Choices or Constraints? Disentangling Preferences from Restrictions in Housing Markets*

Milena Almagro — Chicago Booth & NBER

Aradhya Sood — University of Toronto

April 2, 2026

Abstract

How much of the observed house price differentials and household sorting is due to restrictions in choice sets, arising from *implicit* and *explicit* forms of discrimination, versus household preferences? To answer this question, we build a two-sided housing matching model that combines admission rules with traditional discrete choice models, allowing for heterogeneous choice sets across demographic groups. Additionally, we construct a novel dataset that links households and real-estate developments to the historic street grid of the 1940 Minneapolis metro area. Using an instrumental variable approach, we find that *explicit* discriminatory restrictions in neighborhoods reduce the likelihood of non-White and White Eastern and Southern European immigrant households by 10 and 2.8 percentage points, respectively. We also show that traditional discrete-choice models of neighborhood demand with misspecified choice sets can yield biased estimates of preferences for neighborhood characteristics, especially when there is selection in the characteristics of neighborhoods restricted to a subset of residents. Our two-sided housing matching model jointly estimates heterogeneous choice sets and preference parameters, revealing that different demographic groups faced substantially different choice sets. On average, minority households are 8 percentage points less likely to have a neighborhood in their choice set than non-minority households, even after controlling for *explicit* forms of discrimination and rents. Simulating a counterfactual scenario without these restrictions and preferences for co-patrons, we find that household preferences account for three-quarters of the observed segregation in 1940.

*Authors are listed in alphabetical order. All co-authors contributed equally. We thank the Mapping Prejudice team, and in particular Michael Corey, