PRICE AND PREJUDICE: PREFERENCES AND INCENTIVES IN THE DYNAMICS OF RACIAL RESIDENTIAL SEGREGATION

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ABSTRACT. Schelling's classic tipping model shows how white residents may leave a neighborhood once the minority share exceeds their personal tolerance threshold, causing rapid segregation after only a small increase beyond a tipping point. Yet this framework abstracts from two forces that may be central to tipping: expectations and housing prices. This paper develops an augmented model in which white and minority renters and homeowners interact both spatially, by sharing a neighborhood, and economically, through rents and house prices. The model incorporates heterogeneous preferences and expectations, generating dynamic segregation and allowing forward-looking behavior to influence tipping. Numerical simulations show that housing markets amplify tipping through the distinct incentives facing owners and renters. Forward-looking white homeowners are more likely to exit a tipping neighborhood and less likely to enter one, as expected house price declines raise the opportunity cost of ownership. White renters, by contrast, benefit from falling rents and remain more willing to stay and enter. The model therefore predicts larger tipping effects on white homeowners than renters, stronger racial transition in owner-dominated neighborhoods, and steeper declines in house prices than in rents. To test these predictions, the paper extends the empirical framework of Card et al. (2008a) to analyze neighborhood change from 1970 to 2010 across a large set of US cities. The results confirm that, conditional on tipping, the white homeowner population declines significantly more than the white renter population, and neighborhoods with higher initial homeownership rates experience faster racial change and larger house price declines. These findings suggest that neighborhood tipping, often attributed to social dynamics alone, is substantially amplified by market forces.

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1. Introduction

Racial segregation remains a defining feature of urban neighborhoods in the United States. Young Black and Hispanic individuals who grow up in more segregated cities tend to attain lower levels of education, employment, and income (Massey and Denton, 1993; Cutler and Glaeser, 1997; Chyn, 2018; Chyn, Collinson and Sandler, 2025), and face diminished prospects for upward economic mobility (Chetty, Hendren, Kline and Saez, 2014; Chyn, Haggag and Stuart, 2022). Spatial separation reduces interaction across racial groups and may contribute to increased prejudice and taste-based discrimination (Pettigrew and Tropp, 2000; Lang and Spitzer, 2020).

A widely cited explanation for segregation is the preference of white residents to live among other whites. In a seminal contribution, Schelling (1971) shows that even modest racial prejudice can generate substantial segregation. As the least tolerant white residents leave a neighborhood in response to growing minority presence, the minority share rises further, prompting the exit of more tolerant whites and triggering a cascade of white flight. This dynamic can result in neighborhood tipping behavior, where surpassing a critical minority share leads to rapid racial segregation.

This paper argues that neighborhood tipping may be shaped not only by social preferences but also by the interplay of two factors absent from the original Schelling model: housing prices and expectations. I develop an augmented tipping model in which white and minority homeowners and renters, each with heterogeneous tastes and expectations, interact both spatially, through the neighborhood's minority share, and economically, through rents and house prices. As the minority share rises, white residents' utility declines, reducing overall housing demand and driving down prices and rents. Anticipating future price declines, forward-looking white homeowners sell early when a neighborhood begins to tip, either to buyers with strong idiosyncratic preferences for the neighborhood or those with more optimistic expectations about its trajectory. By the same logic, forward-looking whites also become less likely to purchase homes and enter the neighborhood. In contrast, forward-looking white renters, who are not exposed to capital losses, are more likely to enter or remain in the neighborhood, even when they share the same racial preferences and expectations as homeowners who choose to leave.

Numerical simulations of the model show that, when most residents are forward-looking, neighborhoods with a minority share just above the tipping point experience a faster decline in white homeowners than white renters. In this setting, the incentive to exit early and avoid losses from declining house values outweighs the higher transaction costs associated with selling a home, leading to greater white exit—and lower white entry—among owners than renters. As a result, tipping neighborhoods with a higher share of owner-occupied housing—and a lower share of rentals—undergo more rapid racial change, accompanied by steeper declines in both house prices and rents.

To test the empirical predictions of the model, I conduct a reduced-form empirical analysis using decennial Census data from 1970 to 2010 for a large panel of urban neighborhoods (census tracts) across more than 100 Metropolitan Statistical Areas (MSAs). Building on the influential approach of Card et al. (2008a), the analysis examines whether the magnitude of discontinuous changes in neighborhood composition at estimated tipping points varies with initial homeownership rates. The results show that neighborhoods with higher ownership shares experience significantly larger declines in white population growth and white population shares, as well as more pronounced decreases in house values. Importantly, the decline in white population growth is driven primarily by a relative reduction in white homeowners rather than white renters. These findings support the hypothesis that pecuniary incentives among homeowners amplify white flight from tipping neighborhoods.

The empirical analysis examines several alternative explanations for the pronounced tipping effects in neighborhoods with high homeownership rates. Sensitivity to racial change may reflect a differential demographic composition of neighborhoods in terms of residents' age or the presence of families with children, which are also correlated with homeownership. It may also vary with a neighborhood's location within a city, including its proximity to the central city or to existing high-minority areas. Robustness checks show that while some of these factors are associated with differential tipping effects on white population growth, none explains the disproportionately large responses observed in owner-dominated neighborhoods.

This paper contributes to the theoretical and empirical literature on neighborhood tipping. While the seminal theoretical work of Schelling (1971) omits housing prices, many subsequent tipping models incorporate housing markets in frameworks where households choose to live either inside or outside a focal neighborhood (Becker and Murphy, 2003; Card et al., 2008a; Banzhaf and Walsh, 2013; Accetturo et al., 2014), or where they choose between a multitude of neighborhoods (Moebius and Rosenblat, 2001; Blair, 2023; Davis et al., 2025).[1] These static models assume that house prices (or housing rents) reflect only contemporaneous but not future neighborhood qualities, and tipping is analyzed based on comparative statics. Following the tradition of the bounded neighborhood model in Schelling

[1]A broader literature on neighborhood sorting seeks to infer preference heterogeneity from household behavior and market equilibria (e.g., Bayer et al., 2007; Aliprantis et al., 2022; Li, 2023; Bagagli, 2025; see Kuminoff et al., 2013 and Holmes and Sieg, 2015 for reviews). A key question is whether segregation stems more from racial preferences or from preferences for other attributes such as neighborhood income, though racial preferences are often a dominant factor (De la Roca et al., 2014). While most sorting models focus only on current amenities, some allow for forward-looking behavior but assume that all residents are homeowners or all residents are renters (Bayer et al., 2016; Caetano and Maheshri, 2021; Davis et al., 2024; an exception is Greany et al., 2025). My research interest differs from much of this literature as it treats preferences as given, and then examines the dynamic responses of homeowners and renters as a tipped neighborhood transitions towards a higher-minority steady state.

(1971), I model the binary location choice of households that may live inside or outside a neighborhood, but I introduce a distinction between homeowners and renters, and assess their decisions in a dynamic setting where housing valuations depend not only on current neighborhood composition but also on expectations about future conditions. As in most neighborhood tipping models, I assume that white residents exhibit own-race preferences, while abstracting from explicit racial discrimination in housing market transactions.[2]

Expectations have also been incorporated in the tipping models of Frankel and Pauzner (2002) and Ouazad (2015), who develop dynamic models with frictional housing markets for neighborhoods initially populated by homogeneous white homeowners with rational expectations. The model proposed here advances beyond this work by introducing three additional dimensions of resident heterogeneity beyond race. First, a distinction between homeowners and renters predicts differential mobility responses to anticipated housing cost changes, and thus helps to detect a potential role of price considerations in neighborhood tipping, which I explore both through numerical simulations and reduced-form regression analysis. Second, the presence of both forward-looking and myopic agents enables an analysis of how differences in expectation formation affect the behavior of owners and renters. Third, allowing for heterogeneity in tastes generates gradual neighborhood dynamics in which not all white residents desire to exit a tipping neighborhood at the same time, even when they share tenure status and expectation technology.

Large-scale empirical evidence on neighborhood tipping emerged with the influential study of Card et al. (2008a), which analyzes racial dynamics across a broad panel of U.S. Census tracts from 1970 to 2000. The authors document substantial discontinuous declines in white population at empirically estimated, city-specific tipping points, accompanied by more modest declines in house prices and rents. Subsequent research has identified similar tipping patterns in other settings, including immigrant-native dynamics (Aldén et al., 2014; Böhlmark and Willén, 2020) and the residential sorting of religious groups (Finkelstein, 2018). Davis et al. (2025) examine heterogeneity in racial tipping effects within cities and find differential changes in racial composition for central-city neighborhoods located near existing high-minority areas. My analysis complements this literature by building on the reduced-form framework of Card et al. (2008a) to study how tipping effects vary with neighborhood homeownership rates, while accounting for other potential sources of heterogeneity, including

[2]Discriminatory practices such as redlining (Aaronson et al., 2021), blockbusting (Ouazad, 2015; Hartley and Rose, 2023) and racial discrimination in sales and rental prices (Akbar et al., 2025) were outlawed by the Fair Housing Act of 1968—prior to the 1970–2010 period analyzed in this paper—but left enduring imprints on residential patterns. More recent research documents continued but smaller racial discrimination in rental markets (Hanson and Hawley, 2011; Christensen and Timmins, 2023a), homeownership markets (Bayer et al., 2012; Box-Couillard and Christensen, 2024), and access to mortgage credit (Charles and Hurst, 2002; Hanson et al., 2016).

residential density and proximity to high-minority neighborhoods as emphasized by Davis et al. (2025).

Many studies have explored how homeownership affects social capital and neighborhood amenities (e.g., Sampson et al., 1997; DiPasquale and Glaeser, 1999; Hoff and Sen, 2005; Hausman et al., 2021). This literature argues that homeownership benefits neighborhoods by encouraging greater civic engagement and contributions to local public goods, as homeowners are more invested in their communities than renters. Unlike renters, homeowners benefit not only from the direct consumption of neighborhood amenities but also from their capitalization into property values. The findings in this paper do not contradict that logic. Rather, they highlight a complementary dynamic: the same financial exposure to house prices that can deepen homeowners' commitment to a neighborhood when amenities improve can also accelerate their departure when a decline in neighborhood quality is expected.

The remainder of the paper is structured as follows. Section 2 presents a dynamic model of neighborhood tipping that distinguishes between homeowners and renters. Section 3 provides numerical simulation results based on the model. Section 4 describes the neighborhood-level data and outlines the econometric strategy for the reduced-form analysis. Section 5 presents empirical findings for changes in owner- and renter-occupied housing, white population, and house prices around estimated tipping points. Section 6 concludes.

2. Model

2.1. **Neighborhood Structure and Agents.** The model considers a single neighborhood containing a continuum of identical housing units, normalized to one. A fixed share r of these units are rental properties owned by absentee landlords, while the remaining share $1-r$ consists of owner-occupied homes. The neighborhood is populated by residents (owners or renters) who are drawn from a large continuum of prospective residents.

Each prospective resident is characterized along three dimensions: race, idiosyncratic taste for the neighborhood, and expectation formation. The population of prospective residents consists of a share b of minorities and a share $1-b$ of whites. Assuming that prospective residents are drawn from the city in which the neighborhood is located, b can be interpreted as the city-wide minority share. Within each racial group, individuals differ in their idiosyncratic valuation of the neighborhood. For white prospective residents, this taste parameter κ_i is drawn from a continuous uniform distribution, $\kappa_i \sim U[0, k]$; for minority prospective residents, the corresponding parameter ϕ_i is drawn from $\phi_i \sim U[0, \Phi]$.[3]

Survey evidence and structural model estimates suggest that whites tend to have a stronger own-race preference for the composition of their neighbors than do minorities (Clark,

[3]Expectation technologies are defined in Section 2.3 below.

1991; Charles, 2000; Caetano and Maheshri, 2019).[4] While most whites express comfort with the presence of a small number of minority neighbors, this comfort declines non-linearly as the minority share increases (Farley et al., 1997). To capture these features in a simple way, the model assumes that white residents' utility declines with the product of the individual taste parameter and the square of the ratio between the neighborhood minority share m_t and city-wide minority share b, while the idiosyncratic utility component for minority residents does not depend on the racial composition of the neighborhood. The utility (measured in monetary units) that resident i obtains in period t from either living in the neighborhood as a homeowner or renter, or from living outside the neighborhood, is

$$u_{it} = \begin{cases} y - \kappa_i \left(\frac{m_t}{b}\right)^2 & \text{for whites living in the neighborhood} \\ y - \phi_i & \text{for minorities living in the neighborhood} \\ 0 & \text{for whites or minorities outside the neighborhood} \end{cases} \tag{2.1}$$

The value of the alternative option of living outside the neighborhood is normalized to zero, so that utilities associated with residing in the neighborhood reflect its relative attractiveness. White residents evaluate the neighborhood's minority share m_t relative to the city-wide minority share b, capturing the idea that neighborhood composition is assessed in comparison to other locations in the city (Schelling, 1971; Blair, 2023).

The rental price p_t is set by landlords, while the house price P_t is determined by realtors who act as intermediaries between home sellers and buyers. Both landlords and realtors are profit-maximizing agents who derive no residential utility from the neighborhood. They are atomistic and assumed to be race-neutral in their market behavior.[5] For ease of exposition, I refer collectively to prospective residents, current residents (owners and renters), landlords, and realtors as the agents of the model.

2.2. **Sequence of Neighborhood Change.** House prices, rents and the composition of neighborhood residents are endogenously determined through a discrete-time sequence of neighborhood change:

(i) At the start of a period t, all agents observe the neighborhood's current minority share m_t that determines residential utilities of the current period.

[4]An exception is Bayer et al. (2022) who find little racial differences in preferences for other-race neighbors. Beyond the context of neighborhood composition, Implicit Association Tests indicate that whites have a strong own-group preference while blacks do not (Nosek et al., 2007).

[5]For a model with strategic realtors who practice blockbusting, see Ouazad (2015). Blockbusting real estate brokers systematically induced neighborhood change by steering white house sellers to black buyers in the 1950s and 1960s, but the practice lost importance in the period studied in the present paper (1970-2010), after the Fair Housing Act of 1968 prohibited many discriminatory and deceptive practices associated with blockbusting (Hartley and Rose, 2023).

(ii) Current and prospective residents determine their willingness to pay for housing in period t. These valuations are based on idiosyncratic taste parameters (κ_i and ϕ_i), current and expected future neighborhood minority shares (m_t and $m^e_{t+\tau}$), and expected future gross and net house prices and rents ($P^{g,e}_{t+\tau}$, $P^{n,e}_{t+\tau}$ and $p^e_{t+\tau}$).

(iii) A share δ of current residents exits the neighborhood due to death. This mortality shock is assumed to be random and uncorrelated with any resident characteristics. It ensures that the neighborhood experiences a turnover of residents in every period.

(iv) Landlords set the current period's rent p_t, and realtors determine the gross house price P^g_t, by solving profit maximization problems that account for the distribution of willingness to pay for housing among prospective residents, and the cost associated with searching for these new residents.

(v) Surviving incumbent renters choose whether to remain in the neighborhood and pay the rent p_t, or to leave. Surviving homeowners choose between staying or selling their home. If they sell, they receive a net price P^n_t, which equals the gross price P^g_t minus a realtor fee. All departures from the neighborhood are final and there is no option for later re-entry.

(vi) Landlords fill vacant rental units by making costly sequential random draws from the pool of prospective residents until they find renters willing to pay the prevailing rent p_t. Similarly, realtors fill vacant owner-occupied units by making costly sequential random draws from the pool of prospective residents until they find buyers willing to pay the gross house price P^g_t. Prospective residents who refuse an offer to enter the neighborhood at the prevailing rent or house price do not have the option to enter in a future period.

The remainder of Section 2 is organized as follows. Section 2.3 describes agents' information sets and expectation formation technologies. Sections 2.4 and 2.5 outline the optimizing behavior of homeowners and realtors in the market for owner-occupied housing, and of renters and landlords in the rental market, respectively. Sections 2.6 and **??** characterize and solve for steady states in which no resident who has previously moved into the neighborhood chooses to leave. Section 2.7 examines the off–steady-state dynamics of neighborhood tipping, and Section 2.8 extends the analysis to a setting with endogenous housing supply.

2.3. **Information and Expectations.** The model highlights that residential turnover dynamics are shaped by residents' expectations about future changes in neighborhood minority shares and housing costs. It contrasts two polar expectation frameworks—forward-looking expectations with perfect foresight versus myopia—as a stylized representation of the large heterogeneity in house price expectations (see Kuchler et al. (2023) for a review) and the presence of misinformation among homebuyers (Chinco and Mayer, 2016) that has been documented in empirical studies. This modeling approach helps to isolate the role of expectations in shaping neighborhood transitions, as explored in the simulations in Section 3, which consider scenarios in which most or all residents are either myopic, or forward-looking with perfect foresight.

The two expectation technologies are defined as:

Definition 2.1 (Forward-looking)**.** *Forward-looking agents correctly know or predict all current and future minority shares of the neighborhood,* $m^e_{t+\tau} = m_{t+\tau}$*,* $\forall \tau \geq 0$*, and all current and future house prices and rents,* $P^{g,e}_{t+\tau} = P^g_{t+\tau}$*,* $P^{n,e}_{t+\tau} = P^n_{t+\tau}$ *and* $p^e_{t+\tau} = p_{t+\tau}$*,* $\forall \tau \geq 0$*.*

Definition 2.2 (Myopia)**.** *Agents with myopic expectations correctly know or predict the minority share, house prices and rents only for the current period* t*,* $m^e_t = m_t$*,* $P^{g,e}_t = P^g_t$*,* $P^{n,e}_t = P^n_t$ *and* $p^e_t = p_t$*, but they expect that minority shares, house prices and rents remain constant in all future periods after period* t*,* $m^e_{t+\tau} = m_t$*,* $P^{g,e}_{t+\tau} = P^g_t$*,* $P^{n,e}_{t+\tau} = P^n_t$*, and* $p^e_{t+\tau} = p_t$*,* $\forall \tau \geq 1$*.*

A share x of prospective neighborhood residents form forward-looking expectations about the future while the remaining share $1-x$ are myopic. Expectation technologies are assumed to be uncorrelated with residents' tastes or race.

The commercial actors in the housing market, landlords and realtors, are all forward-looking and have complete knowledge of the distributions of race, taste parameters, and expectation technologies among the current and prospective residents. This information allows them to correctly infer the distribution of willingness to pay for housing among current and prospective residents. While landlords and realtors know the *distribution* of tastes and expectations in the population, they are however not aware of the tastes and expectation technologies of any *individual* current or prospective resident with whom they interact.[6]

2.4. **Market for Owner-Occupied Homes.** A current or prospective homeowner i's willingness to pay for owner-occupied housing in period t is

$$V_{it} = u_{it} + \beta(1-\delta)\max\{V^e_{i(t+1)}, P^{n,e}_{t+1}\} \tag{2.2}$$

where u_{it} is current-period residential utility, β is a time discount factor, $(1-\delta)$ is the probability of surviving to the next period, $V^e_{i(t+1)}$ is the expected valuation in the next period, and $P^{n,e}t+1$ is the expected net sales price in the next period, corresponding to the gross house price $P^{g,e}t+1$ minus the cost for a realtor's service in case of sale. By assumption, homeowners value only the residential utility and sales proceeds generated by the house during their lifetime but disregard any residual value the property may hold after death.

Houses are sold through identical, atomistic, and profit-maximizing realtors who offer to homeowners to sell their house at a net sales price of P^n_t. Since all houses are sold through

[6]The model allows for the possibility that forward-looking residents also know the distribution of race, taste parameters, and expectation technologies among all other agents, although this assumption is not necessary.

identical realtors who determine the same optimal sales price, there is only one house price in any given period t. The heterogeneity among current or prospective homeowners in terms of race, tastes, and expectations determines who is willing to sell or buy at the current price, but it does not generate heterogeneous prices, which facilitates the tractability of the model.

An owner i will choose to sell if the individual valuation for remaining in the neighborhood is smaller than the net sales price, $V_{it} < P_t^n$. Additionally, a share δ of homeowners die in each period, and their properties are also placed on the market and sold through realtors.

To sell a house, a realtor randomly draws another individual i from the pool of prospective residents and offers the property at a gross price P_t^g. The prospective buyer i accepts the offer if $V_{it} \geq P_t^g$, and rejects otherwise. If rejected, the realtor continues to make sequential, random draws from the pool until a buyer with $V_{it} \geq P_t^g$ is found. Each draw incurs a search cost c, and the expected search cost of finding a buyer willing to pay the gross price is given by $S_t(P_t^g) = c/(\mathbb{P}_t(V_{it} \geq P_t^g))$.

Realtors choose the value P of the gross price that maximizes expected profit, which equals the sale price received from the buyer minus both the net price promised to the seller and the expected search cost:

$$P_t^g = \arg\max_P \{P - P_t^n - S_t(P^g)\} \tag{2.3}$$

Realtors compete by bidding up the price P_t^n offered to sellers. Under perfect competition, expected profits are zero, and it holds that $P_t^n = P_t^g - S_t(P_t^g)$.

2.5. **Market for Renter-Occupied Homes.** An individual i's willingness to pay for rental housing in period t is

$$v_{it} = u_{it} + \beta(1-\delta)\max\{v_{i(t+1)}^e - p_{t+1}^e, 0\} \tag{2.4}$$

where $v_{i(t+1)}^e$ is the renter's expected valuation in the next period and p_{t+1}^e is the expected rent.

Identical, atomistic, and infinitely-lived absentee landlords fill vacated rental units by making sequential random draws from the pool of prospective residents at cost c per draw, until they have found a renter with valuation $v_{it} \geq p_t$ who is willing to pay the current rent p_t. All incumbent renters are offered the opportunity to remain in the neighborhood at the same rent p_t that is charged to new entrants.

Landlords who must fill a vacancy choose the optimal value p for the rent in period t that solves the following income maximization problem:

$$\begin{aligned} p_t &= \arg\max_p I_t \\ &= \arg\max_p \{p - s_t(p) + \beta(1-\delta)\mathbb{P}_t(v_{i(t+1)} \geq p_{t+1}^e | v_{it} \geq p) s_{t+1}(p_{t+1}^e) + \beta I_{t+1}^e), \} \end{aligned} \tag{2.5}$$

where $s_t(p) = c/(\mathbb{P}_t(v_{it} \geq p))$ denotes the expected search cost in period t, $\mathbb{P}_t(v_{i(t+1)} \geq p^e_{t+1} | v_{it} \geq p)$ is the conditional probability that a renter found in period t will stay in period $t+1$, $s_{t+1}(p^e_{t+1})$ is the expected search cost in the following period, and I^e_{t+1} is the expected value of the income function at $t+1$. The conditional probability term captures that landlords consider the impact of their current rent setting on expected future search costs. For instance, if the current rent is relatively high and future rents are expected to decline, a renter is more likely to stay, reducing the expected probability of a vacancy and thus lowering future search costs.

A comparison of renters' and owners' willingness to pay, as defined in equations (2.4) and (2.2), reveals a fundamental asymmetry: an owner's valuation *increases* with the expected future house price, whereas a renter's valuation *decreases* with expected future rents. Declining future house prices are unfavorable for homeowners, as they diminish the expected resale value of the property. In contrast, falling future rents are beneficial for renters, as they reduce the expected cost of staying in the neighborhood. As I will demonstrate in the simulations below, this asymmetry implies that in a racially segregating neighborhood, the anticipation of declining house prices and rents can generate a dynamic in which white homeowners exit more rapidly than white renters who share identical preferences and expectations.

A common feature of both the rental and owner-occupied housing markets is that the owners of dwellings—landlords and owner-occupiers—incur costs when searching for new residents. However, the two markets differ in the transaction costs faced by residents. For owner-occupiers, who are both owners and residents, it would be costly to purchase a home at the gross price P^g_t and resell it in the following period at the net price P^n_{t+1}. In contrast, a renter who resides in the neighborhood for a single period incurs only the rental payment p_t, with no additional transaction cost. As shown in the simulation results of Section **??** below, these transaction costs for owner-occupiers can have opposing effects on neighborhood dynamics: they may slow white flight by discouraging incumbent white homeowners from selling, or they may accelerate increases in the minority share by deterring the entry of white buyers who would otherwise consider short-term residence in the neighborhood.

2.6. **Characterization of Steady States.**

Definition 2.3 (Steady state). *The neighborhood has reached a steady state in period t if, for every period $t+\tau \geq t$, no homeowner nor renter residing in the neighborhood at $t+\tau$ prefers to move out of the neighborhood in any future period, and no prospective homeowner nor renter who turns down an offer to move into the neighborhood at $t+\tau$ would prefer to move into the neighborhood in any future period if given another opportunity.*

It follows directly from this definition that, in steady state, neighborhood turnover occurs solely through the replacement of residents who die. The model permits two distinct types of steady states, depending on parameter values. In an *interior steady state*, some individuals from each combination of race and expectation technology choose to move into the neighborhood at current prices, while others prefer to remain outside. In contrast, a *corner steady state* arises when, for at least one race-expectation group, either all or none of its members are willing to enter the neighborhood at prevailing prices.

When the neighborhood is in a steady state, then minority share, house price and rent exhibit the following properties:

Theorem 1. *If the neighborhood is at an interior steady state in period t, it holds that*

$$m^{SS} = m_t = m_{t+\tau}, \quad p^{SS} = p_t = p_{t+\tau}, \quad P^{g,SS} = P^g_t = P^g_{t+\tau}, \quad P^{n,SS} = P^n_t = P^n_{t+\tau}, \quad \forall \tau > 0.$$

If the neighborhood is at a corner steady state in period t, there exist limiting values for the neighborhood minority share, rent and house prices such that

$$m^{SS} = \lim_{t\to\infty} m_t, \quad p^{SS} = \lim_{t\to\infty} p_t, \quad P^{g,SS} = \lim_{t\to\infty} P^g_t, \quad P^{n,SS} = \lim_{t\to\infty} P^n_t$$

where each convergence is monotone.

Proof. See Theory Appendix B.1. □

The theorem establishes that, at an interior steady state, a neighborhood's minority share, house price, and rent remain constant over time. In contrast, at a corner steady state, these characteristics converge monotonically toward their long-run values. The subsequent theoretical exposition and numerical simulations focus on interior steady states. Corner steady states are characterized separately in Theory Appendix B.2.5.

A corollary of Theorem 1 is that, at an interior steady state, the minority share among residents exiting the neighborhood, m_t^{OUT}, must equal the minority share among entering residents, m_t^{IN}, so that the neighborhood minority share m_t remains constant over time. Because vacancies in steady state arise only from the death of incumbent residents, and because mortality risk does not vary by racial group, we have $m_t = m_t^{OUT} = m_t^{IN}$. In addition, future minority shares and housing prices are correctly anticipated at an interior steady state not only by forward-looking residents, but also by myopic residents, since under their beliefs these variables remain constant. Applying these steady-state expectations to the optimization problems for owner-occupied housing (Section 2.4) and renter-occupied housing (Section 2.5), solving for steady-state prices and rents, and then solving for the minority share consistent with $m_t = m_t^{OUT} = m_t^{IN}$ under steady-state housing costs yields:

Theorem 2. *The model admits two interior steady state minority shares:*

$$m^{SS1} = \frac{1}{2} - \frac{\sqrt{k - 4b(1-b)\Phi}}{2\sqrt{k}}, \quad m^{SS2} = \frac{1}{2} + \frac{\sqrt{k - 4b(1-b)\Phi}}{2\sqrt{k}}$$

At these steady states, the rent is

$$p^{SS} = y - \sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}$$

while the gross house price and net house price are

$$P^{g,SS} = \frac{y - \sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}}{\rho}, \quad P^{n,SS} = \frac{y - 2\sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}}{\rho}$$

with $\rho \equiv 1 - \beta(1-\delta)$.

Proof. See Theory Appendix B.2. □

The neighborhood is in steady state both at a minority share $m^{SS1} < 0.5$ and a minority share $m^{SS2} > 0.5$. By plugging either of them into the formula for steady state rents and prices, one obtains that housing costs are higher at m^{SS1} than they are at m^{SS2}.

It bears emphasis that the steady-state minority shares, m^{SS1} and m^{SS2}, depend only on neighborhood racial composition and the distribution of preferences among prospective residents, as captured by the parameters b, k, and Φ. They are independent of both the share of forward-looking residents, x, and the neighborhood renter share, r. The first result follows because, in steady state, the expectations of forward-looking and myopic residents coincide. The second follows because the gross house price in steady state equals the present value of an infinite stream of rents, $P^{g,SS} = p^{SS}/\rho$, so that total expected lifetime housing costs do not vary by tenure status.

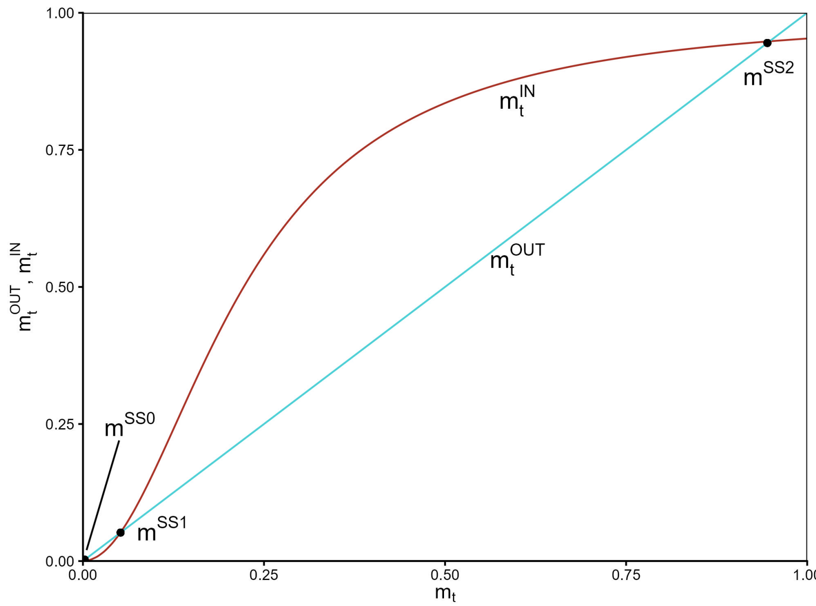
Figure 1 visualizes the steady state condition $m_t = m_t^{OUT} = m_t^{IN}$ for a model parametrization that will be used in the numerical simulations of Section 3 below. The steady state condition is fulfilled at two interior steady states m^{SS1} and m^{SS2} and one corner steady state m^{SS0}.[7] At all other values of the minority share, the replacement of deceased residents with new owners and renters under steady state expectations would create either an increase in the neighborhood minority share (when $m_t^{IN} > m_t^{OUT}$) or a decrease in the minority share (when $m_t^{IN} < m_t^{OUT}$).

2.7. **Neighborhood Tipping.** The subsequent numerical simulations and reduced-form empirical analyses take it as given that neighborhoods can be at an off-steady state minority share at the start of an outcome period.[8] Consider a neighborhood whose minority share

[7]Note that the S-shaped curve m_t^{IN} can intersect the straight line m_t^{OUT} at most three times. Under different model parametrizations, it is possible to have only two steady states (if m_t^{IN} is tangent to m_t^{OUT} at m^{SS1}) or only one steady state (at m^{SS2}).

[8]One could alternatively endogenize the existence of off-steady state neighborhoods by modifying the law of motion for the neighborhood minority share in equation (B.14) to $m_{t+1} - m_t = v_t(m_t^{IN} - m_t^{OUT}) + \epsilon_t$, where $\epsilon_t \sim N(0, \sigma)$ is a small stochastic shock that is not anticipated by forward-looking agents and usually has a value of zero (i.e., $\sigma \to 0$ and $E(\sigma) = 0$). This modification would introduce a small amount of bounded rationality to the expectations of forward-looking agents, for whom definition 2.1 would continue to hold

Figure 1. Determination of Steady States



Notes: The figure indicates the shares of minorities among all residents who exit the neighborhood (m_t^{OUT}, blue line) or enter the neighborhood (m_t^{IN}, red line) as a function of the start-of-period minority share m_t when all agents assume that the neighborhood is in steady state.

$\tilde{m}_t \equiv m^{SS1} + \epsilon$ is marginally larger than the steady state minority share m^{SS1} but that otherwise has the same population composition in terms of residents' taste parameters and expectation technologies. Assume for the moment that all agents perceive the neighborhood to be at a steady state, such that the dynamics of neighborhood change follow the patterns of Figure 1. As seen in the Figure, the minority share of the neighborhood starts to grow because $\tilde{m}_t^{IN} > \tilde{m}_t^{OUT}$, and that growth continues until the neighborhood converges to a new steady state at the much higher minority share value of m^{SS2}. This growth of the minority share stands in stark contrast to the evolution of a neighborhood that begins a period with a slightly smaller initial minority share of m^{SS1} that remains constant over time. I refer to this contrast as *neighborhood tipping*: A marginally higher initial minority share can set neighborhoods on sharply divergent paths, as those just above the tipping point m^{SS1} begin transitioning from a predominantly white to a minority-dominated residential composition.[9]

under the additional condition of zero shocks ($\epsilon_{t+\tau} = 0$, $\forall \tau \geq 0$), and it would generate rare situations where a neighborhood deviates from steady state.

[9]The steady state m^{SS1} in Figure 1 displays two-sided instability. While a positive deviation from this values triggers a large growth of the minority share towards m^{SS2}, a negative deviation induces a transition towards the lower steady state minority share m^{SS0}. However, when the difference between the values of m^{SS1} and m^{SS0} is small as in Figure 1, then the latter transition will not generate a sizable change in the neighborhood minority share. Alternative parametrizations of the model would also allow that the m_t^{IN} curve is tangent to the m_t^{OUT} line at m^{SS1}, such that the steady state at m^{SS1} displays one-sided instability only. In a companion paper to their main article, Card et al. (2008b) do not find evidence of a reverse tipping effect when the neighborhood minority share falls below a critical tipping point value.

The speed of a tipped neighborhood's transition to the high-minority steady state depends on current and prospective residents' expectations. While forward-looking and myopic individuals have the same expectations when the neighborhood is in steady state, their expectations differ in a tipped neighborhood where only forward-looking agents foresee the subsequent rise in minority share and fall in housing costs. This difference in expected future neighborhood outcomes affects current and prospective residents' decision to exit or enter the neighborhood. By combining the valuations of owners and renters from equations (2.2) and (2.4) with the expectation technologies of definitions 2.1 and 2.2, one obtains that incumbent residents will stay in the neighborhood in a period t, and prospective residents will enter the neighborhood in period t, if:

$$u_{it} \geq \begin{cases} P_t^n - (1-\rho)\max\{V_{i(t+1)}, P_{t+1}^n\}, & \text{for forward-looking incumbent owners} \quad (2.6a) \\ P_t^n - (1-\rho)\dfrac{u_{it}}{\rho}, & \text{for myopic incumbent owners} \quad (2.6b) \\ P_t^g - (1-\rho)\max\{V_{i(t+1)}, P_{t+1}^n\}, & \text{for forward-looking prospective owners} \quad (2.6c) \\ P_t^g - (1-\rho)\dfrac{u_{it}}{\rho}, & \text{for myopic prospective owners} \quad (2.6d) \\ p_t - (1-\rho)\max\{v_{i(t+1)} - p_{t+1}, 0\}, & \text{for forward-looking inc./prosp. renters} \quad (2.6e) \\ p_t - (1-\rho)\dfrac{u_{it} - p_t}{\rho}, & \text{for myopic inc./prosp. renters} \quad (2.6f) \end{cases}$$

The left-hand side of these conditions indicates the benefit of living in the neighborhood during period t, while the right-hand side shows the expected opportunity costs, which differ across individuals with the same race, taste parameter and tenure status depending on whether they form forward-looking or myopic expectations.

For residents with any given combination of race and tenure status, one can determine whether forward-looking expectations make them differentially likely to exit or enter a tipped neighborhood:

Theorem 3. *In a tipped neighborhood with minority share m_t where $m^{SS1} < m_t < m^{SS2}$, forward-looking white homeowners are weakly more likely to leave and less likely to enter in period t compared to myopic white homeowners with the same taste parameter. Conversely, forward-looking white renters are weakly less likely to leave and more likely to enter in period t compared to their myopic peers. The location decisions of minority residents do not differ between forward-looking and myopic individuals except for a higher likelihood of entry among forward-looking minority renters.*

Proof. See Theory Appendix B.3. □

A key implication of this theorem is that white homeowners are the only group whose propensity to leave a tipped neighborhood rises when expectations are forward-looking rather than myopic. Even white homeowners with weak racial preferences—who would still derive substantial residential utility from living in a tipped neighborhood with minority share $\tilde{m}_t$ in period t—may choose to leave quickly to avoid anticipated declines in their homes' asset values. This voluntary out-migration can substantially accelerate growth in the neighborhood's minority share, both by increasing the number of vacant units available to new entrants and by widening the minority-share gap between incoming and outgoing residents. Moreover, while forward-looking prospective white renters may temporarily move into a tipping neighborhood while the minority share remains low, such temporary entry is unattractive for forward-looking white homeowners because of transaction costs and the expected house price declines. This behavior of prospective residents thus further accelerates racial transition among the neighborhood's homeowners.

In the absence of forward-looking expectations, the owner-renter differences described in Theorem 3 would not arise. Even so, mobility behavior may still differ because transaction costs in the market for owner-occupied housing create a wedge between the gross house price P_t^g paid by new owners and the net price P_t^n received by incumbent owners after realtor fees. Consider a myopic white renter and a myopic white homeowner who were both indifferent about entering the neighborhood in period $t-1$. After observing an increase in minority share in period t, the marginal renter exits unless rents fall enough to offset the loss in residential utility. By contrast, the marginal homeowner's willingness to pay may fall below the gross purchase price while remaining above the net sale price, in which case the owner stays even though she would no longer choose to enter under current conditions. Transaction costs therefore tend, all else equal, to slow the exit of white homeowners relative to renters. A faster racial transition among owners than among renters is thus contingent on forward-looking behavior.

I conduct two quantitative analyses to examine neighborhood tipping and highlight the differential behavior of owners and renters, as well as of owner-dominated and renter-dominated neighborhoods. First, Section 3 presents numerical simulations of the model's transition dynamics from $\tilde{m}_t$ to m^{SS2}. These simulations show how residential mobility patterns among homeowners and renters depend on expectation formation. Second, Section 5 presents a reduced-form regression analysis of tipping discontinuities around empirically estimated tipping points following Card et al. (2008a), allowing me to test whether the magnitude of neighborhood tipping varies systematically with a neighborhood's owner and renter shares.

2.8. **Endogenous Housing Supply.** Models of neighborhood change often assume a fixed housing stock and no steady-state resident turnover. In that environment, any increase in the minority share m_t requires some white residents to leave the neighborhood and an equal number of minority residents to enter. Accordingly, some prior literature defines neighborhood tipping as the joint occurrence of 'white flight' and minority entry (Davis et al., 2025).

The definition of neighborhood tipping adopted in Section 2.7 is broader. In a model with ongoing resident turnover in steady state, a neighborhood's minority share can change through either a change in the racial composition of residents who exit or a change in the racial composition of new residents who enter the neighborhood, without requiring both.

Because the reduced-form analysis of tipping discontinuities in Section 5 examines neighborhoods that, on average, experienced substantial growth in both housing stock and population during the outcome period, this section further considers a version of the model model that allows for endogenous growth in housing and population. The central insight is that once neighborhood tipping influences housing growth, changes in racial composition no longer require equally large offsetting changes in white and minority population stocks. Instead, tipping can emerge from a sharp slowdown in white population growth combined with a more modest change in minority population growth.

Unlike the baseline model, which assumes a fixed housing stock, the time-varying measure of housing units in the neighborhood at the beginning of period $t+1$ is

$$h_{t+1} = h_t + g(P_t^g, h_t) \tag{2.7}$$

where function $g(P_t^g, h_t) \geq 0$ specifies the supply of new houses to the neighborhood. New houses are built by real estate developers, sold at price P_t^g, occupied by new residents within the same period t, and provide the same utility as existing houses.[10] The supply of new housing is larger when house prices are higher ($\frac{\delta g(\cdot)}{\delta P_t^g} \geq 0$), where this derivative holds with equality when prices are so low that developers no longer find it worthwhile to build.[11] The supply of housing is also weakly decreasing in the size of the current housing stock ($\frac{\delta g(\cdot)}{\delta h_t} \leq 0$), as construction of new housing becomes increasingly costly when a neighborhood is already densely populated.[12]

Theorem 4. *Relative to a neighborhood at the steady state with minority share m^{SS1} and housing growth $g_t^{SS1} > 0$, a tipped neighborhood with minority share $\tilde{m}_t \equiv m^{SS1} + \epsilon$ differs along two dimensions. First, tipping reduces housing growth (a scale effect). Second, the*

[10]A fraction r of the new houses are sold to landlords who subsequently fill the units with new renters, while a fraction $1-r$ of houses are sold to realtors who resell the houses to owner-occupiers.

[11]Due to the elastic supply of prospective residents to the neighborhood, house prices depend only on the distribution of willingness to pay for housing among prospective residents, but not on the amount of vacant houses due to departure of incumbent residents or construction of new buildings.

[12]A larger housing stock is equivalent to greater housing density in a neighborhood with fixed land area. It can thus be understood as proxy for lower availability of land that can be used for construction. See Baum-Snow and Duranton (2025) for an in-depth treatise of housing supply.

minority share among entering residents exceeds that among exiting residents (a composition effect). As a result, tipping strictly lowers the growth rate of the white population, whereas its effect on the growth rate of the minority population is ambiguous.

Proof. See Theory Appendix B.4. □

The key insight that tipping should result reduce white population growth but not necessarily increases minority population growth motivates a focus on the former variable as a key outcome in the reduced-form empirical analysis, consistent with Card et al. (2008a).[13] The empirical analysis will also explore how tipping affects total population, the share of white population in a neighborhood, and the probability of a large decline in this share.

3. Simulated Neighborhood Transitions

3.1. **Setup.** The numerical simulations examine transition dynamics from a minority share $\tilde{m}_t$, which is minimally above the low-minority steady state m^{SS1}, to the high-minority steady state m^{SS2}. A faster transition indicates stronger racial tipping: neighborhoods with an initial minority share slightly above m^{SS1} experience a larger decline in white population over a given time period compared to neighborhoods at the steady state m^{SS1}.

These simulations serve two main purposes. First, they generate model-based predictions for how racial tipping effects differ between homeowners and renters, and across neighborhoods with varying renter shares. Section 5 tests these predictions using reduced-form regressions that build on the empirical framework of Card et al. (2008a), leveraging granular spatial data on racial composition, homeownership status, house prices, and rents. Second, the simulations illustrate how differential mobility between homeowners and renters depends on residents' expectation formation—an element not observed in the microdata that is therefore assessed via simulations.

The simulations consider the baseline model with fixed housing stock, so that the growth function $g(P_t^g, h_t)$ does not need to be parametrized. The other parameters of the model are calibrated to broadly reflect conditions in Chicago in 1970 (see Appendix C.3 and Appendix Table C1 for details): The minority share among prospective residents is set to $b = 0.16$, matching the city's overall minority share in 1970. Discount and death rates are set to empirical targets, and taste parameters are chosen so that equation (B.16) yields a steady-state minority share of $m^{SS1} = 0.052$, consistent with empirical estimates of the tipping point in Chicago at the time (see Section 4.2). The model period length is set to 3.33

[13]A corollary of Theorem 4 is that the scale effect should be weaker in neighborhoods with a large housing stock and therefore high density, since limited scope for additional housing growth constrains steady-state population adjustment. This prediction is also investigated in the empirical analysis.

years to match the observed speed of neighborhood change in 1970s Chicago.[14] The baseline simulation assumes a renter share of $r = 0.4$, similar to the 1970 Chicago average, and a fraction $x = 0.8$ of forward-looking residents. To explore the role of homeownership and expectations in neighborhood tipping, I compare this baseline to alternative parametrizations that vary r and x.

The simulation employs an iterative algorithm to determine the expectations of forward-looking agents. These agents anticipate that a neighborhood with a minority share just above the tipping point m^{SS1} will eventually transition to the high-minority steady state m^{SS2}, accompanied by declining house prices and rents. The procedure begins by specifying an initial, exogenous path for agents' expectations regarding the evolution of the minority share, house prices, and rents. Based on these expectations, the model computes the actual transition path. If the realized paths for minority share, prices, or rents differ from the initial expectations, then those expectations are inconsistent with the forward-looking expectations of definition 2.1. The algorithm uses the simulated outcomes to update expectations and repeats the process until convergence, i.e., when expectations match outcomes. Appendix C describes this procedure in detail and shows that it reliably converges to a unique transition path consistent with forward-looking expectations, regardless of the initial assumptions about the timing or shape of the transition (see Appendix Figure C1).[15]

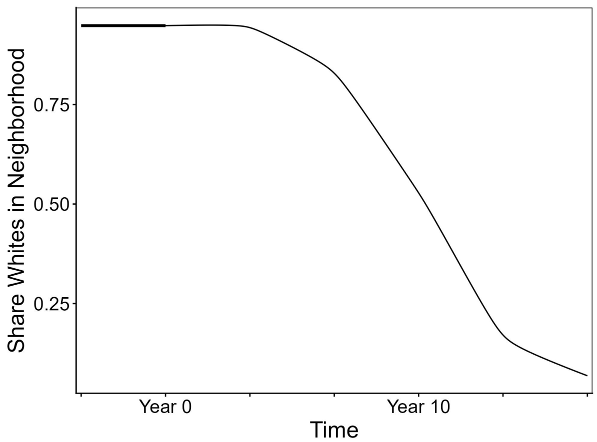
3.2. **Simulation Results.** Figure 2 presents simulation results for a neighborhood initially at the steady state m^{SS1}, which receives an unanticipated shock at year 0 that raises the minority share to $\tilde{m}_t = m^{SS1} + \epsilon$, triggering a transition toward the high-minority steady state m^{SS2}.[16] Panel A shows the resulting decline in the white population share. The transition unfolds gradually: white population initially decreases slowly, then more rapidly, before leveling off as the neighborhood approaches m^{SS2}. Although the model would allow for the simultaneous exit of all whites, the gradual pattern reflects the willingness of some whites to stay in or enter the neighborhood while the white share remains relatively high. These residents exit only as the minority share increases further and the neighborhood nears

[14] Since the model allows all incumbents to move in each period without frictions, the period length sets a lower bound for full population turnover. By contrast, the tipping model of Frankel and Pauzner (2002) constrains the speed of neighborhood transition through moving frictions—only a random subset of residents may exit per period—because agents are homogeneous in preferences and expectations in their model, and would all leave simultaneously absent frictions.

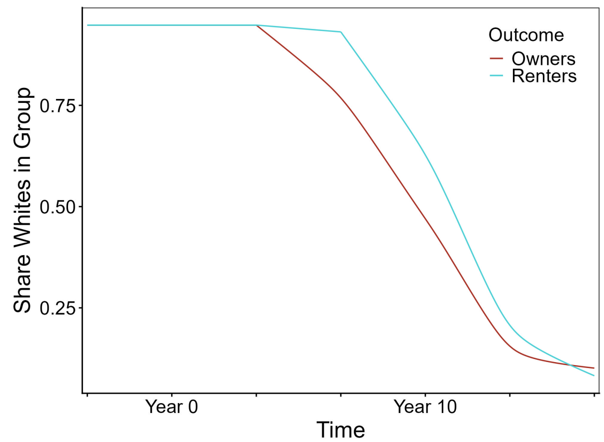
[15] There is no multiplicity of equilibria because the sequence of neighborhood change in Section 2.2 stipulates that the utility-generating minority share is observed at the start of each period prior to residents' decision to exit or enter the neighborhood. A resident's expectation about others' concurrent moving behavior will thus affect expected residential utility for the next period but not the current period.

[16] In line with model notation, the minority share m_t is observed at the start of period t, while m_{t+1} reflects the share after residential turnover during period t. House prices P^g_t and rents p_t are determined within period t.

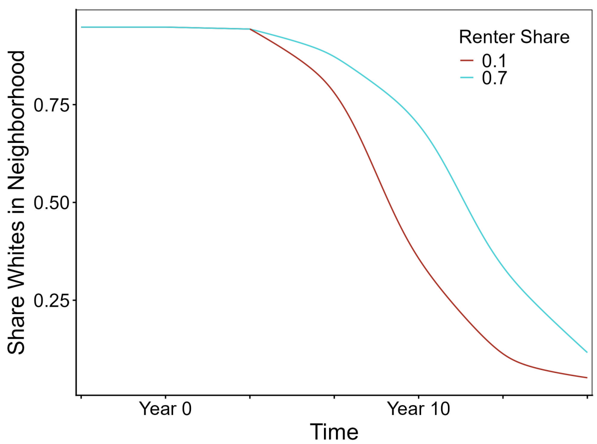
FIGURE 2. Simulated Neighborhood Transitions



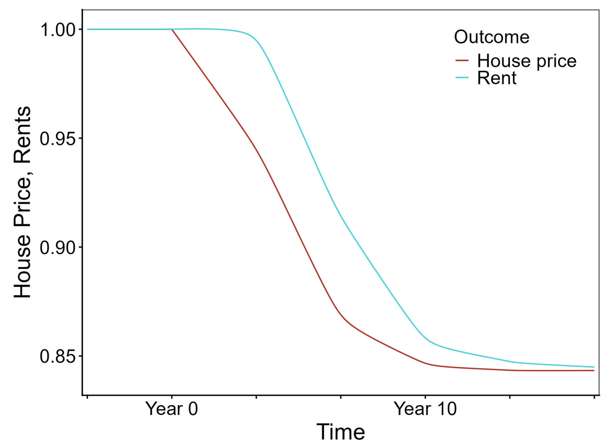
(A) Change in white population



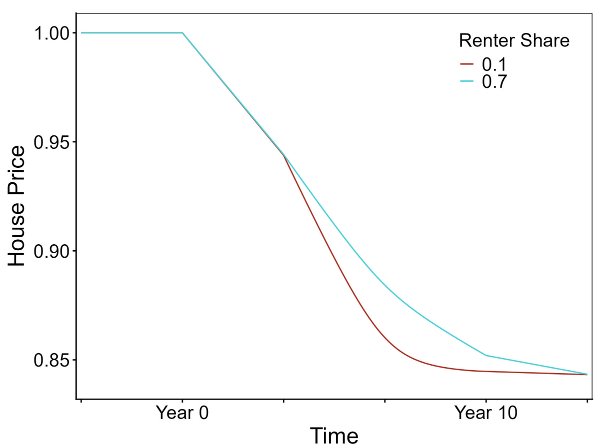
(B) Change in white pop. among owners and renters



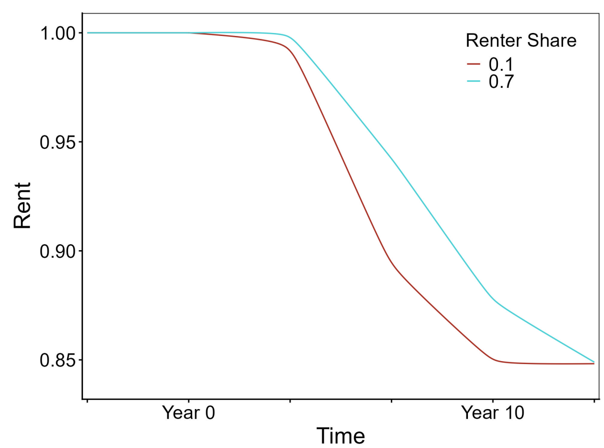
(C) Change in white pop. by neighborhood renter share



(D) Change in house prices and rents



(E) Change in house prices by neighborhood renter share



(F) Change in rents by neighborhood renter share

Notes: Simulation results report outcomes for a neighborhood whose minority share increases from m^{SS1} to $\tilde{m} = m^{SS1} + \epsilon$ in year 0. The gross house prices in Panels D and E and the rents in Panels D and F are indexed to 1 in the initial steady state. All figures indicate smoothed polynomials (R command geom_xspline) fitted through the outcome values generated by the discrete time simulation.

its new steady state. Importantly, this willingness to remain in a tipped neighborhood may differ between homeowners and renters, a distinction explored in the following panels.

Panel B of Figure 2 shows results from the same simulation as Panel A, but indicates the share of white population separately among owners and renters. The decline in white population occurs notably faster among homeowners than among renters, before the transition paths of both groups converge as the neighborhood approaches its new steady state. Panel C explores the role of renter share by simulating two neighborhoods, one owner-dominated ($r = 0.1$) and one renter-dominated ($r = 0.7$). White population declines more quickly in the owner-dominated neighborhood, consistent with stronger tipping effects when fewer residents are renters.[17]

Panels D–F examine housing costs, indexed to one prior to tipping. Panel D (baseline case) shows that house prices fall faster than rents. Panels E and F repeat this comparison across low and high renter-share neighborhoods. Panel E finds that house prices decline equally fast or faster in owner-dominated neighborhoods. Panel F shows that rents initially remain stable in both types but drop sooner in owner-dominated neighborhoods that experience a faster racial transition.

Together, Panels B to F in Figure 2 yield the following simulation-based predictions, which will be tested in the reduced-form empirical analysis:

Prediction 1. *Tipping effects are larger for white owner than for white renter population*

Prediction 2. *Tipping effects for white pop. are decreasing in the neighborhood renter share*

Prediction 3. *Tipping induces a decline in house prices and a weaker decline in rents*

Prediction 4. *Tipping effects for prices and rents are decreasing in the renter share*

As discussed in Section 2.7, homeowners and renters respond differently when a neighborhood tips because expected housing-cost declines and transaction costs affect them in distinct ways. Appendix C.4 further illustrates these differences by showing how opportunity costs for marginal white residents vary by tenure status and expectation type, building on equations (2.6a) to (2.6f). It also reports simulations that vary the share of forward-looking residents.

These appendix results yield three main insights. First, even small expected house price declines can cause forward-looking white homeowners to leave a tipping neighborhood faster than renters. Under equation (2.6a) and the model's baseline calibration, an anticipated

[17] Since both owner- and renter-dominated neighborhoods eventually reach the steady-state minority share m^{SS2}, white population declines differ over a decade only if the transition takes longer than ten years, as in the simulation. In reality, more rapid change is exceedingly rare: in the neighborhood data introduced in Section 4, just 0.07 percent of neighborhoods with an initial minority share below 20% exceed 80% by a decade's end.

house price decline of just 1 percent is sufficient to raise incumbent homeowners' opportunity costs or remaining in the neighborhood above those of renters, thereby inducing faster exit.

Second, forward-looking white homeowners are less likely than renters to temporarily enter a tipped neighborhood because they are deterred by both anticipated house price declines and transaction costs in the housing market. Faster racial transition among owners can therefore result from both higher white exit and lower white entry.

Third, forward-looking expectations are central to explaining why the white homeowner population may decline faster than the renter population in a tipping neighborhood. Simulations with alternative shares of forward-looking residents show that when all or most residents are myopic, tipping produces only gradual changes in racial composition, with slower adjustment among homeowners because transaction costs impede mobility. By contrast, when most or all residents are forward-looking, the white population declines more sharply among homeowners than among renters.

4. Data and Empirical Framework for Reduced-Form Analysis

The reduced-form empirical analysis tests the model's predictions for tipping effects in white owner and renter populations, total white population, house prices, and rents across neighborhoods with varying renter shares. It builds on the empirical framework of Card et al. (2008a) to identify tipping points and assess the size of resulting discontinuities.

4.1. **Data and Descriptive Statistics.** The empirical analysis draws on the Neighborhood Change Database (Geolytics, 2017), which maps information from the 1970, 1980, 1990, 2000 and 2010 US Decennial Population Censuses to current census tract boundaries.[18] Census tracts comprise a population of about $3,000$ to $4,500$ individuals and are often used as a proxy for neighborhoods (e.g., Chetty et al. (2018)). The empirical analysis studies changes in tract characteristics in decadal intervals and pools data for the four periods of 1970-1980, 1980-1990, 1990-2000 and 2000-2010, thus extending the sample of Card et al. (2008a) by one decade. The cities considered in the empirical analysis are metropolitan statistical areas (MSAs) that include at least 100 tracts each. Appendix D provides further details on sample and variable construction, and Appendix Table D1 provides descriptive statistics. At the midpoint of the outcome period in 1990, the sample includes 46,595 tracts across 111 MSAs—an average of about 420 tracts per MSA.[19] With an average of 3,491 residents

[18] While tract databases typically use current boundaries, it would be conceptually preferable to define tracts by their initial boundaries, as later ones can be endogenous (Glaeser et al., 2025). Card et al. (2008a) report similar tipping effect estimates for a subsample of tracts with unchanged boundaries.

[19] The sample is smallest in 1970, with 38,479 tracts in 90 cities, as the Census Bureau had not yet subdivided the full US landmass into tracts. Sample size also varies slightly in later years due to sampling criteria detailed in Appendix D.

per tract, the sample covers a total of 162.6 million people—roughly two-thirds of the U.S. population.

Throughout the empirical analysis, the term *white population* refers to non-Hispanic whites, while *minority population* refers primarily to Black and Hispanic residents but also includes Native Americans, Asians, Pacific Islanders, and other nonwhite groups.[20] Although early studies of residential segregation focused mainly on the divide between whites and Blacks, segregation of Hispanics is also substantial and persistent (De la Roca et al., 2014), with well-documented adverse economic consequences (De la Roca et al., 2018).[21] In the sample, the average minority share rose sharply from 15.4 percent in 1970 to 42.2 percent in 2010, reflecting faster growth in the minority population. By contrast, the share of rental housing—the other key variable in the analysis—remained comparatively stable, increasing only modestly from 34.3 to 38.0 percent over the same period.

Standard measures indicate that racial segregation in US cities has declined gradually over time (Cutler et al., 1999, 2008; Fryer Jr, 2011; Massey and Tannen, 2015). Consistent with this pattern, Appendix Table D1 shows that the dissimilarity index fell from 0.56 in 1970 to 0.45 in 2010. Yet this decline does not imply that the racial composition of most neighborhoods now resembles that of the overall population. On the contrary, the share of tracts whose minority share differs from the sample average by more than 20 percentage points rose sharply from 16 to 64 percent, driven by the rapid growth of minority-dominated neighborhoods.

Population dynamics vary with initial tract minority share. White population growth is highest in nearly all-white neighborhoods, and lowest in nearly-all minority neighborhoods. Sharp changes in the minority share are less likely in such neighborhoods than in mixed-race neighborhoods. In each decade, between 7 and 15 percent of tracts experience a sharp decline in white population share of at least 20 percentage points. Although some neighborhoods have gentrified (Baum-Snow and Hartley, 2020; Couture et al., 2023), fewer than 1 percent of tracts experience an increase in white share of 20 percentage points or more.

4.2. **Tipping Points.** A key outcome in the empirical analysis is the decadal change in a neighborhood's white population, measured as a share of its initial population. If tipping occurs, neighborhoods whose minority share at the beginning of the decade lies just above the tipping point should experience significantly lower white population growth than those just below it. Appendix Figure A1 illustrates this pattern. Panel A plots decadal white

[20]The NCDB provides racial and ethnic breakdowns for many neighborhood variables beginning in 1970, but data specifically on non-Hispanic whites are available only from 1980 or 1990 onward. Appendix D describes the imputations for the non-Hispanic white population in 1970, following Card et al. (2008a), as well as for non-Hispanic white owners and renters in 1970 and 1980.

[21]Card et al. (2008a) find similar tipping effects whether minorities are defined as all nonwhite and non-Hispanic groups or are limited to Blacks and Hispanics.

population growth against a neighborhood's initial minority share in the model simulation from Section 3.2, calibrated to Chicago in the 1970s. Panel B presents the corresponding binned scatterplot for observed tract-level data from Chicago in that decade. In both the simulated and observed data, white population growth declines by more than 40 percentage points around a tipping-point minority share of 0.05 and remains depressed in neighborhoods that begin the decade with minority shares above this threshold.[22]

Section 4.2.1 outlines the empirical strategy used to identify a candidate tipping point for each city and decade, while Section 4.2.2 relates the resulting estimates to the parameters of the theoretical model.

4.2.1. *Identifying Tipping Points.* To identify the location of an empirically derived tipping point m^*_{ct} for each city c in the start year t of a given decade, I apply the fixed point algorithm of Card et al. (2008a), which is described below. Appendix E provides additional detail and describes three other methods to identify tipping points–the structural break method of Card et al. (2008a), the local kernel approach of Porter and Yu (2015), and the lasso method of Lee et al. (2016), which are used in robustness checks.[23]

Using the same data to identify tipping points and estimate discontinuities would bias results towards finding larger discontinuities and would inflate rejection rates for hypothesis tests. To avoid this, the analysis employs a split-sample approach where tipping points are estimated from a random two-thirds subsample of tracts, while discontinuity magnitudes are assessed using the remaining third. This separation permits valid inference using standard hypothesis tests (Card et al., 2008a).

The fixed-point method is based on the observation that white population tends to grow more in low-minority neighborhoods and less in high-minority ones (see Table D1). It seeks to identify an intermittent value of the minority share at which predicted white population growth matches the citywide average. For each city c and decade τ, it regresses the change in white population in neighborhoods i, $\Delta w_{ic\tau}$, on a fourth-order polynomial of the neighborhood minority share at the start of the period, $f(m_{ict})$, and solves for m^*_{ct} such that the regression-predicted growth, $\widehat{\Delta w_{ic\tau}} = f(m^*_{ct})$, equates to the city-level average growth. If several values of m fulfill this condition, the one with most negative slope of $f(m)$ is chosen.

Appendix Table E1 reports that the average tipping point obtained with the fixed-point method rose from 10.2% in 1970 to 17.8% in 2000, with other estimation methods yield

[22] As noted in earlier work (Massey and Denton, 1989; Card et al., 2008a), Chicago exhibited unusually high segregation and especially pronounced tipping dynamics. Davis et al. (2025) show that this tipping pattern was driven primarily by neighborhoods with low population density. Section 5.2.2 examines heterogeneity in tipping effects by tract density.

[23] Related work by Blair (2023) estimates tipping points using a structural model of neighborhood choice, but its assumptions are not aligned with the forward-looking behavior modeled here.

similar tipping point levels and trends. Since empirically estimated tipping points may be sensitive to outliers in the underlying data, I conduct three tests to systematically assess the stability of each estimation method. Methods that are less prone to outliers should arguably produce tipping point estimates that exhibit: (i) higher cross-sectional correlation with other methods, (ii) higher serial correlation across decades, and (iii) lower variability when estimates are recomputed using alternative random subsamples of tracts. Results in columns 5–7 of Appendix Table E1 show that the fixed-point method yields the most stable estimates according to all three criteria, and I thus use the fixed-point estimates as baseline tipping point values in the subsequent analysis. Appendix Table E2 provides additional descriptive statistics for neighborhoods with minority shares within two percentage points of these tipping points.

4.2.2. *Determinants of Tipping Points.* To connect the empirically derived tipping points m^*_{ct} to the theoretical model, I assess their consistency with the formula for m^{SS1} in equation (B.16), which predicts that tipping points increase with the citywide minority share ($\frac{\partial m^{SS1}}{\partial b} > 0$), decrease with white racial intolerance ($\frac{\partial m^{SS1}}{\partial k} < 0$), and are unrelated to the renter share ($\frac{\partial m^{SS1}}{\partial r} = 0$). Appendix Table A1 presents the results of city-level regressions of minority share tipping points on city-level minority shares, a racial intolerance index based on the General Social Survey (Card et al., 2008a), and the city-level renter share, controlling for decade fixed effects.[24] The results confirm all three theoretical predictions: tipping point values are significantly higher in cities with larger minority populations, lower where white prejudice is stronger, and uncorrelated with the renter share.

4.3. **Regression Framework.** The empirical analysis investigates the presence of large changes in population and housing outcomes around the estimated tipping points. Following both Card et al. (2008a) and recent studies of neighborhood tipping (Böhlmark and Willén, 2020; Davis et al., 2025), I estimate regressions of the following form:

$$\Delta y_{ic\tau} = \alpha_{c\tau} + f(d_{ict}) + \gamma_1 1[d_{ict} > 0] + \beta_1 r_{ict} + X_{ict}\beta_2 + \epsilon_{ic\tau} \tag{4.1}$$

where $\Delta y_{ic\tau}$ is the decadal change in outcome y for tract i in city c over decade τ, $f(\cdot)$ is a quartic polynomial in the distance between a tract's minority share and the city-level tipping point identified by the fixed-point method, with $d_{ict} \equiv m_{ict} - m^*ct$ measured in year t at the start of decade τ, and γ_1 is the coefficient on the indicator $1[dict > 0]$, which captures the local discontinuity at the tipping point. The regressions control for city-decade fixed effects $\alpha_{c\tau}$, the initial renter share r_{ict}, and a vector of other neighborhood characteristics X_{ict} also used by Card et al. (2008a)—log average family income, unemployment rate, share

[24]Appendix F details the construction of the racial intolerance index.

of single-unit homes, share of vacant homes, and share of public transport commuters—with all variables measured at the start of the decade.

An extended model allows the tipping effect to vary with the renter share:

$$\Delta y_{ic\tau} = \alpha_{c\tau} + f(d_{ict}) + \gamma_1 1[d_{ict} > 0] + \gamma_2 1[d_{ict} > 0] \times r_{ict} + \beta_1 r_{ict} + X_{ict}\beta_2 + \epsilon_{ic\tau} \qquad (4.2)$$

Here, γ_1 captures the tipping effect in fully owner-occupied neighborhoods, while γ_2 indicates how the magnitude of tipping effects varies for neighborhoods with higher renter shares.

To evaluate the robustness of the regression results, I estimate several modified versions of equations (4.1) and (4.2). These consider alternative polynomial specifications, local linear regressions, and the use of alternative estimates for the location of tipping points.

All regressions are conducted on the one-third of tracts not used to identify tipping points. The split-sample design allows for valid inference without specification search bias (Card et al., 2008a). Standard errors are clustered at the MSA level.

5. Empirical Estimates of Tipping Effects

5.1. **Changes in Owner-Occupied and Renter-Occupied Homes.** The first testable prediction from the model simulation in Section 3.2 is that neighborhood tipping is associated with a larger decline in the white owner than the white renter population.

Table 1 reports estimates of equation (4.1) using the log change in white owner-occupied or white renter-occupied housing units as outcome variables. Column 1 shows a significant tipping effect for white owners: neighborhoods just above the tipping point see a −9.82 log point lower decadal growth in white owner-occupied homes (t-statistic −4.4). In contrast, the effect for white renters of −5.42 in column 2 is only about half as large (t-statistic −2.8). A Wald test strongly rejects the null hypothesis that the coefficients for the homeowner and renter outcomes in columns 1 and 2 are equal ($p = 0.001$). This result confirms the model's prediction that tipping effects are stronger for white homeowners than for white renters.

Regression discontinuity analyses often include data plots to aid informal visual inference. Korting et al. (2023) provide guidance on best practices for such plots to avoid inflated type I error rates—falsely suggesting a discontinuity. However, a remaining limitation of their approach is a high risk of type II errors: visual plots may fail to show a discontinuity even when one exists, particularly when the effect size is small relative to the outcome's standard deviation. For example, the significant discontinuity in white owner-occupied housing in the first column of Panel A in Table 1 represents less than one-fifth of the outcome's standard deviation, implying low signal-to-noise for visual inspection.[25] With this caveat in mind,

[25]Korting et al. (2023) estimate that when the data contains a discontinuity corresponding to 0.19 of a standard deviation, visual inference produces a type II error rate of greater than 80 percent, while local linear regression analysis detects true discontinuities more reliably.

Table 1. Change in White Owner- and Renter-Occupied Housing

	Own	Rent
	(1)	(2)
Beyond tipping point	-9.816	-5.415
	(2.253)	(1.934)
R-squared	0.212	0.221
Observations	56,715	56,695
Wald test Own = Rent	p = 0.001	

Notes: Dependent variables are the decadal log changes in white owner-occupied or white renter-occupied housing units, measured in log points. The mean (s.d.) of the outcome variables are 4.35 (64.31) in column 1, and 6.06 (77.23) in column 2. Regressions are based on pooled decadal data from 1970 to 2010 and include only tracts from the 1/3 holdout sample that has not been used to determine tipping point locations. All regressions control for MSA-decade fixed effects, and a neighborhood's share of rental homes, log average family income, unemployment rate, share of single-unit homes, share of vacant homes, and share of public transport commuters at the start of a decade. Standard errors are clustered by MSA.

Appendix Figure A2 presents bin scatter plots for changes in white owner- and renter-occupied housing using the visual approach recommended by Korting et al. (2023). While the bin scatters are noisy, commensurate with the absence of a sharp policy discontinuity, the visual evidence is stronger for homeowners: growth in white owner population is above average in most neighborhoods just below the tipping point, and more often below average in neighborhoods just above. For renters, visual differences are less salient, consistent with the smaller estimates in Table 1.

5.2. **Changes in White, Minority and Overall Population.** The main outcome in the analysis of Card et al. (2008a) is the decadal change in a neighborhood's white population, measured as a percentage of its initial total population. This section replicates results for this outcome, as well as the changes in minority population, total population, and share of white residents. It additionally examines whether the discontinuities in population outcomes are larger in neighborhoods with lower renter shares. Section 5.2.1 presents baseline estimates; Section 5.2.2 explores additional heterogeneity patterns; and Section 5.2.3 tests robustness using alternative tipping point methods or regression specifications.

5.2.1. *Baseline Results.* Panel A of Table 2 reports results from the regression model in equation (4.1), using the decadal change in white population as a percentage of initial tract population as the outcome. The column 1 estimate indicates that neighborhoods just above the tipping point experience a -10.8 percentage point (pp) lower growth in white population than those just below it.

The simulation in Section 3.2 predicts stronger tipping effects in neighborhoods with lower renter shares, consistent with the larger effect for white homeowners than for white

Table 2. Change in White, Minority and Overall Population, White Share

	A. White pop		B. Minority pop		C. Total pop	
	(1)	(2)	(3)	(4)	(5)	(6)
Beyond tipping point	-10.840	-26.989	2.920	4.526	-7.920	-22.463
	(1.400)	(2.052)	(0.691)	(1.273)	(1.673)	(2.524)
Beyond TP x renter share		51.800		-5.151		46.649
		(5.758)		(3.170)		(6.187)
R-squared	0.209	0.218	0.117	0.117	0.164	0.168

	D. White share		E. 100 $\times$ 1{Chg. Wh. sh. $\leq -20pp$}	
	(7)	(8)	(9)	(10)
Beyond tipping point	-3.065	-5.184	5.362	7.616
	(0.419)	(0.629)	(1.145)	(1.306)
Beyond TP x renter share		6.796		-7.227
		(1.248)		(2.796)
R-squared	0.232	0.236	0.186	0.187

Notes: Dependent variables are the decadal changes in white, minority or total neighborhood population, expressed in percentage points of total population at the start of a decade, the decadal change in white share of neighborhood population in percentage points, and 100 times an indicator for a decline in white share of at least -20pp. The mean (s.d.) of the outcome variables are 12.79 (53.90) in Panel A, 13.23 (37.50) in Panel B, 26.02 (73.59) in Panel C, -7.09 (10.60) in Panel D, and 10.16 (30.21) in Panel E. Regressions are based on pooled decadal data from 1970 to 2010 and include only tracts from the 1/3 holdout sample that has not been used to determine tipping point locations. All regressions control for MSA-decade fixed effects, and a neighborhood's share of rental homes, log average family income, unemployment rate, share of single-unit homes, share of vacant homes, and share of public transport commuters at the start of a decade. Standard errors are clustered by MSA. The number of observations is 58,364 for every regression.

renters documented in Section 5.1. Column 2 of Panel A tests this prediction using regression model (4.2) and confirms significant heterogeneity by renter share. To illustrate the magnitude of the estimates, consider two neighborhoods whose renter shares are at the 25th and 75th percentiles of the renter-share distribution among neighborhoods near the tipping point. For a neighborhood at the 25th percentile, with a renter share of 0.150 (Appendix Table E2), the estimated coefficients in column 2 of Panel A imply a tipping effect of -19.2pp ($= -27.0 + 0.15 \times 51.8$). By contrast, for a neighborhood at the 75th percentile, with a renter share of 0.395, the implied effect is only -6.5pp, about one-third as large.

Panel B repeats the analysis for minority population growth, measured in percentage of initial tract population. If total population in neighborhoods were constant, tipping effects for minorities would have the same magnitude as those for whites, but in the opposite direction. While coefficients in Panel B indeed have opposite signs than those in Panel A, they are considerably smaller in magnitude. Comparing columns 1 and 3, only about a quarter of the decline in white population growth is offset by minority gains, and column 4 indicates a more muted heterogeneity with regard to the renter share.

Panel C analyzes changes in total neighborhood population, which by construction equate to the sum of white and minority population change. The column 5 estimate indicates that tipping substantially reduces neighborhood population growth, where this effect is more pronounced in neighborhoods with low renter shares according to the column 6 model. Taken together, the results in Panels A to C are consistent with the model version in Section 2.8 that allows for endogenous housing supply, which predicts that tipping reduces overall and white population growth, while having a more muted impact on minority population growth.

The negative effect of tipping on white population growth and the positive effect on minority population growth imply a shift in neighborhood racial composition toward a lower white population share. Panel D quantifies this effect. The coefficient estimate in column 7 indicates a precisely estimated decline of -3.1pp in the white population share. Thus, the change in a tipping neighborhood's white population share is notably smaller than the corresponding change in white population growth, as emphasized by Davis et al. (2025).[26]

This average effect may, however, mask substantial heterogeneity in tipping magnitudes. It is, for instance, conceivable that tipping effects are harder to detect in some locations because measurement error in estimated tipping points attenuates the average treatment effect. Panel E therefore examines whether tipping increases the probability that a neighborhood's white population share declines by 20 percentage points or more. As noted in Section 4.1, such large declines are rare: they occur in only 10 percent of all neighborhoods and in just 6 percent of neighborhoods whose minority share lies within 2 percentage points of the tipping point. The estimate in column 9 indicates that tipping raises the likelihood of such a large decline in white share by 5.4pp, which is substantial given the low baseline prevalence of large shifts in neighborhood racial composition. The results in columns 8 and 10 provide further support for the prediction that racial tipping effects are stronger in neighborhoods with higher homeownership rates: these neighborhoods experience both larger declines in white population shares and larger increases in the probability of a substantial decline in the white share.

5.2.2. *Alternative Hypotheses.* To isolate the role of tenure status in neighborhood tipping, the model in Section 2 assumes that homeowners and renters differ only in terms of their tenure status. In practice, however, the two groups can differ in their attributes, and neighborhood renter shares are correlated with other neighborhood characteristics. Appendix

[26] To illustrate how a large change in white population growth can correspond to a smaller change in the white population share, consider a neighborhood with 950 white and 50 minority residents. Suppose that, absent tipping, both groups would grow by 10 percent, yielding 1,045 white residents and 55 minority residents. Now assume that tipping lowers white population growth by 11 percentage points of the initial tract population and raises minority population growth by 3 percentage points. The neighborhood then ends up with 935 rather than 1,045 white residents, a decline of 110, and 85 rather than 55 minority residents, an increase of 30. As a result, the white share is 92 percent (=935/(935+85)) rather than 95 percent (=1045/(1045+55)), implying a decline of 3 percentage points.

Table E2 shows that, among neighborhoods near the tipping point, higher renter shares are associated with fewer families with children, more young adults, higher population density, and closer proximity to majority non-White and Hispanic neighborhoods. The heterogeneous tipping effects in Table 2 could therefore reflect these correlated characteristics rather than tenure structure itself.

Appendix Table A2 examines this issue for white population change. Column 1 repeats the baseline interacted specification from equation (4.2), while subsequent columns add controls for the indicated correlates of the renter share and their interactions with the tipping-point indicator.

Column 2 shows that tipping-induced white population decline is larger in neighborhoods with more families with children, consistent with the idea that parents may be especially sensitive to neighborhood composition.[27] Controlling for this factor reduces the renter-share interaction by about one-third. Column 3 instead shows larger tipping effects in neighborhoods with more young adults, consistent with their greater mobility (Molloy et al., 2011; Kaplan and Schulhofer-Wohl, 2017). When both variables are included in column 4, the young-adult effect remains strong, implying a 10.7pp larger tipping effect at the 75th than at the 25th percentile of the young-adult share, while the family-share effect becomes much smaller. The renter-share interaction remains close to its baseline magnitude.

Spatial factors may also shape the magnitude of neighborhood tipping. Section 2.8 argues that in lower-density areas, where housing supply has more scope to expand, tipping generates larger declines in white population growth because it reduces white population in the existing housing stock and slows new housing supply. The estimates in column 5 support this prediction: neighborhoods with higher log population density exhibit weaker tipping effects on white population growth. Comparing neighborhoods at the 25th and 75th percentiles of population density, the implied tipping-induced decline in white population growth is 7.0 percentage points larger in the less dense neighborhood. Controlling for density also reduces the coefficients on the tipping-point indicator and its interaction with renter share.

Davis et al. (2025) argue that tipping effects are stronger in neighborhoods located near pre-existing high-minority areas, consistent with the spacial proximity theory of Schelling (1971). To examine this possibility, columns 6 to 8 additionally control for whether a tract lies within 5 kilometers of at least one neighborhood whose minority share exceeds 50 percent at the start of the decade.[28] Conditional on density, neighborhoods near high-minority

[27] Families with children are more common among homeowners (Goodman and Mayer, 2018), and school demographics may be one reason why parents respond strongly to racial composition (Charles, 2000). For related work on racial segregation across schools, see Guryan (2004), Card and Rothstein (2007), Billings et al. (2014), and Anstreicher et al. (2022).

[28] For the average tract in the sample, 4.7% of the tracts from the same MSA are within this radius.

areas show stronger tipping effects on white population growth, although the estimates are imprecise. In the most demanding specification in column 8, which includes all additional covariate interactions simultaneously, the estimates for the tipping-point discontinuity and its interaction with renter share remain only modestly smaller than in the baseline specification of column 1. At the same time, neighborhood age composition and population density emerge as additional significant determinants of tipping magnitudes.

The subsequent panels of Table A2 examine whether the baseline results also remain robust for changes in minority population (Panel B), total population (Panel C), white population share (Panel D), and the probability of a decline in white share of at least 20 percentage points (Panel E) when the interacted covariates from Panel A are included. Across all panels, the baseline estimates for the tipping-point indicator and its interaction with renter share remain only modestly affected by the inclusion of the additional population and location controls.

5.2.3. *Robustness to Alternative Specifications.* Appendix Table A3 further tests the robustness of the results for white population growth to the use of alternative tipping point definitions, polynomial specifications, local discontinuity models, and period-specific regressions.

Columns 1–2 in Panel A replicate the baseline results from Table 2 using the tipping points obtained with the fixed-point method of Card et al. (2008a), while the subsequent columns in Panel A apply the structural break, lasso, and kernel approaches (see Section 4.2.1). Across all methods, regressions consistently produce negative estimates for the tipping discontinuity (γ_1) and positive estimates for its interaction with renter share (γ_2), with both highly statistically significant. Coefficient magnitudes are similar across the fixed point and structural break methodologies, and modestly smaller with the lasso and kernel tipping points.

Although the global polynomial regression approach can offer greater precision than non-parametric methods, it is difficult to identify the correct functional form for the polynomial (Lee and Lemieux, 2010). Columns 1-6 probe the robustness of the baseline results to the use of lower- and higher-order polynomials, while columns 7-8 show results for the quartic polynomial regression while suppressing the neighborhood covariate vector X_{ict}. None of these modifications has an important qualitative or quantitative impact.

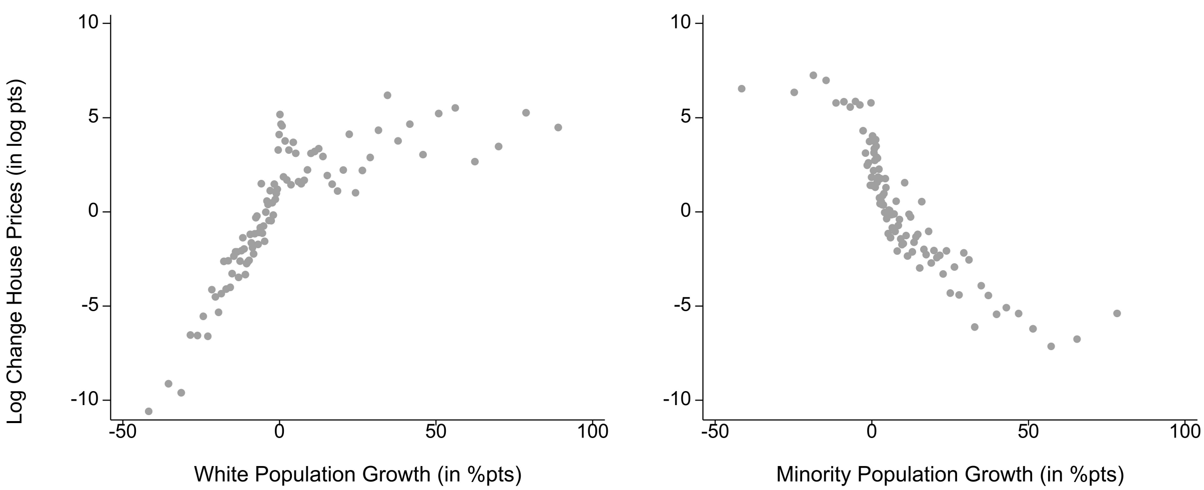
Although the neighborhood tipping literature has typically relied on global polynomial specifications (Card et al., 2008a; Böhlmark and Willén, 2020; Davis et al., 2025), discontinuity effects can also be estimated using local spline models, as recommended in regression discontinuity settings with well-defined thresholds (Gelman and Imbens, 2019). Column 1 of Panel C reports estimates from a local linear spline model using the distance between a neighborhood's minority share and the tipping point, d_{ict}, over the asymmetric bandwidth

$-0.04 \leq d_{ict} \leq 0.12$.[29] The estimated tipping effect is about three-fifths as large as in the baseline model, but remains highly statistically significant. Further modifications—using the endogenous bandwidth of Calonico et al. (2014) (columns 3–4), fitting a quadratic spline (columns 5–6), or omitting the covariate vector X_{ict}—do not materially change the results.

Panel D presents results for the baseline regression models separately by decade. There are little differences across the 1970s, 1980s and 1990s, while tipping effects appear more muted in the 2000s. A Wald test however fails to reject the null hypothesis of equally large tipping discontinuities in columns 1, 3, 5 and 7 at the conventional 5% significance level ($p = 0.09$), consistent with broadly stable effects over time.

5.3. **Changes in House Prices and Rents.** House prices tend to be lower in neighborhoods with higher minority shares, even after controlling for housing quality (Perry et al., 2018; Grodzicki et al., 2024). It is therefore plausible that changes in racial composition are linked to changes in house prices, as posited in the Section 2 model.[30]

FIGURE 3. Growth of Population by Race and Change in House Prices



Notes: The graph is based on the full sample of Census tracts as described in Table D1 and pooled across decades. Tracts are aggregated into 100 evenly sized bins based on their decadal growth of white population (in Panel A) or minority population (in Panel B), each expressed as a percentage of tract population at the start of the decade. Log changes in house prices are measured as deviations from MSA-decade averages.

[29] The asymmetric bandwidth accounts for the lower density of neighborhoods just above the tipping point, consistent with the rapid transitions shown in Panel A of Figure A1. It also yields roughly balanced samples on either side of the threshold, with 12,214 neighborhoods below and 11,194 above. For a similar use of asymmetric bandwidths in a setting with skewed running-variable density, see Carlson et al. (2022).

[30] In related work, Saiz and Wachter (2011) find a negative relationship between the growth in a neighborhood's foreign-born population share and the change in house prices, where this effect is largely driven by nonwhite immigrants. Akbar et al. (2025) show that Census blocks that were all-white in 1930 but transitioned to a black share of around 50% in 1940 experienced declines in both house prices and rents. They emphasize that rents increased in blocks that became predominantly black, as blacks were charged a 50% rent premium relative to whites, which considerably exceeds estimates of racial discrimination in housing markets for more recent periods (Christensen and Timmins, 2023b).

Figure 3 provides basic correlational evidence. It pools the full sample of tracts across decades and indicates a bin scatter for changes in neighborhood population by race (measured as for the outcome variables in Panels A and B of Table 2) and changes in log house prices (measured in deviations from average log house price growth in the corresponding MSA and decade). Panel A shows a strong positive association between white population growth and house price growth especially in neighborhoods where white population declines. Panel B indicates a strikingly different pattern for the relationship between house prices and the growth of minority population: Neighborhoods with greater increases in minority residents experience substantially lower house price appreciation.

Since neighborhood tipping leads to a significant decline in white population growth and a modest rise in minority population growth (Table 2), the correlational patterns in Figure 3 suggest that tipping is likely associated with falling house prices. The model simulation in Section 3 generate three testable predictions regarding housing costs: (i) tipping reduces house prices, (ii) house prices fall more sharply than rents, and (iii) both declines are larger in neighborhoods with lower renter shares.

Table 3. Change in House Prices and Rents

	A. House prices		B. Rents	
	(1)	(2)	(3)	(4)
Beyond tipping point	-5.706	-14.830	-0.485	-2.435
	(0.975)	(1.542)	(0.778)	(1.131)
Beyond TP x renter share		29.163		6.293
		(3.029)		(2.107)
R-squared	0.535	0.539	0.588	0.588
Observations	54,313	54,313	44,098	44,098

Notes: Dependent variables are the log change in average house prices and the log change in average rents, measured in log points. The mean (s.d.) of the outcome variables are 26.53 (45.13) in Panel A and 30.34 (86.47) in Panel B. Regressions are based on pooled decadal data from 1970 to 2010 for house prices, while the analysis for rents is restricted to the 1980 to 2010 period due to missing data in 1970. Regressions include only tracts from the 1/3 holdout sample that has not been used to determine tipping point locations. The regressions in Panel A for the log average house price at the start of a decade, while the regressions in Panel B control for the log average rent at the start of a decade. All regressions control for MSA-decade fixed effects, and a neighborhood's share of rental homes, log average family income, unemployment rate, share of single-unit homes, share of vacant homes, and share of public transport commuters at the start of a decade. Standard errors are clustered by MSA.

Table 3 tests these predictions using regressions in which the outcomes are decadal changes in log average house prices (Panel A) and log average rents (Panel B). The specifications follow equations (4.1) and (4.2), augmented with controls for initial log house prices or rents to account for mean reversion in housing costs (Case and Shiller, 1989; Saiz and

Wachter, 2011).[31] Because rent data are limited in 1970, the rent regressions use data from 1980 onward only.[32]

Column 1 of Panel A shows that neighborhoods just above the tipping point experience house price growth that is 5.7 log points lower than in neighborhoods just below the threshold (t-statistic = −5.9). This effect is sizable, and the model simulation in Section **??** suggests that even a substantially smaller expected decline in house prices would be sufficient to induce a faster decline in the white homeowner population than in the white renter population.

Column 2 tests the additional prediction that tipping effects on house prices are ever larger in neighborhoods with lower renter shares. Consistent with this prediction, the interaction between the tipping indicator and the neighborhood renter share is positive, sizable, and highly statistically significant. The coefficient estimates imply predicted tipping effects on house prices of −10.5 log points for neighborhoods at the 25th percentile of the renter-share distribution, nearly double the average effect.

Columns 3 and 4 repeat the analysis for log rent growth. Consistent with the model's predictions, rents decline less than house prices in tipping neighborhoods. Column 3 indicates an economically small and statistically insignificant reduction of 0.5 log points in rents at the tipping point, and a Wald test strongly rejects the null hypothesis that house prices and rents decline by the same amount in columns 1 and 3 ($p = 0.00$). Column 4 further shows that, as with house prices, rent declines are larger in neighborhoods with lower renter shares. Even so, the estimated magnitude remains modest: the coefficient estimates imply a rent decline of only 1.5 log points for neighborhoods at the 25th percentile of the renter-share distribution.

Overall, these results provide strong support for the model's central prediction that housing markets amplify neighborhood tipping. Tipping depresses house price growth and, to a lesser extent, rent growth, with the largest effects in low-renter neighborhoods—the very places undergoing the most rapid racial transformation.

