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TIEBOUT SORTING AND NEIGHBORHOOD STRATIFICATION

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ABSTRACT

Tiebout's classic 1956 paper has strong implications regarding stratification across and within jurisdictions, predicting in the simplest instance a hierarchy of internally homogeneous communities ordered by income. Typically, urban areas are less than fully stratified, and the question arises how much departures from standard Tiebout assumptions contribute to observed within-neighborhood mixing. This paper quantifies the separate effects on neighborhood stratification of employment geography (via costly commuting) and preferences for housing attributes. It does so using an equilibrium sorting model, estimated with rich Census micro-data. Simulations based on the model using credible preference estimates show that counterfactual reductions in commuting costs lead to marked increases in racial and education segregation and, to a lesser degree, increases in income segregation, given that households now find it easier to locate in neighborhoods with like households. While turning off preferences for housing characteristics increases racial segregation, especially for blacks, doing so reduces income segregation, indicating that heterogeneity in the housing stock serves to stratify households based on ability-to-pay. Further, we show that differences in housing also help accentuate differences in the consumption of local amenities.

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1 INTRODUCTION

Tiebout's classic 1956 paper emphasized the efficiency of decentralized public goods provision in a system of local jurisdictions. In doing so, it provided a provocative response to Samuelson's seminal 1954 article, which had voiced skepticism as to the efficacy of decentralized systems for providing public goods. Yet beyond its enduring relevance to the debate about public goods provision, Tiebout's paper has also served as an immensely fertile starting point for economists interested in understanding endogenous neighborhood stratification in an urban setting, motivated in part by concerns that excessive segregation may have adverse welfare consequences.[1]

Tiebout's basic treatment was highly stylized – in his words, "extreme." It focused on a simple setting in which consumers were "fully mobile" (his Assumption 1), moving costlessly to their preferred jurisdiction when choosing among a large number of competing jurisdictions (Assumption 3), which differed only in the exogenous public goods and taxation packages they offered. With the neighborhood segregation theme in mind, Tiebout's stylized theory[2] has strong implications regarding stratification across and within jurisdictions. For example, in the simplest case where households are heterogeneous only in terms of their income, a hierarchy of internally homogeneous communities ordered by income is predicted.

In practice, urban areas tend to exhibit varying degrees of within-neighborhood mixing, and it is natural to trace this discrepancy to departures from the standard Tiebout assumptions.[3] The potential list of such departures is long. But given the burden in Tiebout's theory – preferences being revealed through a process of 'voting with feet' – the character of household preferences and the role of mobility provide an obvious starting point. In terms of the former, household tastes when making residential choices are likely to vary according to the household's own characteristics (education, income, race and family size, for instance), and this inherent preference heterogeneity will tend to lead households in a given neighborhood to differ in terms of, say, income.[4] Household tastes will also typically depend on a whole range of choice attributes – housing characteristics, local amenities, the characteristics of neighbors, geographic

[1] Benabou (1993) and Cutler and Glaeser (1997) provide well-known developments of this theme.
[2] The informality of Tiebout's original presentation has prompted an important literature seeking to place the rather implicit 'theory' on more solid foundations. See, for instance, Bewley (1981).
[3] The development of richer theoretical models of systems of jurisdictions has been a central preoccupation in local public finance over the past three decades. Notable here is the work of Epple and coauthors, who show in a series of papers how housing and endogenously determined public goods can be incorporated into rigorous multi-community equilibrium models with mobile households.
[4] On this point, Epple and Platt (1998) show theoretically that some degree of within-jurisdiction income mixing can arise when households are heterogeneous both in terms of income and tastes for public goods.

convenience – rather than just different expenditure and revenue patterns across communities (as in Tiebout's Assumption 2). The distribution of housing characteristics, for example, will often vary markedly across a metropolitan area, given the complexity of local zoning and the durability of the housing stock, and this may serve to sort heterogeneous households into given communities. Likewise geography: while Tiebout abstracted from "restrictions due to employment opportunities,"[5] the geographic distribution of jobs combined with imperfect mobility (non-zero commuting costs) should help spread households out across the urban area and contribute to within-community mixing. Simply put, households may prefer a house in a neighborhood close to the workplace, especially if commutes are costly, even if it means trading off against other attributes such as living with similar neighbors.

The goal of this paper is to quantify the separate effects on observed residential mixing of employment geography (via the disutility of commuting) and heterogeneous preferences for housing. Doing so is of clear interest, given concerns about the adverse consequences of sociodemographic stratification across neighborhoods.[6] Yet such quantification is far from straightforward, not least because it requires the researcher to assess the extent of neighborhood stratification in a counterfactual environment.

One general approach to conducting such counterfactuals – and few viable alternatives come to mind – would start with a realistic specification of the preferences that underlie the existing pattern of residential sorting, and then simulate a counterfactual change in household preferences, tracing the impact of this change on stratification and other outcomes in the counterfactual equilibrium. To implement this kind of notional experiment, one would need credible preference estimates, along with a coherent model of the sorting process that allows counterfactual equilibria to be simulated.

In this paper, we apply an estimation-simulation approach set out in two prior papers that attempts to track this type of notional counterfactual exercise. Specifically, we combine the equilibrium sorting model in Bayer, McMillan and Rueben (2011) and an approach to estimating sorting models with rich preference heterogeneity presented in Bayer, Ferreira and McMillan (2007) in order to quantify possible determinants of residential stratification. Our general approach builds on two strands of literature. A large body of theoretical research, including papers by Epple, Filimon and Romer (1984, 1993), Epple and Romano (1996, 1998), Benabou

In this instance, the type space is partitioned in equilibrium into a series of diagonal slices, implying that the across-neighborhood income hierarchy still obtains, conditioning on tastes.

[5] "Restrictions due to employment opportunities are not considered" (Tiebout's Assumption 4).

(1993, 1996), Anas and Kim (1996), Fernandez and Rogerson (1996, 1998), and Nechyba (1999, 2000), has developed equilibrium sorting models, using them to analyze the way that interdependent individual decisions in the housing market aggregate up to determine the equilibrium structure of a metropolitan area. More recently, a related line of research has sought to take these models to the data. Epple and Sieg (1999) develop an estimator for the equilibrium sorting model of Epple, Filimon, and Romer, providing the first unified treatment of theory and empirics in the literature. In the same vein, Sieg *et al.* (2004) use this approach to explore the general equilibrium impacts of air quality improvements in the Los Angeles Basin. And Ferreyra (2007) develops an estimator building on the work of Nechyba, using this to simulate the effects of school vouchers in an equilibrium setting.

By way of a quick overview of the elements of our approach, we start with an equilibrium framework in which households choose residential locations from the set of available houses in the metropolitan area, given the employment locations of household heads, in order to maximize their utility. In terms of locational preferences, the model permits a considerable amount of household taste heterogeneity, with tastes being allowed to vary over a wide range of housing and neighborhood characteristics, including those that are endogenously determined through the sorting process; tastes are also allowed to vary with a range of observable household characteristics. Neighborhood residential compositions are endogenous, and house prices adjust to equate demand with fixed supply. In equilibrium, no household can gain from moving and all local housing markets clear.

We estimate the sorting model using an econometric approach set out in Bayer *et al.* (2007). This introduces unobserved neighborhood attributes into McFadden's (1978) discrete-choice housing demand model. Doing so brings an important endogeneity problem to the fore, as prices and neighborhood compositions – key choice characteristics – are likely to be correlated with the neighborhood unobservables. To address the potential endogeneity of these endogenous choice attributes, we develop instruments for price based on exogenous choice characteristics, here following Berry, Levinsohn and Pakes (1995); and to account for the potential endogeneity of school quality and sorting-dependent sociodemographics, we further extend the boundary discontinuity approach introduced by Black (1999), making use of sharp changes in school quality and sociodemographics in the vicinity of school attendance zone boundaries.

In taking the model to the data, we make use of restricted-access Census microdata on a very large and representative sample (1-in-7) of households in the Bay Area. The long form of

[6] It is worth adding that job location is given as the single most important factor influencing residential choices in the American Housing Survey, and there has been limited recent research examining the effects

the Census provides detailed information about a wide set of household characteristics, including education, income, age, family structure, and race. It also provides information about the chosen housing unit – its size, when built, whether owned, and more. Because the restricted-access version of the Census we are using specifies residential locations down to the Census block, we can merge in a great deal of additional data, relating to local amenities, land use and the characteristics of immediate neighbors. We can also construct a boundary sub-sample, based on distance to the closest school attendance zone boundary, in order to implement the boundary identification approach mentioned above. Particularly valuable for our purposes is the fact that the restricted-access version of the Census also includes information on places of work down to the block. This affords a very detailed picture of the employment geography of the metropolitan area, which we use to anchor household location decisions, taking place of work as given.[7]

Estimates of the model provide a rich characterization of heterogeneous household preferences for a variety of housing and neighborhood characteristics, including local public goods such as school quality and crime, as well as the characteristics of neighbors. Applying the identification strategies just referred to yields reasonable estimates of household willingness-to-pay for these choice attributes. As one might expect, households with higher education levels and incomes are willing to pay more for better schools, as are households with children, though the extent of the heterogeneity in willingness to pay is rather muted. While some choice characteristics are likely to be ranked similarly by all households, the rankings of others might be expected to vary depending on a household's own characteristics (their race, for example). In line with this, we find evidence of strong racial interactions in the utility function, with households of the same race showing a strong willingness-to-pay to live with like neighbors.

In combination with these rich preference estimates, our equilibrium model serves as a useful device for exploring the implications of changes in model primitives for residential stratification and household consumption levels. In that vein, the main analysis in this paper consists of a series of counterfactual simulations intended to shed light on the factors that contribute in practice to observed residential mixing. Following on from the above discussion, we focus on the possible effects of employment geography combined with costly commuting (taking a queue from Tiebout directly) and also heterogeneity in preferences for housing. We explore the former by counterfactually reducing households' estimated disutility of commuting to work, first cutting the estimated disutility in half and then switching it off entirely, in both cases while holding the distribution of employment in the study area fixed. And we shed light on the

of employment geography on residential segregation, an exception being Bajari and Kahn (2005).

latter by counterfactually switching off household preferences for housing characteristics while keeping the geographic distribution of the existing housing stock fixed.

Our first set of simulations shows that counterfactual reductions in the disutility of commuting lead to marked increases in racial and education segregation and, to a lesser degree, increases in income segregation, as households now find it easier to form neighborhoods with like households. While turning off preferences for housing characteristics increases education segregation and racial segregation, especially for blacks, it actually *reduces* income segregation, indicating that the non-uniform distribution of housing characteristics serves to stratify households based on ability to pay. Further, we show that differences in housing help accentuate differences in the consumption of local amenities, our estimates providing a sense of the magnitudes involved.

The rest of the paper is organized as follows: in Sections 2-4, we provide a brief overview of the approach we apply for assessing the relevant counterfactuals. Specifically, the next section sets out the equilibrium sorting model and its main properties, drawing on the comprehensive treatment in Bayer *et al.* (2011); the estimation of the model, based on Bayer *et al.* (2007), is described in Section 3; Section 4 describes the detailed Census microdata drawn from the Bay Area briefly, along with the model estimates. Sections 5 and 6 represent the core of the paper, Section 5 summarizing our simulation approach and presenting benchmark measures of fit, and Section 6 describing results from a series of counterfactual simulations that shed light on the determinants of residential mixing. Section 7 concludes.

2 THEORETICAL MODEL

The counterfactual simulations at the heart of the paper make use of a version of the equilibrium residential sorting model developed in Bayer *et al.* (2011). In order to provide a self-contained account of the relevant ingredients that feed into the simulation exercise, we begin with a brief outline of the equilibrium model. This model combines two key elements: the household residential location choice problem and a market-clearing condition. In terms of the former, households have heterogeneous preferences defined over housing and neighborhood attributes in a flexible way.[8] The model also allows housing prices and neighborhood sociodemographic compositions to be determined in equilibrium, through market-clearing.

[7] It is feasible, if more challenging, to further endogenize the place of work in the household choice process. Doing so is beyond the scope of the current analysis.
[8] It is important to point out that this flexibility is made possible because we abstract from issues related to local politics. As Epple, Filimon, and Romer (1993) note, incorporating local politics into models of

The Residential Location Decision. We model the residential location decision of each household as a discrete choice of a single residence from a set of house types available in the market. To explain the relevant notation, let X_h represent the observable characteristics of housing choice h, including characteristics of the house itself (e.g., the house's age and size), its tenure status (whether rented or owned), and the characteristics of the surrounding neighborhood (e.g., local land use and topography). We use Z_h to represent the average sociodemographic characteristics of the corresponding neighborhood, writing this separately from the other housing and neighborhood attributes to make explicit the fact that these sociodemographics are determined in equilibrium. Let p_h denote the price of housing choice h, and let d_h^i denote the distance from residence h to the primary work location of household i (where we take that work location as given).

Each household chooses its residence h to maximize its indirect utility function V_h^i:

$$(1) \qquad \underset{(h)}{Max} \quad V_h^i = \alpha_X^i X_h + \alpha_Z^i Z_h - \alpha_p^i p_h - \alpha_d^i d_h^i + \xi_h + \varepsilon_h^i.$$

The error structure of the indirect utility function is divided into a correlated component associated with each housing choice that is valued the same by all households, ξ_h, and an individual-specific term, $\varepsilon^i{}_h$, each household i drawing a vector of taste shocks, one for each housing type. A useful interpretation of ξ_h is that it captures the unobserved quality of each housing choice, including any unobserved quality associated with its neighborhood.

We define a household type based on K observable household characteristics. Each household i's valuation of given choice characteristics is allowed to vary with its own observable characteristics, z^i, including education, income, race, employment status, and household composition. Specifically, we let each parameter associated with housing and neighborhood characteristics and price, α^i_j, for $j \in \{X, Z, p, d\}$, vary with a household's own characteristics according to:

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residential sorting requires restrictions to be placed on preferences in order to guarantee the existence of an equilibrium. Accordingly, recent papers by Epple and Sieg (1999) and Epple, Romer and Sieg (2001) estimate equilibrium models that include voting over the level of public goods, restricting households to have shared rankings over a single public goods index. We view our model as having a comparative rather than absolute advantage over the papers in that line of research, suitable for exploring research questions, such as those related to segregation, where a vertical restriction is less appealing, or for use in an

(2) $$\alpha_j^i = \alpha_{0j} + \sum_{k=1}^{K} \alpha_{kj} z_k^i \, ,$$

with equation (2) describing household i's preference for choice characteristic j.

This specification of the utility function gives rise to a horizontal model of sorting in which household preferences may vary in an unrestricted way over each choice characteristic, including housing features, commuting distance, school quality and neighborhood sociodemographic characteristics. This contrasts with vertical models, which restrict households to have preferences over a single locational index, thereby constraining households to have the same preference ordering across locations. The additional flexibility of the horizontal model is especially relevant for this paper as it is the magnitude of the heterogeneity in preferences for various locational factors (including housing and commuting distance) that will determine the extent of stratification across neighborhoods.

Characterizing the Housing Market. We assume that the housing market can be fully characterized by a set of housing types that is a subset of the full set of available houses in the study area, reflecting the fact that we are working with a 1-in-7 sample of the universe of houses in the Bay Area. Let the supply of housing of type h be given by S_h, with all houses being occupied in equilibrium. We assume that each household observed in the sample represents a continuum of households with the same observable characteristics;[9] accordingly, the distribution of idiosyncratic tastes ε^i_h maps into a set of choice probabilities that characterize the distribution of housing choices that would result for the continuum of households with a given set of observed characteristics.

Given the household's problem described in equations (1)-(2), household i chooses housing type h if the utility that it receives from this choice exceeds the utility that it receives from all other possible house choices – that is, when

(3) $$V_h^i > V_k^i \quad \Rightarrow \quad W_h^i + \varepsilon_h^i > W_k^i + \varepsilon_k^i \quad \Rightarrow \quad \varepsilon_h^i - \varepsilon_k^i > W_k^i - W_h^i, \qquad \forall \quad k \neq h,$$

where W^i_h includes all of the non-idiosyncratic components of the utility function V^i_h. As the inequalities in (3) imply, the probability that a household chooses any particular choice depends

institutional setting as in California, where Proposition 13 leaves almost no discretion over property tax rates or the level of public goods spending at the local level.

[9] This assumption facilitates the proof of the existence of an equilibrium in the model.

in general on the characteristics of the full set of possible house types. Thus the probability P^i_h that household i chooses housing type h can be written as a function of the full vectors of housing and neighborhood characteristics (both observed and unobserved) and prices, given by {$\mathbf{X}$, $\mathbf{Z}$, $\mathbf{p}$, $\boldsymbol{\xi}$}, as well as the household's own characteristics z^i:[10]

$$(4) \qquad P_h^i = f_h(z^i, \mathbf{Z}, \mathbf{X}, \mathbf{p}, \boldsymbol{\xi}).$$

Aggregating the probabilities in equation (4) over all observed households yields the predicted demand for each housing type h, D_h:

$$(5) \qquad D_h = \sum_i P_h^i.$$

In order for the housing market to clear, the demand for houses of type h must equal the supply of such houses, and so:

$$(6) \qquad D_h = S_h, \quad \forall h \quad \Rightarrow \quad \sum_i P_h^i = S_h \quad \forall h.$$

Given the decentralized nature of the housing market, prices are assumed to adjust in order to clear the market. The implications of the market clearing condition defined in equation (6) for prices are very standard, with excess demand for a housing type causing price to be bid up and excess supply leading to a fall in price. Given the indirect utility function defined in equation (1) and a fixed set of housing and neighborhood attributes, Bayer, McMillan, and Rueben (2011) show that a unique set of prices (up to a scale) clears the market.

Given that some neighborhood attributes are endogenously determined by the sorting process itself, we define a sorting equilibrium as a set of residential location decisions and a vector of housing prices such that the housing market clears and each household makes its optimal location decision given the location decisions of all other households. In equilibrium, the vector of neighborhood sociodemographic characteristics along with the corresponding vector of market-clearing prices must give rise to choice probabilities in equation (4) that aggregate back

[10] For the purposes of characterizing the equilibrium properties of the model, we include an individual's employment location in z^i and the residential location in X_h.

up to the same vector of neighborhood sociodemographics.[11] Whether this model gives rise to multiple equilibria depends on the distributions of preferences and available housing choices as well as the utility function parameters. In general, it is not possible to establish that the equilibrium is unique *a priori*. However, estimation of the model does not require the computation of an equilibrium nor uniqueness more generally, as we describe in the next section.

3 ESTIMATION

Estimation of the model follows a two-stage procedure closely related to that in Berry, Levinsohn, and Pakes (1995). This section outlines the estimation procedure; a rigorous presentation is contained in Bayer *et al.* (2007).

It is helpful in describing the estimation approach to introduce some additional notation. In particular, we rewrite the indirect utility function as:

$$(7) \qquad V_h^i = \delta_h + \lambda_h^i + \varepsilon_h^i$$

where

$$(8) \qquad \delta_h = \alpha_{0X} X_h + \alpha_{0Z} Z_h - \alpha_{0p} p_h + \theta_{bh} + \xi_h$$

and

$$(9) \qquad \lambda_h^i = \left(\sum_{k=1}^{K} \alpha_{kX} z_k^i \right) X_h + \left(\sum_{k=1}^{K} \alpha_{kZ} z_k^i \right) Z_h - \left(\sum_{k=1}^{K} \alpha_{kp} z_k^i \right) p_h - \left(\sum_{k=1}^{K} \alpha_{kd} z_k^i \right) d_h^i .$$

In equations (7) and (8), δ_h captures the portion of utility provided by housing type h that is common to all households, and in (9), k indexes household characteristics. When the household characteristics included in the model are constructed to have mean zero, δ_h is the mean indirect utility provided by housing choice h. The unobservable component of δ_h, ξ_h, captures the portion of unobserved preferences for housing choice h that is correlated across households, while ε^i_h represents unobserved preferences over and above this shared component. (In equation (8), the term θ_{bh} represents a vector of boundary fixed effects, described below.)

The first step of the estimation procedure is equivalent to a Maximum Likelihood estimator applied to the individual location decisions, taking prices and neighborhood

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[11] Bayer, McMillan, and Rueben (2011) establish the existence of a sorting equilibrium as long as (i) the indirect utility function shown in equation (2) is decreasing in housing prices for all households; (ii)

sociodemographic compositions as given. This returns estimates of the heterogeneous parameters in λ and mean indirect utilities, δ_h. The estimator is based simply on maximizing the probability that the model correctly matches each household observed in the sample with its chosen house type. In particular, for any combination of the heterogeneous parameters in λ and mean indirect utilities, δ_h, the model predicts the probability that each household i chooses house type h. We assume that ε_h^i is drawn from the Type 1 extreme value distribution, in which case this probability can be written:

$$(10) \qquad P_h^i = \mathbf{exp}(\delta_h + \hat{\lambda}_h^i) \Big/ \sum_k \mathbf{exp}(\delta_k + \hat{\lambda}_k^i)$$

Maximizing the probability that each household makes its correct housing choice gives rise to the following quasi-log-likelihood function:

$$(11) \qquad \tilde{\ell} = \sum_i \sum_h I_h^i \, \mathbf{ln}(P_h^i),$$

where I^i_h is an indicator variable that equals 1 if household i chooses house type h in the data and 0 otherwise. The first stage of the estimation procedure then consists of searching over the parameters in λ and the vector of mean indirect utilities to maximize $\tilde{\ell}$.

The Endogeneity of School Quality and Neighborhood Sociodemographic Composition. Having estimated the vector of mean indirect utilities in the first stage of the estimation procedure, the second stage involves decomposing $\boldsymbol{\delta}$ into observable and unobservable components according to the regression equation (8).[12] In estimating equation (8), important endogeneity problems need to be confronted. First, to the extent that house prices partly capture house and neighborhood quality unobserved to the econometrician, so the price variable will be endogenous, and estimation via least squares will lead to price coefficients biased towards zero, producing misleading willingness-to-pay estimates for a whole range of choice characteristics. This issue arises in the context of any differentiated products demand estimation and we follow the approach described in Bayer *et al.* (2007) to instrument for price.

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indirect utility is a continuous function of neighborhood sociodemographic characteristics; and (iii) $\boldsymbol{\varepsilon}$ is drawn from a continuous density function.

[12] Notice that the set of observed residential choices provides no information that distinguishes the components of $\boldsymbol{\delta}$. That is, however $\boldsymbol{\delta}$ is broken into components, the effect on the probabilities shown in equation (10) is identical.

A second identification issue involves the correlation of neighborhood sociodemographic characteristics ***Z*** and school quality with unobserved housing and neighborhood quality, ξ_h. To properly estimate preferences in the face of this endogeneity problem, we adapt an appealing technique previously developed by Black (1999). Black's strategy makes use of a sample of houses near school attendance zone boundaries, estimating a hedonic price regression that includes boundary fixed effects. Intuitively, the idea is to compare houses in the same local neighborhood but on opposite sides of the boundary, exploiting the discontinuity in the right to attend a given school. Differences in valuation will then reflect differences in school quality, controlling for other neighborhood characteristics (both observed and unobserved).

As shown in Bayer *et al.* (2007), however, households clearly sort with respect to these boundaries. Thus, while the boundary fixed effects are likely to control well for differences in unobserved fixed factors, neighborhood sociodemographics are likely to vary discontinuously at the boundary. This is important: it implies that boundary fixed effects isolate variation in both school quality and neighborhood sociodemographics in a small region in which unobserved fixed features (e.g., access to the transportation network) are likely to vary only slightly, thereby providing an appealing way to account for the correlation of both school quality *and* neighborhood sociodemographics with unobservable neighborhood quality. The approach thus allows us to treat a range of local public goods as endogenous.

We incorporate school attendance zone boundary fixed effects θ_{bh} when estimating equation (8). In particular, we create a series of indicator variables for each Census block that equal one if the block is within a given distance of each unique school attendance zone boundary in the metropolitan area. Bayer *et al.* (2007) provide extensive descriptive evidence regarding the significant extent that the school quality and neighborhood demographics vary at these boundaries and, important for the identification approach, the essentially continuous way that other housing and neighborhood attributes run through the boundary.

4 DATA and ESTIMATES

The analysis uses restricted-access Census data from 1990 that combine the detailed individual, household, and housing variables found in the public-use version of the Census with information about the location of individual residences and workplaces at a very disaggregate level. We use data from six contiguous counties in the San Francisco Bay Area: Alameda, Contra Costa, Marin, San Mateo, San Francisco, and Santa Clara – a sample of 242,100 households drawn from over 39,000 Census blocks.

The Census provides a wealth of data on the individuals in the sample – race, age, educational attainment, income from various sources, household size and structure, occupation, and employment location. In addition, it provides a variety of housing characteristics: whether the unit is owned or rented, the corresponding rent or owner-reported value, number of rooms, number of bedrooms, type of structure, and the age of the building. We use these housing characteristics directly, and also construct neighborhood variables, such as neighborhood racial, education and income distributions, based on the households within the same Census block group (a Census region containing approximately 500 housing units). We merge additional data describing local conditions with each house record, constructing variables related to crime rates, land use, local schools, topography, and urban density. The list of the principal housing and neighborhood variables used in the analysis, along with means and standard deviations, is given in the first two columns of Table 1.[13]

School Boundaries. In order to implement the boundary discontinuity design, we gathered school attendance zone maps for as many elementary schools as possible in the Bay Area, for the period around the 1990 Census. Our final attendance zone sample consists of 195 elementary schools – just under a third of the total number in the Bay Area. From this boundary sample, we excluded portions of boundaries coinciding with school district boundaries, city boundaries, or large roads, since they could potentially confound our identification strategy.

For our main boundary analysis, we focus on houses in all Census blocks that are within 0.20 miles of the closest school attendance zone boundary. The average distance to the boundary for this subsample is thus quite a lot smaller than 0.20 miles. For comparison (results not reported here), we also analyzed a further subsample, consisting of houses assigned to Census blocks within 0.10 miles of the closest attendance zone boundary. Although the 0.10-mile subsample includes approximately half the number of observations, it provides a closer approximation to the ideal comparison of houses on the opposite sides of the same street, though in separate attendance zones. Results applying this tighter sample are very similar, if somewhat less precise.

Table 1 displays descriptive statistics for various samples related to the boundaries. The first two columns report means and standard deviations for the full sample while the third column reports means for the sample of houses within 0.2 miles of the closest school attendance zone

[13] For each of these measures, a detailed description of the process by which the original data were assigned to each house is provided in the Data Appendix to Bayer *et al.* (2007).

boundaries.[14] Comparing the first column to the third column of the table, the houses near school attendance zone boundaries are reasonably representative of those in the Bay Area as a whole. The fourth and fifth columns report means for houses within 0.2 miles of a boundary, comparing houses on the high versus low average test score side of the each boundary; the seventh column reporting associated t-tests for the difference in means. Comparing these differences reveals that houses on the high side cost $18,700 more (on a mean of $250,000) and are assigned to schools with test scores that are 74 points higher on average. Moreover, houses on the high quality side of the boundary are more likely to be inhabited by white households and households with more education and income. These types of across-boundary differences in sociodemographic composition are what one would expect if households sort on the basis of preferences for school quality. Given that other housing characteristics are reasonably smooth across these boundaries, we expect the use of boundary fixed effects to control well for much of the variation in unobserved housing and neighborhood quality in the boundary region, thereby giving rise to accurate estimates of mean preferences for neighborhood sociodemographics and school quality. We now turn to the complete set of preference estimates.

Preference Estimates

The estimation of the full model returns over 150 parameter estimates that characterize heterogeneous household preferences for housing and neighborhood attributes as well as commuting distance. While we presented some aspects of these parameter estimates in Bayer *et al.* (2007), the focus of that paper was more narrowly on the impact of including boundary fixed effects on the estimates of preferences for school quality and neighborhood demographics.[15] A much richer set of parameters is relevant for this paper, however, as the counterfactuals that we conduct below consider the effects of employment geography and heterogeneous housing preferences on the extent of residential stratification. To that end, we present a much broader set of parameter estimates here. Accordingly, Table 2 reports estimates of mean preferences for key housing and neighborhood characteristics for two specifications of equation (8). In estimating equation (8), we report results here for a specification that restricts the sample to houses within 0.2 miles of boundaries.[16]

[14] Table 1 is taken directly from Bayer *et al.* (2007). We provide it here to make the current description of the approach self-contained.
[15] In Bayer *et al.* (2007), we provide a detailed discussion of the impact of instrumenting for price. Doing so is essential in order for the willingness-to-pay estimates to be reasonable. Otherwise, the price coefficient tends to be biased towards zero, inflating all WTP measures.
[16] We show in Bayer *et al.* (2007) that these results are robust to changes in the distance that is used, reporting, for example, a series of results for 0.1 mile boundaries.

The second column shows the impact of including boundary fixed effects on the estimates of mean preferences. Comparing these columns reveals a pattern of results that one would expect if boundary fixed effects control in part for unobserved neighborhood quality and unobserved quality is positively correlated with neighborhood income and education and negatively correlated with the fraction of non-white households. Key parameter estimates include a marginal willingness-to-pay (MWTP) of just under \$100 per month for newly constructed housing (relative to older housing) and for each additional room and just over \$50 per month for avoiding each additional mile of commuting distance.[17]

Given our subsequent simulation exercises, it is important that housing preferences and the disutility of commutes be credibility identified. While we do not develop tailor-made identification strategies for these two sets of preference parameters, we would argue that the relevant parameter estimates are reasonable, for three main reasons: First, our very rich restricted-access Census data provide us with a wealth of information, in this case on housing features for a very large sample (1-in-7) of all housing units in the Bay Area, and also very detailed information about actual commutes for a very large sample of workers. There is no equivalent micro data set with the same coverage. Second, the detailed geographic information allows us to apply two identification approaches that help account for the endogeneity of confounding local unobservables, likely to be a concern for estimates of housing characteristics and commuting, among other attributes. In this respect, our estimates are an improvement on prior estimates in the literature. Third, our choice model allows us to go beyond hedonic estimates that ignore heterogeneity, based on the revealed pattern of choices by a huge sample of households in our data set.

Following on from that point, Table 3 reports the implied estimates of the heterogeneity in MWTP for a wide variety of housing and neighborhood attributes for our preferred specification, which includes boundary fixed effects. The estimates of the heterogeneity in the MWTP for neighborhood sociodemographic characteristics reveal that while all households prefer to live in higher-income neighborhoods, *conditional on neighborhood income* households prefer to self-segregate on the basis of both race and education. In particular, the estimates imply that college-educated households are willing to pay \$58 per month more than those without a

[17] That the estimated cost of commuting increases with the inclusion of boundary fixed effects (BFEs) is driven by the fact that this estimate is very sensitive to the estimated mean price coefficient, which roughly doubles in magnitude when boundary fixed effects are included. In general, the price coefficient is biased upwards (less negative than it should be) because price is positively correlated with unobserved quality. That the price coefficient becomes significantly more negative with the inclusion of BFEs is likely due to the fact that the BFEs help deal with some residual correlation of the price instruments and unobserved neighborhood quality.

college degree to live in a neighborhood that has 10 percent more college-educated households. When combined with the estimated mean MWTP of $10 per month reported in the first row, this estimate implies that households at each level of educational attainment prefer neighbors with like education levels: while college-educated households would pay an addition $32 per month to live in a neighborhood that had 10 percent more college-educated households, households without a college degree would actually need *compensating* to live in a neighborhood with 10 percent more college-educated neighbors, to the tune of $26 per month.

Similarly, the heterogeneity estimates imply that blacks are willing to pay $98 more per month than whites to live in a neighborhood that has 10 percent more black versus white households. The mean MWTP for such an increase is -$10.5 per month, primarily reflecting the negative valuation of the white majority. Thus $98 is the difference between the *positive* MWTP of black households for this change and the *negative* MWTP of white households, indicating that households have strong self-segregating racial preferences.[18]

In contrast to education and race, neighborhood income is a normal good for all households, perhaps in part because higher income neighborhoods are better able to maintain their properties. Not surprisingly, households with children have stronger preferences for larger and older houses as well as higher quality schools and the demand for owner-occupancy increases sharply with income, education and for white and especially Asian households.[19] The latter results are likely due in large part to the relative wealth of white and Asian households compared to that of their black and Hispanic counterparts.

5 SIMULATION PRELIMINARIES

Having laid out the necessary background to the simulation approach (the model, estimation procedure, data and preference estimates), we now turn to the simulations that make up the

[18] It is also important to point out that these interactions pick up any direct preferences for living near others of the same race (e.g., a recent immigrant from China may want to interact with neighbors who also have immigrated from China) as well as any unobservable neighborhood or housing amenities valued more strongly by households of this group (e.g., recent immigrants from China may have similar tastes for shops, restaurants, and other neighborhood amenities).

[19] That the mean and heterogeneity in estimated willingness to pay is small for school quality relative to neighborhood socioeconomic characteristics such as education and income may reflect the fact that households face a difficult identification problem when attempting to distinguish the value added by a school from its socioeconomic distribution. Given the correlation of the published average test scores with socioeconomic characteristics, these scores may do little more than serve as a signal of the underlying socioeconomic composition of the school and neighborhood. It may also be that much of what households and parents are really willing to pay for when they speak about paying for better schools is the increased education and income of the peer group in the local school and neighborhood.

paper's primary contribution. We begin this section by describing our simulation procedure, before discussing the construction of the exposure rate and consumption measures that constitute the model output. We then compare results from the benchmark ('pre-experiment') simulations with the sample to provide an indication of model fit. The results from the pre-experiment benchmarks also serve as a useful point of comparison when assessing the counterfactual simulation results in the next section.

Simulation Procedure

The basic structure of the computation of a new equilibrium consists of a 'price' loop within a larger 'sociodemographics' loop. Having changed some primitive in the model, we first calculate a new set of prices that clears the market. Here, Berry (1994) ensures that there is such a unique set of market-clearing prices (up to scale); in addition, Berry *et al*. (1995) provide a quick means of computing the market-clearing price vector.

We then take the new prices and the initial sociodemographic compositions of each neighborhood and go on to calculate the probability that each household chooses each housing type. Aggregating these choices to the neighborhood level, we also compute the corresponding predicted sociodemographic composition of each neighborhood. We then replace the initial neighborhood sociodemographic compositions with these new measures and start the price loop again, calculating a new set of market clearing prices given these updated neighborhood sociodemographic measures. We continue this process until the neighborhood sociodemographics converge.[20] The household location decisions corresponding to the final sociodemographic measures, along with the vector of housing prices that clears the market, then constitute the new equilibrium, based on which we construct a variety of predicted segregation and consumption measures.

Pre-experiment Benchmark and Sample

As noted above, equilibria are not computed during the estimation process. This is important for the feasibility of our estimator, given that the class of models that ours falls into do not have generically unique equilibria. This point also matters from the perspective of carrying out simulations. Specifically, it is unlikely that the prices and neighborhood compositions seen in the data constitute an equilibrium in the context of our sorting model, given the preference

[20] In one variant of the simulation code, we allow school quality and crime rates to adjust further in light of changing local demographics, allowing for further compounding. In the simulation results reported in this paper, we close down this channel of adjustment. We view this as a conservative choice that will lead us to understate the effects of changes in primitives on stratification.

estimates we recover – this is something we are able to check computationally. For the purposes of carrying out simulations, it is therefore useful to start from a comparable benchmark in order to provide an appropriate comparison with subsequent counterfactuals.[21] To this end, we take the full set of model estimates and the simple structure of the equilibrium model, and slightly perturb tastes, say, over commuting. This sets in motion changes in market-clearing prices and neighborhood compositions until a corresponding equilibrium is found, which – in many instances – is close to the non-equilibrium predictions of the estimated model.[22]

Based on this 'pre-experiment' equilibrium, it is straightforward to compute predicted measures of neighborhood stratification and the consumption of amenities for households with given sociodemographic characteristics; and these can be compared to the corresponding sample measures, as well as segregation and consumption measures predicted by the model directly, without imposing any equilibrium requirement.[23] The presentation of the results from the 'pre-experiment' benchmark follows the same format as the results from the counterfactual simulations, so it is worth commenting on the general structure: for each equilibrium, we compute exposure rate measures of neighborhood segregation and predicted consumption measures for housing and neighborhood amenities, separately for households depending on their education, income, and race.[24] We now describe the construction of these measures.

For our education categorization, we assign households to three exhaustive, mutually exclusive categories, based on the educational attainment of the household head: high school or less, some college, and college degree or more. For income, we simply assign households to one of the four income quartiles, where the relevant cutoffs are set based on the sample income distribution. And for race, we categorize households into one of three mutually exclusive, exhaustive racial groups, again based on the reported race of the household head – white, black and 'other' races (defined as non-white and non-black, combining Asians, Hispanics, and native Americans). In contrast to education and income, which have the character of vertical attributes,

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[21] We note that multiplicity arises because of the presence of social interactions in the utility function – that is, the potential dependence of household tastes on the characteristics of neighbors. None of the simulations we report involve shutting down these interactions, and so there is no guarantee that the counterfactual equilibria that we describe are unique.

[22] On the multiplicity point, we have experimented with perturbing the model by adding noise to covariates to see whether the equilibria that emerge are markedly different. We find that they are not. Based on these robustness exercises, multiplicity appears not to be a major concern, which we attribute to the high degree of smoothness in the model.

[23] We do not report segregation and consumption measures based on these simple model predictions here. For the most part, they are very close to the corresponding sample quantities, consistent with the close fit of the econometric model to the data.

[24] We also computed segregation as well as 'amenity' consumption measures on the basis of household education (whether the household head has a college degree or not) combined with an indicator denoting children present in the household – thus 2×2 categories. These results are available upon request.

race introduces potentially interesting heterogeneity in household choices across race, which we will examine below.

Exposure rates provide intuitive measures of the degree of neighborhood stratification (in this application, at the block group level) faced by households in a particular cell, whether defined by education, income or race. Take, for instance, a given household in a given education cell. Based on the model predictions, the probability mass associated with that household is spread over housing units in the sample, and it is possible to construct the implied sociodemographic (in this case, educational) composition of each neighborhood that the household is associated with, having netted out the probability mass associated with the household's own presence. Averaging these predicted neighborhood compositions, using the household's probabilities across neighborhoods as weights, it is possible to form the predicted average neighborhood compositions for the given household, based on the full set of choices in the choice set. In turn, we can average across all like households – for instance, households in the bottom education category – to determine the education exposure rates for households in that category. We construct analogous exposure rates for households with some college or a college degree, and separately, on the basis of household income and race.

For comparison, we also construct *sample* exposure rate measures, separately on the basis of education and income and race. Here, for our sample education exposure rates, we simply record the block group neighborhood education composition for a household in a given category, then average the neighborhood compositions over all like households. Both for the pre-experiment and the sample, we obtain measures of the average neighborhood education compositions that households in each education category are exposed to, giving a total of nine exposure rates. These are arranged in columns of three, each column corresponding to the education compositions – either predicted or sample – for households falling into the education category denoted by the column heading. In the corresponding case of income, the relevant matrix of income quartile exposure rates – again, either predicted or sample – consists of 16 numbers, in four columns of four. For race, the relevant exposure rate matrices each have nine elements – three individual race categories by three neighborhood racial proportions.

Table 4 shows education exposure rates for the sample (uppermost panel) and the pre-experiment predictions (bottom panel), with Table 5 showing corresponding income exposure rates, and Table 6 showing racial exposure rates. To be clear about how one should read the tables, the top panel of Table 4 shows sample education exposure rates. The top left-most entry, 0.431, indicates that in the sample, the typical household with no more than a high school education is found in a neighborhood (here, a census block group) in which 43.1 percent of households has no more than a high school education. Looking down the first column, the remainder of the typical neighbors that less educated households are exposed to consists of households with some college (22.5 percent), and households with a college degree (34.4 percent). The column entries necessarily sum to one.

The middle panel in the table gives the overall education distribution for the sample for comparison: 33.8 percent of households have at most a high school education, 22.3 percent have some college, and 43.8 percent have a college degree or more. It is clear that there is some degree of education segregation in the Bay Area sample, at least at the top and bottom ends of the education spectrum, with households tending to locate in neighborhoods where more households of their own education level are found, relative to the no-stratification case in which the education composition of all neighborhoods simply equaled the overall sample proportions. Thus, highly educated households are, on average, located in neighborhoods that are 51.8 percent highly educated (i.e. in the top education category), as opposed to 43.8 percent highly educated if there was 'even spreading.' This sample over-exposure comes at the expense of households in the two lower education categories, but especially households in the bottom education category (26.6 percent average exposure in contrast to the overall 33.8 percent). At the same time, it is worth noting that there is far from complete education stratification in the sample. Households in each education category tend to be found in neighborhoods that have reasonably high proportions of households in the other two categories.

A similar general pattern emerges for the sample income exposure rates. Looking at the top panel of Table 5, even income spreading would imply that all cell entries equaled 25 percent. Yet the largest numbers in each column are all found on the main diagonal of the 4-by-4 sample exposure rate matrix. And for households in the top income quartile, for instance, they are on average exposed to 37.2 rather than 25 percent highly educated neighbors; similar own-quartile over-exposure is apparent for households in the bottom quartile.

Turning to race, the top panel of Table 6 shows sample segregation measures for each of the three racial groups. The first column of that panel indicates that the typical white household lives in a neighborhood (census block group) that is 76 percent white, 4 percent black, and just under 20 percent 'other' race. Given that the Bay Area as a whole consists of around 69 percent white households, just under 8 percent black, and around 24 percent other (see the overall proportions in the middle panel), there is clear descriptive evidence of racial segregation on the part of white households: whites are over-exposed to other whites and under-exposed to other racial groups, relative to the case where racial groups were evenly distributed across all neighborhoods. The same is true for blacks, apparent from the second column in the top panel:

the typical black household in the Bay Area is greatly over-exposed to other blacks (by a factor of almost five) relative to even spreading, somewhat over-exposed to the 'other' category, and greatly under-exposed to whites.

It is instructive, from the point of view of gauging model fit, to compare our sample exposure rates on the basis of education, income and race with the equilibrium exposure rates corresponding to a slight perturbation of household tastes. (As noted above, the straight predictions from the choice model, ignoring equilibrium considerations, are for the most part very close to the sample exposure rates.) In the case of education, given in the bottom panel of Table 4, the implied exposure rates exhibit somewhat greater 'own-type' stratification than the sample, especially at the top end. This may reflect the strong education interactions we estimate in the utility function, with highly educated households willing to pay relatively large amounts to live with similar highly educated households. Of note, this over-exposure pattern is *not* apparent for our income quartile exposure rate predictions (see Table 5). That is, the pre-experiment predictions for income are really rather similar to the sample, except at the very bottom end; and further, the predicted income segregation measures exhibit somewhat lower 'own-cell' stratification than the sample itself, rather than higher in the case of education. Comparing the sample to the pre-experiment predictions on the basis of race in Table 6, the own-race exposure rates for blacks and whites are similar, though the predictions are around 10 percent higher than the sample in either case. Conversely, the model somewhat under-predicts exposure of whites to blacks (and vice-versa) relative to the sample. This may be due to the strength of racial interactions that we find in the utility function, leading to compounding effects when computing the pre-experiment equilibria: on this note, the corresponding non-equilibrium predictions of the choice model are closer to the sample for each cell.

We also report sample and predicted *consumption* measures based on the same household categorization – separately for three education categories, four income quartile categories, and three racial groups. The sample consumption measures, for housing (whether owned, and number of rooms) and local amenities (school quality and crime), are computed simply by averaging housing consumption and amenity levels over all households in a given cell, based on education or income quartile. In contrast, the predicted consumption measures use the equilibrium probabilities that spread households over the different choices in the choice set, from which we construct weighted-average consumption measures for households in a given education group or income quartile.

Considering first the sample consumption measures by education (see panel (1) of Table 10), ownership rates and houses sizes are all increasing in the education of the household head, as one might expect. For instance, while households with 'some college' have average ownership rates just over 55 percent, households with a college degree or more have ownership rates over 65 percent. There is a similar positive gradient in terms of school quality (as measured by average test scores), increasing from a score around 505 for the lowest to around 547 for the highest education group. And crime rates decline by about 35 percent on average, moving from the lowest to the most highly educated households.

The sample consumption measures by income quartile, shown in the top panel of Table 11, show a similar pattern, though the gradients tend to be steeper:[25] households in the top quartile have ownership rates of around 85 percent, contrasting sharply with households in the bottom quartile, whose ownership rates are well under half that (just over 37 percent); and house sizes are around 60 percent larger, comparing bottom to top quartile. School quality exhibits a similar positive gradient, and the crime rate declines steeply, by almost 60 percent, moving from the bottom to the top income quartile.

Table 12 reports consumption measures by race, the top panel showing sample measures. This makes clear the striking across-race differences found in practice in the consumption of housing and neighborhood attributes. In terms of housing, ownership rates for whites are over 50 percent higher than for blacks, with 'other' races in the middle; and whites on average live in houses that have 0.8 of an additional room than both blacks and other races. The school quality differences by race are substantial: whites live in neighborhoods with public schools that score an average of 15 percent higher than blacks (8 percent higher than blacks for the other races). And the crime rates faced by blacks are almost three times as high as those faced by whites, and almost twice as high as those for other races.

Comparing sample with the pre-experiment consumption predictions – the top two panels of Table 10 (for education), Table 11 (for income quartiles) and Table 12 (for racial groups) – it is clear that the overall fit is very close indeed. It tends to be especially close for the housing characteristics (ownership rates and number of rooms), reasonably close for test scores, and close for crime if we look at income quartiles. In terms of household education, the predicted crime pattern shows a slight upturn not apparent in the sample, and the predicted consumption profile for school quality is slightly flatter than in the sample; and for race, there is a mild over-prediction of the crime rate faced by whites. Of the choice characteristics we include, neighborhood crime is almost certainly measured with the most error.

[25] Part of this is mechanical, as there are four, not three, categories.

6 COUNTERFACTUAL SIMULATIONS

In this section, we present the main results from a set of counterfactual simulations designed to shed light on the role of preferences for commutes and housing in shaping the extent of neighborhood sociodemographic mixing. We take the pre-experiment exposure rates and consumption measures by education, income and race discussed in the previous section as our benchmarks, then examine the resulting counterfactual changes in segregation and consumption measures by education, income and race associated with each experiment. The goal in each case is to shed light on the relative importance of factors that may in practice contribute to residential mixing, apparent from the size of the changes compared to the benchmark.[26]

Counterfactual Simulations – Commuting

As we noted in the Introduction, employment considerations are abstracted from in the Tiebout model: everyone lives on dividend income. Further, households are assumed to be fully mobile, which can be taken to mean that moving costs are zero (in a dynamic setting), as are commuting costs. In practice, employment considerations play an important role in the residential choice decision, especially given that commuting is costly.

One way of capturing the impact of 'employment geography' on neighborhood stratification within our static framework involves scaling the parameters on commuting distance counterfactually. In our model, we condition on the place of work of the primary worker in the household,[27] and are able to measure distance to work very accurately using the restricted version of the Census. The willingness-to-pay estimates we obtain for commuting distance indicate strong disutility associated with commutes, these estimates including the financial costs of travel in addition to the time and psychic costs, especially in the presence of congestion. And the distaste for long commutes on average is likely to bring households closer to their primary places of work in equilibrium, with possible implications for neighborhood stratification.

To examine these quantitatively, we begin with two experiments that adjust tastes over commuting. In the econometric model, household preferences over commuting distance (the distance between each housing choice and the place of work of the household head) are allowed to vary with observable household characteristics, including their education, income, race, age,

[26] In interpreting the magnitudes of the counterfactual simulation results, a reviewer noted that our abstracting from moving costs will tend to lead us to overstate the full impacts of counterfactual changes. To do full justice to that issue would require the specification and estimation of a dynamic equilibrium model, beyond the scope of the current study.

and family structure. The first experiment takes our taste estimates, which measure heterogeneous disutility of commuting, and reduces them by 50 percent. The second experiment is more extreme, switching off any disutility of commuting entirely. This second experiment is akin to removing geographic considerations from the residential decision process, aside from the pre-existing geographic variation in choice characteristics (including local public goods) across the urban area.[28]

Neighborhood Stratification. We start by examining counterfactual education exposure rates, comparing the predicted stratification from the two commuting experiments (panels (2) and (3) of Table 7) against the pre-experiment benchmark (the top panel of Table 7). It is clear that education stratification increases in both of the counterfactual simulations relative to the pre-experiment case, evident in the increase in the entries on the main diagonals of the second and third panels. For instance, the exposure of households in the top education category ('college degree') to like households increases by around 11 percent when commuting disutilities are cut in half, and by a further 7 percent when they are switched off entirely – the top education category accounts for 43 percent of the sample. There is also a slight tendency for those increases to come more at the expense of the bottom, rather than the middle, education category, consistent with there being increased educational stratification. In terms of the magnitudes of the changes, proportionately larger effects also occur for the bottom education category ('high school or less,' 34 percent of the sample) when moving from the pre-experiment to the counterfactual that cuts commuting disutilities by half, relative to the change between pre-experiment and switching off commuting disutilities entirely. For the middle category ('some college'), which accounts for around a fifth of the sample, the effects are smaller and approximately linear.

Considering counterfactual income exposure rates (see the top three panels of Table 8), there is a similar qualitative pattern: the increases in segregation are larger at the extremes (especially the top) of the distribution and smaller in the middle; and the increased segregation appears to come most at the expense of the income category furthest away. It is interesting to note, though, that the changes in income stratification are more muted – for instance, own-income segregation increasing by 5.4 and 7.6 percent, respectively, relative to the benchmark for households in the top income quartile.

[27] A more general treatment would endogenize choice of workplace, and also firm locations. Doing so is beyond the scope of the current analysis.
[28] Additional counterfactual experiments come to mind. In Bayer *et al.* (2011), for example, we explore the consequences of racial sorting through counterfactual changes in race preferences.

The counterfactual changes in racial exposure rates associated with the two commuting experiments are apparent from the top three panels of Table 9. Again, reducing the disutility of commutes leads to increased segregation, and the effects are non-linear, the larger proportionate increases relative to the baseline coming from the experiment that cuts the disutility of commuting in half, rather than switching it of entirely. Of note, the counterfactual increases in segregation appear to be more marked for blacks than whites. For example, cutting commuting disutilities in half is predicted to raise black exposure to other blacks by over 9 percent, in contrast to the 2.4 percent increase in terms of white exposure to other whites.

Consumption. The consumption patterns are shown in panels (2) – (4) of Tables 10, 11 and 12 for education, income and race measures, respectively. Starting with education, there are essentially no effects on the consumption of housing characteristics across different education categories. For neighborhood attributes, the consumption gradients for crime and school quality become slightly steeper, with consumption of amenities rising slightly for the most highly educated households, falling slightly for the middle education group, and falling proportionately more for the bottom education category. This indicates that more highly educated households find it easier to sort into neighborhoods providing better amenities when commuting costs fall, the reverse being true for the lowest educated (partly because of fixity of supply overall). In terms of income, again the commuting experiments have relatively minor effects on housing consumption (there are very slight increases in housing consumption at the top end, for instance), changes in consumption of school quality are barely perceptible, and there is only a very slight increase in the crime gradient, which again steepens. For race, we see more noticeable changes on the housing consumption side, at least for blacks, whose ownership rates increase slightly along with house size. At the same time, blacks appear to be moving into lower crime neighborhoods when the disutility of commutes falls. There is little impact on the housing consumption of whites, though exposure to crime declines as the disutility of commuting falls. As one might expect, commuting distances do increase overall (results not reported in the tables), by about 50 percent overall relative to the pre-experiment levels when commuting disutilities are halved, and by around 100 percent when they cease to matter at all.

In sum, the two commuting experiments indicate that reducing the importance of commuting in the household location decision results in monotonic but successively smaller increases in stratification on the basis of education, income and race.[29] Commuting distance

[29] Even with the elimination of commuting costs and housing preferences from the model, there are still a number of factors that give rise to heterogeneous preferences that prevent perfect neighborhood

increases across the board, and consumption of local amenities tends to increase for highly educated households and decline for other education groups; the changes when broken down by income are slight, as are the changes on the basis of race. Of note, even if commuting ceased to matter in the utility function at all, our counterfactuals suggest that there would still be a good deal of within-neighborhood mixing on the basis of each of these key sociodemographic characteristics, which is just to say that other factors in the model still serve to bring heterogeneous households together in given neighborhoods. Accordingly, our next experiment looks at the role of housing.

Counterfactual Simulations – Housing

Housing did not play an explicit role in Tiebout's original formulation, though subsequent research (see, for instance, the contributions of Oates and Hamilton) has made good this deficit. Analogous to the heterogeneous preferences over commuting distance, our sorting model interacts observable household characteristics with observed features of the housing stock (including the house price, whether owned, and house size). In our third counterfactual simulation, we switch off these heterogeneous housing preferences entirely. And again, we consider the associated effects on education, income and racial stratification as well as household consumption patterns, disaggregated separately by household education category, income quartile, and race.

Stratification. In terms of stratification, this counterfactual experiment leads to increases in education segregation (see Table 7) that are remarkably similar to the effects of the first commuting experiment (that cut the disutility of commutes in half). This makes clear that the existing distribution of housing serves to integrate households on the basis of education to quite a sizeable degree. In marked contrast, switching off housing preferences leads to *reductions* in income stratification (panel (4) of Table 8), producing reductions in own-quartile income segregation across the board. This shows that the differential affordability of larger housing serves to segregate households on the basis of income: our computations give us a sense of how much by. (At the bottom of the income distribution, for example, own-income segregation is predicted to fall by 3.8 percent: at the top, it is predicted to fall by a full 8 percent.) More

stratification. The model continues to include heterogeneous preferences for neighborhood and housing quality (through the heterogeneous price coefficient), idiosyncratic locational preferences (through the logit error), and heterogeneous preferences for neighborhood attributes and sociodemographic characteristics. Also, as discussed above, we do not adjust crime rates and school quality with changing neighborhood compositions in the simulations, viewing this as a conservative approach to estimating the extent to which generally, it indicates that income and education stratification do not work in an exactly co-linear way.

Turning to racial segregation (see Table 9), there is a general tendency for the experiment to increase own-race segregation, as with the commuting cost experiments. What is noticeable is the heterogeneity in the strength of the segregation effect looking at different races. For whites and 'other' racial groups, the magnitude of the changes is very much in line with those in the first commuting experiment, which halved the disutility of commutes, while for blacks, the segregation effects are altogether much stronger. This clearly indicates that differential preferences for housing attributes by race serve to integrate different racial groups, but especially so for blacks.

Consumption. When we look at the effects of the housing experiment on consumption, switching off housing tastes leads, as one would anticipate, to a partial equalization of housing consumption (see panel (5) of Tables 10, 11, and 12), especially on the basis of income and comparing blacks versus whites. Similarly, there is a narrowing in the consumption of local amenities, with the gaps in the consumption of school quality and crime declining somewhat, especially across income quartiles.

Counterfactual Simulations – Commuting and Housing Combined

As a final experiment, we explore the consequences of switching off commuting preferences and preferences over housing at the same time. In terms of education stratification, the individual experiments are mutually reinforcing, as is apparent from panel (5) of Table 7; the combined experiment gives rise to the highest levels of education segregation relative to the pre-experiment benchmark. Even so, despite the radical nature of the experiment, education stratification is still far from complete: highly educated households still live in neighborhoods that also contain over 16 percent of households, on average, with no more than a high school education; and households in the bottom education category live in neighborhoods with 21 percent of households who are highly educated. A roughly similar pattern is evident in terms of race – see panel (5) in Table 9 – with the combined experiment giving rise to a compounding effect on own-race segregation.

Consistent with the results from the housing experiment, the net effect on income segregation from the combined experiment (see panel (5) of Table 8) looks remarkably like income segregation in the pre-experiment simulations, implying that the two experiments are almost entirely offsetting.

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commuting costs and housing preferences contribute to neighborhood stratification.

7 CONCLUSION

In this paper, we used a counterfactual equilibrium approach to shed new light on factors that may contribute to the widespread sociodemographic mixing observed in US cities. Generally speaking, the approach we use allows us to change the primitives of an econometric sorting model, estimated using rich Census data, and then compute the implied stratification associated with counterfactual equilibria that arise.

Our first simulations explored the role of changing the disutility of commutes on residential mixing counterfactually. The benchmark Tiebout model abstracts from employment considerations, yet commuting to work is often costly and the location of the workplace is typically an important influence on households' choice of residence. Thus counterfactual reductions in the disutility associated with commuting should help gauge how much this factor contributes to observed stratification. We find that as commuting matters less (counterfactually) to households, so residential stratification at the census block level increases markedly, especially on the basis of education and race. This makes clear that in practice, employment geography and non-trivial commuting costs serve to bring heterogeneous households together in the same residential neighborhoods. As has been noted by Oates and Schwab (1988), among others, firm production typically requires complementary labor inputs, combining low and high skill workers and, consistent with our findings, this serves as an integrating force. Never-the-less, even when commuting considerations are switched off entirely, a fairly high degree of residential *mixing* on the basis of education, income and race persists. When we look at the implied consumption of amenities, our results suggest – as is plausible – that as distance to work matters relatively less than other considerations in the household location choice, so stratification on the basis of local public goods consumption increases: highly educated households tend to locate in neighborhoods with better schools and lower crime than in the benchmark pre-experiment equilibrium, while the reverse is true for less-educated households, for example.

Examining the separate contribution of heterogeneous tastes for housing, our findings point to an interesting contrast: while switching off tastes for housing leads to quite marked increases in racial and education stratification, income stratification *declines*, drawing attention to the way the distribution of housing (with larger houses being found in more affluent neighborhoods) serves to segregate households on the basis of income. When housing characteristics cease to matter directly in the household location decision, we see some equalization in the consumption of amenities (in addition to the predictable equalization in housing consumption).

It is worth noting that our static approach takes as given the distribution of employment and the characteristics of housing. In terms of the former, research by Anas (see, for instance, Anas (1982)) has sought to endogenize firm locations, and one could also allow households to make joint residential and employment choices. Both types of extension are technically challenging. Recent research has also sought to endogenized housing supply, Murphy (2011) being an excellent example. Estimable dynamic equilibrium models that incorporate housing and that are amenable to counterfactual analysis are highly appealing; as yet, they remain beyond the frontier of current research.

