1970 represents a peak period of segregation in U.S. MSAs as measured by the dissimilarity index, and they argue that the evolution represents the "end of the segregated century." By the scalar dissimilarity index, this is absolutely correct. But Figure VII underscores that the advances are uneven. Consistent with that thesis, the gradient at the boundary $\{-1, 1\}$ declines from 57 p.p. in 1970 to only 41 p.p. in 2000. The Minority share in Minority mode clusters remains virtually unchanged as we move far to the interior, and indeed they expand in size from 5 layers to 6. Thus most of the decline in the dissimilarity index would appear to be a softening of the border gradient and a rise in the Minority share in White mode clusters. When we examine instead the two groups Black and Non-Black, there is change, but it is more limited (see Figure A.VI). This is progress, but only partial.

[28] It should also be clear that working at a *higher* level of spatial aggregation will not rescue the bounded neighborhood model without suppressing the variation of interest.

Figure VIII:
Relative Rental Prices, All MSAs 1970-2000



95% confidence bands are provided for each mean. The numbers at the top of each bar are the point estimates.

have higher homophily preferences, they will pay a premium to occupy locations with a high White share.[29] For the bounded neighborhood model, there will be a discrete jump at the boundary of racial clusters and no variation within clusters. Our version of the spatial proximity model, by contrast, has three predictions. In line with the bounded neighborhood model, prices should be higher in the White cluster as Whites pay a premium to avoid the Minority cluster. The absence of homophily preferences by Minorities implies that housing prices inside the Minority clusters should not vary by distance to the boundary. But Whites will pay a premium that rises from the border of the boundary. As suggested through our simulation, this pattern should arise even absent other neighborhood fundamentals that vary across space.

Empirically, we can investigate this using tabulated rental price data from the Census. To make prices easily comparable across cities, locations, and decades, they are first normalized by the city-specific median rent and then expressed relative to the rent paid in Minority-mode tracts that are 2 tracts away from the racial cluster boundary.

[29] This is consistent with the evidence from Cutler et al. (1999) that by 1970 "decentralized racism" leads Whites to pay more for equivalent housing. Here we explore the spatial patterns of these differences as we move from the boundary into the respective racial clusters. This likewise arises in the Card et al. (2008a) setting, since they also assume asymmetric homophily.

The results can be examined in Figure VIII. Within the Minority cluster, the relative homogeneity of prices is particularly striking in 1970 and 1980. Under this interpretation, the fact that in the later decades prices rise somewhat within the Minority cluster as we approach the boundary would indicate for Minorities a positive valuation for living in these more mixed race tracts within which they are still the mode. For Whites this suggests there is a smaller discount required to live in these neighborhoods. In all decades, there is a rising price gradient as we move within the White cluster away from the boundary with the Minority cluster. Very similar patterns can be observed for relative home values displayed in appendix Figure A.X. As with Minority shares, one can have concerns about measurement here if the boundaries of tracts don't conform to the boundaries of appropriate neighborhoods. Three features in the tract data give some comfort that we are capturing racial attitudes. The first is that these boundaries move significantly over time, yet the broad patterns persist. The second, consistent with the hypothesis of diminished White aversion over time to proximity to Minority neighborhoods, is that the maximum rent gap (always at $l = 3$) falls from 47% in 1970 to 37% in 2000. Finally, the 1990 Census permits us to examine both rents and house prices at the block level. This shows the same crucial pattern in this spatially more granular data (see Appendix Figure A.V). Prices are relatively flat inside of the Minority cluster before rising near the boundary of and into the White cluster. The patterns thus appear robust to the degree of spatial aggregation.

3.6 Summary of Empirical Evidence

Overall we interpret this empirical evidence as being strongly in line with the predictions of our simulated spatial proximity model. Racial clusters are a ubiquitous feature of US cities across all time periods of our investigation. Racial change is highly concentrated at the boundary of clusters and the more drastic the change considered, the more it is concentrated at this boundary. Minority shares change steeply but non-precipitously at cluster boundaries. Rental prices show little variation internal to Minority clusters, but rise strongly as we move from the boundary to the interior of White clusters.

We would like to emphasize that while the evidence we provide for the relevance of spatial spillovers is not causal, it remains highly suggestive. For example, one might be concerned that sorting by income, in combination with spatially correlated residential amenities exogenous to racial sorting, could explain part of the observed clustering in the cross-section. We are not over-concerned about this case. There are significant differences in mean income between Whites and Minorities, but there is still substantial overlap in these distributions during the time periods we consider. If racial clustering was truly due to income sorting, then we would expect to observe substantially more spatial integration of households with similar income but different race than we see empirically.

When considering alternative explanations, such as income sorting, spatially correlated labor market access, or discrimination in the housing market, it is important to keep in mind that, in principle and ex-post, the bounded neighborhood model can rationalize any spatial distribution of Whites and Minorities simply through the adjustment of the race-specific exogenous fundamentals η_{rj}. It can also match any dynamics through respective *changes* to those exogenous shocks across periods. However, it does not provide a deep explanation for why these shocks should evolve precisely in the way necessary to generate the data. By contrast, and as we show here, the spatial proximity model generates patterns that match the cross-section as well as the dynamics of racial residential segregation remarkably well. Spatial spillovers in racial preferences thus provide a parsimonious explanation for what we observe and so are key in rationalizing the cross-section and dynamics of neighborhood racial change.

4 Evidence on Location and Tipping for All MSAs

One of the main predictions of the spatial proximity model is that drastic racial change is concentrated at the boundaries of racial clusters. In our empirical investigation focusing on decadal changes in census tracts' racial composition we found powerful supporting evidence. Figures I and VI showed that fully 80% of drastic racial change is concentrated there. This result stands in strong contrast with the evidence presented by Card et al. (2008a). The authors develop a reduced form approach to identify tipping points at the MSA-level using the same census data. They find significant tipping points for many cities, compare the magnitude of tipping points across cities, and track their development over the decades from 1970 until 2000.[30] They develop a spatial stratification extension to their main results, on which we will build in Section 4.3. As noted earlier, they found tipping effects to be most powerful far from existing Minority clusters.

Our results contrast most sharply with those of Card et al. (2008a) on the *locus* of racial change. To understand where drastic racial change occurs and specifically the role of neighborhood tipping in this, we revisit their findings. This comes in two parts. The first will examine in detail a case study for Chicago in the period 1970-1980. We will then use insights from this case study to re-examine all MSAs in the three decades 1970-2000 of our study. We provide a new, theoretically-motivated spatial stratification that emphasizes distinct social

[30] More detail on Card et al.'s approach to finding MSA tipping points appears in Section 4.3 below.

processes in different regions of the MSAs, revising the interpretation and measurement of tipping and drastic racial change.

4.1 A Re-examination of Chicago, 1970-1980

The most striking visual evidence supporting the tipping hypothesis appears in Card et al. (2008a) as their Figure 1. Examining Chicago in the period 1970-1980, they find that when the initial Minority share of a census tract passes a tipping point of 5.7%, there is a discontinuous drop in the decadal growth of the White population in excess of 30 percentage points. Exactly because this appears to provide powerful evidence in favor of the tipping hypothesis, we find it a propitious setting to explore the forces at work. Because our theory emphasizes spatial aspects of the evolution of racial neighborhood change, it is a big advantage as well to investigate a specific city and time where maps can shed light on these forces.

Data: Binned, Unbinned, and Mapped

We begin, then, by reproducing the Card et al. (2008a) Figure 1 as the top panel of our Figure IX. This plots the binned change in the White population 1970-1980 as a share of the tract's 1970 total population on the vertical axis against a tract's initial Minority share in 1970 on the horizontal axis.[31] The vertical line in Figure IX is the posited tipping point of 5.7% in 1970 for Chicago using Card et al.'s preferred fixed point estimation method. The horizontal line is the unconditional mean for the change in White population. We can take these vertical and horizontal lines as defining quadrants that will be helpful in our discussion of the evidence for tipping.

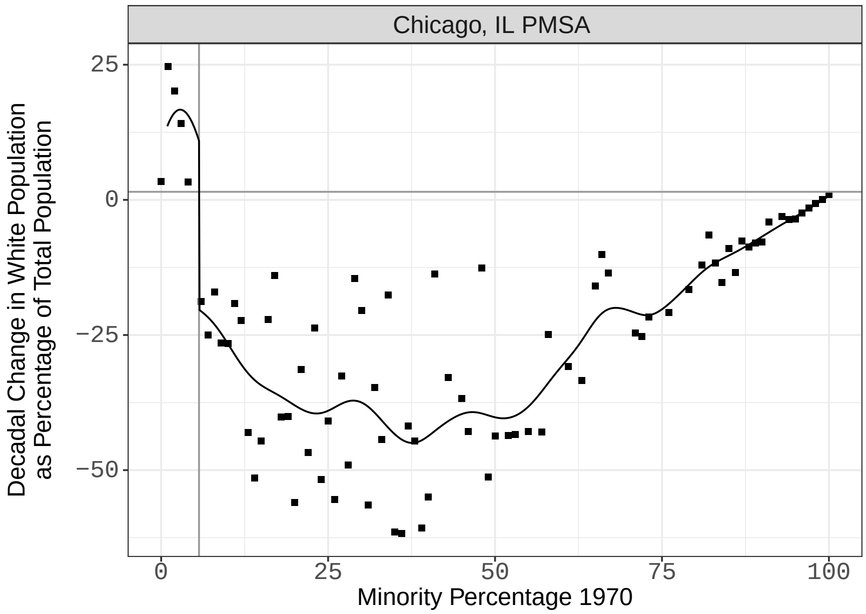
The partial equilibrium bounded neighborhood model that Card et al. (2008a) rely on is closely related to the bid-rent functions we presented in Section 2.1 and it has clear predictions about how locations should evolve above and below the tipping point.[32] Tracts above the tipping point in the initial period should see a loss of White population in the subsequent period. This is powerfully supported in the binned data, as the first quadrant is entirely empty, hence all of the binned observations are in the fourth quadrant, showing a decline in

[31] To be precise, the y-variable is defined as "(tract-level White population in 1980 minus tract-level White population in 1970) divided by tract-level total population in 1970." Tract geographies are standardized at 2000 Census geographies to allow for cross-decadal comparisons. This y-variable is the same as used in Card et al. (2008a); we maintain their restrictions to the set of tracts in the estimation sample, which are explained in-depth in their paper.

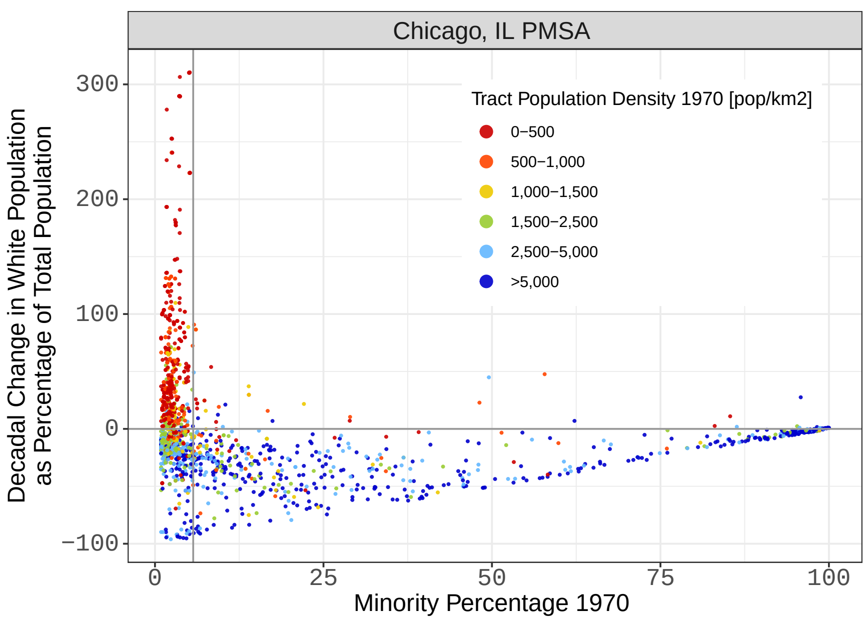
[32] The logic of why Card et al. (2008a) predict drastic White exit above the tipping point and stability below the tipping point is explained in Appendix Figure A.XI. The figure provides a simple way to think about the link between their theory and main data exercise.

Figure IX:
Binned and Unbinned Neighborhood Change, Chicago 1970-1980

(a) Binned Data for Chicago



(b) Unbinned Data for Chicago, with Density



Panel (a) contains 100 scattered points of width 1 percent (in terms of Minority percentage) which represent the average change in White population for all tracts in that Minority percentage band. A kernel mean smoother is overlaid. This replicates Figure 1 in Card et al. (2008a). Panel (b) illustrates the unbinned, raw data. The vertical line represents the fixed-point estimated tipping point for Chicago in 1970 (5.7%). Colors in Panel (b) indicate tract population density.

the White population.

Below the tipping point, the theory holds that the locations should be racially stable, hence we would hope to see the data clustered around zero White population growth. The binned data below the tipping point are not perfect in this respect. Two of these bins are close to zero White population growth, while others show growth of 13% to 25%. The third quadrant (declines in White population and below the tipping point) is entirely empty in the binned data. In short, while less than perfect, the contrast between the change in the White population growth just below and just above the tipping point in the binned data appears to provide powerful evidence in favor of the tipping hypothesis.