6. Conclusions

Racial segregation in American cities has long been linked to white residents' preferences for living among other whites. Once a neighborhood's minority share crosses a critical threshold, such preferences can generate tipping dynamics. This paper argues that neighborhood tipping is not driven by social preferences alone. Housing markets can amplify the process

[31] The regression analysis in Card et al. (2008a) does not consider mean reversion, which leads to smaller and less precisely estimated negative effects of tipping on house prices.

[32] Rent data are available from 1980 onward for 97% of tracts used in the population analysis, and house price data are available from 1970 onward for 94% of those tracts. Both variables are based on self-reports in the decennial Census. Although self-reported house values are noisy at the individual level, they track transaction-based measures reasonably well in the aggregate (Banzhaf and Farooque, 2013; Dreesen and Damen, 2023).

in a systematic and quantitatively important way through the distinct financial incentives faced by homeowners and renters.

To study this mechanism, the paper develops a dynamic model of neighborhood turnover in which residents differ by race, individual tastes, tenure status, and expectations. When a neighborhood has a minority share that is marginally above a tipping point, the neighborhood begins to converge toward a new steady state with a substantially higher minority share. The speed of this transition depends critically on tenure structure and expectation formation. When many residents are forward-looking, white homeowners anticipate future declines in property values and therefore have a financial incentive to sell early, in addition to any preferences they hold over neighborhood composition. For the same reason, forward-looking white homeowners are less willing to enter tipping neighborhoods. This financial incentive is absent for white renters, who instead benefit from declining rents and are therefore less likely to exit and more likely to enter than otherwise identical homeowners. Numerical simulations show that an expected house-price decline of as little as 1 percent is sufficient to raise homeowners' opportunity cost of residing in the neighborhood above that of renters, causing forward-looking owners to leave more quickly despite the higher transaction costs of owner-occupied housing.

The model delivers several testable predictions for how population composition and housing costs should evolve in tipping neighborhoods with different tenure structures. I evaluate these predictions using decennial Census data from 1970 to 2010 for neighborhoods in more than 100 Metropolitan Statistical Areas, extending the empirical framework of Card et al. (2008a). The results show that neighborhoods just above the tipping point experience a substantial decline in white population growth of -10.8pp relative to neighborhoods just below it. This decline is much larger in neighborhoods with high homeownership rates: comparing neighborhoods near the tipping point at the 25th and 75th percentiles of the renter-share distribution, the implied tipping effect on white population growth is about three times as large in the lower-renter neighborhood. The evidence also shows that this decline is driven primarily by a stronger reduction in white owner occupancy than in white renter occupancy, as predicted by the model. The analysis likewise supports the model's predictions for housing costs. Neighborhoods just above the tipping point experience house price growth that is -5.7 log points lower than in neighborhoods just below it, and this decline is especially pronounced in neighborhoods with low renter shares.

Homeownership is often associated with positive externalities, including greater civic engagement, stronger investment in local public goods, and deeper attachment to community quality. The findings here highlight a complementary and more problematic implication of that same financial exposure. Even a white homeowner with only weak racial preferences may choose to sell early when a neighborhood tips in order to avoid a capital loss, while prospective white buyers with similarly weak preferences may be reluctant to purchase in a neighborhood undergoing racial transition for the same reason. These results suggest that efforts to promote residential integration could be extended beyond a focus on changing racial attitudes or reducing discriminatory barriers. Financial incentives operating through housing markets constitute an additional force that can sustain segregation. Policies that stabilize expectations about neighborhood fundamentals, broaden access to owner-occupation in transitioning areas, and reduce the sensitivity of household balance sheets to localized house price declines may therefore help stabilize integrated neighborhoods. Neighborhood tipping, long understood primarily as a social phenomenon, is also a financial one, and any complete account of residential segregation should consider the market forces that can substantially amplify residential change.

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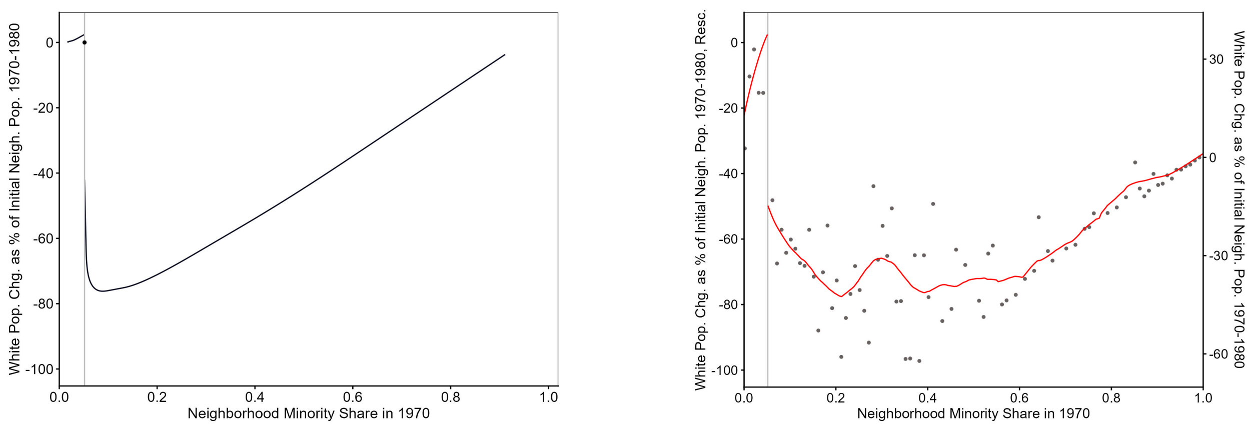
Appendix A. Additional Figures and Tables

Figure A1. Neighborhood Change in 1970s Chicago: Simulation vs. Data



(a) Simulation (b) Census tract data

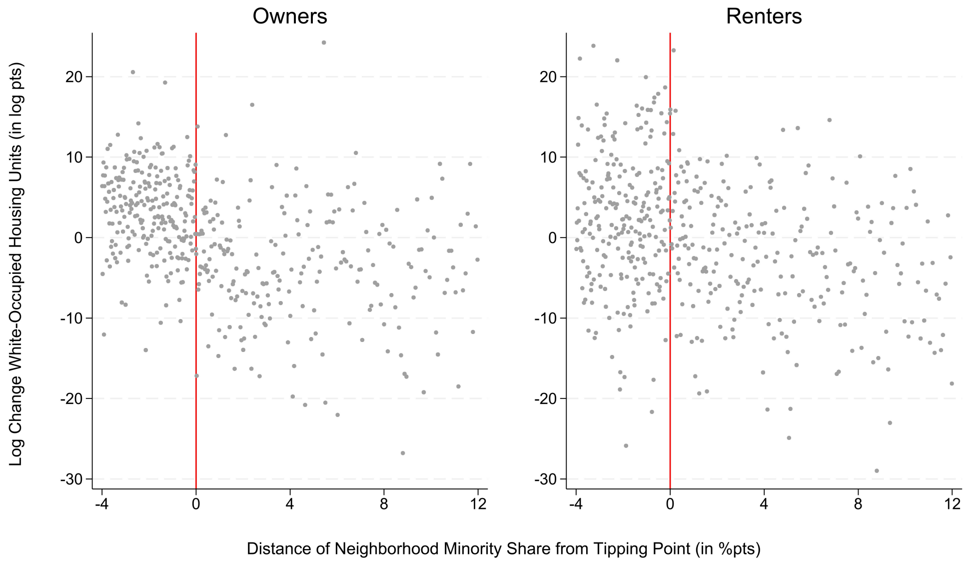
Notes: The vertical lines in both panels mark a tipping minority share of 0.052 that was obtained with fixed-point method of Card et al. (2008a). Panel A shows simulated decadal white population growth from the baseline calibration of the model (as in Panel A of Figure 2), with values below the tipping point based on a separate simulation that is initialized at $m^{SS1} - \varepsilon$. Panel B uses NCDB data aggregated into 100 evenly spaced bins by initial minority share; the red line shows a kernel-weighted local average using an Epanechnikov kernel with bandwidth 4 and bin weights proportional to the number of neighborhoods. The left-hand y-axis in Panel B is rescaled to match white population growth just below the tipping point in Panel A.

Table A1. Determinants of Tipping Point Locations

	(1)	(2)	(3)
Minority share (in %pts)	0.534	0.452	0.476
	(0.043)	(0.057)	(0.074)
Racial intolerance index		-2.400	-2.555
		(0.930)	(0.982)
Renter share (in %pts)			-0.068
			(0.137)
R-squared	0.609	0.519	0.520
Observations	415	167	167

Notes: The dependent variable is the fixed-point tipping point location for an MSA-decade cell, measured in percentage points. The Racial Intolerance Index is constructed using individual-level data from the pooled 1972–2018 General Social Survey (GSS) which is matched to MSAs. All regressions include decade fixed effects, and standard errors are clustered at the MSA level.

Figure A2. Change in White Owner- and Renter-Occupied Housing



Notes: The bin scatter plot is constructed based on best practices for the visual representation of regression discontinuity designs as proposed by Korting et al. (2023). The Mimicking Variance (MV) method of Calonico et al. (2022), implemented in Stata package `rdplot`, is applied separately on each side of the cutoff for the two outcomes. For owners, there are 233 bins on the left side of the cutoff and 219 on the right. For renters, the number of bins are 231 and 238, respectively. Each of the resulting bins on each side of the tipping point aggregates the same fraction of neighborhoods and indicates average values for these neighborhoods. The outcome variables have been residualized with respect to MSA-year fixed effects and the neighborhood covariates used throughout the regression analysis.

Table A2. Change in Neighborhood Population: Additional Interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. White population								
Beyond tipping point	-26.989	-21.338	-32.355	-29.299	-16.320	-20.895	-14.690	-20.981
	(2.052)	(2.416)	(2.279)	(2.977)	(1.739)	(2.079)	(1.745)	(2.586)
Beyond TP x renter share	51.800	33.620	68.386	59.498	28.974	39.637	25.286	43.105
	(5.758)	(6.707)	(7.783)	(10.271)	(5.929)	(6.420)	(5.795)	(10.484)
Beyond TP x sh families w/ children		-55.010		-9.298				0.582
		(7.830)		(11.446)				(12.421)
Beyond TP x share adults age < 35			-95.552	-82.582				-84.384
			(6.884)	(10.820)				(12.192)
Beyond TP x population density					3.335		3.322	2.436
					(0.665)		(0.723)	(0.718)
Beyond TP x proximity to high-min						4.491	-0.064	-1.977
						(1.452)	(1.623)	(1.600)
R-squared	0.218	0.237	0.247	0.250	0.284	0.243	0.290	0.315
B. Minority population	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	4.526	6.195	4.768	5.342	4.312	4.694	4.472	4.852
	(1.273)	(1.421)	(1.330)	(1.612)	(1.253)	(1.581)	(1.413)	(1.608)
Beyond TP x renter share	-5.151	-9.286	-6.765	-7.504	-3.664	-5.125	-2.717	-3.643
	(3.170)	(3.618)	(3.407)	(4.485)	(2.983)	(3.668)	(3.075)	(4.038)
R-squared	0.117	0.124	0.127	0.129	0.122	0.118	0.124	0.137
C. Total population	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	-22.463	-15.144	-27.587	-23.957	-12.008	-16.201	-10.218	-16.129
	(2.524)	(2.909)	(2.807)	(3.524)	(2.216)	(2.876)	(2.371)	(3.233)
Beyond TP x renter share	46.649	24.335	61.621	51.994	25.309	34.511	22.569	39.462
	(6.187)	(6.730)	(7.737)	(10.053)	(6.197)	(7.276)	(6.158)	(9.986)
R-squared	0.168	0.187	0.196	0.200	0.215	0.179	0.216	0.245
D. White share	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	-5.184	-5.319	-4.865	-4.697	-6.370	-5.393	-6.091	-5.918
	(0.629)	(0.580)	(0.631)	(0.602)	(0.553)	(0.537)	(0.524)	(0.532)
Beyond TP x renter share	6.796	7.078	5.751	4.902	10.595	6.495	9.591	8.440
	(1.248)	(1.335)	(1.342)	(1.611)	(1.169)	(1.191)	(1.150)	(1.384)
R-squared	0.236	0.237	0.237	0.238	0.280	0.271	0.296	0.301
E. 100 $\times$ 1{Chg. White share $\leq -20pp$}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	7.616	7.689	7.484	7.036	10.577	8.570	10.235	10.392
	(1.306)	(1.248)	(1.346)	(1.328)	(1.310)	(1.149)	(1.190)	(1.293)
Beyond TP x renter share	-7.227	-6.932	-6.835	-4.649	-15.970	-7.476	-13.942	-12.851
	(2.796)	(3.255)	(3.115)	(4.241)	(2.603)	(2.867)	(2.628)	(3.749)
R-squared	0.187	0.187	0.187	0.188	0.202	0.205	0.212	0.215

Notes: Dependent variables are the decadal changes in white, minority or total neighborhood population, expressed in percentage points of total population at the start of a decade, the decadal change in white share of neighborhood population in percentage points, and 100 times an indicator for a decline in white share of at least -20pp. All regression models in column 1 correspond to those in Table 2. The additional covariates, consisting always of a main effect and an interaction term between the de-meaned control variable and the tipping point indicator, are: the share of families with children among all household (columns 2, 4 and 8), the share of residents below age 35 among all adults age 20 and older (columns 3, 4 and 8), the log of population density in terms of number of people per square kilometer (columns 5, 7 and 8), and an indicator for tracts that are located within a 5km distance of a tract with a population majority of non-whites and Hispanics (columns 6, 7 and 8). The number of observations is 58,364 for all the regressions, except for the ones controlling for population density, where the number is 58,289.

Table A3. Change in White Population: Alternative Specifications

A. Alternative Tipping Points								
	A1. Fixed point		A2. Structural break		A3. Lasso		A4. Kernel	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	-10.840	-26.989	-14.982	-29.354	-8.041	-20.968	-7.582	-18.044
	(1.400)	(2.052)	(1.168)	(2.280)	(1.578)	(2.627)	(1.457)	(2.875)
Beyond TP x renter share		51.800		47.163		40.913		36.764
		(5.758)		(5.458)		(4.488)		(6.725)
R-squared	0.209	0.218	0.210	0.218	0.203	0.209	0.205	0.210
Observations	58,364	58,364	59,003	59,003	59,003	59,003	59,003	59,003
B. Alternative Polynomial Models								
	B1. TP Distance^2		B2. TP Distance^6		B3. TP Distance^8		B4. No controls X_{ict}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	-13.486	-29.653	-10.687	-26.747	-10.442	-26.430	-11.151	-27.335
	(1.416)	(2.321)	(1.650)	(2.176)	(1.699)	(2.199)	(1.376)	(2.296)
Beyond TP x renter share		51.533		52.021		52.074		51.998
		(5.712)		(5.792)		(5.822)		(6.290)
R-squared	0.208	0.217	0.209	0.218	0.209	0.218	0.175	0.185
Observations	58,364	58,364	58,364	58,364	58,364	58,364	58,364	58,364
C. Local Spline Models								
	C1. BW: -4, 12		C2. Optimal BW		C3. TP Distance^2		C4. No controls X_{ict}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	-6.465	-14.812	-6.499	-15.474	-6.179	-14.376	-7.272	-15.885
	(1.705)	(2.617)	(1.497)	(2.443)	(1.920)	(2.793)	(1.771)	(2.822)
Beyond TP x renter share		26.953		29.124		27.045		27.816
		(4.615)		(4.541)		(4.590)		(4.861)
R-squared	0.234	0.236	0.231	0.233	0.234	0.236	0.192	0.194
Observations	23,408	23,408	22,694	22,694	23,408	23,408	23,408	23,408
D. Global Quartic Models by Decade								
	D1. 1970s		D2. 1980s		D3. 1990s		D4. 2000s	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beyond tipping point	-9.091	-25.960	-12.813	-29.349	-11.451	-26.375	-3.977	-14.322
	(2.437)	(4.289)	(2.346)	(3.511)	(1.754)	(2.796)	(2.034)	(3.035)
Beyond TP x renter share		50.899		49.201		48.762		37.745
		(11.563)		(6.943)		(4.731)		(6.935)
R-squared	0.259	0.265	0.296	0.305	0.174	0.185	0.108	0.114
Observations	12,830	12,830	14,665	14,665	15,537	15,537	15,332	15,332

Notes: The dependent variable is the decadal change in white population expressed as a percentage of total population at the start of a decade. Panel A1 repeat the estimates of columns 1-2 in of Table 2. The subsequent regression models change the following features of the regression specifications: Panels A2 to A4 consider alternative tipping point definitions. Panels B1 to B3 use different polynomial orders for the running variable, and Panel B4 omits the vector of neighborhood controls that is included in the baseline model. Panel C1 uses a local linear spline model with a bandwidth of -4, +12 for the percentage point difference between tract minority share and city-level tipping point, while the subsequent panels modify this setup by either using a slightly wider endogenous bandwidth of -3.5, +13.8 based on Calonico et al. (2014) in Panel C2, a quadratic spline in Panel C3, and omitting baseline control variables in Panel C4. The regressions in Panel D repeat the estimates of columns 1-2 of Table 2 for each decade.

ONLINE APPENDIX

Appendix B. Theory

The Theory Appendix comprises four sections. Section B.1 proves Theorem 1 on steady state (SS) dynamics. Section B.2 proves Theorem 2 on interior SS, and additionally characterizes corner SS. Section B.3 proves Theorem 3 on transition dynamics. Section B.4 proves Theorem 4 on tipping dynamics under endogenous housing supply.

B.1. **Steady State Dynamics.**

Theorem 1. *If the neighborhood is at an interior steady state in period t, it holds that*

$$m^{SS} = m_t = m_{t+\tau}, \quad p^{SS} = p_t = p_{t+\tau}, \quad P^{g,SS} = P^g_t = P^g_{t+\tau}, \quad P^{n,SS} = P^n_t = P^n_{t+\tau}, \quad \forall \tau > 0. \tag{B.1}$$

If the neighborhood is at a corner steady state in period t, there exist limiting values for the neighborhood minority share, rent and house prices such that

$$m^{SS} = \lim_{t\to\infty} m_t, \quad p^{SS} = \lim_{t\to\infty} p_t, \quad P^{g,SS} = \lim_{t\to\infty} P^g_t, \quad P^{n,SS} = \lim_{t\to\infty} P^n_t \tag{B.2}$$

where each convergence is monotone.

Proof. The proof for this theorem proceeds in three steps. It first considers interior steady states in a neighborhood where all agents are forward-looking, then considers corner SS under the same expectations, and finally considers SS in the presence of myopic agents. All proofs are based on the behavior of renters, but one can readily derive analogous proofs for homeowners.

B.1.1. *Interior Steady States without Myopic Agents.* Assume first that the neighborhood is at an interior SS in period t. Denote by κ_0 and ϕ_0 the taste parameters of the marginal white and minority prospective renters, i.e., the renters with largest (dis-)taste parameters among those who are willing to move into the neighborhood at t. An interior SS requires that some but not all minorities and some but not all whites want to move in, hence $\kappa_0 \in \langle 0, k\rangle$ and $\phi_0 \in \langle 0, \Phi\rangle$. This implies that the marginal renters of both racial groups are exactly indifferent between moving into the neighborhood or remaining outside the neighborhood in period t because their willingness to pay for renting in the neighborhood is equal to the current rent. Using the fact that the agents are forward-looking ($p^e_{t+\tau} = p_{t+\tau}$, $m^e_{t+\tau} = m_{t+\tau}$), one obtains:

$$0 = \sum_{\tau \geq 0} (1-\rho)^{\tau} (y - \kappa_0 (\frac{m_{t+\tau}}{b})^2 - p_{t+\tau}) \tag{B.3}$$

$$0 = \sum_{\tau \geq 0} (1-\rho)^{\tau} (y - \phi_0 - p_{t+\tau}) \tag{B.4}$$

From the definition of the SS, it follows that a neighborhood which is in SS in period t will also be in SS in all subsequent periods, and the marginal white and minority renters who enter the neighborhood in these subsequent periods will have taste parameters κ_0 and ϕ_0. Thus the equations (B.3) and (B.4) also hold if the lower bounds of the summations are increased to 1, i.e., if the summation includes all periods $\tau \geq 1$. This implies:

$$0 = y - \kappa_0 (\frac{m_t}{b})^2 - p_t$$

$$0 = y - \phi_0 - p_t$$

From the second equation one gets $p_t = y - \phi_0 = p^{SS}$, and analogously (increasing the lower bound of summation further), $p_\tau = y - \phi_0 = p^{SS}$ for periods $\tau \geq t$. Plugging this expression into the first equation and using the fact that it holds for any period after t, one gets $m_\tau = \sqrt{\frac{y-p^{SS}}{\kappa_0/b^2}} = m^{SS}$ for all periods following t, which proofs the theorem for interior steady states.

B.1.2. *Corner Steady States without Myopic Agents.* Now assume that the neighborhood is at a corner SS with $\kappa_0 \in \langle 0, k \rangle$ and $\phi_0 = \Phi$, such that all prospective minority renters prefer to move into the neighborhood. Since marginal potential renters do not change over time in SS, as shown above, it again holds that the minority share among incoming residents is constant: $m_t^{IN} = m^{IN}$. The replication of residents is driven solely by the death of a fraction δ of current residents in each period, and one thus gets:

$$m_{t+1} = \delta m^{IN} + (1-\delta) m_t \to m^{IN} \tag{B.5}$$

Analogously to the first part of the proof, it then follows from the marginal white renter's utility that $p_t = y - \kappa_0 m_t^2$, so p_t converges monotonically when m_t converges monotonically.

Assume instead that the neighborhood is at a corner SS where $\phi_0 \in \langle 0, \Phi \rangle$ and $\kappa_0 = k$, such that all prospective white renters prefer to move into the neighborhood. The taste parameter of the marginal minority renter does not change over time in SS, which implies a constant rent $p_{SS} = y - \phi_0$. As in case of the first type of corner SS, it is again the case that neighborhood turnover due to deaths leads to a minority share that converges according to equation (B.5), which proofs the theorem for corner steady states without myopic agents.