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Table 1. Sample Statistics Comparing the Full Sample with Houses within 0.20 miles of a Boundary

Sample	**full sample**		**within 0.20 miles of boundaries**				
			boundary sample	**high test score side**	**low test score side**	**difference in means**	**test of difference**
Observations	**242,100**		**27,548**	**13,612**	**13,936**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	S.D.	Mean	Mean	Mean	((4) - (5))	t-statistic
Housing Prices							
House value (if owned)	297,700	178,479	250,005	259,475	240,756	18,719	4.15
Monthly rent (if rented)	744	316	678	688	669	18.80	1.73
School Quality							
Average test score	527	74	507	544	471	74	25.44
Housing Characteristics							
1 if unit owned	0.60	0.49	0.54	0.55	0.53	0.02	0.89
Number of rooms	5.11	1.99	4.96	5.02	4.90	0.12	1.56
1 if built in 1980s	0.14	0.35	0.11	0.11	0.11	0.00	-0.31
1 if built in 1960s or 1970s	0.39	0.49	0.34	0.35	0.33	0.01	0.84
Elevation	210	179	176	178	173	6	1.64
Population density	0.43	0.50	0.39	0.38	0.40	-0.02	-1.38
Neighborhood Sociodemographics							
% Census block group white	0.68	0.23	0.61	0.63	0.60	0.03	3.40
% Census block group black	0.08	0.16	0.18	0.17	0.20	-0.03	-3.15
% Census block group coll deg or more	0.44	0.20	0.41	0.44	0.39	0.05	6.18
Average block group income	54,742	26,075	46,271	47,718	44,857	2,861	2.61

Note: This table reports summary statistics for the key variables included in the analysis. The boundary sample includes all houses located within 0.20 miles of a boundary with another school attendance zone. A house is considered to be on the 'high' ('low') side of a boundary if the test score at its local school is greater (less) than the corresponding test score for the closest house on the opposite side of an attendance zone boundary. Sample statistics are reported for the high- and low-side of boundaries for which the test score gap is in excess of the median gap (38.4 points) in columns (4) and (5), respectively. Column (7) reports the t-statistic for a test of the hypothesis that the mean of the variable listed in the row heading does not vary across school attendance zone boundaries. This test conditions on boundary fixed effects (so as to compare houses on opposite sides of the same boundary) and adjusts for the clustering of observations at the Census block group level.

Table 2: Delta Regressions - Implied Mean Willingness to Pay

Sample	**Within 0.20 Miles of Boundary**	
Observations	**27,458**	
Boundary Fixed Effects	**No**	**Yes**
Number of Rooms	91.7	91.5
	(7.1)	(13.9)
Built in 1980s	92.0	95.4
	(9.8)	(15.1)
Built in 1960s/70s	9.2	7.3
	(3.3)	(2.4)
Owner-occupied	69.1	51.0
	(4.7)	(6.1)
Average Test Score (in standard deviations)	18.0	19.7
	(8.3)	(7.4)
% Neighborhood Black	-404.8	-104.8
	(41.4)	(36.9)
% Neighborhood Hispanic	-88.4	-3.5
	(32.5)	(31.0)
% Neighborhood Asian	-39.7	-5.3
	(30.2)	(32.4)
% Neighborhood College Degree or more	183.5	104.6
	(26.4)	(31.8)
Average Neighborhood Income (/10000)	30.7	36.3
	(3.7)	(6.6)
Distance to Work	-25.6	-52.2
	(0.3)	(0.5)

Note: All regressions shown in the table also include controls for whether house was built in 1960-1979, elevation, population density, crime, land use (% industrial, % residential, % commercial, % open space, % other) in 1, 2 and 3 mile rings around each location. The dependent variable is the monthly user cost of housing, which equals monthly rent for renter-occupied units and a monthly user cost for owner-occupied housing, calculated as described in the text. Standard errors corrected for clustering at the school level are reported in parentheses.

Table 3. Heterogeneity in Marginal Willingness to Pay for Housing and Neighborhood Characteristics

	House Characteristics			**Neighborhood Characteristics**					
	Own vs. Rent	+1 Room	Built in 1980s vs. pre-1960	+10% Black vs. White	+10% Hisp vs. White	+10% Asian vs. White	+10% College Educated	Blk Group Avg Income + $10,000	Average Test Score +1 s.d.
Mean MWTP	51.0	91.5	95.4	-10.5	-0.4	-0.5	10.5	36.3	19.7
	(6.1)	(13.9)	(15.1)	(3.7)	(3.1)	(3.2)	(3.2)	(6.6)	(7.4)
Household Income (+$10,000)	21.7	4.8	9.3	-1.2	0.8	0.1	1.4	0.9	1.4
	(0.7)	(0.2)	(0.8)	(0.4)	(0.4)	(0.3)	(0.2)	(0.1)	(0.3)
Children Under 18 vs.	-13.3	37.5	-26.0	11.9	17.2	12.6	-16.1	2.4	7.4
No Children	(7.0)	(1.8)	(8.5)	(3.0)	(3.3)	(2.7)	(2.2)	(1.2)	(3.6)
Black vs. White	-67.7	3.8	5.4	98.3	46.7	48.3	18.4	-1.2	-14.3
	(13.0)	(3.5)	(17.4)	(3.9)	(5.6)	(5.1)	(4.5)	(2.2)	(7.4)
Hispanic vs. White	-8.2	-14.5	-6.3	30.9	85.6	18.0	6.3	1.1	-4.1
	(10.1)	(2.7)	(12.2)	(3.9)	(4.0)	(4.2)	(3.4)	(1.4)	(6.0)
Asian vs. White	113.5	-22.1	43.9	28.1	22.3	95.2	0.4	0.7	7.0
	(9.6)	(2.2)	(11.3)	(3.8)	(4.4)	(3.5)	(2.6)	(1.5)	(5.5)
College Degree or More vs.	37.6	-0.6	40.2	9.2	-4.6	-13.4	58.0	0.3	13.0
Some College or Less	(8.1)	(2.2)	(9.7)	(3.1)	(3.9)	(3.0)	(2.3)	(1.4)	(3.6)

Note: The first row of the table reports the mean marginal willingness-to-pay for the change reported in the column heading. The remaining rows report the difference in willingness to pay associated with the change listed in the row heading, holding all other factors equal. The full heterogeneous choice model includes 135 interactions between nine household characteristics and fifteen housing and neighborhood characteristics. The included household characteristics are household income, the presence of children under 18, and the race/ethnicity (Asian, black, Hispanic, white), educational attainment (some college, college degree or more), work status, and age of the household head. The housing and neighborhood characteristics are the monthly user cost of housing, distance to work, average test score, whether the house is owner-occupied, number of rooms, year built (1980s, 1960-1979, pre-1960), elevation, population density, crime, and the racial composition (% Asian, % black, % Hispanic, % white) and average education (% college degree) and household income for the corresponding Census block group. Standard errors are reported in parentheses.

Table 4: Education Exposure Rates - Sample and Pre-Experiment

Sample Exposure Rates

	Household Education Level		
	≤ High school	Some college	≥ College degree
Neighborhood percent ≤ High school	0.431	0.341	0.266
Neighborhood percent with Some college	0.225	0.235	0.216
Neighborhood percent ≥ College degree	0.344	0.424	0.518
Total	1.000	1.000	1.000

Sample Education Distribution

Household Education Level		
≤ High school	Some college	≥ College degree
0.338	0.223	0.438

Pre-experiment Simulation Exposure Rates

	Household Education Level		
	≤ High school	Some college	≥ College degree
Neighborhood percent ≤ High school	0.449	0.367	0.238
Neighborhood percent with Some college	0.243	0.245	0.198
Neighborhood percent ≥ College degree	0.308	0.388	0.564
Total	1.000	1.000	1.000

Notes:

Each column gives the average exposure of households whose type is given by the relevant column heading to neighbors in the row category.

Neighborhoods are defined at the block group level.

Table 5: Income Exposure Rates - Sample and Pre-experiment

Sample Exposure Rates

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Neighborhood percent Income Quartile 1	0.351	0.271	0.218	0.164
Neighborhood percent Income Quartile 2	0.268	0.271	0.250	0.206
Neighborhood percent Income Quartile 3	0.217	0.252	0.273	0.258
Neighborhood percent Income Quartile 4	0.163	0.207	0.258	0.372
	1.000	1.000	1.000	1.000

Pre-experiment Simulation Exposure Rates

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Neighborhood percent Income Quartile 1	0.319	0.278	0.239	0.169
Neighborhood percent Income Quartile 2	0.275	0.265	0.249	0.206
Neighborhood percent Income Quartile 3	0.238	0.250	0.257	0.256
Neighborhood percent Income Quartile 4	0.168	0.207	0.255	0.369
	1.000	1.000	1.000	1.000

Notes

Each column gives the average exposure of households whose type is given by the relevant column heading to neighbors in the row category.

Neighborhoods are defined at the block group level.

Table 6: Race Exposure Rates - Sample and Pre-Experiment

Sample Exposure Rates

	Household Race		
	White	Black	Other
Neighborhood percent White	0.760	0.377	0.571
Neighborhood percent Black	0.042	0.384	0.076
Neighborhood percent Other	0.198	0.239	0.353
Total	1.000	1.000	1.000

Sample Race Distribution

Household Race		
White	Black	Other
0.686	0.076	0.238

Pre-experiment Simulation Exposure Rates

	Household Race		
	White	Black	Other
Neighborhood percent White	0.847	0.290	0.349
Neighborhood percent Black	0.032	0.421	0.092
Neighborhood percent Other	0.121	0.289	0.559
Total	1.000	1.000	1.000

Notes:
"Household race" is taken to be the race of the householder.
The three race categories are defined to be exclusive and exhaustive.
Each column gives the average exposure of households whose type is given by the relevant column heading to neighbors in the row category.
Neighborhoods are defined at the block group level.