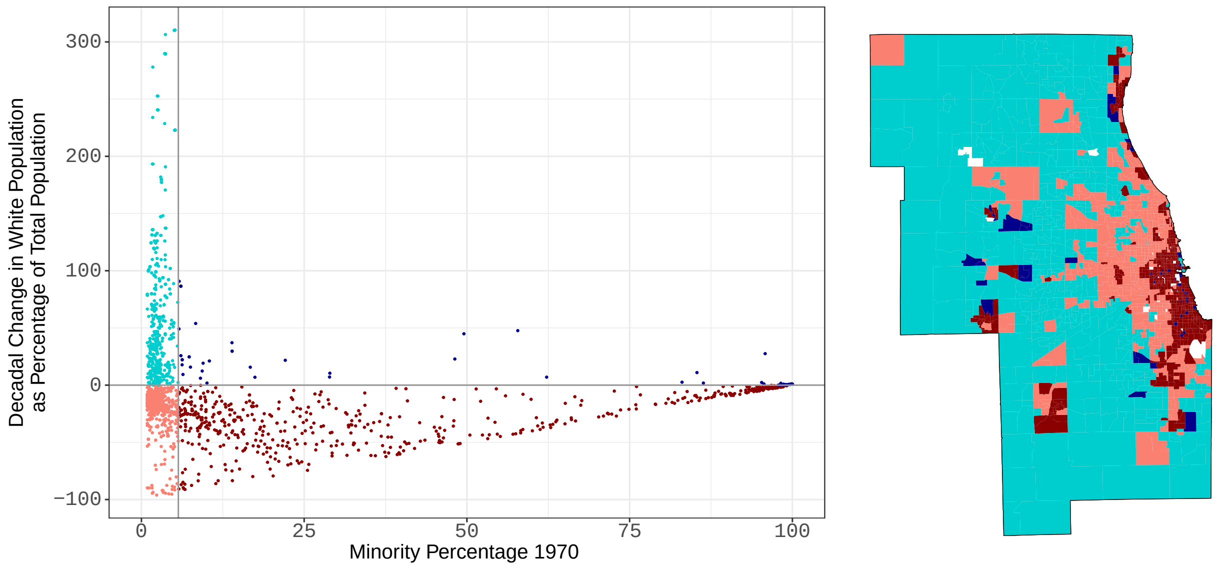
Naturally, binning shrouds heterogeneity. But the heterogeneity may provide insight to the forces contributing to the discontinuity at the tipping point. So we next turn to the unbinned data for Chicago, which we show in the bottom panel of Figure IX. While unbinning the data will yield more heterogeneity, we would like it not to fundamentally change the conclusions we drew from the binned data.

Consider first the unbinned data above the tipping point. Theory predicts that these tracts will show a loss in White population. And this is overwhelmingly what we see in the unbinned data. There are a modest number of tracts in quadrant 1, reflecting a rise in the White population, but the vast majority of observations are in quadrant 4, reflecting a loss of White population. The unbinned data strongly endorses the conclusions from the binned data about evolution above the tipping point.

Now consider the unbinned data below the tipping point. Again, the partial equilibrium bounded neighborhood theory tells us these tracts should have a stable White population. The binned data exhibited this stability, if imperfectly. When we unbin the data for the tracts below the tipping point, though, what we see is a veritable explosion of heterogeneity. Instead of seeing the data clustered around zero White change, we see tracts with a change of White population ranging from close to -100% to above 300%. This explosion of heterogeneity below the tipping point is not something the bounded neighborhood theory predicted, so we would like to explore it further.

A first step in this exploration takes advantage of another feature of the unbinned data presented in the lower panel of Figure IX. Specifically, we have used colors to distinguish population densities of the tracts. At one end, dark blue indicates a population density of $5,000$ or more per square kilometer, while at the other end, dark red indicates a population density below 500 per square kilometer. Above the tipping point, the observations are

Figure X:
White Population Change by Quadrant, Chicago 1970-1980

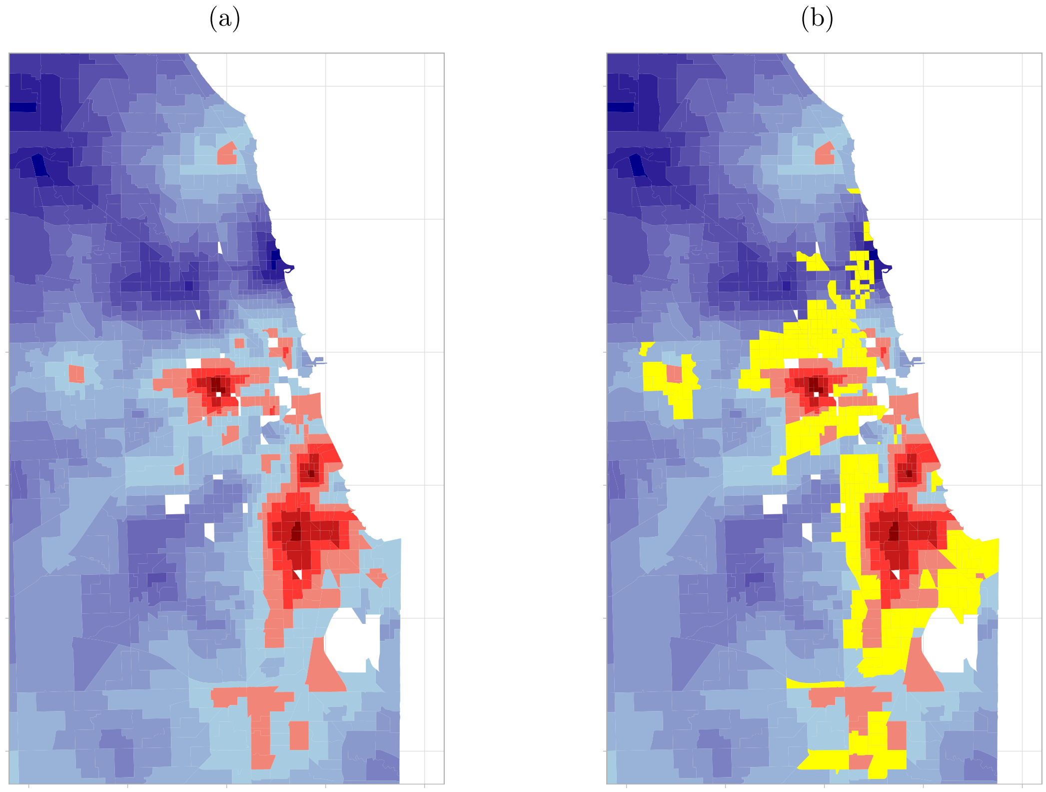


The unbinned data for changes in White population in Chicago MSA Census tracts for 1970-1980 is plotted on a map, with colors indicating the quadrant of change for that tract.

overwhelmingly high density and concentrated in the fourth quadrant. Below the tipping point, there is a sharp contrast. Those in the second quadrant, hence with strong White population growth, are overwhelmingly low density. Those in the third quadrant, with strong declines in White population, tend to be high density. This is a dimension of the data not properly situated in the theory.

Since we are looking at Chicago just in the period of 1970-1980, we can explore more directly the spatial patterns suggested by this variation in density. We implement this in Figure X. There we simply plot on a map of the Chicago MSA the data colored according to the quadrant in which it appears in the unbinned data. The tracts above the tipping point that lose White population, hence the dark red-colored tracts in the fourth quadrant, are heavily concentrated in central Chicago and its South Side. The modest number of dark blue-colored tracts above the tipping point that gain White population in quadrant 1 appear to have a higher tendency to be more remote from the center of Chicago. Below the tipping point, the salmon-colored tracts in the third quadrant that lose White population are for the most part at the outer boundary of the dark-red tracts that dominate above the tipping point. Finally the light blue tracts of the second quadrant that are below the tipping point but have powerful growth of the White population are primarily remote from the central city, i.e. suburban.

Figure XI:
Drastic Loss of White Population, Central Chicago 1970-1980



Panel (a) shows 1970 racial modes and locations relative to the boundary of the clusters. In panel (b) tracts colored yellow lost 25 p.p. or more of White population between 1970-1980.

These suggest that neighborhood racial change has a strong and systematic spatial character that needs to be understood.

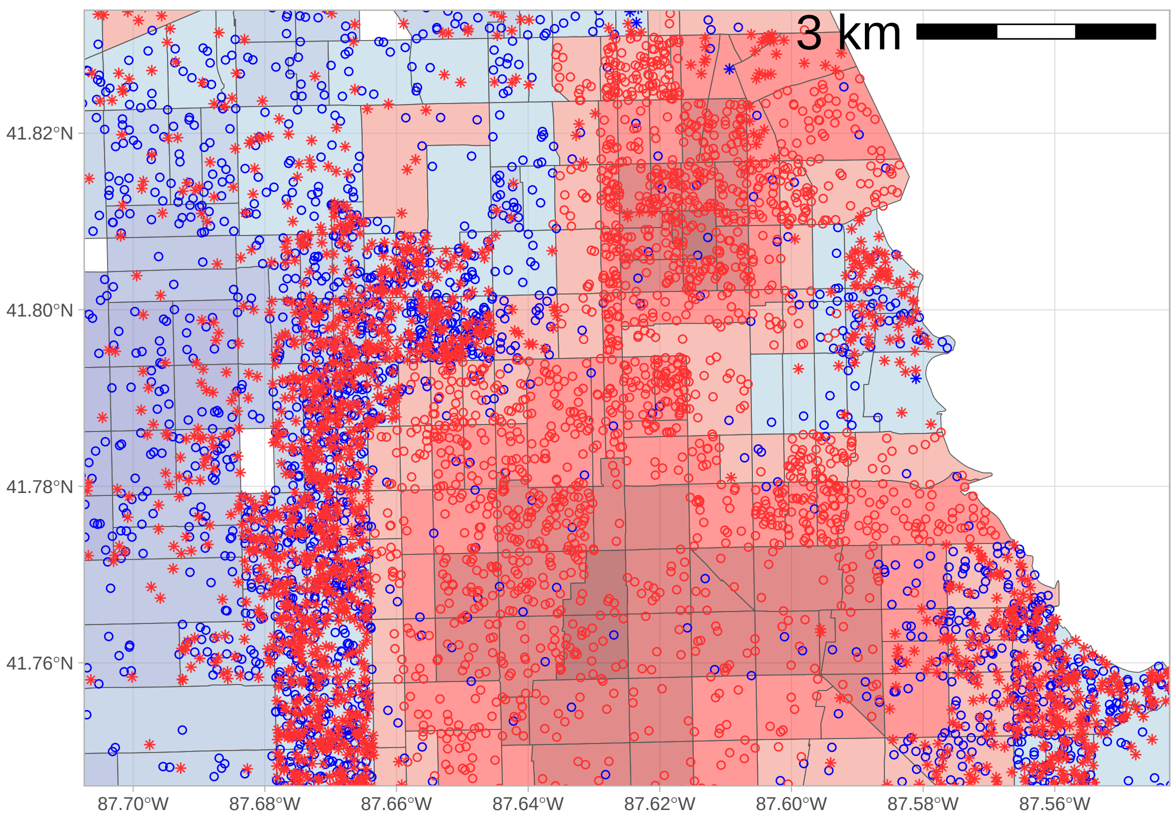
The Locus of Racial Change in Chicago 1970-1980

One of the central conclusions from our examination above of the dynamics of segregation in Section 3.3 is that racial change happens at the boundary of clusters. We can revisit this for the case of central Chicago in 1970-1980.[33] Figure XI has two maps. On the left, the color indicates the modal race in tracts and the shade indicates the distance from the boundary of clusters for central Chicago in 1970. In the map on the right, we color as yellow all tracts that had a drastic decline of 25 p.p. or more in the White population between 1970-1980. We can see that these are overwhelmingly concentrated at the boundary of the White and Minority clusters. This is precisely as expected in a spatial proximity world.

[33]The counterpart for the Chicago metro area can be viewed in Appendix Figure A.VII

We can examine this drastic change with more granularity in Figure XII by plotting a dot map of changes in population by group at the census tract level. Each dot is either a star, representing a net entry of 75 people, or an open circle, representing a net exit of 75 people. As before, Minorities are red and Whites are blue. Summing dots per census tract gives the total change by group for that tract. Zooming into this dot map for the South Side of Chicago around the University of Chicago, we observe intense churning right at the boundary of the racial clusters, with the entrance into White-mode boundary tracts by Minorities (red stars) coupled with White exit from these tracts (blue circles). At relatively modest distance from the boundary of the tracts, the intensity of racial churning declines sharply. Again, this is precisely what one would expect in a spatial proximity world.

Figure XII:
Entry and Exit by Race, South Side of Chicago, 1970-1980



Dots on the map represent bins of people, colored blue for Whites and red for Minorities. An open circle represent a loss of 75 people of a given type in that tract. A star represents a gain of 75 people of a given type in that tract. Sum of dots in each tract represent the total inflow or outflow of Whites and Minorities from the tract between 1970 and 1980. The base color of census tracts is the racial mode of that census tract in 1970, with lighter shades representing tracts closer to a boundary.

Even these very simple approaches to visualizing the data indicate that they contain powerful spatial patterns. This suggests, as well, that simply pooling all tract observations to identify an MSA-specific tipping point risks conflating very different social processes in the different locations. The next section seeks to understand these spatial dimensions in more depth.

4.2 A Spatial Stratification for all MSAs

We now turn to examine the data for all MSAs in our sample from 1970-2000. We want to do so in light of what we learn from the case of Chicago 1970-1980. This examination will build on the approach of Card et al. (2008a), but looking through a different spatial prism and tying what we do more closely to our underlying theory.

We begin by looking at the unbinned pooled data for all MSAs in 1970-1980, which appears in Panel (a) of Figure XIII. The y-axis is as before, the change in the tract White population from 1970-1980 divided by the total initial population. The x-axis now shows a tract's initial Minority share relative to the metro-specific tipping point from Card et al. (2008a). One can say that the unbinned pooled all-MSA data for this period looks broadly similar to what we saw for the case of Chicago alone. Notably there is enhanced heterogeneity below the (pooled) tipping point.

We now do a single split of the data. Define urban areas to be the set of tracts with a population density above 1,000 per km^2. With a slight abuse of nomenclature, we will call tracts suburban if their population density is below 1,000 per km^2, since these are tracts with potential to be converted to suburbs. The partition is in each case according to density at the outset of a decade.

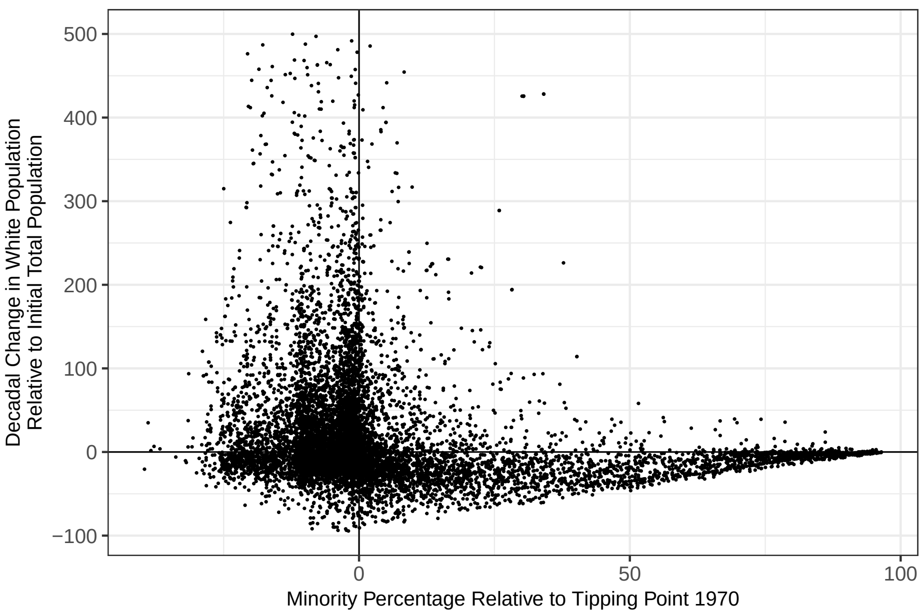
Panel (b) of Figure XIII shows this split of the data. What one sees is not subtle. The urban and suburban areas are experiencing radically different social processes, and we can relate these to the concept of tipping.

First, tipping means something specific. To be precise, tipping is the *entry of Minorities* to a tract, which induces massive *White exit*. The urban areas are indeed dominated by White *exit*. But the suburban areas are not. Instead they are overwhelmingly characterized by White *entry*. The social processes in the suburbs may have a racial character. What they are *not*, though, is tipping. In the urban areas, where White exit dominates, we can use regression analysis to investigate the presence of tipping. If the suburban data shows a discontinuity, then we will characterize this as "biased White suburbanization," where massive White entry tends to avoid areas with significant initial Minority presence.

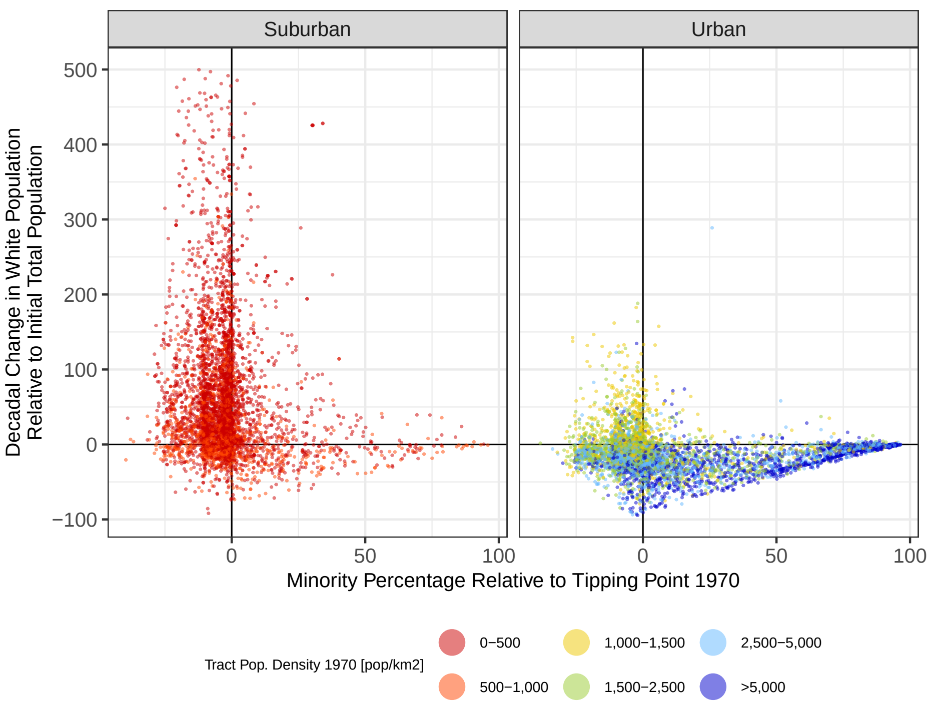
This provides a crucial path to reconsider the link here between theory and data. The empirical approach of Card et al. (2008a) may be thought of as a pooled partial equilibrium.

Figure XIII:
White Population Change, All MSAs 1970-1980

(a) Pooled



(b) Urban and Suburban



Change in tract White population relative to initial total population 1970-80, pooled for all MSAs. The X-axis shows the initial Minority share relative to metro-specific tipping points. The bottom subfigures do this separately for suburban and urban tracts and indicate initial tract population density. Urban tracts are those with a population density above 1,000 per km^2.

The narrative is built on what happens in a single neighborhood generalized to an entire metro area. But everyone who leaves one neighborhood must go somewhere, as the adding up constraints of general equilibrium bind. In broad outlines, this is the contrast between evolution in the urban and suburban areas: Whites exit the first and enter the second.

The striking contrast in social processes revealed in the unbinned urban and suburban data thus has a consequence. One cannot simply pool the two, estimate a discontinuity, and think of the resulting estimate as a characterization of the magnitude of tipping. For this reason, our focus will be on spatially stratified regressions.

An additional important lesson arises powerfully from our case study of Chicago: Location *within* the urban area matters. Central urban areas, close to existing Minority clusters, may evolve differently than urban areas more remote from Minority clusters. Our Chicago case study vividly illustrates how the results on the locus of racial change for all MSAs in the more stylized geography of Section 3.3 appears in a natural geography.

We can tie each of these locational characteristics to elements of our underlying theories. Restricting attention to urban areas, the spatial proximity model holds that drastic change should be concentrated in tracts close to the boundary of the existing Minority cluster. The bounded neighborhood model focuses only on the racial characteristics of the tracts themselves, so says proximity to the existing Minority cluster should not matter. Evolution in urban areas remote from the boundary of racial clusters thus provides an unconfounded test of pure tipping in the bounded neighborhood model. Suburban areas should be little affected by tipping, i.e. White exit in response to Minority entry. Instead, they should experience tremendous White entry (Boustan, 2010), with White avoidance of areas with higher initial shares of Minorities (Ellen, 2000). They should experience what we term *biased White suburbanization.*

We can operationalize these. From above, we divide urban from suburban tracts as those with an initial population density respectively above versus below 1,000 per km^2. We can further divide the urban tracts into those more- versus less-exposed to Minority clusters, at locations of $l \leq 2$ versus $l > 2$ relative to the boundary of the racial clusters. The three categories, suburban, plus urban more- and less-exposed to Minority clusters, will be the basis for our stratified regression analyses.

The bottom of Table III provides summary statistics on both overall and drastic racial change, which confirms that our sample period 1970-2000 was one of strong racial evolution. The White share of our 100+ MSAs fell on average roughly 7 percent each decade. Yet there was substantial heterogeneity across locations within the MSAs. The White share in the urban more-exposed locations fell on average more than 11%, while this was only roughly 3% in suburban areas. The 1970s were the period of most dramatic change. In that decade, drastic change of a fall in the White share of 25 p.p. or more occurred in nearly 25% of tracts in the urban more-exposed areas but less than 4% of those in the suburban areas. The differences in this dimension remained substantial in all periods. The experience of the urban less-exposed areas in these measures always fall between the other two.

Our summary statistics for the all-MSA data confirm a fundamental fact: There are dramatic differences in the racial evolution of urban and suburban tracts, and more subtle differences even among urban tracts more- versus less-exposed to the boundary of racial clusters. In the section that follows, we will replicate the all-MSA regressions from Card et al. (2008a) that pool these locations. Because we view pooling as conflating quite distinct social processes, however, our emphasis will be on the spatially stratified regressions that follow, which also can be tied to elements of our theory.

4.3 Methods, Regressions Pooled and Spatially Stratified

For purposes of comparability, we will stay methodologically close to the approach of Card et al. (2008a), yet distinct in the spatial stratification we develop and in the theory within which we interpret results. Their approach proceeds in two steps. In their preferred "fixed point" estimation method, they first identify an MSA-specific tipping point as the Minority share at which the White population grows at the same rate as the MSA as a whole. Having used two-thirds of their data to identify candidate tipping points, the remainder of the data is then pooled across MSAs and used to estimate the magnitude of the jump at the discontinuity, relying on a regression discontinuity design using quartic polynomials, MSA fixed effects, and several tract-level controls.[34] For simplicity, we follow the same procedure. Importantly, however, we are going to test for the magnitude of tipping points separately across different strata of the pooled data by running our regressions separately on the three individual subsamples. The pooled discontinuity will not necessarily be an average of the three subsamples, because the estimated discontinuities are derived from separate polynomials fit

[34]We discussed in Section 2.2 why it might be difficult empirically to distinguish drastic racial change associated with elastic White responses to a Minority share shock from a true tipping bifurcation. Card et al. (2008a) sidestep this issue when they emphasize that there may instead be a steep downward sloping (but continuous) curve in the neighborhood of their "tipping" points rather than a true discontinuity. If one were to take the discontinuity seriously, the appropriate specification would use local linear regressions. We have implemented these with population weighting and find that the measured discontinuities are insignificantly different from zero. But this may be taking the strict discontinuity too seriously. For these reasons, and for comparability, we follow their approach. This should be kept in mind when we use the terms "tipping" and "discontinuity," where we adopt their usage in reference to results in the all-MSA regressions.

for each subsample.

Table III shows our estimation results for tipping for all MSAs from 1970-2000 both in the pooled version that was the centerpiece of Card et al. (2008a) and in a spatially stratified version. We examine two types of dependent variables, which for concreteness we refer to as "levels" and "shares." The first (levels) is the change in the tract's by-group population divided by the total initial population. The range of feasible outcomes for the change in levels is $[-100\%, \infty)$. This allows comparability with the core results of Card et al. (2008a). It also focuses attention to changes in by-group population *levels*, so helps to sharply distinguish the social processes evolving in the urban versus suburban areas.

The second dependent variable we will consider (shares) is the change in the tract White share. The range of feasible outcomes in shares is symmetric $[-100\%, 100\%]$. One attraction of this alternative is that the theoretical derivation in Card et al. (2008a) leads to a focus on the racial *share*, not the *level*.[35] And, of course, the main point of the tipping literature is to understand the change in racial composition. We may learn a great deal, though, by comparing levels and shares results.

4.3.1 Pooled Regression Results

The first column of Table III replicates the pooled results from Card et al. (2008a). In each decade, when the initial Minority share crosses from just below to just above the posited tipping point, there are modest and sometimes insignificant changes in Minority population; sharp drops in the White population; and consequently equal magnitude drops in total population. Card et al. (2008a) interpret the discontinuity in the White population as tipping, where the tipping discontinuities are $(-12\%, -14\%, -7\%)$ for the 1970s, 1980s, and 1990s respectively. The estimates are visualized in the first column of Figure XIVa.

These headline results are quite striking and, understandably, have commanded a great deal of attention. To cross a simple threshold in the initial tract Minority share and on average have an 11 percent decline in the White population growth is on its face a powerful empirical confirmation of tipping.

[35] They acknowledge this, but explain the shift to levels based on the observation that their theory does not provide for the expansion of housing and population, phenomena present in their data. However they do not present any reason that these matter for their underlying theoretical predictions. Indeed, the theory that yields shares as the appropriate dependent variable is the entire basis for pooling observations at the MSA level, given that the cross section within an MSA itself has considerable variation in population, housing, and the opportunities for expansion of each. Examination of levels, as noted, introduces a fundamental asymmetry in the range of feasible outcomes. In the specific setting of the pooled levels regressions, this asymmetry may favor findings of large tipping effects.

However, as noted above, the pooled regressions conflate outcomes from radically different social processes in urban and suburban areas, hence we now turn to spatially stratified regressions.

4.3.2 Urban Less-Exposed

Next we move to the spatially stratified analysis using our tripartite split.[36] Results from this investigation are displayed in columns 2-4 of Table III and are visualized for levels in columns 2-4 of Figure XIVa and for shares in columns 2-4 of Figure XIVb.

We start by focusing on the estimated tipping discontinuities in the urban less-exposed tracts. This should be the clearest case for finding the kind of tipping predicted by the bounded neighborhood model, since here the results are less prone to being confounded by concerns of the role of spatial proximity to the existing Minority cluster or alternatively suburban tracts possibly prone to discontinuous White entry.