B.1.3. *Steady States with Myopic Agents.* When the neighborhood and the pool of prospective residents contain both forward-looking and myopic agents, then expected rents $p_{t+\tau}^{e,MY}$, $p_{t+\tau}^{e,PF}$

and minority shares $m_{t+\tau}^{e,MY}, m_{t+\tau}^{e,PF}$ can differ across the two groups, and there may be separate marginal taste parameters $\kappa_0^{MY}, \phi_0^{MY}$ for myopic agents and $\kappa_0^{PF}, \phi_0^{PF}$ for forward-looking agents.

Focusing first on the marginal minority renters at an interior steady state, one gets:

$$\begin{aligned} 0 &= \sum_{\tau \geq 0} (1-\rho)^\tau (y - \phi_0^{PF} - p_{t+\tau}^{e,PF}) \\ &= \sum_{\tau \geq 0} (1-\rho)^\tau (y - \phi_0^{MY} - p_{t+\tau}^{e,MY}) \end{aligned}$$

For myopic agents it holds that $m_{t+\tau}^{e,MY} = m_t$ and $p_{t+\tau}^{e,MY} = p_t$, whereas forward-looking agents predict the future values. Applying the same technique as in the proof for a forward-looking-only neighborhood, one gets:

$$\begin{aligned} 0 &= y - \phi_0^{PF} - p_{t+\tau}, \quad \forall \tau \geq 0 \\ 0 &= y - \phi_0^{MY} - p_t \end{aligned}$$

The first equation implies that $p_t = p^{SS}$ is constant, and then plugging in $\tau = 0$, it follows that $\phi_0^{PF} = \phi_0^{MY}$. It is straightforward to similarly obtain $\kappa_0^{PF} = \kappa_0^{MY}$ for white renters. Since the marginal myopic renters have the same taste parameters as the marginal forward-looking renters, the rest of the proof is then same as in the case of forward-looking renters only. The proof of the theorem for corner SS with forward-looking renters also readily generalizes to the case where some renters hold myopic expectations, as turnover due to deaths again leads to a convergence of the minority share according to equation (B.5). □

B.2. **Characterization of Interior Steady States.**

Theorem 2. *The model admits two interior steady state minority shares:*

$$m^{SS1} = \frac{1}{2} - \frac{\sqrt{k - 4b(1-b)\Phi}}{2\sqrt{k}}, \quad m^{SS2} = \frac{1}{2} + \frac{\sqrt{k - 4b(1-b)\Phi}}{2\sqrt{k}}$$

At these steady states, the rent is

$$p^{SS} = y - \sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}$$

while the gross house price and net house price are

$$P^{g,SS} = \frac{y - \sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}}{\rho}, \quad P^{n,SS} = \frac{y - 2\sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}}{\rho}$$

with $\rho \equiv 1 - \beta(1-\delta)$.

Proof. The proof proceeds in four steps. First, it calculates the house prices that would prevail if the neighborhood were in SS at a given minority share m_t. Second, it implements a corresponding calculation for rents. Third, it checks whether for the given value of m_t and associated SS prices and rents, the inflow of new residents replacing deceased ones leaves the minority share unchanged, thus satisfying the condition for an SS. Fourth, it establishes parameter restrictions for the existence of interior SS.

B.2.1. *Steady State House Prices.* At an interior SS, the willingness to pay for housing by current and prospective homeowners, as defined in equation (2.2), simplifies to

$$V_{it} = \frac{u_{it}}{\rho} \tag{B.6}$$

where $\rho \equiv 1 - \beta(1-\delta)$. In SS, homeowners expect to remain in the neighborhood for the remainder of their lifetime, as there are no anticipated changes in house prices or neighborhood composition that would induce future relocation. Accordingly, their willingness to pay reflects the present discounted value of a constant stream of per-period residential utility, which is uniformly distributed within each racial group as specified in equation (2.1).

The probability that a realtor successfully draws a prospective resident willing to pay a gross price P_t^g can then be computed from the probabilities of drawing a minority ($w_i = 0$) or white ($w_i = 1$) buyer, along with the conditional probability that an individual from each racial group has a valuation equal to or exceeding the offered price:

$$\begin{aligned} \mathbb{P}_t(V_{it} \geq P_t^g) &= \mathbb{P}(w_i = 0)\mathbb{P}_t(V_{it} \geq P_t^g | w_i = 0) + \mathbb{P}(w_i = 1)\mathbb{P}_t(V_{it} \geq P_t^g | w_i = 1) \\ &= (y - \rho P_t^g)\frac{bkm_t^2 + b^2(1-b)\Phi}{\Phi k m_t^2} \end{aligned} \tag{B.7}$$

Using (B.7), the realtor's optimization problem (2.3) solves to the gross house price

$$P^{g,SS} = \frac{y - \sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}}{\rho} \tag{B.8}$$

and subtracting the expected search cost from the gross price yields the net house price

$$P^{n,SS} = \frac{y - 2\sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}}}{\rho} \tag{B.9}$$

The SS price formulas (B.8) and (B.9) indicate that both gross and net prices decline with the neighborhood minority share m_t, reflecting the reduced residential utility experienced by white residents as m_t increases. Prices also decrease with higher search costs c, as sellers will settle for lower prices when the search for buyers is more costly.

B.2.2. *Steady State Rents.* At an interior SS, prospective and current renters' willingness to pay according to equation (2.4) simplifies to

$$v_{it} = \frac{u_{it}}{\rho} - \frac{(1-\rho)p_{t+1}^e}{\rho} \tag{B.10}$$

where p_{t+1}^e is the rent level that renters expect for all future periods. Equation (B.10) implies that individual i's willingness to pay for rental housing in period t corresponds to the present value of residential utility during a lifetime in the neighborhood, net of expected future rental payments. Since everyone expects the same future rents, individual valuations only differ according to u_{it}, which is uniformly distributed within each racial group according to equation (2.1).

By the definition of an SS, a renter who is willing to pay rent p_t at time t will also stay in the neighborhood during all subsequent periods and thus $\mathbb{P}_t(v_{i,t+1} \geq p_{t+1}^e | v_{it} \geq p_t) = 1$. Applying this to (2.5), landlords' optimization problem simplifies to

$$p_t = \arg\max_p I_t = \arg\max_p \{p - s_t(p)\} \tag{B.11}$$

where $s_t(p) = \frac{c_r}{\mathbb{P}_t(v_{it} \geq p_t)}$. The probability that a randomly drawn prospective renter is willing to pay the rent p_t is

$$\begin{aligned}\mathbb{P}_t(v_{it} \geq p_t) &= \mathbb{P}(w_i = 0)\mathbb{P}_t(v_{it} \geq p_t | w_i = 0) + \mathbb{P}(w_i = 1)\mathbb{P}_t(v_{it} \geq p_t | w_i = 1) \\ &= (y - (1-\rho)p_{t+1}^e - \rho p_t)\frac{bkm_t^2 + b^2(1-b)\Phi}{\Phi k m_t^2}\end{aligned} \tag{B.12}$$

Under the expectation of constant rental prices $p_{t+1}^e = p_t$, the maximization of (B.11) using (B.12) yields

$$p^{SS} = y - \sqrt{c\rho \frac{\Phi k m_t^2}{bkm_t^2 + b^2(1-b)\Phi}} \tag{B.13}$$

which is decreasing in both the minority share m_t and search costs c.

B.2.3. *Steady State Minority Shares.* The law of motion for the neighborhood minority share is

$$m_{t+1} - m_t = v_t(m_t^{IN} - m_t^{OUT}) \tag{B.14}$$

where v_t is the number of vacancies in the neighborhood, m_t^{OUT} is the minority share among residents who exit the neighborhood, and m_t^{IN} is the minority share among new neighborhood entrants. The neighborhood is at an interior SS if, given the current minority share m_t and corresponding SS prices (B.8) and SS rents (B.13), it holds that $m_t^{IN} = m_t^{OUT}$. In SS, residents exit the neighborhood solely due to death. Since the mortality risk δ is uncorrelated with race or ownership status, the minority share among departing (deceased) residents equals the neighborhood's current minority share, $m_t^{OUT} = m_t$. The minority share among incoming residents who are willing to pay the SS house price or rent at an internal SS is

$$m_t^{IN} = \frac{bkm_t^2}{bkm_t^2 + b^2(1-b)\Phi} \equiv g(m_t), \qquad m_t \in [\underline{m}, \overline{m}] \tag{B.15}$$

where this condition holds over the interval $[\underline{m}, \overline{m}]$. This interval denotes the minority shares at which some, but not all prospective white and minority residents want to move into the neighborhood in SS.

Applying the condition $m_t^{IN} = m_t^{OUT} = m_t$, solving for the minority share (assuming $m_t^{SS} > 0$) yields the SS minority shares

$$m^{SS1,2} = \frac{1}{2} \pm \frac{\sqrt{k - 4b(1-b)\Phi}}{2\sqrt{k}} \tag{B.16}$$

B.2.4. *Parameter Restrictions for Interior Steady States.* In order for the model to have two interior steady state minority shares, equation (B.16) requires that $k > 4b(1-b)\Phi$. This implies that

$$b > \frac{1 + \sqrt{1 - k/\Phi}}{2} \textit{ or } b < \frac{1 - \sqrt{1 - k/\Phi}}{2} \tag{B.17}$$

Additionally, the condition that some but not all individuals of each racial group want to move into the neighborhood implies:

$$\begin{aligned} p^{SS} &> y - \frac{k(m^{SS})^2}{b^2} && \text{(whites)} \\ p^{SS} &> y - \Phi && \text{(minorities)} \end{aligned}$$

Simple algebra gives the following equivalent conditions for the interval $[\underline{m}, \overline{m}]$ in which any interior SS must lie:

$$m^{SS} > b\sqrt[3]{\frac{c\rho\Phi}{k^2}} = \underline{m} \qquad \text{(whites)} \tag{B.18}$$

$$m^{SS} < \frac{b\Phi}{c\rho} = \overline{m} \qquad \text{(minorities)} \tag{B.19}$$

This interval is bounded by a low minority share $\underline{m}$ at which all whites want enter in SS, and a high minority share $\overline{m}$ at which all minorities want to move in. □

B.2.5. *Characterization of Corner Steady States.* As shown by theorem 1, on the interval $[\underline{m}, \overline{m}]$ the interior SS are characterized by $m_t^{IN} = m_t$. However, outside of the interval $[\underline{m}, \overline{m}]$, the neighborhood can be at a corner SS where the minority share among those moving in differs from the current neighborhood minority share.

Let us first consider minority shares lower than $\underline{m}$, at which all whites want to enter the neighborhood. Assume that $m_t = \underline{m} - \epsilon$, for $\epsilon > 0$ arbitrarily small. In a neighborhood with minority share m_t, landlords choose rents in order to maximize I_t as shown in (B.11). Additionally, the prospective white renter with largest taste parameter ($\kappa_i = k$) has the valuation of $v_{it} = y - km_t^2/b^2 \equiv \underline{p_t}$, so I_t is not differentiable at $\underline{p_t}$. However, right and left derivatives exist at $\underline{p_t}$, and are of opposite signs (by definition of $\underline{m}$),

$$I'_{t+}(\underline{p_t}) = 1 - \frac{c\mathbb{P}'_+(v_{it} \geq \underline{p_t})}{\mathbb{P}^2(v_{it} \geq \underline{p_t})} = 1 - c\rho \frac{\frac{b}{\Phi} + \frac{b^2(1-b)}{km_t^2}}{(\frac{km_t^2}{b\Phi} + 1 - b)^2} < 0$$

$$I'_{t-}(\underline{p_t}) = 1 - \frac{c\mathbb{P}'_-(v_{it} \geq \underline{p_t})}{\mathbb{P}^2(v_{it} \geq \underline{p_t})} = 1 - c\rho \frac{\frac{b}{\Phi}}{(\frac{km_t^2}{b\Phi} + 1 - b)^2} > 0,$$

so landlords set $p_t = \underline{p_t}$ in order to maximize profits. This means that at a minority share $m_t = \underline{m} - \epsilon$, landlords demand a rent that equals the valuation of the prospective white renter with maximum taste parameter k. One can readily verify that in this case, $m_t^{IN} = g(m_t)$, since the derivation of (B.15) holds whenever the marginal renter of each racial group is indifferent between moving into or staying out of the neighborhood at rent p_t. However, by the definition of $\underline{m}$, $g(m_t) \neq m_t$ for $m_t = \underline{m} - \epsilon$. Thus, the minority share changes in the following period ($m_{t+1} \neq m_t$), and the analysis of landlords' optimization shows that the rent must change in period $t+1$. This means that the marginal minority renters must change, which cannot happen if the neighborhood has reached a SS at period t. Finally, one can conclude that as long as two inequalities from above hold, i.e. as long as the optimal rent is chosen at the point of non-differentiability of landlords' optimization function, the neighborhood has not reached a SS.

It also is clear that $I'_{t-}(\underline{p_t})$ falls as m_t decreases, until eventually $I'_{t-}(\underline{p_t}) = 0$ for $m_t = \underline{\underline{m}}$, where $\underline{\underline{m}} = \sqrt{\frac{b\Phi}{k}\left(\sqrt{\frac{c\rho b}{\Phi}} - (1-b)\right)}$. Here, a parametrization such that $\underline{\underline{m}}^2 > 0$ is assumed.[33] If the minority share is weakly below $\underline{\underline{m}}$ ($m_t \leq \underline{\underline{m}}$), then the optimal rent is chosen at the same level as at $\underline{\underline{m}}$ ($\underline{p_t} = y - (k\underline{\underline{m}}^2)/b^2 \equiv \underline{\underline{p}}$). Note that, by the definition of $\underline{m}$ and since $\underline{\underline{m}} < \underline{m}$, when $m_t = \underline{\underline{m}}$, the minority share of new entrants is lower than that of the neighborhood, i.e. $m_t^{IN} = g(\underline{\underline{m}}) < \underline{\underline{m}}$. Thus the minority share of residents decreases until $m_t = m_t^{IN} = g(\underline{\underline{m}})$. If instead $m_t < g(\underline{\underline{m}})$, then the minority share increases towards the same limiting minority share. Finally, notice that for all periods t with minority share $m_t < \underline{\underline{m}}$, there exists a path of neighborhood characteristics expected by forward-looking agents such that the neighborhood is at SS at t.

Summarizing the discussion above, one can conclude that when $m_t < \underline{m}$ and all agents assume that the neighborhood is in SS, landlords choose the optimal rent according to:

$$p_t = \begin{cases} \underline{\underline{p}} = y - \frac{k\underline{\underline{m}}^2}{b^2}, & \text{if } m_t < \underline{\underline{m}} \\ \underline{p_t} = y - \frac{km_t^2}{b^2}, & \text{if } \underline{\underline{m}} \leq m_t < \underline{m} \end{cases} \tag{B.20}$$

Intuitively, landlords set the rent equal to the valuation of the prospective white resident with lowest valuation only as long as $\underline{\underline{m}} \leq m_t < \underline{m}$. When m_t declines within this range,

[33] In the alternative case where $\underline{\underline{m}}^2 \leq 0$, one can plug in the value of $\underline{\underline{m}} = 0$ wherever $\underline{\underline{m}}$ is used.

then landlords ask higher rents p_t since the valuation of the marginal white resident grows as m_t falls. However, a higher rent p_t increases landlords' search costs to find a suitable renter, since in addition to all whites, a falling fraction of minorities is willing to enter the neighborhood when p_t increases. Once the minority share falls below $m_t = \underline{\underline{m}}$, then it is no longer worthwhile for landlords to increase the rent further since the marginal revenue conditional on finding a renter becomes smaller than the marginal additional search cost. Landlords thus set a constant rent $\underline{\underline{p}}$ in this case.

Correspondingly, the minority share among individuals who move into a neighborhood with $m_t < \underline{m}$ under steady state expectations is:

$$m_t^{IN} = \begin{cases} \frac{\frac{k\underline{\underline{m}}^2}{b\Phi}}{\frac{k\underline{\underline{m}}^2}{b\Phi}+1-b} = g(\underline{\underline{m}}), & \text{if } m_t < \underline{\underline{m}} \\ \frac{\frac{km_t^2}{b\Phi}}{\frac{km_t^2}{b\Phi}+1-b} = g(m_t), & \text{if } \underline{\underline{m}} \leq m_t < \underline{m} \end{cases} = g(max\{m_t, \underline{\underline{m}}\}) \tag{B.21}$$

Let us next consider minority shares higher than $\overline{m}$, at which all prospective minority residents want to enter the neighborhood. Assume that the neighborhood minority share is $m_t = \overline{m} + \epsilon$, for $\epsilon > 0$ arbitrarily small.[34] Similar to the previous case, landlords' profits I_t are not differentiable at $p_t = y - \Phi \equiv \overline{p}$, but the right derivative is:

$$I'_{t+}(\overline{p}) = 1 - \frac{c\mathbb{P}'_+(v_{it} \geq \overline{p})}{\mathbb{P}^2(v_{it} \geq \overline{p})} = 1 - \frac{c\rho}{\Phi^2(\frac{b}{\Phi} + \frac{b^2(1-b)}{km_t^2})} < 0$$

whenever $m_t > \overline{m}$. It follows that $p_t \leq \overline{p}$ when $m_t > \overline{m}$, so the share of incoming minority residents $m_t^{IN}(m_t) \equiv f(m_t)$ is weakly smaller that it would be if $\overline{p}$ were charged:

$$m_t^{IN}(m_t) = f(m_t) \leq \frac{1}{1 + b(1-b)\frac{\Phi}{km_t^2}} = \frac{km_t^2}{km_t^2 + b(1-b)\Phi} = g(m_t)$$

Now, since $m_t > \overline{m}$, by the definition of $\overline{m}$ it holds that $m_t^{IN}(\overline{m}) < m_t$. Thus, no periods t in which $m_t > \overline{m}$ can constitute an SS.

B.2.6. *Summary.* In summary, studying the relationship of the minority share among incoming renters (m_t^{IN}) and the current minority share of the neighborhood (m_t) under the assumption that all agents believe that a SS has been reached at t, leads to the following result:

$$m_t^{IN}(m_t) = \begin{cases} g(\underline{\underline{m}}), & \text{if } m_t < \underline{\underline{m}} \\ g(m_t), & \text{if } m_t \in [\underline{\underline{m}}, \overline{m}] \\ f(m_t) < g(m_t), & \text{if } m_t > \overline{m} \end{cases} \tag{B.22}$$

[34] If $\overline{m} \geq 1$, this condition is, obviously, meaningless. However, as is proven below, there is no SS for $m_t \geq \overline{m}$, so the number of SSs does not depend on whether or not $\overline{m} \geq 1$.

The analysis above allows us to pin down the set of all SS. Under appropriate calibration, there are two interior steady states m^{SS1} and m^{SS2}, as well as a continuum of steady states $\left[0, \underline{\underline{m}}\right]$ from which the minority share converges to a fixed value $m_t \to g(\underline{\underline{m}}) = \frac{k\underline{\underline{m}}^2}{k\underline{\underline{m}}^2 + b(1-b)\Phi} = m^{SS0}$.

B.3. **Neighborhood Transition Dynamics.** When the neighborhood is not at a steady state minority share, the choice to exit or enter the neighborhood can differ for individuals with the same race, taste and tenure status depending on their individual expectation technology.

Theorem 3. *In a tipped neighborhood with minority share m_t where $m^{SS1} < m_t < m^{SS2}$, forward-looking white homeowners are weakly more likely to leave and less likely to enter in period t compared to myopic white homeowners with the same taste parameter. Conversely, forward-looking white renters are weakly less likely to leave and more likely to enter in period t compared to their myopic peers. The location decisions of minority residents do not differ between forward-looking and myopic individuals except for a higher likelihood of entry among forward-looking minority renters.*

Proof. The proof for this theorem proceeds in three steps. It first establishes that forward-looking agents expect a rising minority share and falling house prices and rents. It then characterizes the impact of these expectations on owners' decisions to exit or enter the neighborhood, and concludes by characterizing renters' moving decisions.

B.3.1. *Forward-looking Expectations.* Forward-looking expectations according to definition 2.1 require a correct prediction of future neighborhood minority shares, $m^e_{t+\tau} = m_{t+\tau}, \forall\tau \geq 0$. I assume that forward-looking agents arrive at this prediction through an iterative process. They first consider whether the minority share would remain constant if all forward-looking agents expected a constant minority share. If conditional on this expectation, the resulting housing market transactions yield a rising (or falling) neighborhood minority share, then forward-looking agents correct their expectations to anticipate a corresponding rise (or fall) of the minority share. This process continues until conditional on an expected evolution of the minority share, the housing market yields a path of the minority share that matches the expectations, so that the definition 2.1 for forward-looking expectations is satisfied.

For a neighborhood with current minority share m_t where $m^{SS1} < m_t < m^{SS2}$, the expectation $m^e_{t+\tau} = m_t$, $\forall\tau \geq 0$ (constant minority share m_t) would generate $m^{IN}_t > m^{OUT}_t$ as shown in Figure 1. Forward-looking agents thus expect $m_{t+1} > m_t$, and as long as m_{t+1} is not a steady state minority share, they expect subsequent increases of the minority share until it converges to m^{SS2}. Numerical simulations in section 3 indicate that this process of determining expectations yields a unique solution for the expected minority share path that is consistent with the forward-looking expectation technology.

Since residential utility is weakly decreasing in the minority share for all residents according to equation 2.1, a rising minority share implies that aggregate willingness to pay for housing will be weakly declining over time as the minority share grows. The optimization problems for real estate agents and landlords in equations 2.3 and 2.5 imply that it is optimal to ask for lower house prices and rents when willingness to pay for housing is lower. As the neighborhood converges towards the high-minority steady state m^{SS2}, house prices and rents fall towards new steady state values $P^{g,SS}(m^{SS2})$ and $p^{SS}(m^{SS2})$ as determined by equations B.8 and B.13. Consistent with their expectation of a rising minority share, forward-looking agents thus also expect weakly falling house prices and rents.