Table 7: Education Exposure Rates - Simulation Results

(1) Pre-experiment

	Household Education Level		
	≤ High school	Some college	≥ College degree
Neighborhood percent ≤ High school	0.449	0.367	0.238
Neighborhood percent with Some college	0.243	0.245	0.198
Neighborhood percent ≥ College degree	0.308	0.388	0.564

(2) Counterfactual: ***cut disutility of commutes in half***

	Household Education Level		
	≤ High school	Some college	≥ College degree
Neighborhood percent ≤ High school	0.485	0.392	0.197
Neighborhood percent with Some college	0.259	0.259	0.178
Neighborhood percent ≥ College degree	0.256	0.349	0.624

(3) Counterfactual: ***switch off disutility of commutes***

	Household Education Level		
	≤ High school	Some college	≥ College degree
Neighborhood percent ≤ High school	0.503	0.410	0.174
Neighborhood percent with Some college	0.271	0.273	0.161
Neighborhood percent ≥ College degree	0.226	0.316	0.664

(4) Counterfactual: ***switch off housing preferences***

	Household Education Level		
	≤ High school	Some college	≥ College degree
Neighborhood percent ≤ High school	0.478	0.396	0.202
Neighborhood percent with Some college	0.261	0.261	0.175
Neighborhood percent ≥ College degree	0.261	0.344	0.623

(5) Counterfactual: ***switch off disutility of commutes and housing preferences***

	Household Education Level		
	≤ High school	Some college	≥ College degree
Neighborhood percent ≤ High school	0.507	0.428	0.162
Neighborhood percent with Some college	0.282	0.288	0.145
Neighborhood percent ≥ College degree	0.210	0.285	0.693

Notes:

Each column gives the average exposure of households whose type is given by the relevant column heading to neighbors in the row category.

All the columns sum to 1.

Neighborhoods are defined at the block group level.

Table 8: Income Exposure Rates - Simulation results

(1) Pre-experiment

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Neighborhood percent Income Quartile 1	0.319	0.278	0.239	0.169
Neighborhood percent Income Quartile 2	0.275	0.265	0.249	0.206
Neighborhood percent Income Quartile 3	0.238	0.250	0.257	0.256
Neighborhood percent Income Quartile 4	0.168	0.207	0.255	0.369

(2) Counterfactual: ***cut disutility of commutes in half***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Neighborhood percent Income Quartile 1	0.326	0.281	0.238	0.159
Neighborhood percent Income Quartile 2	0.278	0.268	0.250	0.199
Neighborhood percent Income Quartile 3	0.237	0.251	0.260	0.253
Neighborhood percent Income Quartile 4	0.158	0.199	0.253	0.389

(3) Counterfactual: ***switch off disutility of commutes***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Neighborhood percent Income Quartile 1	0.332	0.282	0.237	0.154
Neighborhood percent Income Quartile 2	0.279	0.269	0.250	0.196
Neighborhood percent Income Quartile 3	0.236	0.252	0.261	0.253
Neighborhood percent Income Quartile 4	0.153	0.197	0.252	0.397

(4) Counterfactual: ***switch off housing preferences***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Neighborhood percent Income Quartile 1	0.306	0.270	0.242	0.187
Neighborhood percent Income Quartile 2	0.267	0.259	0.249	0.220
Neighborhood percent Income Quartile 3	0.241	0.250	0.256	0.254
Neighborhood percent Income Quartile 4	0.186	0.220	0.254	0.339

(5) Counterfactual: ***switch off disutility of commutes and housing preferences***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Neighborhood percent Income Quartile 1	0.314	0.274	0.242	0.175
Neighborhood percent Income Quartile 2	0.271	0.263	0.251	0.211
Neighborhood percent Income Quartile 3	0.241	0.252	0.257	0.251
Neighborhood percent Income Quartile 4	0.174	0.211	0.250	0.364

Notes

Each column gives the average exposure of households whose type is given by the relevant column heading to neighbors in the row category.

All the columns sum to 1.

Neighborhoods are defined at the block group level.

Table 9: Race Exposure Rates - Simulation Results

(1) Pre-experiment

	Household Race		
	White	Black	Other
Neighborhood percent White	0.847	0.290	0.349
Neighborhood percent Black	0.032	0.421	0.092
Neighborhood percent Other	0.121	0.289	0.559

(2) Counterfactual: ***cut disutility of commutes in half***

	Household Race		
	White	Black	Other
Neighborhood percent White	0.868	0.263	0.299
Neighborhood percent Black	0.029	0.460	0.088
Neighborhood percent Other	0.103	0.277	0.613

(3) Counterfactual: ***switch off disutility of commutes***

	Household Race		
	White	Black	Other
Neighborhood percent White	0.882	0.243	0.263
Neighborhood percent Black	0.027	0.464	0.093
Neighborhood percent Other	0.091	0.293	0.644

(4) Counterfactual: ***switch off housing preferences***

	Household Race		
	White	Black	Other
Neighborhood percent White	0.870	0.253	0.296
Neighborhood percent Black	0.028	0.482	0.084
Neighborhood percent Other	0.103	0.265	0.620

(5) Counterfactual: ***switch off disutility of commutes and housing preferences***

	Household Race		
	White	Black	Other
Neighborhood percent White	0.902	0.208	0.217
Neighborhood percent Black	0.023	0.526	0.084
Neighborhood percent Other	0.075	0.266	0.699

Notes:
Each column gives the average exposure of households whose type is given by the relevant column heading to neighbors in the row category.
All the columns sum to 1.
Neighborhoods are defined at the block group level.

Table 10: Consumption Rates by Education Category

(1) Sample

	Household Education Level		
	≤ High school	Some college	≥ College degree
ownership rate	0.549	0.555	0.655
number of rooms	4.7	5.0	5.5
school test score	504.7	525.5	546.8
crime rate	10.4	7.5	6.8

Simulation results:

(2) Pre-experiment

	Household Education Level		
	≤ High school	Some college	≥ College degree
ownership rate	0.547	0.561	0.653
number of rooms	4.73	5.10	5.42
school test score	508.54	529.60	541.77
crime rate	9.75	7.16	7.50

(3) Counterfactual: ***cut disutility of commutes in half***

	Household Education Level		
	≤ High school	Some college	≥ College degree
ownership rate	0.552	0.562	0.649
number of rooms	4.70	5.08	5.45
school test score	504.79	527.94	545.42
crime rate	10.96	7.44	6.42

(4) Counterfactual: ***switch off disutility of commutes***

	Household Education Level		
	≤ High school	Some college	≥ College degree
ownership rate	0.550	0.564	0.650
number of rooms	4.69	5.09	5.45
school test score	504.41	527.74	545.92
crime rate	11.49	7.65	5.89

(5) Counterfactual: ***switch off housing preferences***

	Household Education Level		
	≤ High school	Some college	≥ College degree
ownership rate	0.579	0.616	0.601
number of rooms	4.91	5.21	5.23
school test score	510.89	529.91	539.84
crime rate	9.38	6.97	7.86

(6) Counterfactual: ***switch off disutility of commutes and housing preferences***

	Household Education Level		
	≤ High school	Some college	≥ College degree
ownership rate	0.534	0.604	0.642
number of rooms	4.70	5.14	5.42
school test score	505.73	527.56	544.96
crime rate	11.10	7.43	6.33

Note: Table gives average consumption levels of the row characteristic for households in the column heading category.

Table 11: Consumption Rates by Income Quartile

(1) Sample

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
ownership rate	0.373	0.499	0.671	0.847
number of rooms	3.9	4.6	5.4	6.5
school test score	504.2	518.5	530.0	558.6
crime rate	12.4	8.6	6.7	5.0

Simulation results
(2) Pre-experiment

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
ownership rate	0.420	0.491	0.625	0.852
number of rooms	4.21	4.62	5.24	6.38
school test score	506.43	518.09	530.09	556.69
crime rate	11.52	9.09	7.19	4.93

(3) Counterfactual: ***cut disutility of commutes in half***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
ownership rate	0.416	0.485	0.625	0.862
number of rooms	4.18	4.59	5.24	6.45
school test score	505.32	517.29	529.91	558.63
crime rate	12.09	9.14	7.05	4.45

(4) Counterfactual: ***switch off disutility of commutes***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
ownership rate	0.410	0.483	0.627	0.867
number of rooms	4.16	4.59	5.24	6.48
school test score	505.08	517.57	530.23	558.45
crime rate	12.39	9.12	6.92	4.29

(5) Counterfactual: ***switch off housing preferences***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
ownership rate	0.539	0.568	0.603	0.679
number of rooms	4.72	4.91	5.15	5.68
school test score	508.86	519.99	530.15	552.37
crime rate	10.56	8.66	7.44	6.04

(6) Counterfactual: ***switch off disutility of commutes and housing preferences***

	Household Income			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
ownership rate	0.510	0.559	0.604	0.716
number of rooms	4.57	4.85	5.15	5.88
school test score	506.59	518.52	529.62	556.53
crime rate	11.59	8.77	7.23	5.16

Note: Table gives average consumption levels of the row characteristic for households in the column heading category.

Table 12: Consumption Rates by Racial Group

(1) Sample

	Household Race		
	White	Black	Other
ownership rate	0.639	0.402	0.539
number of rooms	5.37	4.57	4.55
school test score	541.5	466.3	507.9
crime rate	6.16	17.96	10.92

Simulation results:
(2) Pre-experiment

	Household Race		
	White	Black	Other
ownership rate	0.636	0.388	0.552
number of rooms	5.33	4.45	4.69
school test score	538.60	473.99	513.81
crime rate	6.80	17.71	9.14

(3) Counterfactual: ***cut disutility of commutes in half***

	Household Race		
	White	Black	Other
ownership rate	0.627	0.424	0.565
number of rooms	5.32	4.57	4.68
school test score	540.70	468.46	509.34
crime rate	6.40	17.19	10.47

(4) Counterfactual: ***switch off disutility of commutes***

	Household Race		
	White	Black	Other
ownership rate	0.624	0.424	0.574
number of rooms	5.31	4.55	4.72
school test score	541.75	467.07	506.93
crime rate	6.42	16.95	10.48

(5) Counterfactual: ***switch off housing preferences***

	Household Race		
	White	Black	Other
ownership rate	0.590	0.570	0.626
number of rooms	5.10	4.86	5.24
school test score	536.59	467.68	521.68
crime rate	7.05	16.75	8.70

(6) Counterfactual: ***switch off disutility of commutes <u>and</u> housing preferences***

	Household Race		
	≤ High school	Some college	≥ College degree
ownership rate	0.604	0.548	0.592
number of rooms	5.18	4.74	5.06
school test score	540.73	463.20	511.05
crime rate	6.48	17.72	10.10

Note: Table gives average consumption levels of the row characteristic for households in the column heading category.