The results in the levels regressions are stark. Tipping discontinuities in the urban less-exposed tracts are small and insignificant in all decades for Minorities and total population, as well as for Whites in the 1970s and 1980s. The only significant discontinuity for the urban less-exposed tracts comes for Whites in the 1990s. The measured discontinuity even in that period is only -3.9%, so in a substantive sense pretty modest.

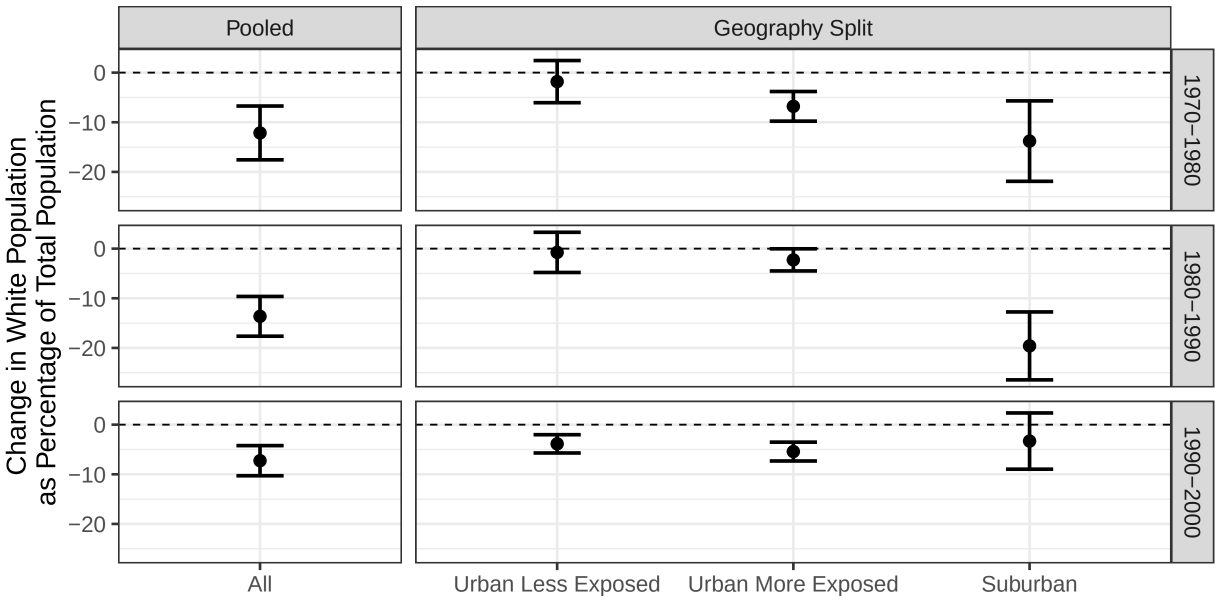
The shares regressions in the urban less-exposed area yield broadly similar results. Discontinuities for White shares are insignificant in the 1970s and always small (2% or less).

In short, the purest, unconfounded test of the bounded neighborhood model, in the urban less-exposed areas, suggests that tipping there is either small or non-existent.

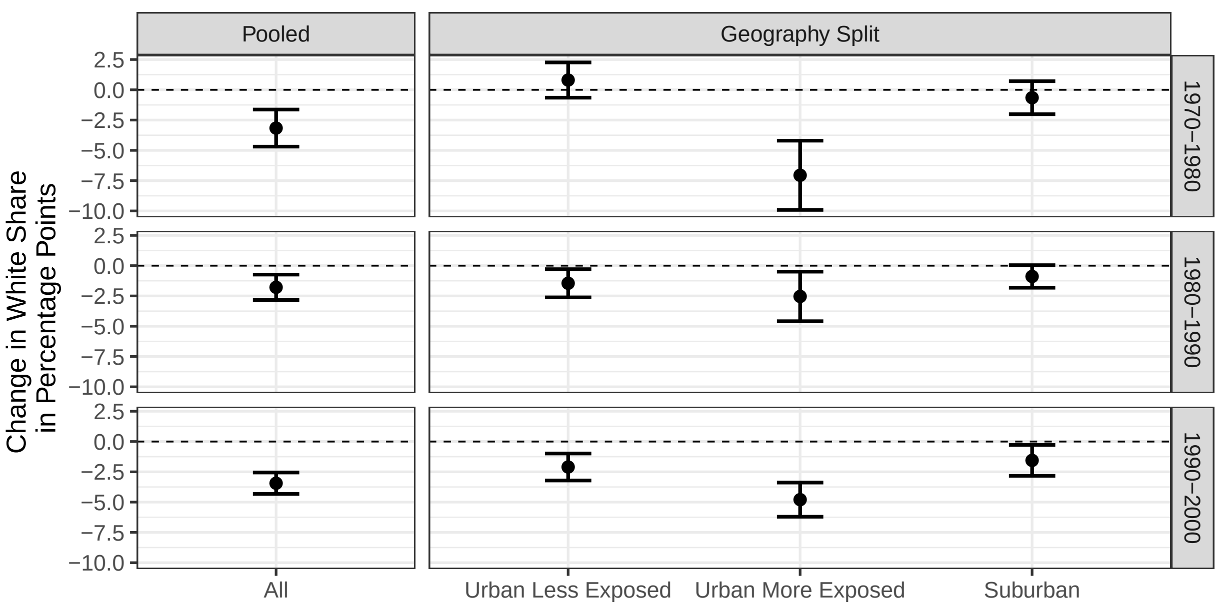
[36] In table VII of their paper, Card et al. (2008a) provide a set of robustness checks that may appear similar to our spatial stratification. There they investigate if tipping discontinuities are significant (1) by central city vs. remainder of the MSA, (2) by distance to the nearest high-minority-share tract, and (3) by having a neighboring tract with a Minority share above the tipping point or not. In these three robustness checks, Card et al. (2008a) find that tipping effects are usually smaller in the central city, and larger when moving further away from high-Minority-share tracts and tracts that are beyond the tipping point. This leads them to conclude that the expanding ghetto (spatial proximity) model cannot explain the tipping dynamics they observe. In all of the splits, however, their findings are driven by suburbanization and discontinuous White entry into low density tracts. Split (1) is prone to confounding because Card et al. (2008a) use 2000 central city definitions and thus include tracts in the central city that were not urbanized in the early decades. Splits (2) and (3) are affected since tracts that are far from existing Minority tracts also are predominantly located outside of the city center and are thus suburban. Our spatial stratification avoids these issues, first, because we classify suburban tracts, which are prone to discontinuous White entry, based on their initial population density in the decade of interest and not on the 2000 central city indicator. Second, we consider distance from a Minority cluster as well as urban or suburban status simultaneously in the same stratification.

Figure XIV:
Geographic Splits and Tipping Point Magnitudes, All MSAs 1970-2000

(a) Change in Levels



(b) Change in Shares



Coefficients for pooled and spatially stratified regressions in which the dependent variable is (a) the "levels" version (change in total White population by tract divided by total initial tract population) or (b) the "shares" version (change in tract White share).

Table III: Estimated Tipping Discontinuities, Pooled Sample and Three Groups by Geography

	Pooled	Triple Split		
		Urban Less Exposed	Urban More Exposed	Suburban
1970 - 1980				
Change in White population	-12.1	-1.8	-6.8	-13.8
	(2.7)	(2.1)	(1.5)	(4.1)
Change in Minority population	2.0	-1.5	7.6	-2.1
	(1.0)	(1.0)	(1.7)	(2.3)
Change in total population	-10.1	-3.3	0.8	-15.9
	(3.0)	(2.3)	(1.7)	(4.9)
Change in White share	-3.2	0.8	-7.1	-0.7
	(0.8)	(0.7)	(1.4)	(0.7)
Average Change in White share	-8.0	-7.0	-15.5	-3.8
Fraction Change in White share < -25 p.p.	10.8%	7.2%	24.8%	3.8%
Observations	11,611	3,162	3,346	5,103
1980 - 1990				
Change in White population	-13.6	-0.8	-2.3	-19.6
	(2.0)	(2.0)	(1.1)	(3.5)
Change in Minority population	-1.1	1.6	0.2	-2.6
	(1.1)	(0.9)	(1.5)	(1.5)
Change in total population	-14.7	0.8	-2.1	-22.2
	(2.6)	(2.2)	(1.4)	(4.3)
Change in White share	-1.8	-1.5	-2.5	-0.9
	(0.5)	(0.6)	(1.0)	(0.5)
Average Change in White share	-5.9	-5.6	-8.9	-3.6
Fraction Change in White share < -25 p.p.	4.5%	2.6%	8.6%	2.2%
Observations	12,151	2,643	3,976	5,532
1990 - 2000				
Change in White population	-7.3	-3.9	-5.4	-3.3
	(1.5)	(0.9)	(1.0)	(2.9)
Change in Minority population	2.9	1.6	4.0	2.7
	(1.1)	(0.8)	(0.9)	(2.0)
Change in total population	-4.3	-2.3	-1.4	-0.6
	(2.1)	(1.2)	(0.9)	(4.1)
Change in White share	-3.4	-2.1	-4.8	-1.6
	(0.4)	(0.6)	(0.7)	(0.6)
Average Change in White share	-7.8	-8.0	-9.9	-5.6
Fraction Change in White share < -25 p.p.	6.9%	5.0%	10.7%	3.8%
Observations	13,371	2,543	5,478	5,350

Notes: Regressions performed on pooled sample of all MSAs as well as tracts split by population density and proximity to White and Minority cluster boundaries. The *levels* regressions use the decadal change in by-group population divided by the total initial population as the dependent variable. The *shares* regressions use the percentage point change in the White tract share. For each sample and decade, the average percentage point change in the White share and the fraction of tracts which experienced a drastic drop in White share of 25 p.p. or more are provided.

4.3.3 Urban More-Exposed

We next turn to the urban more-exposed area results. The spatial proximity model suggests these tracts should be more prone to drastic change, so perhaps also to tipping, because this area includes locations proximate to the boundary between the racial clusters.

Our results in the levels regressions are as follows. In all decades, there are only small and insignificant effects at the tipping point for total population. In all decades, there are significant declines in the White population at the tipping point. In both the 1970s and 1990s, the change in the Minority population at the tipping point is of opposite sign and similar magnitude as the growth in the White population. The one exception is the 1980s, in which there is a small and insignificant effect on the Minority population. This presence of Minority entry and White exit is consistent with tipping.

It is notable, though, that even in the more-exposed urban areas the magnitudes are not large in the levels regressions. In the 1970s, 1980s, and 1990s the tipping discontinuities in the White population are respectively (-7%, -2%, -5%). These changes are statistically significant and economically meaningful.

Still, the urban more-exposed tracts should be the very epicenter of tipping. In each decade in our sample, it is these tracts that have the largest average decline in the White share and the largest fraction of tracts with drastic declines in the White share of 25 p.p. or more. Yet the measured discontinuities average less than 5% across the decades – less than half the magnitude of the pooled regressions.

We now examine the White shares regressions in the urban more-exposed tracts. These discontinuities in the change in White shares for the 1970s, 1980s, and 1990s respectively are (-7%, -3%, and -5%). From the White levels regressions, we know that these are associated with little measurable change in population and that we primarily see the simultaneous entry of Minorities and exit of Whites in roughly the same magnitudes.

The spatial proximity model does imply that drastic racial change will happen at the boundary of clusters, so the presence of larger measured tipping in the urban more-exposed areas is certainly in the spirit of that model.

Overall, though, the magnitude of changes in the White share in a decade even in the urban more-exposed areas is pretty modest, and so seems remote from the drastic change of racial tipping in common discussion.

4.3.4 Suburban

We now examine levels results for the suburban tracts. Of our stratified areas, these most strongly parallel the Card et al. (2008a) pooled results. That may not be too surprising, given that in the first two decades suburban tracts constitute a plurality of all tracts.

The change for Minorities at the MSA-specific tipping point is small and insignificant in all decades. The discontinuities for the White and total population are even larger than in the spatially pooled regressions in the 1970s and 1980s, but insignificant in the 1990s. The White tipping discontinuities in the 1970s and 1980s, accordingly, are -14% and -20%, with even larger population discontinuities.

Even with this strikingly large measured tipping in the 1970s and 1980s, drastic decline in the White share of 25 p.p. or more occurred in only 2% and 4% of all suburban tracts in those decades. That is, the levels approach is finding powerful tipping effects precisely in a region in which drastic White exit is rare. This is in line with what we saw when we plotted the raw data in Figure IXb. The suburbs, both below and above the tipping point, are dominated by White entry.

We can examine this, as well, with the share regressions. The discontinuities among suburban tracts are (-1%, -1%, -2%), with only the last being significantly different from zero.

On its face, this might seem a contradiction. The levels regressions are telling us suburban tracts experience dramatically different White growth in the first two decades on different sides of the tipping point. The shares regressions tell us that crossing the tipping point has tiny or precisely measured zero effects on the change in the White share of these tracts.

The reconciliation in these two perspectives comes from returning to basics. There is a racial story here, but it is not tipping. Tipping means Minority entry that induces White exit. But Minority entry to the suburbs in this period is minimal and White exit rare. Instead what we see is the kind of avoidance of Minority areas that supports biased White suburbanization. Even spectacular White entry to these already low Minority share tracts hardly changes the racial composition.

To state it pointedly, the dramatic discontinuities measured in the levels regressions for suburban areas in the 1970s and 1980s are not tipping. There is no Minority entry inducing White exit. Instead it reflects general equilibrium effects wholly outside the partial equilibrium theory of Card et al. (2008a). The resulting pattern is biased White suburbanization, in which Whites surging from the urban areas to the suburbs don't move as readily into initially higher Minority share tracts there. The shares regressions for suburban areas endorse this result, with zero or tiny measured discontinuities.

5 Conclusion

Our research began with the first nesting of Schelling's bounded neighborhood and spatial proximity models amenable to empirical testing. We develop this within a discrete neighborhood choice model akin to Bayer et al. (2007), where the absence or presence of spatial racial spillovers distinguishes the models. Simulations allowed us to articulate four key empirical contrasts between the models and then examine these for 100+ MSAs from 1970-2000. The presence of powerful racial clustering; the fact that drastic racial change is extraordinarily concentrated at the boundary of racial clusters; and the non-precipitous change of racial shares and housing prices at the boundary of clusters all point to the spatial proximity model as the appropriate foundation for understanding the cross-section and dynamics of racial segregation across neighborhoods.

There is an influential and rapidly-growing economics literature on neighborhood change, nearly all of which instead takes as its foundation the bounded neighborhood version of Bayer et al. (2007). Implementations of these models ignore cross-location spillovers in racial preferences and so may suffer from an omitted variable bias. This does not by itself invalidate results reported in that literature. But it does suggest that where a setting has racial or other social characteristics that have direct spillovers *within* a location, one should then ideally investigate the extent to which they also have spillovers *across* locations. The works of Redding and Sturm (2024) and Bagagli (2023) are exemplary in this dimension.

Our results fundamentally change the field's understanding of how to measure racial neighborhood tipping, the associated magnitudes, and the location where tipping is at work. Headline results from the work of Card et al. (2008a) pool all tracts within an MSA and suggest average decadal tipping effects of -11% when crossing a metro-specific tipping point in the 1970s through the 1990s. We hold that these pooled results across all neighborhoods within an MSA are not meaningful. They conflate areas experiencing massive White exit in urban areas, which may be tipping, with those experiencing massive White entry in suburban areas, which is not tipping.

Location is absolutely critical for understanding how drastic racial change takes place, with 80% of this happening contiguous to the boundary of racial clusters. Our spatially stratified regressions show that location is likewise critical to measuring and interpreting tipping. Using the approach closest to the prior work, the largest measured tipping effects across all locations and all decades are close to -20% in suburban areas in the 1980s in the levels approach. However this is also the location and time that had the smallest total decline in the White population share, the smallest proportion (2.2%) of tracts with a drastic decline in the White share, and an insignificant decline in the White share at the postulated tipping point. White entry rather than exit dominated these tracts. The shares regressions confirm that changes in racial composition there were either zero or tiny. This underscores that in the suburban areas the process was not tipping, but biased White suburbanization.

Tipping varies by location within the urban areas. In urban areas less-exposed to Minority clusters, tipping effects are either insignificant or very modest in all decades and dramatically lower than the headline pooled results from the prior work. In urban areas more-exposed to Minority clusters, we do find significant tipping effects in all periods. The average magnitude across decades is less than 5%, though, so even in the area most consistently experiencing tipping, the magnitudes are less than half the reported pooled results in the prior work.

There have been extraordinary advances in the last decade in understanding how neighborhoods, including their racial composition, affect life outcomes. This naturally invites consideration of moving beyond zero-measure experiments to at-scale interventions that may have large and lasting effects on poverty and social integration. This immediately and forcefully raises the question of the stability of neighborhoods to the contemplated interventions. Where neighborhoods are unstable, drastic exit could wholly undo the altered racial composition that is the proximate target of policy. Our work shows that the answer to these stability questions is fundamentally tied not only to a location's own composition, but also depends on that of a broader set of nearby locations. Neighborhoods near to existing Minority clusters are likely much more vulnerable to drastic change in response to such interventions than neighborhoods more remote from these clusters. Future research should focus on establishing the parameters that govern the impact of spatial racial spillovers both in terms of the characteristics of the neighborhoods and the magnitudes of interventions.

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Supplementary Material for Segregation, Spillovers, and the Locus of Racial Change

A Additional Tables and Figures

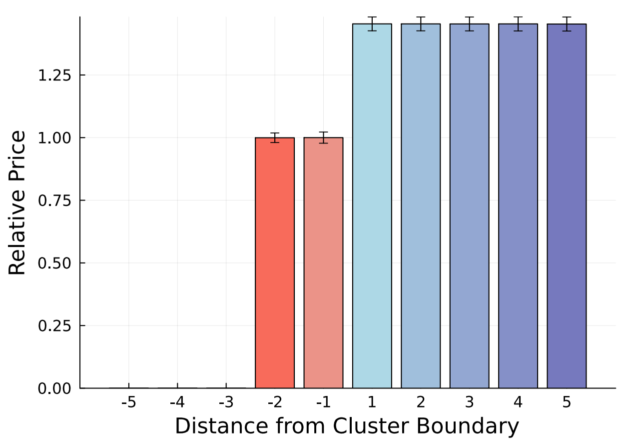
Table A.I: Percentage Population Living in Own-Race Clusters by Minimum Cluster Size

		5 Tracts			10 Tracts			20 Tracts		
Year	Minority Share	**M**	W	All	**M**	W	All	**M**	W	All
1970	18	**54**	96	89	**49**	96	88	**42**	96	86
1980	24	**58**	95	86	**55**	95	85	**49**	95	84
1990	29	**58**	94	83	**56**	93	83	**52**	93	81
2000	36	**62**	90	80	**60**	90	79	**57**	89	78

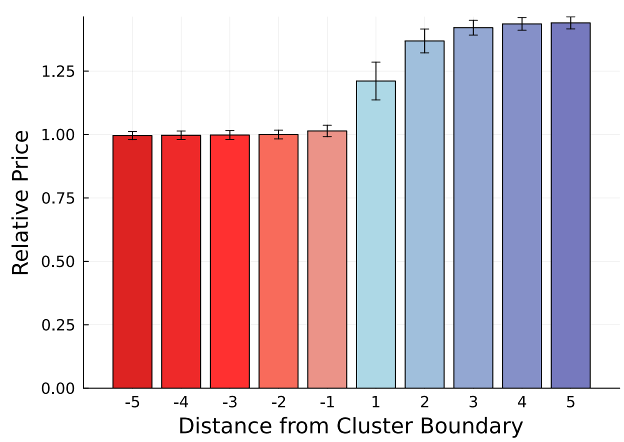
Notes: "Minority Share" is the share of the overall population which is not White Non-Hispanic. "W" refers to White and "M" refers to Minority. All numbers in percent.

Figure A.I:
Mean Relative Price by Distance from the Cluster Boundary

(a) Bounded Neighborhood



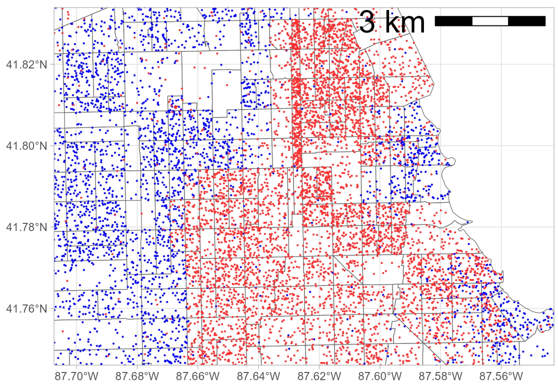
(b) Spatial Proximity



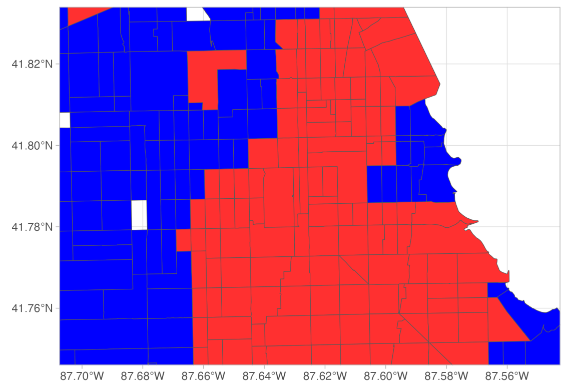
Notes: Bar plots show averages across 1000 different initializations. Observations with a distance from the cluster boundary larger than 5 are dropped to focus on patterns close to the cluster boundary. Prices are expressed relative to a distance of -2.

Figure A.II:
Construction of Clusters and Distance Bins, South Side of Chicago 1970-1980