B.3.2. *Moving Decisions of Homeowners.* Consider first a myopic and a forward-looking incumbent white owner who have the same taste parameter $\kappa_i > 0$ that satisfies $\frac{u_{it}}{\rho} = P_t^n$. The myopic owner does not expect any future changes in minority share or house prices that could prompt a future departure from the neighborhood. Her willingness to pay for housing in period t is thus $u_{it} + (1-\rho)\frac{u_{it}}{\rho}$ where u_{it} is residential utility for the current period and $(1-\rho)\frac{u_{it}}{\rho}$ is the continuation value of entering period $t+1$ as an incumbent owner. Since $u_{it} + (1-\rho)\frac{u_{it}}{\rho} = P_t^n$, equation (2.6b) implies that the myopic owner will marginally decide to stay in period t. Conversely, the forward-looking owner expects that residential utility will decline over time, and thus anticipates a lower continuation value. Her willingness to pay for housing in period t is $u_{it} + (1-\rho)\max\{V_{i(t+1)}, P_{t+1}^n\} < u_{it} + (1-\rho)\frac{u_{it}}{\rho} = P_t^n$, which prompts her to leave in period t according to equation (2.6a) . One can readily show that for incumbent white owners with other values of the taste parameter, willingness to pay for housing in period t is always weakly lower for an individual with forward-looking expectations compared to a myopic peer with same tastes, and forward-looking white owners are thus weakly more likely to exit the neighborhood. By an analogous set of arguments, equations (2.6c) and (2.6d) imply that forward-looking whites are also weakly less likely to enter the neighborhood as owners than myopic whites with the same taste parameter.

For minority homeowners, the expectation technology affects only expected future house price changes but not expected future residential utility. Consider a myopic and a forward-looking incumbent minority homeowner who have the same taste parameter $\phi_i > 0$ that satisfies $\frac{u_{it}}{\rho} = P_t^n$. The myopic owner will stay in the neighborhood in period t according to equation (2.6b) because the net sales price for the house matches but does not exceed her willingness to pay for housing, $V_{i(t)} = u_{it} + (1-\rho)\frac{u_{it}}{\rho}$. The forward-looking owner expects constant future residential utility combined with falling house prices, which implies $\frac{u_{it+\tau}}{\rho} > P_{t+\tau}^n, \forall \tau > 0$. The willingness to pay for housing is thus $V_{i(t)} = u_{it} + (1-\rho)\max\{V_{i(t+1)}, P_{t+1}^n\} = u_{it} + (1-\rho)\frac{u_{it}}{\rho}$, so that the forward-looking minority owners' decision problem according to equation (2.6a) becomes equivalent to myopic minority owners' decision problem according to equation (2.6b). By an analogous set of arguments, this equivalence in moving behaviors for forward-looking and myopic individuals also holds for incumbent minority owners with different taste parameters, and for prospective minority owners based on equations (2.6c) and (2.6d).

B.3.3. *Moving Decisions of Renters.* Consider first a white renter who is myopic. Equation (2.6f) implies that the renter will enter the neighborhood or will remain in the neighborhood in period t if and only if her taste parameter implies a current period utility of $u_{it} \geq p_t$. Consider next a white renter with the same taste parameter who is forward-looking. A current period utility of $u_{it} \geq p_t$ is a sufficient but not a necessary condition for residing in the neighborhood in period t according to equation (2.6e). For some forward-looking renters, it can be optimal to stay in the neighborhood in period t despite $u_{it} < p_t$. This is the case when they anticipate that the rent falls more rapidly than residential utility during at least some future periods, and the net utility gain in future periods outweighs the net utility loss in the current period (e.g., if $u_{it+1} > p_{t+1}$ implies $u_{it} + (1-\rho)u_{it+1} > p_{it} + (1-\rho)p_{t+1}$, then it is optimal for the renter to reside in the neighborhood in period t despite $u_{it} < p_t$). As a consequence, forward-looking white renters are weakly less likely to leave the neighborhood and weakly more likely to enter compared to myopic renters with the same taste parameter.

Minority renters expect that their residential utility in the neighborhood will be constant over time, and that rents are either constant (with myopic expectations) or falling (with forward-looking expectations). Therefore, all minority renters who enter the neighborhood expect to remain permanently, and they indeed do remain permanently given constant utility and falling rents. For any two incumbent minority residents with the same taste parameter, the decision on whether to stay in the neighborhood does hence not vary with the expectation technology. Conversely, whereas myopic prospective minority renters will enter the neighborhood only if $u_{it} \geq p_t$, some forward-looking prospective minority renters will enter even if $u_{it} < p_t$ because they expect falling rents and positive residential utilities net of rent in future period. The lone impact of the different expectation technologies on the moving behavior of minorities is thus that forward-looking prospective minority renters are weakly more likely to enter the neighborhood than myopic prospective minority renters with the same taste parameter. □

B.4. **Endogenous Housing Supply.** When the neighborhood housing stock is not fixed but instead is growing according to $h_{t+1} = h_t + g(P_t^g, h_t)$, then neighborhood tipping can affect overall housing supply.

Theorem 4. *Relative to a neighborhood at the steady state with minority share m^{SS1} and housing growth $g_t^{SS1} > 0$, a tipped neighborhood with minority share $\tilde{m}_t \equiv m^{SS1} + \epsilon$ differs along two dimensions. First, tipping reduces housing growth (a scale effect). Second, the minority share among entering residents exceeds that among exiting residents (a composition* *effect). As a result, tipping strictly lowers the growth rate of the white population, whereas its effect on the growth rate of the minority population is ambiguous.*

Proof. The difference in the growth of white population between the tipped neighborhood and the steady state neighborhood is given by

$$\begin{aligned}\frac{\tilde{W}_{t+1}-\tilde{W}_t}{h_t}-\frac{W^{SS1}_{t+1}-W^{SS1}_t}{h_t}=&-\delta[(1-r)(\tilde{m}^{IN,o}_t-\tilde{m}_t)+r(\tilde{m}^{IN,r}_t-\tilde{m}_t)]\\&-(1-\delta)(1-\tilde{m}_t)[(1-r)\tilde{\gamma}^o_t\tilde{m}^{IN,o}_t+r\tilde{\gamma}^r_t\tilde{m}^{IN,r}_t]\\&-(g^{SS1}_t-\tilde{g}_t)(1-m^{SS1}_t)\\&-\tilde{g}_t[(1-r)(\tilde{m}^{IN,o}_t-m^{SS1}_t)+r(\tilde{m}^{IN,r}_t-m^{SS1}_t)]\quad<0.\end{aligned}\tag{B.23}$$

The first two arguments on the right-hand side of equation (B.23) indicate components of the tipping effect in white population growth that are also present in the baseline model with fixed housing supply. First, the fraction δ of incumbent residents who died is replaced with new residents among whom the minority share is larger than among the deceased residents, thus reducing white population. Second, a fraction $\tilde{\gamma}^o_t$ of the surviving white owners and a fraction $\tilde{\gamma}^r_t$ of the surviving white renters decide to leave the tipped neighborhood. Since some of the homes they vacate are newly occupied by incoming minority residents, white population declines further. With endogenous housing supply, there are two additional factors that depress white population growth in the tipped versus the steady state neighborhood: The third term on the right hand side of equation (B.23) indicates a scale effect where a reduced supply of new housing in the tipped neighborhood reduces white population growth relative to steady state for a given racial composition of new residents, while the fourth term captures that a lower fraction of new houses will be occupied by whites for a given level of housing growth.

It can be readily shown that the corresponding expression for the relative growth in minority population in the tipped versus steady state neighborhood can be written as

$$\frac{\tilde{M}_{t+1}-\tilde{M}_t}{h_t}-\frac{M^{SS1}_{t+1}-M^{SS1}_t}{h_t}=\underbrace{-\left(\frac{\tilde{W}_{t+1}-\tilde{W}_t}{h_t}-\frac{W^{SS1}_{t+1}-W^{SS1}_t}{h_t}\right)}_{>0}\underbrace{-(g^{SS1}_t-\tilde{g}_t)}_{\leq 0}\gtreqless 0\tag{B.24}$$

The two parentheses on the right hand side of (B.24) indicate a composition effect and a scale effect. If housing supply is fixed ($g_t=\tilde{g}_t=0$), only the composition effect is present, and the differentially larger growth of minority population in the tipped versus the steady state neighborhood exactly offsets a differentially larger decline of the white population. If instead housing supply is growing in steady state ($g_t>0$), then the reduced housing growth in the tipped neighborhood dampens the growth in minority population relative to the steady state neighborhood. Depending on the relative magnitude of the composition and scale effects on the right-hand side of equation (B.24), it is possible that the tipped neighborhood experiences no differential growth or even a differential decline in the growth of minority population compared to the steady state neighborhood. □

Appendix C. Model Simulation

C.1. **Simulation Structure.** The model simulation generates numerical transition dynamics for a neighborhood whose minority share rises from $m_1 = m^{SS1} + \epsilon$ to $m_T = m^{SS2}$. It approximates the continua of current and prospective neighborhood residents with large discrete numbers (10,000 for current and 250,000 for prospective residents) and computes changes in neighborhood composition during a neighborhood transition where some of the current residents leave the neighborhood and some of the prospective residents move in to replace them. The distribution of taste parameters among the neighborhood's initial residents is uniform within each racial group, and the fraction of initial forward-looking residents is proportional to the corresponding share among prospective residents.[35]

The simulation nests two iterative loops. Each iteration of the outer loop computes a complete transition path for the neighborhood from $m_1 = m^{SS1} + \epsilon$ to $m_T = m^{SS2}$. In the first of these iterations, the expectations of forward-looking agents in terms of minority shares, house prices and rents are exogenously imposed by the researcher. In subsequent iterations, these expectations are updated using the simulated transition paths of previous iterations. The simulation continues until the simulated transition paths coincide with the paths that were expected by forward-looking agents. Each iteration of the outer loop nests many iterations of the inner loop, which compute prices and changes in neighborhood composition for one single time period within a transition path.

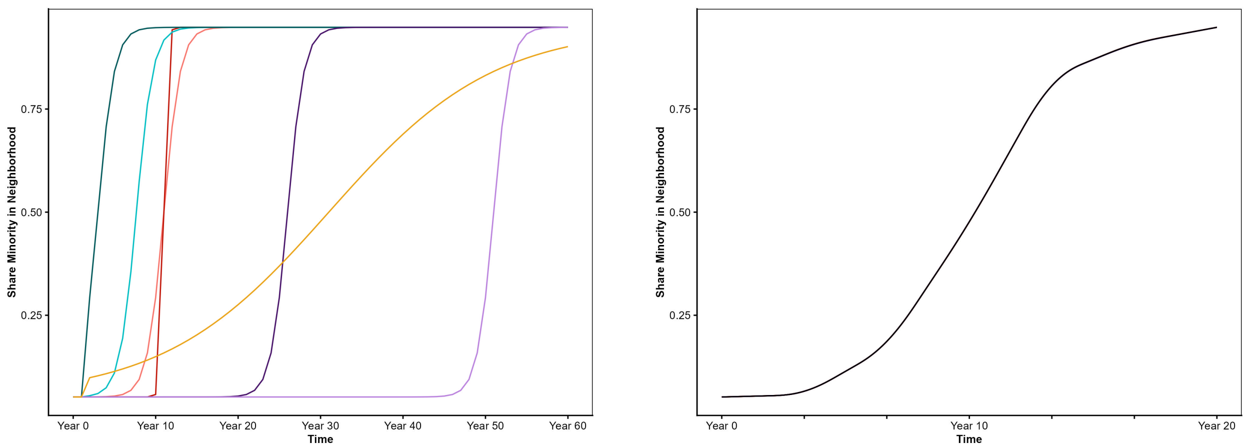
C.2. **Simulation Sequence.**

C.2.1. *Initial Expectations.* The simulation makes an initial assumption on the number of periods $T - 1$ that are required for the transition to a new steady state with minority share m^{SS2}, net house price $P^{n,SS2}$ and rent p^{SS2}. It also makes an exogenous assumption on the functional form of the period-by-period changes of the minority share from $m_1 = m^{SS1} + \epsilon$ to $m_T = m^{SS2}$, net house price from $P^{n,SS1}$ to $P^{n,SS2}$, and rent from p^{SS1} to p^{SS2}. The baseline simulation initializes expectations about future minority shares (and similarly, expectations

[35] These distributions result endogenously in a steady state neighborhood as the ongoing replacement of deceased residents with new residents produces a convergence of residents' taste and expectation distributions to the corresponding distributions among the prospective residents who are willing to buy or rent in the neighborhood under steady state conditions.

about prices and rents) with the sigmoid function $m^e_{1+\tau} = m_1 + \frac{m_T - m_1}{1+e^{-s(\tau-d)}}$ with path length $T = 20$ and shape parameters $s = 5$ and $d = T/2$. Panel A of Figure C1 visualizes this as well as alternative initializations of the minority share transition paths that vary path lengths ($T = 4$, $T = 20$ or $T = 100$) and the parameter determining the slope of the sigmoid function at time $T/2$ ($s = 2$, $s = 5$ or $s = 6$). Panel B of the Figure indicates that the simulation converges to the same final transition path with each of these very different initializations, which suggests that the simulation results are not sensitive to arbitrary initial assumptions on expected transition paths.

Figure C1. Insensitivity of Simulation Outcome to Initial Conditions



(A) Initial paths

(B) Converged paths

Notes: Panel A indicates different time paths for the increase in neighborhood minority share as expected by forward-looking agents that were alternatively used to initialize the simulation. Panel B shows that for each of the different initial paths, the simulation always converged to the same final path which is consistent with forward-looking expectations. All simulations are based on the calibration values indicated in Appendix Table C1.

C.2.2. *Simulating a Transition Path.* The sequence of neighborhood change in Section 2.2 posits that upon observing $m_1 = m^{SS1} + \epsilon$, current and prospective residents determine their valuations for living in the neighborhood as an owner or as a renter. The valuations of forward-looking agents are determined recursively based on their expectations regarding future minority shares, house prices and rents. Specifically, these agents expect the neighborhood to be at the new state in period T, at which point current and potential residents' willingness to pay for owner-occupied and rental housing is given by the steady state valuations (B.6) and (B.10). In the preceding period $T - 1$, the valuations for owning and for renting are given by the Bellman equations (2.2) and (2.4), and further iterative backward induction yields valuations for the current period $t = 1$. The willingness to pay for housing among myopic individuals results from a straightforward calculation based on their expectation of no changes to neighborhood composition and housing costs in future periods.

The simulation then solves realtors' optimization problem (2.3) and landlords' optimization problem (2.5) which determine the optimal house price P_1^g and rent p_1 for period $t = 1$ based on search costs in the housing market and the distribution of willingness to pay among prospective owners or potential renters.

The simulation then ranks all current residents by their willingness to pay, and selects an evenly spaced fraction δ of these individuals as deaths for period $t = 1$, such that death shocks are not systematically correlated with resident characteristics per the model's assumption. In addition, it determines all current residents who choose to leave the neighborhood (homeowners with valuations $V_{i1} < P_1^n$ and renters with with valuations $v_{i1} < p_1$). Next, all prospective homeowners who would be willing to move into the neighborhood (for whom $V_{i1} \geq P_1^g$) are sorted according to their valuations, and an evenly spaced fraction of these individuals is chosen to replace deceased and departed homeowners, thus approximating the expected distribution of characteristics among new homeowners that would result from sampling from a continuum of prospective residents. Vacant rental units are filled accordingly with prospective renters who are willing to pay the current rent p_1. The result of this exit from and entry into the neighborhood is a new minority share m_2.

The simulation then computes willingness to pay, house prices and rents in period $t = 2$, determines resident turnover during that period, and obtains the next minority share m_3. That sequence is repeated until the minority share converges towards m^{SS2}.[36]

C.2.3. *Updating Expectations and Checking for Convergence.* After the simulation of a first minority share transition path from $m_1 = m^{SS1} + \epsilon$ to $m_T = m^{SS2}$, the initially exogenously imposed expectations of forward-looking agents are replaced with this simulated path. From the third iteration onward, the expectation for the minority share path is the average of the last two simulated paths. The expected paths for house prices and rents are updated accordingly.

After the simulation has computed three neighborhood transitions, it checks whether the simulated paths for minority shares, house prices and rents match the paths that forward-looking agents expected as input to the last simulated transition. The minority share path is considered to have converged if in an average time period, expected and realized minority shares differ by no more than a sixth of a percentage point. The simulation similarly checks for convergence between expectations and realized outcomes for the paths of house prices and rents. If at least one of the three paths for minority share, house prices and rents

[36]The minority share tends to asymptote towards m^{SS2}, which can lead to transition paths with a very large number of periods in which neighborhood composition and prices barely change. A larger number of periods required for the neighborhood transition nonlinearly increases the computational burden of the simulation. Therefore, the simulation determines the transition of the minority share only until it closely approximates m^{SS2}. Once the minority share exceeds $m^{SS2} - 0.015$ in some period t, then the simulation linearly extrapolates the growth of the minority share $m_t - m_{t-1}$ up to m^{SS2}.

fails the convergence condition, then the simulation continues and computes a subsequent neighborhood transition, after which it again checks for convergence.[37]

C.3. **Calibration.** The baseline model with fixed housing supply is calibrated to broadly match values for the city of Chicago in 1970, for whose neighborhoods Card et al. (2008a) observe a particularly large tipping effect. Table C1 indicates parameter values and, if applicable, their empirical benchmarks. The city-wide minority share $b = 0.159$ is set to the corresponding value for Chicago in 1970, while the renter share $r = 0.400$ for the baseline simulation approximates the city-wide average value for Chicago in the same year.

TABLE C1. Calibration of Simulation

Parameter	Value	Benchmark	Concept
Calibrated Parameters			
b	0.159	0.159	Minority share in MSA Chicago 1970
r	0.400	0.374	Renter share in MSA Chicago 1970
δ	0.065	0.064	Death rate age 30+ in Cook County 1970, adj. for period length
β	0.900	0.915	Discount factor based on real mortgage rate in US 1970, adjusted for period length
Other Parameters			
t	3.333	-	Period length in years
y	3.500	-	Maximum per-period utility
k	2.714	-	Dispersion of taste parameters among whites
Φ	1.000	-	Dispersion of taste parameters among minorities
c	0.500	-	Cost of drawing a prospective resident
Calibrated Functions of Parameters			
m^{SS1}	0.052	0.052	Minority share tipping point, Chicago 1970
S_0/P_0^n	0.051	0.065	Cost of real estate broker in % of house value, US 1970s

Sources for benchmark values. The average minority share and renter share in Chicago in 1970 are based on NCDB tract data (see Section 4.1). The median age of home buyers in the US in 1970 was 31 years (Zillow, 2015), and the death rate is calibrated to a benchmark for individuals age 30+, which is obtained as the average of the one-year death rates for individuals older than 25 (1.7%) and older than 35 (2.2%) in Cook County IL (Centers for Disease Control and Prevention, 2025), scaled to a period length of $t = 3.333$ years. The real mortgage interest rate in the US in 1970 was 2.7% based on a nominal mortgage interest rate of 8.5% (The New York Times, 1981) and consumer price inflation of 5.8% (Federal Reserve Bank of Minneapolis, 2025), and the benchmark discount factor adjusted for period length is constructed as $(1/1.027)^{3.333}$. The minority share tipping point in Chicago is obtained using the fixed-point method described in Section 4.2. A report by the United States Department of Justice (2007) states that costs for real estate brokers amounted to 6 to 7 percent of house values for a majority of house sales in the US during the 1970s.

[37]Convergence criteria are slightly relaxed for later iterations of the simulation. From the 15th simulated neighborhood transition onward, the minority share path is considered to have converged if expected and realized values are within half a percentage point in the average time period.

The model simulates periods with a length of $t = 3.333$ years, which generates a speed of neighborhood transition in the baseline simulation that corresponds to observed patterns of population change in Chicago during the 1970s. The simulation might alternatively achieve a similar transition speed by combining a shorter period length with the additional assumption that only a fraction of all incumbent residents get the opportunity to move in each period, as in Frankel and Pauzner (2002). However, the chosen setup without moving frictions for incumbents but longer period length is both simpler conceptually and computationally advantageous. Neighborhood transitions with fewer periods are faster to compute, and the longer period length implies a larger per-period death rate and thus a larger minimum turnover of neighborhood residents in every period, which improves precision when the model's continua of exiting and entering residents are approximated with discrete numbers in the simulation. The calibrated 3.3-year death rate of $\delta = 0.065$ is based on mortality statistics for adults age 30 and older in Chicago's Cook County in 1970.

The parameter values for the utility distributions of whites ($k = 2.714$) and minorities ($\Phi = 1$) are chosen such that equation (B.16) generates a steady state value for the minority share of $m^{SS1} = 0.052$, which matches the tipping point value for Chicago in 1970 obtained with the fixed-point method as discussed in Section 4.2.

House prices and rents in the neighborhood depend on two additional calibrated parameters. The discount factor $\beta = 0.900$ is based on a nominal annual mortgage interest rate of 8.5% in the US in 1970 (The New York Times, 1981) adjusted for an inflation of 5.8% (Federal Reserve Bank of Minneapolis, 2025) and scaled to period length. The cost parameter $c = 0.500$ is calibrated such that the cost of a house sale as a fraction of the house price is $\frac{S_0}{P_0^n} = 0.051$, which is modestly smaller than the house sale cost of $6 - 7\%$ that a report by the United States Department of Justice (2007) reported for most sales of the 1970s in the US, or the value of 6.0% used in a model calibration by Bayer et al. (2016).

C.4. **Additional Simulation Results.** Figure 2 in Section 3.2 presents the main simulation results. This appendix section further examines how residents' opportunity costs evolve during neighborhood transition and how outcomes depend on the share x of residents with forward-looking expectations.

Figure C2 reports these additional results. Each row shows a separate simulation based on the calibration in Table C1, varying only the value of x. Column 1 shows the decline in the white share among owners and renters, while column 2 reports the corresponding declines in house prices and rents. Columns 3 and 4 show the opportunity costs for marginal white residents with myopic expectations (column 3) and forward-looking expectations (column 4). As shown in equations (2.6a) to (2.6f), these opportunity costs differ across incumbent homeowners, prospective homeowners, and renters within each expectation group. They are derived for marginal individuals who are indifferent between living inside or outside the neighborhood in period t, and assume that marginal forward-looking individuals will consider to stay during at most the current period t once the neighborhood tipped.[38] They therefore indicate how high residential utility in period t must be for a marginal incumbent to stay or for a marginal prospective resident to enter. All opportunity costs are expressed as a fraction of the steady-state rent p^{SS1}, which serves as the benchmark cost of residing in the low-minority steady state.