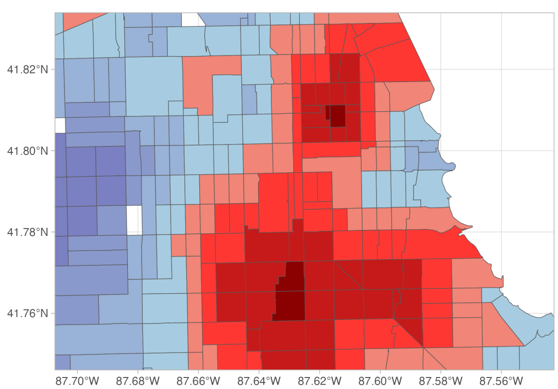
(a) Dot Map



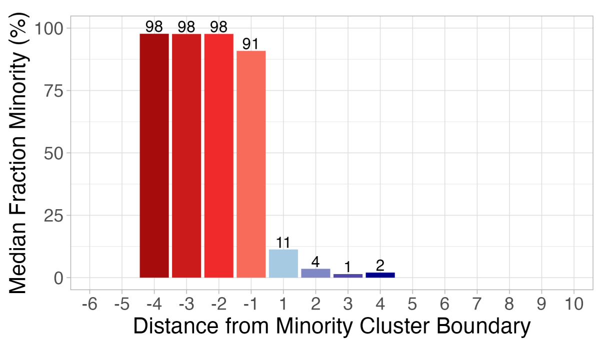
(b) Tract Modes



(c) Distance to Cluster Boundary

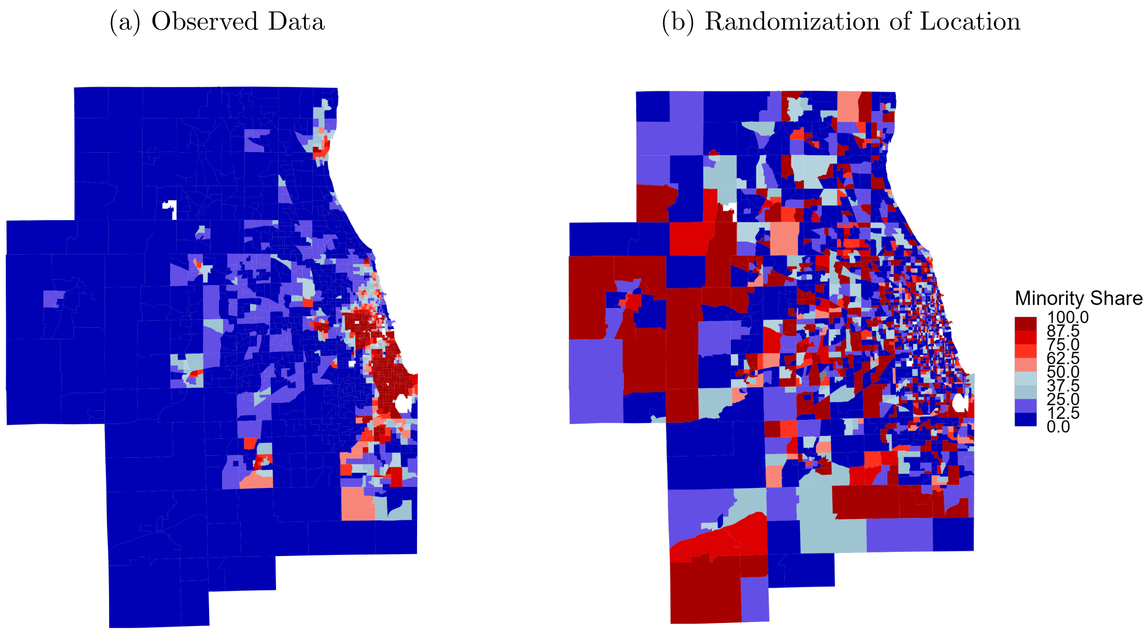


(d) Histogram by Distance Bin



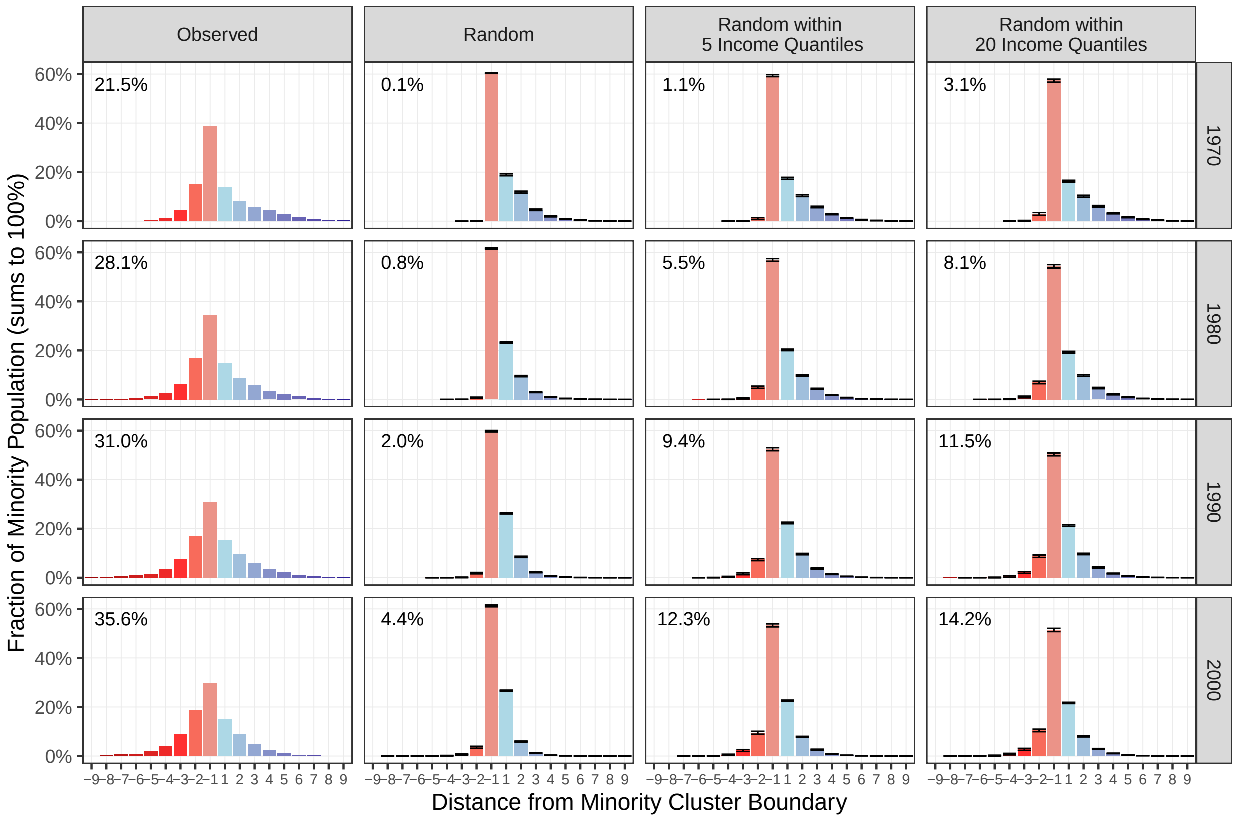
Notes: These four panels highlight different aspects of the same data, as we move from tract population data on race to our representation of minority share by location. Panel (a) illustrates population counts by census tracts; each dot represents 100 individuals, with red dots representing Minorities and blue dots representing Whites. Panel (b) colors census tracts by modal race given the underlying data from panel (a). Panel (c) shades tracts by distance from Minority cluster boundary, with lighter colors indicating closer to a boundary. Panel (d) is a histogram of median fraction Minority by distance bin for all tracts in this sample. Census tract geometries are 2000 geographies; cluster size is set to 1.

Figure A.III:
Observed and Simulated Randomized Minority Tract Locations, Chicago 1990



Notes: The map on the left is the actual data showing the Minority share of each census tract for Chicago in 1990; the map on the right is *exactly the same data*, but an example where we randomize the location of the tracts, as would occur in a bounded neighborhood world that had no spatial racial links across tracts. One cannot possibly mistake which is data and which randomization. In the main text we provide statistics to verify the intuition, but this contrast is a first indication why the assumption of zero spatial spillovers in racial preferences is implausible.

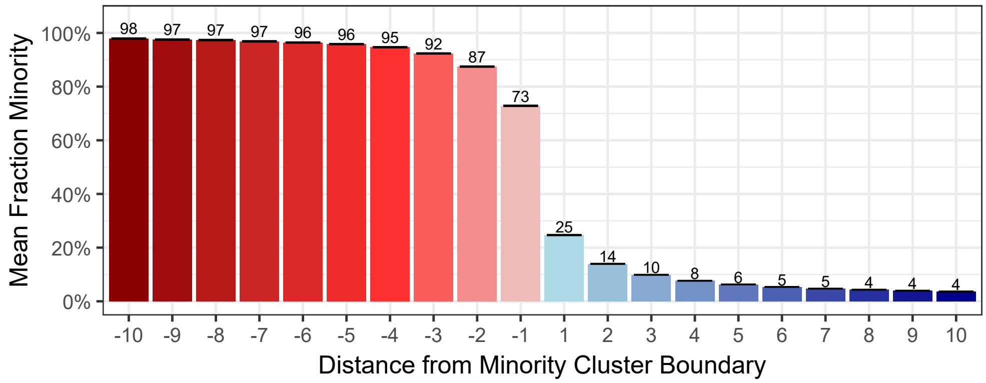
Figure A.IV:
Distributions of Observed and Randomized Tract-Level Minority Populations,
All MSAs, 1970-2000



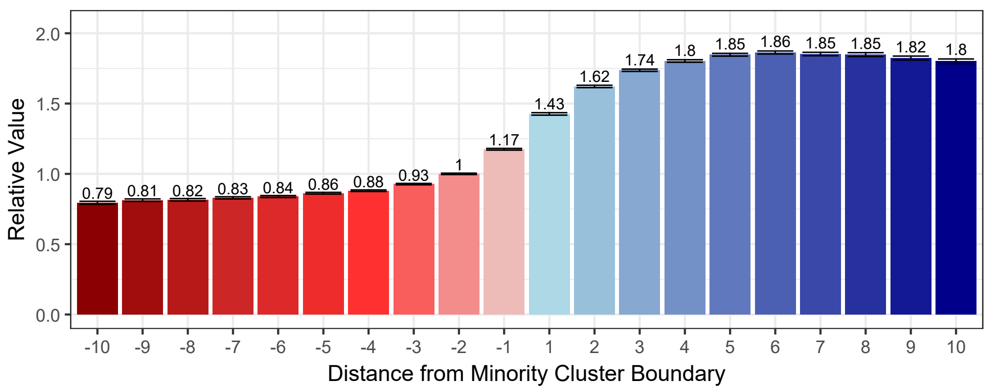
Notes: The first column shows histograms displaying the fraction of the Minority population at each location relative to the boundary of racial clusters for all MSAs. The second column does the same when, per the bounded neighborhood model, the *location* of tracts is randomized. The last two columns repeat the randomization while constraining tracts to only swap locations within the same income-constrained bins. The percentage written in the upper left in each is the fraction of the Minority population living strictly interior to Minority clusters, i.e. at locations $l \leq -2$, hence indicating the importance of racial clusters. For the simulated columns two, three, and four, averages and standard deviations across 100 randomizations are displayed.

Figure A.V:
Block-Level Gradients, All MSAs, 1990

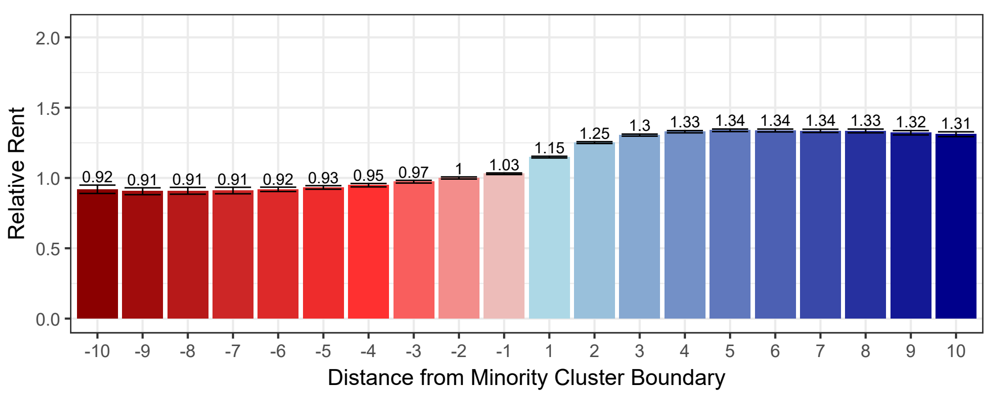
(a) Mean Fraction Minority



(b) Mean Relative Values (Normalized at Distance -2)



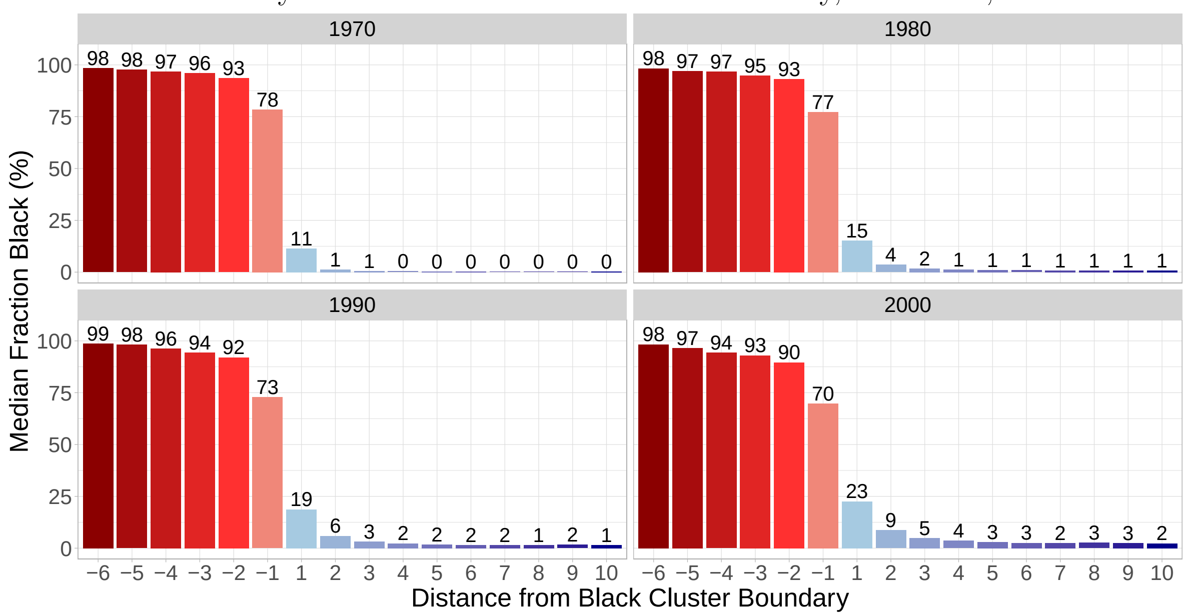
(c) Mean Relative Rents (Normalized at Distance -2)



Notes: Robustness check using information from block-level as opposed to tract-level information. Block-level information on racial composition, house values, and rents is only available for the 1990 census. Positive (negative) distances are computed as the number of contiguous blocks that need to be traversed to reach a block with a Minority share larger (smaller) than 50%. Blocks that do not house population are dropped in that calculation.

Figure A.VI

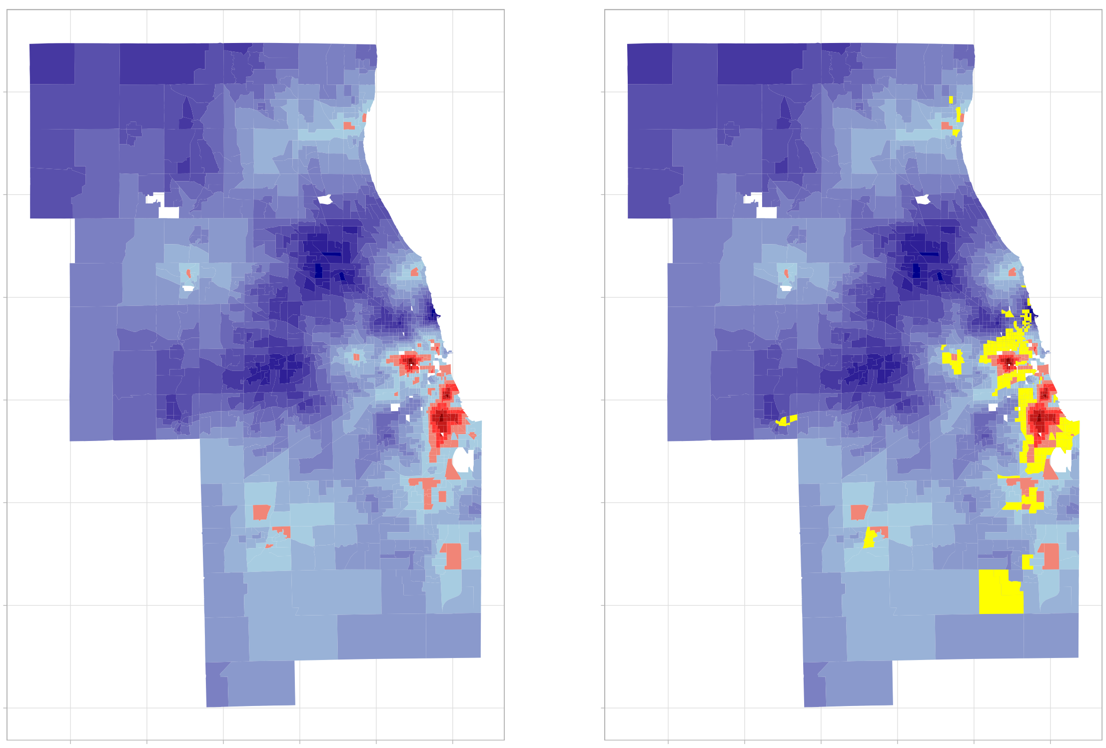
Fraction Black by Distance from Black Cluster Boundary, All MSAs, 1970-2000



Notes: Robustness check under alternative racial groups. Gradients are large at the boundary of Black/non-Black clusters across MSAs, though they do smooth out over time.

Figure A.VII:
Drastic Loss of White population, Chicago MSA 1970-1980

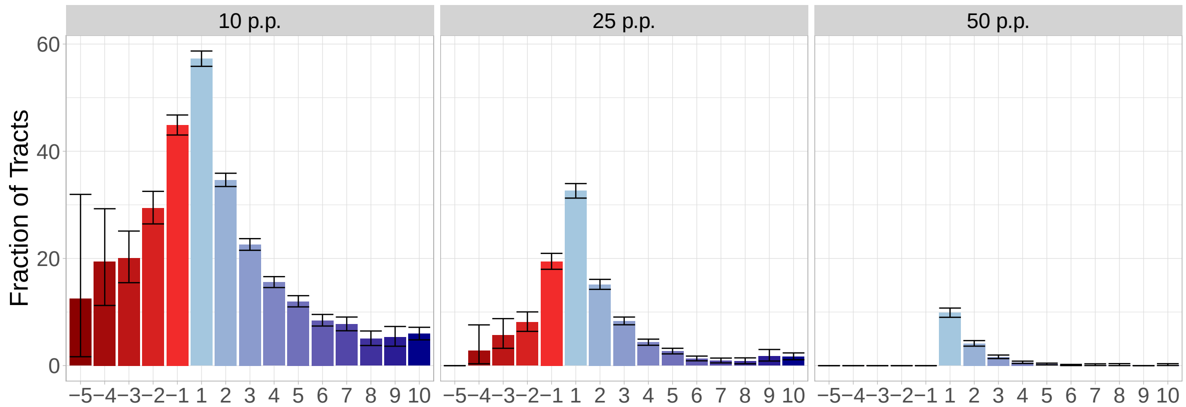
(a) (b)



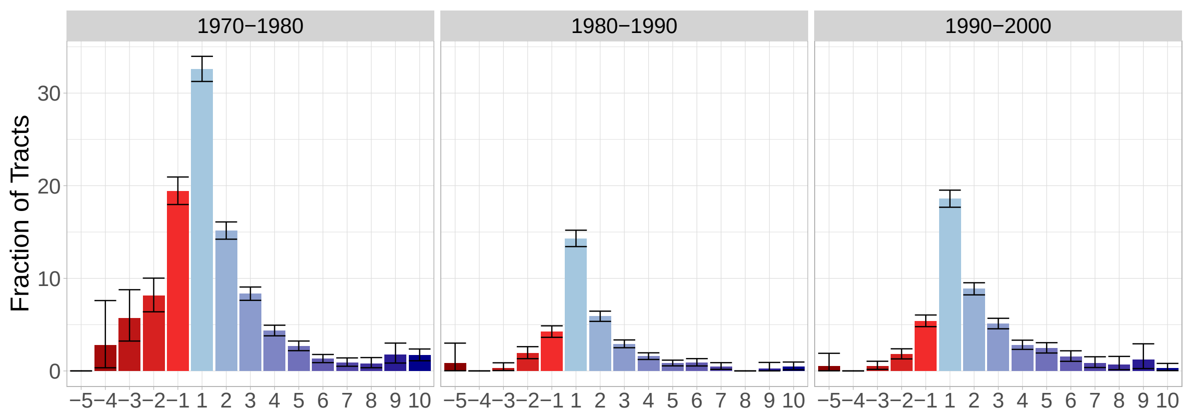
Notes: Tracts colored yellow lost 25 p.p. or more of White population.

Figure A.VIII:
Fraction of Tracts with Decline in White Share by Location, All MSAs, 1970-2000

(a) Different Thresholds, 1970



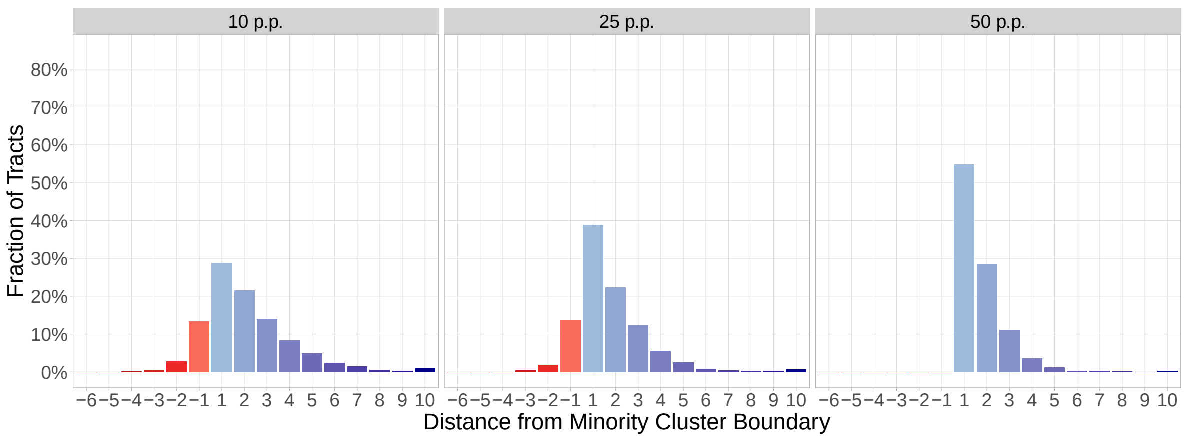
(b) 25 p.p. Change, 1970-2000



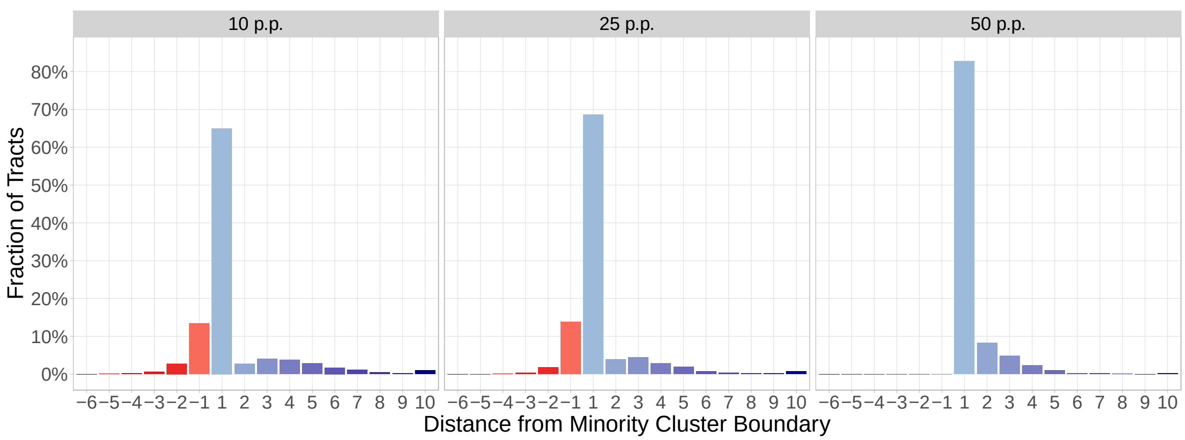
Notes: Racial change occurs predominantly at tracts near to cluster boundaries across decades for all MSAs. This figure computes P(Decline in White Share of 25 p.p. or more | Cluster Distance $= l$). This is different from the main text where we compute P(Cluster Distance $= l$ | Decline in White Share of 25 p.p. or more). 95% confidence bands are provided around each point estimate.

Figure A.IX:
Decline in White Share of 10, 25, 50 p.p. or More, All MSAs, 1970

(a) By Location



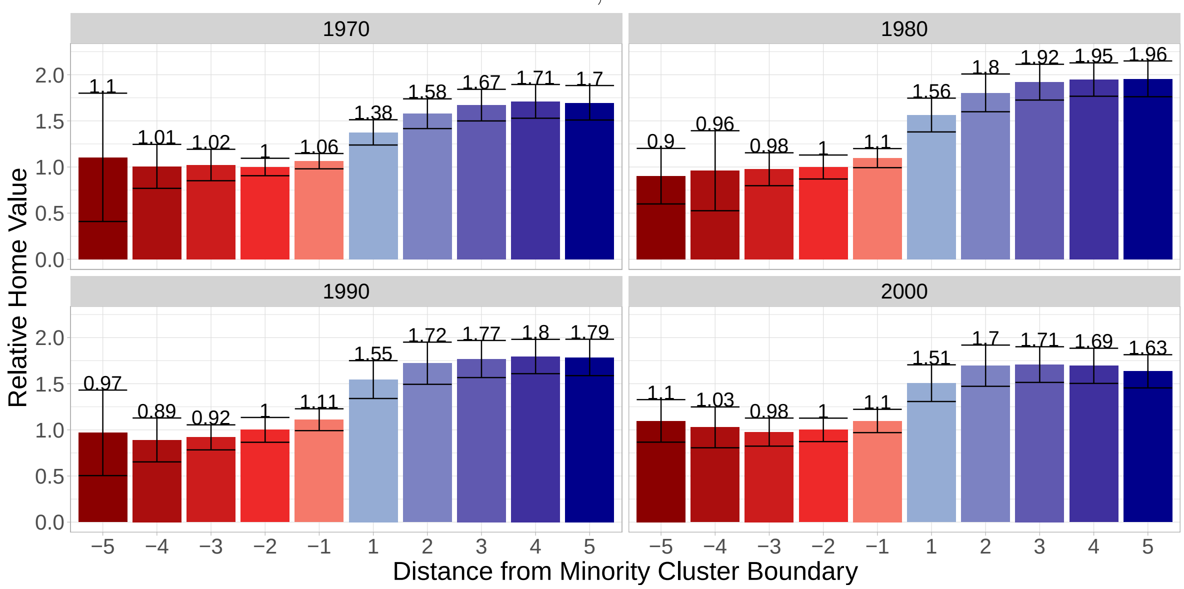
(b) Contiguous Tracts to Boundary



Notes: The more stringent the definition of drastic racial change, the more concentrated it is at the boundary of clusters.

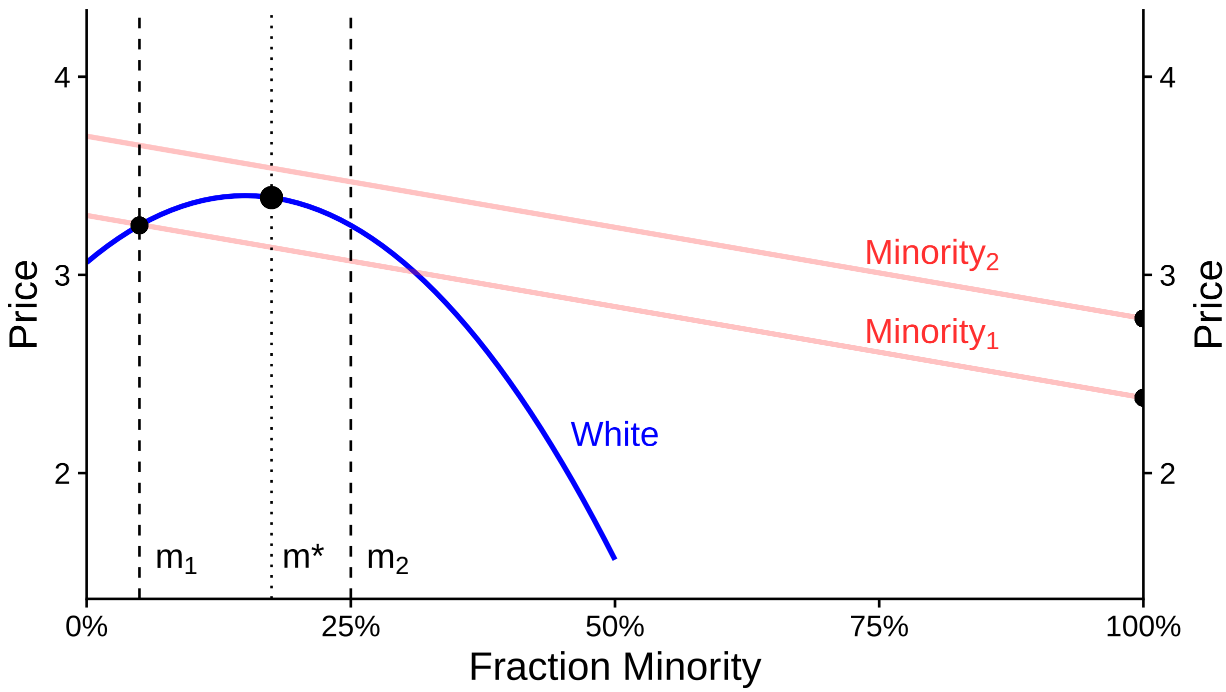
Figure A.X

Relative Home Values, All MSAs 1970-2000



Notes: Home values are first normalized by the MSA-specific median home value and then expressed relative to home values at a distance of -2. 95% confidence bands are provided around each point estimate.

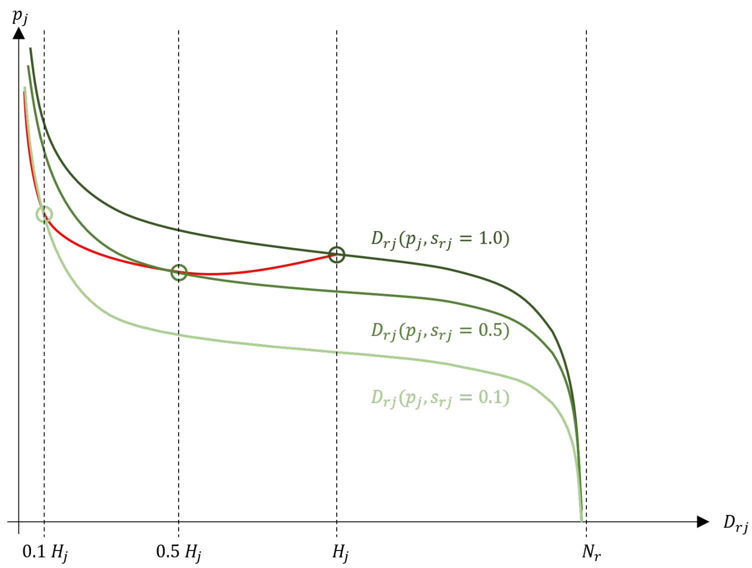
Figure A.XI:
Dynamics of Tipping in Card et al. (2008a)



Notes: This provides a simple way to think about the central empirical exercise in Card et al. (2008a). A common metro-specific tipping point at Minority share $m*$ requires a tangency between Minority and White bid-rent functions to always be at $m*$. The simplest version of this is illustrated, with all White tracts having a common bid-rent function and Minority bid-rent functions differing only by an intercept shift. If in an initial census, we observe two tracts with $m_1 < m* < m_2$, then tract 1 is in a stable equilibrium, while tract 2 has *already tipped*, with the long-run equilibrium at $m_2 = 1$. Assuming the new shocks between the initial and terminal census are small, tracts like tract 1 with initial Minority share $m < m*$ should be stable. From the theory, the expected change in the White population through the next census is zero. Location 2 by contrast, has already tipped and the relevant empirical question is how fast adjustment will take place. In their headline results, this is measured by the discontinuity at $m*$ in the change in White population in successive censuses divided by total initial population.