Consider first Panels F1–F5, which correspond to the baseline calibration with a forward-looking share of $x = 0.8$. Panels F1 and F2 repeat Panels A and D of Figure 2, showing a faster decline in the white owner share than in the white renter share, alongside a sharper fall in house prices than in rents. Panel F3 shows that among myopic residents, prospective homeowners and renters face very similar opportunity costs, both of which decline as prices and rents fall. By contrast, incumbent homeowners face consistently lower opportunity costs because selling yields only the lower net house price rather than the gross purchase price. As a result, white exit is faster among myopic renters than among myopic owners.

A strikingly different pattern emerges for forward-looking residents in Panel F4. As house prices decline, opportunity costs for incumbent owners rise sharply above those of renters—temporarily exceeding 1.6 times the steady-state rent—as owners anticipate future capital losses. Even white owners with weak racial preferences may therefore choose to sell early to avoid further depreciation. Opportunity costs rise even more for prospective forward-looking owners, since temporary entry is unattractive when buying requires paying the gross price while resale yields only the lower net price after realtor costs, in addition to expected house price declines. This sharp rise in owners' opportunity costs generates faster white exit and lower white entry among forward-looking owners than renters. Since forward-looking residents dominate in the baseline calibration, racial transition is therefore faster among owners overall, as shown in Panel F1.

Panels A–E and G–H of Figure C2 examine alternative values of x, ranging from 0 in Panel A to 1 in Panel H. Column 1 shows that the white homeowner population declines faster than the renter population when a majority of residents are forward-looking ($x \geq 0.6$), whereas renters exit faster when most residents are myopic ($x \leq 0.4$). This reflects the fact that opportunity costs are generally higher for owners among forward-looking residents, but lower for owners among myopic residents. A higher value of x also accelerates overall convergence of neighborhood composition and housing prices to their new steady state.

his relationship is not fully monotonic, however. At very high values of x, anticipated price declines become front-loaded: prices fall sharply immediately after tipping and quickly

[38]Under these assumptions, the opportunity costs in equations (2.6a) to (2.6f) simplify to $\rho P_t^n + (1-\rho)(P_t^n - P_{t+1}^n)$ for forward-looking incumbent owners, $\rho P_t^g + (1-\rho)(P_t^g - P_{t+1}^n)$ for forward-looking prospective owners, ρP_t^n for myopic incumbent owners, ρP_t^g for myopic prospective owners, and p_t for all renters in the tipped neighborhood.

approach their high-minority steady state. As a result, forward-looking owners expect only small additional declines, which limits their incentive to exit. In the corner case of $x = 1$, opportunity costs for incumbent owners remain below those of renters (Panel H4), and owner departures are slower than in simulations with some myopic agents. Nevertheless, forward-looking expectations still affect entry behavior, since temporary entry remains substantially less attractive for owners than for renters (Panel H4). Consequently, fewer white owners than white renters enter the neighborhood, and the decline in the white population remains slightly faster among owners even in the case of $x = 1$.

How large must an expected house price decline be for forward-looking homeowners to exit faster than renters? Using equation (2.6a), the calibrated parameters, and assuming that the price-to-rent ratio remains at its initial steady-state level, an expected house price decline of just 1 percent is sufficient to raise owners' opportunity costs above those of renters.[39] Thus, even small anticipated house price declines can cause forward-looking white homeowners to leave a tipping neighborhood faster than renters.

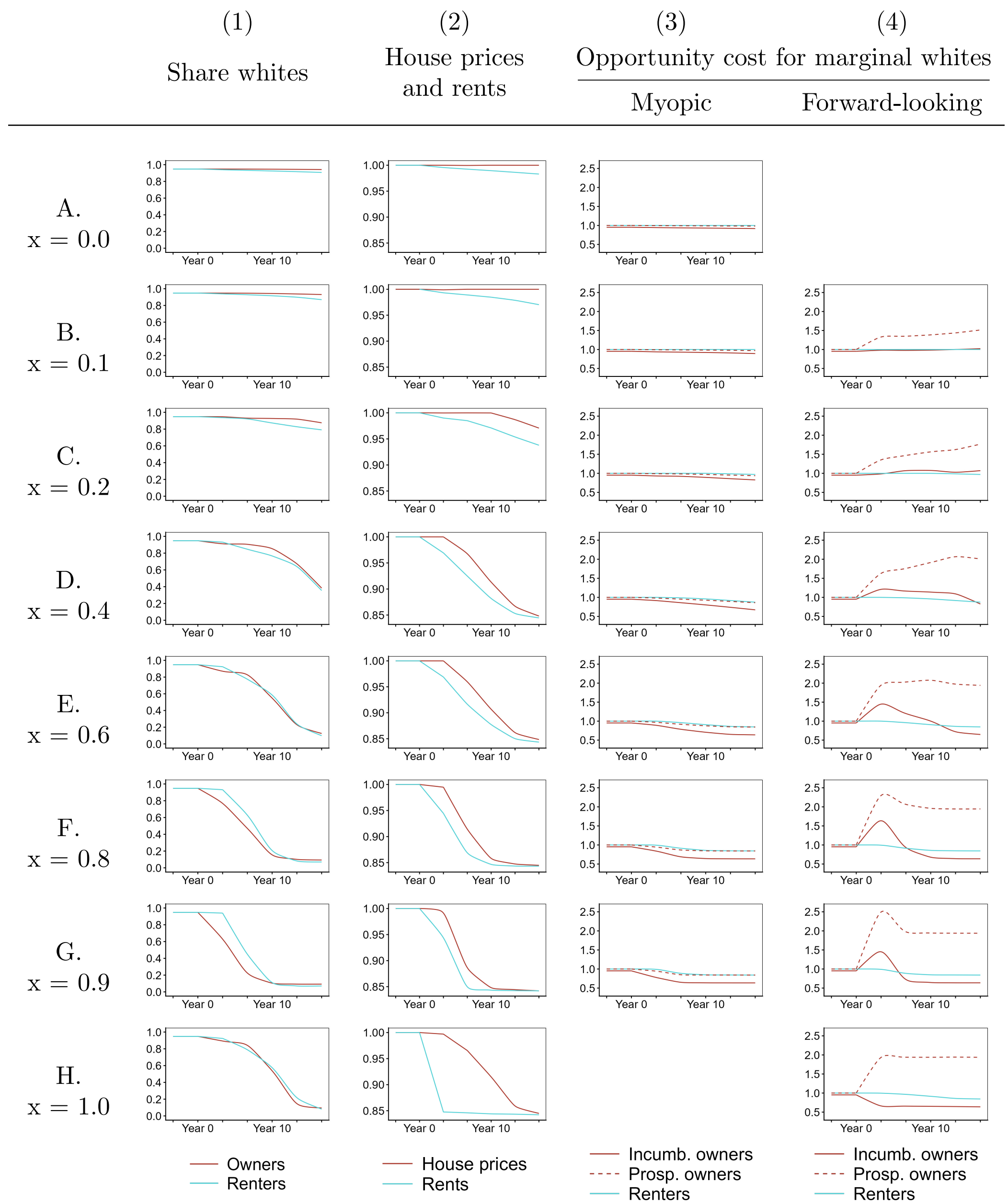
Appendix D. Neighborhood Data

The empirical analysis draws on data from the Neighborhood Change Database (NCDB) which maps data from the 1970, 1980, 1990, 2000 and 2010 U.S. Population Censuses to time-consistent tract boundaries based on the 2010 classification of tracts. Following the sampling criteria of Card et al. (2008a), tracts were excluded from the analysis if no population for the tract is reported at the start or end of a decade, if initial tract population was below 200, or if the decadal growth rate in white population exceeded 500 percent. For each decade, the final sample retains the data of all Metropolitan Statistical Areas (MSAs) that comprise at least 100 tracts that satisfy the criteria above, and for which a tipping point location could be determined with the fixed-point method of Card et al. (2008a).

Throughout the analysis, the term 'white population' refers to white non-Hispanics, while 'minority population' comprises all blacks, Hispanics, native Americans, Asians, Pacific Islanders, and members of other nonwhite races. The NCDB reports neighborhood population counts separately for non-Hispanic whites and for minorities from 1980 onward. In 1970, population is indicated by race or by Hispanic and non-Hispanic ethnicity but not for the intersection of whites and non-Hispanics. Following Card et al. (2008a), I estimate a regression of the white non-Hispanic population share in a tract on the white, black, and Hispanic shares in the 1980 data, and then use the coefficient estimates from this regression to predict the white non-Hispanic share of tract populations in 1970.

[39]Equating opportunity costs for forward-looking whites choosing between exiting in period t or $t+1$ yields $(P^n_{t+1} - P^n_t)/P^n_t = -\frac{p_t}{P^n_t}/(1-\rho)$. This equals approximately -0.0095 when $\frac{p_t}{P^n_t}$ is at its steady-state level.

Figure C2. Simulated Neighborhood Transitions Using Alternative Shares of Forward-Looking Residents



Notes: Simulation results report outcomes for a neighborhood whose minority share increases from m^{SS1} to $\tilde{m} = m^{SS1} + \epsilon$ in year 0. The gross house prices and rents in column 2 are indexed to 1 in the initial steady state. Opportunity costs are derived for marginal individuals for whom equations (2.6a) to (2.6f) hold with equality, and assume that marginal forward-looking individuals consider residing in the neighborhood for at most one additional period. All figures indicate smoothed polynomials (R command geom_xspline) fitted through the outcome values generated by the discrete time simulation.

The NCDB data indicates for each tract the number of owner-occupied and the number of renter-occupied housing units. The renter share is defined as the share of renter-occupied housing units among all occupied housing units. The counts of owner- and renter-occupied units are also provided separately for non-Hispanic whites and for other population groups from 1990 onward. The corresponding values for earlier years are imputed with the gradient boosting decision tree model of Ke et al. (2017).[40] The model is trained to predict the share of owner-occupied homes that are occupied by whites, and the share of renter-occupied homes occupied by whites using the following contemporaneous tract-level variables: number of occupied housing units, share of renter-occupied housing units, number of white residents, number of minority residents, average log family income, unemployment rate, share single-family homes, share vacant homes, and share commuters using public transport. The estimates from this model are used to impute the outcomes for 1970 and 1980.

[40]The tree model uses the HistGradientBoostingRegressor command in Python which is part of the Scikit-Learn package. It is based on the concept of histogram-based decision tree learning, which bins continuous features into discrete intervals to significantly reduce memory usage and computation time.

Table D1. Descriptive Statistics for 1970-2010 Neighborhood Data

	1970	1980	1990	2000	2010
Sample size					
No. of MSAs	90	105	111	109	111
No. of tracts	38,479	43,988	46,595	45,989	46,696
No. of tracts in evaluation sample	12,830	14,665	15,537	15,332	-
Population, minority share and renter share					
Mean (s.d.) tract population	3,078.0	3,161.8	3,490.6	3,915.4	4,329.5
	(2,164.3)	(1,919.7)	(1,889.5)	(1,660.8)	(1,958.6)
Mean (s.d.) tract minority share	0.152	0.221	0.275	0.350	0.422
	(0.231)	(0.280)	(0.298)	(0.312)	(0.311)
Mean (s.d.) tract renter share	0.343	0.358	0.372	0.362	0.380
	(0.237)	(0.246)	(0.240)	(0.248)	(0.241)
Racial segregation					
Mean dissimilarity index	0.56	0.55	0.51	0.48	0.45
Frac. tracts with min. sh. outside 20pp of sample mean	0.16	0.48	0.58	0.64	0.64
Full sample					
Growth in total population	34.0%	27.5%	22.7%	20.9%	-
Growth in white population	21.9%	15.9%	8.4%	6.3%	-
% tracts with white share change $\geq$ 20pp	0.4%	0.3%	0.2%	0.6%	-
% tracts with white share change $\leq$ –20pp	14.8%	8.0%	11.7%	7.4%	-
Subsample: tracts with 0% - 10% min. sh. in the base year					
Fraction of all tracts	0.67	0.52	0.40	0.27	0.16
Growth in total population	37.4%	27.6%	24.8%	20.4%	-
Growth in white population	29.1%	21.7%	17.6%	13.0%	-
Subsample: tracts with 10% - 50% min. sh. in the base year					
Fraction of all tracts	0.24	0.32	0.39	0.44	0.48
Growth in total population	41.0%	38.3%	27.8%	27.9%	-
Growth in white population	14.2%	16.4%	5.6%	7.0%	-
Subsample: tracts with 50% - 90% min. sh. in the base year					
Fraction of all tracts	0.06	0.10	0.13	0.18	0.24
Growth in total population	–1.7%	11.3%	14.2%	17.6%	-
Growth in white population	–13.0%	–6.2%	–6.4%	–2.4%	-
Subsample: tracts with 90% - 100% min. sh. in the base year					
Fraction of all tracts	0.03	0.06	0.08	0.10	0.12
Growth in total population	–18.5%	–4.3%	–0.3%	–2.3%	-
Growth in white population	–1.8%	–0.8%	–0.3%	0.6%	-

Notes: Descriptive statistics are shown for the full sample of tracts. A random subsample of two thirds of these tracts is used as 'search sample' to determine potential tipping point locations. The remaining third of tracts are used as 'evaluation sample' in the regression analysis if the corresponding tract is also in the sample at the end of a given decade. Statistics for the decadal growth in population and minority share are reported for the year at the start of a decade, and are thus missing for 2010 which is the end year of the sample. The dissimilarity index is defined as $D_t = 0.5 \sum_i |\frac{a_{it}}{A_t} - \frac{b_{it}}{B_t}|$, where a_{it} and b_{it} are the populations of groups a and b in tract i at time t, and A_t and B_t are the total populations of the two groups at t.

Appendix E. Estimation and Characteristics of Tipping Points

E.1. **Determining Tipping Points.** Tipping points are estimated separately for each city and decade using four different methodologies: the fixed point and structural break methods applied by Card et al. (2008a), the local kernel method of Porter and Yu (2015) and the lasso method of Lee et al. (2016). All of these methods seek to identify a critical value of the minority share in whose vicinity there is a particularly large change in the decadal growth rate of white population (measured in percentage of initial neighborhood population). For each estimation strategy, the eligible tipping point values are minority shares that are observed in at least one tract of the city, and that lie between the 10th and 90th percentile of the minority share distribution among the tracts of a city, excluding tracts where the minority share is 60 percent or higher. Each of the methods below involves a grid search that separately considers each eligible tipping point value m and then determines the optimal value m^* at which some test statistic is optimized. The tipping points are estimated separately for each city based on a random sample of 2/3 of a city's tracts, while the subsequent regression analyses that quantifies tipping discontinuities (if any) are based on the remaining 1/3 of tracts.

E.1.1. *Fixed Point Method.* The fixed point method identifies the minority share at which a census tract's change in white population is equal to the average change in white population in the city, whereas tracts with smaller minority share experience a greater, and tracts with higher minority share experience a smaller growth in white population. It is obtained using the following steps: (i) regress the decadal change in white population (as percentage of initial tract population) on a fourth-order polynomial of tracts' start-of-decade minority share, excluding tracts where the minority share exceeded 60 percent, (ii) compute predicted effects from that regression in order to obtain a smoothed series of white population growth as a function of initial tract minority share, (iii) identify tracts for which the predicted growth in white population is above the city-level average, while it is below average for the tract with next higher minority share in the data, (iv) if several tracts satisfy the previous condition, select the one at which the polynomial for predicted growth in white population has the most negative slope, (v) to obtain greater precision, retain only tracts with minority shares within plus/minus 10 percentage points of the tract identified in the previous step and then repeat steps (i) to (iv) to identify the final tipping point (if fewer than 4 tracts are retained, then no tipping point is estimated).

E.1.2. *Structural Break Method.* The structural break method regresses the decadal change in white population (in percentage of initial tract population) on a constant and an indicator variable for tracts with an initial minority share above m. The regression is run separately for each city in each decade using only tracts with initial minority shares of up to 60 percent, and is repeated for each value of m within the range of potential tipping point values. The structural break tipping point for each city-decade cell is the value of m^* that produces the largest absolute t-statistic for a negative coefficient estimate on the indicator variable.

E.1.3. *Lasso Method.* The estimator of Lee et al. (2016) uses lasso to identify a break point conditional on a high dimensional set of covariates. Similar to the structural break method, the estimator seeks to explain the growth in white population with an indicator variable for tracts whose minority share is above m. In addition to this variable, lasso is allowed to choose between the following variables: log average family income, share of families with children under age 18, unemployment rate, share of vacancies, and share of single-unit homes. In addition, the possible lasso covariates include the squares of these variables, and any interactions between these variables and the indicator for minority shares above m. The regression models under consideration thus allow for two separate flexible sets of covariates on either side of m. For each potential tipping point value m, a rigorous lasso (Belloni et al., 2012) selects the appropriate model. The lasso tipping point value for each city-decade cell is the value of m^* at which the penalized minimized squared errors statistic of the lasso estimation is the lowest.

E.1.4. *Local Kernel Method.* The difference kernel estimator of Porter and Yu (2015) was developed in the context of regression discontinuity designs with unknown discontinuity point. It uses a local polynomial kernel estimator to measure the relationship between the change in white population and the initial minority share locally around every candidate tipping point value m. The bandwidth for the kernel is determined based on the optimal bandwidth of Imbens and Kalyanaraman (2012). The local kernel tipping point for each city-decade cell is the value of m^* at which the local polynomial has the most negative slope.

E.2. **Characteristics of Tipping Points.**

E.2.1. *Descriptives for Tipping Point Estimates.* The first four columns of Table E1 report average tipping-point estimates by decade and estimation method. Columns 5 through 7 present additional statistics that help assess the stability of each method. The cross-sectional correlations in column 5 measure, for each method, the average correlation between its tipping-point estimates and those obtained using the other three methods. The serial correlations in column 6 indicate whether the cross-city distribution of tipping-point estimates remains persistent across decades. Column 7 reports the standard deviation of tipping-point estimates obtained when each method is applied to 10 alternative random subsamples of tracts. By all three measures, the fixed-point method is the most stable: it has the highest cross-sectional and serial correlations and the lowest standard deviation across subsamples. The structural-break method performs similarly well in terms of cross-sectional correlation and subsample variation, but is weaker on serial correlation. The lasso and kernel methods perform worst across all three stability tests.

E.2.2. *Descriptives for Neighborhoods Near the Tipping Point.* Table E2 reports descriptive statistics for neighborhoods whose minority share lies within two percentage points of the city-level tipping point, pooling observations across decades. These neighborhoods exhibit substantial variation in renter shares, which range from 0.150 at the 25th percentile of the distribution to 0.395 at the 75th percentile. The table also documents several other neighborhood characteristics that are correlated with renter share.

Table E1. Descriptive Statistics for MSA-Level Tipping Point Estimates

	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) cross corr.	(6) serial corr.	(7) std. dev.
Fixed point	10.17	11.87	13.77	17.76	0.69	0.75	1.98
	(10.92)	(9.56)	(10.48)	(11.64)			
Structural break	10.60	12.97	13.25	15.30	0.67	0.47	1.99
	(10.60)	(10.15)	(8.82)	(10.48)			
Lasso	10.22	12.98	12.61	12.55	0.59	0.45	2.46
	(11.12)	(9.10)	(9.23)	(10.25)			
Local kernel	9.99	11.69	11.83	15.90	0.60	0.46	3.39
	(11.00)	(10.67)	(9.70)	(12.54)			
No. of MSAs	90	105	111	109			

Notes: Column 5 ('cross corr.') shows the average cross-sectional correlation between tipping points estimated with the indicated methodology and those obtained with each of the other three methodologies (averaged over 3 pairwise correlations of methods x 4 years). Column 6 ('serial corr.') shows the average serial correlation between tipping points estimated with the indicated methodology across pairs of consecutive decades (average of correlations for 1970/1980, 1980/1990, 1990/2000). Column 7 ('std. dev.') indicates how sensitive the tipping points obtained with each methodology are to the random draw of the tract subsample used for the derivation of the tipping points. For each decade, 10 different random subsamples containing two thirds of the tract data are drawn to calculate 10 different tipping point values for each city, decade and methodology. The table indicates the standard deviation of the 10 values averaged over cities and decades.

Table E2. Descriptive Statistics for Neighborhoods near the Tipping Point

	(1) Mean	(2) p25	(3) p75	(4) Corr. w/ Renter share
Renter share	0.295	0.150	0.395	1.000
Share families w/ children	0.530	0.451	0.612	-0.377
Share adults age < 35	0.347	0.278	0.406	0.322
Population density	6.420	5.447	7.548	0.426
Proximity to high-minority	0.276	0.000	1.000	0.290

Notes: The table shows statistics for the 9,874 neighborhoods whose start-of-period minority share is within 2ppt of the fixed-point tipping point value. The indicated neighborhood variables are the share of rental homes among total homes , the share of families with children among all households, the share of residents below age 35 among all adults age 20 and older, the log of population density (number of people per square kilometer), and an indicator for whether a tract is located within a 5km distance of a tract with a population majority of non-whites and Hispanics. The last column of the table indicates the correlation coefficient between the indicated variable and the neighborhood renter share.

Appendix F. GSS Racial Attitude Data

The General Social Survey (GSS) includes several questions on racial attitudes. Following Card et al. (2008a), I construct a racial intolerance index from individual-level data in the pooled 1972–2018 General Social Survey (GSS). Because geographic identifiers in the GSS are limited, the index can be constructed only for a subset of MSAs, as detailed location information is unavailable for smaller areas. The index is based on four survey questions concerning attitudes toward interracial marriage (Do you think there should be laws against marriages between blacks and whites?), the busing of children to other neighborhoods (In general, do you favor or oppose the busing of black and white school children from one school district to another?), and Black residents' access to neighborhoods (How strongly do you agree or disagree with the statement: "White people have a right to keep blacks out of their neighborhoods if they want to, and blacks should respect that right"?) and homeownership (Suppose there is a community-wide vote on the general housing issue. Which (of the following two) laws would you vote for: A. One law says that a homeowner can decide for himself whom to sell his house to, even if he prefers not to sell to blacks. B. The second law says that a homeowner cannot refuse to sell to someone because of his or her race or color.). Each question is converted into a binary indicator for an intolerant response. For each indicator, a linear probability model is estimated using only white respondents matched to an MSA. These regressions include MSA fixed effects and controls for gender, age, education, a socioeconomic status index, and survey-year fixed effects. The estimated MSA fixed effects are then extracted, averaged across the four questions, and standardized to have mean zero and standard deviation one.