B Derivation of bid-rent functions

Figure A.XII:
Construction of Bid-Rent Curves from Demand Functions



Notes: Green curves show demand for tract j at different hypothetical Minority shares s_{rj}. Red curve shows the resulting bid-rent function.

A partial equilibrium bid rent-function $b_{rj}(s_{mj})$ describes the maximum willingness to pay of a marginal household of group r to move into location j if the Minority share at that location is s_{mj}. In our setting, it is implicitly defined through the equation

$$D_{rj}(b_{rj}(s_{mj}), s_{mj}; N_r, \eta_{rj}) - H_j s_{rj} = 0,$$

assuming that $\{p_k, s_{mk}, \eta_{rk}\}$ remain unchanged for $j \neq k$. Figure A.XII provides graphical intuition for how the bid rent curve is constructed. As both, the White and the Minority bid rent curve depend on s_{mj}, they can be plotted in the same diagram with crossings pinning down (partial) equilibrium Minority shares and neighborhood prices. Stable equilibria are characterized through $b'_{wj} < b'_{mj}$ while intersections where $b'_{wj} > b'_{mj}$ are unstable equilibria.[37] Changes in population sizes N_r or location fundamentals η_{rj} (relative to outside options) can shift the bid-rent curves up and down. If such shifts lead to an intersection where $b'_{wj} = b'_{mj}$ this is a tipping point.

[37] Caetano and Maheshri (2017) refer to such unstable equilibria as tipping points using a closely related "S" shape approach to identify them. We follow the approach of Card et al. (2008a) in what we label a tipping point in partial equilibrium.

C Multiple clusters

The spatial proximity model introduced in the main text provides one mechanism through which multiple racial clusters can arise: the spatial range of racial preference spillovers κ. For relatively local spillovers, i.e. large values of κ, multiple clusters are stable equilibrium configurations. This is illustrated in figure A.XIII.

Another mechanism that can easily be introduced into the model and that can also lead to multiple racial clusters is the presence of multiple employment centers. If people have specific skill sets and industries, that value these skill sets differentially, locate in distinct areas of the city, this will provide a dispersion force. Being close to the employment center that values one's own skill most is going to be more attractive which hence increases the likelihood of multiple racial residential clusters to arise.

The simplest way of introducing multiple employment centers is to allow for an exogenous number of people of each race to work at location l. We denote that number with N_{rl}. Across races, we maintain the assumption that location fundamentals are valued in the same manner, but now households have different valuations for a place depending on where they work. Effectively this corresponds to introducing additional population groups where each group is characterized by a work location l and race r and has utility:

$$u_{rlj} = -\alpha_r \log p_j + \beta_r \sum_k w_{jk} s_k + \eta_{lj}$$

To obtain race specific demand for a location we now need to aggregate demand across work locations, i.e.

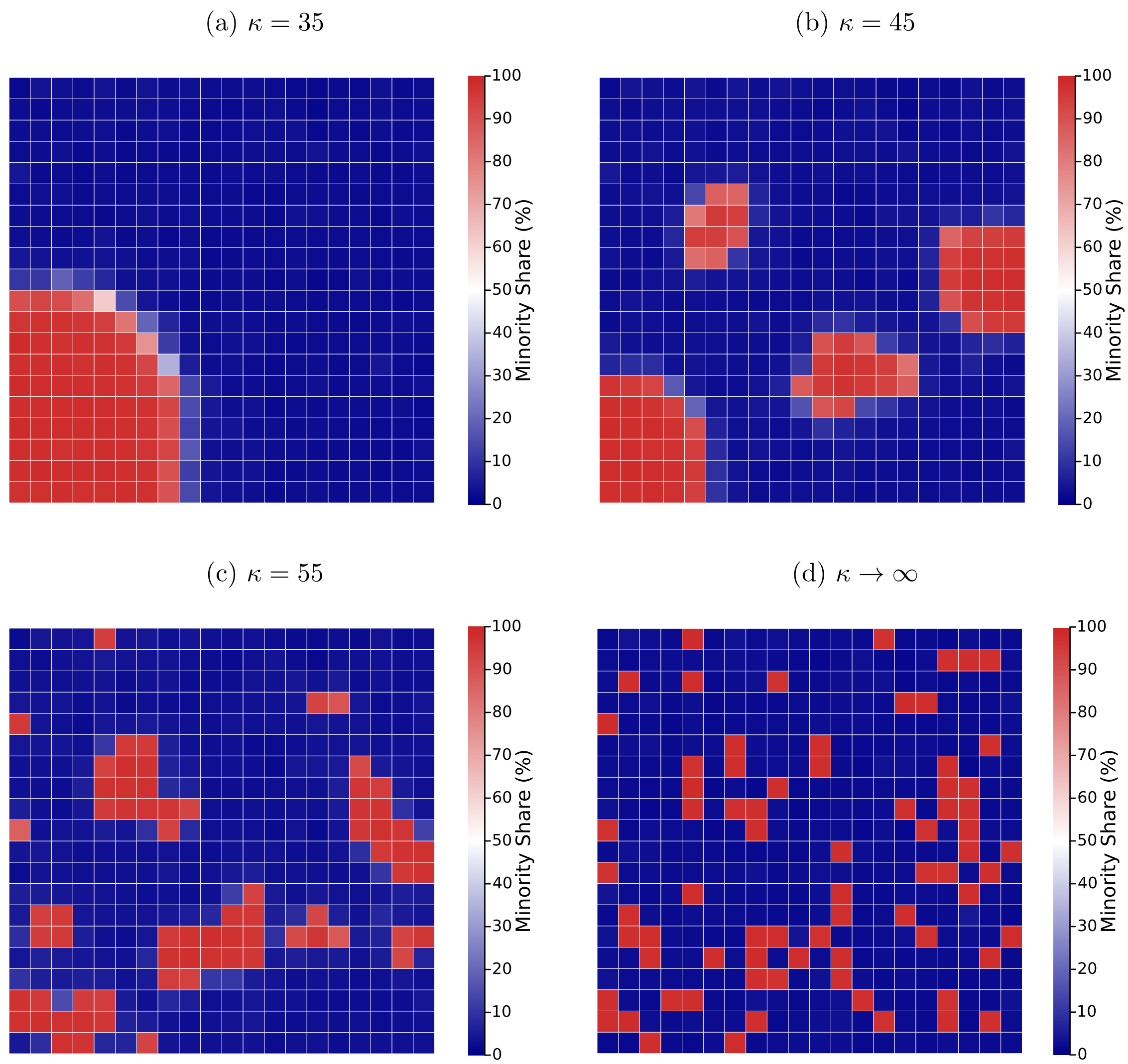
$$D_{rj} = \sum_l \left[N_{rl} \frac{\exp(u_{rlj})}{\sum_{k \in J} \exp(u_{rlk})} \right].$$

With this alteration all other equilibrium conditions remain as specified in 4 and 5.

Results from simulations with multiple employment centers are shown in figure A.XIV. There we assume two employment centers, each employing half of each racial group: One is located in the southwest and one in the northeast of the city at coordinates $[0.2, 0.2]$ and $[0.8, 0.8]$ respectively. Employment-specific fundamentals are given by $\eta_{lj} = 5 \exp(-d_{jl})$ where d_{jl} is the Euclidean distance between location j and employment center k. With the exception of this alteration, we maintain all other parameters from the main simulations: Minority households make 20% of the city population at baseline, only White households have racial preferences with $\beta_w = 8$ and that decay with $\kappa = 35$.

While the introduction of multiple employment centers has implications for prices (locations closer to workplaces demand higher rents as seen in panel c of Figure A.XIV) the main conclusions of the spatial proximity model remain virtually unchanged: Minority clusters arise due to spatial spillovers in homophily preferences of Whites. White households pay extra to self-segregate and Minority households locate in areas that demand lower relative rents as they are unwilling to pay a premium to live with Whites. At the edges of clusters both Minority shares and rental prices exhibit a smooth gradient, and neighborhood racial change in response to a citywide increase in the Minority share from 20% to 25% is concentrated at the edges of clusters.

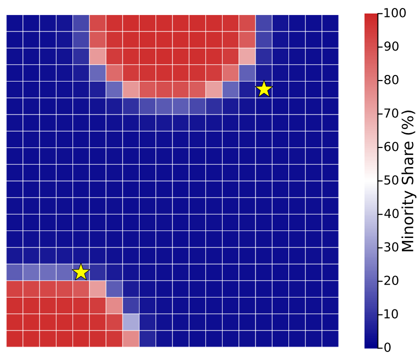
Figure A.XIII:
Multiple Clusters Arise due to More Local Spillovers



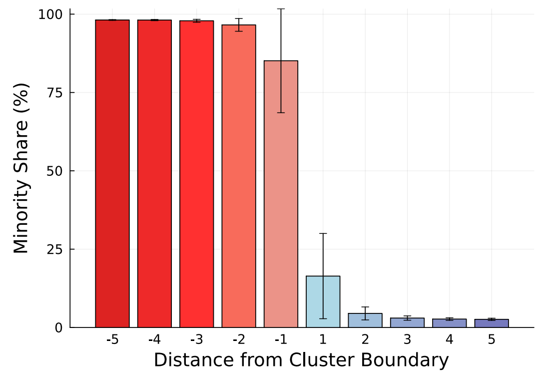
Notes: Equilibrium Minority shares for the same random initialization but different values for the spatial range of racial preference spillovers κ. For larger values of κ, spillovers are more localized which leads to more racial clusters. In the limiting case of $\kappa \to \infty$ the equilibrium of the bounded neighborhood model arises. In this case clustering is not endogenous but reflects the random initialization.

Figure A.XIV:
Multiple Clusters Arise due to Different Employment Centers

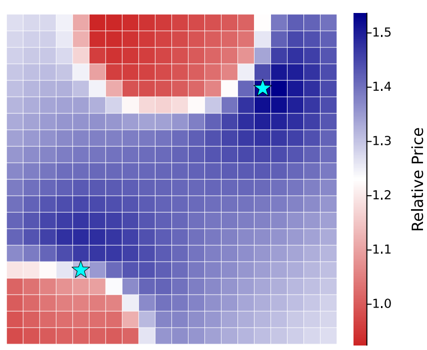
(a) Equilibrium Minority Shares
Random Initialization



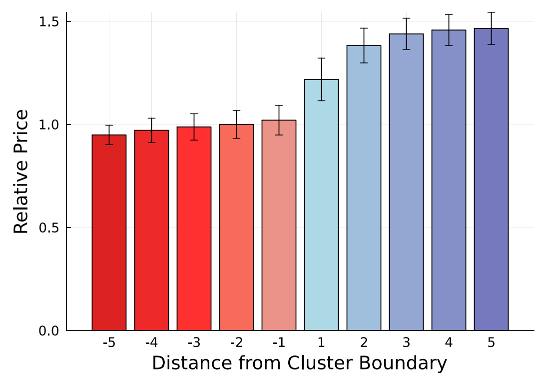
(b) Equilibrium Minority Shares
Across 1000 Initializations



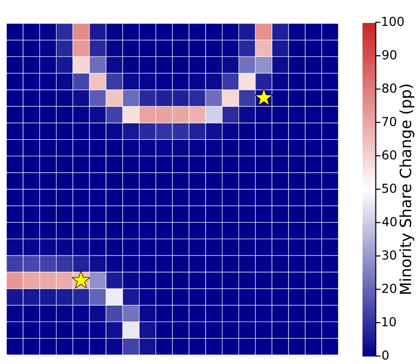
(c) Equilibrium Prices
Random Initialization



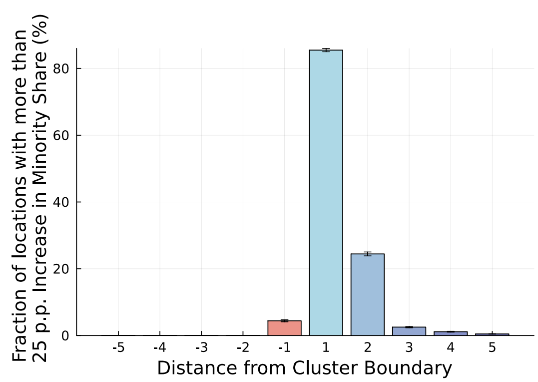
(d) Equilibrium Prices
Across 1000 Initializations



(e) Location of Racial Change
Random Initialization



(f) Location of Racial Change
Across 1000 Initializations



Notes: The maps and barplots show equilibrium outcomes when simulating the spatial proximity model as outlined in appendix C assuming two employment centers (highlighted by the stars on the maps). The first column shows equilibrium outcomes for a single random initialization. The second column shows the average equilibrium outcome across 1000 initializations. Panels (a) and (b) show equilibrium Minority shares, (c) and (d) show equilibrium prices, and (e) and (f) show the location of racial change when the city-wide Minority share increases from 20% to 25%.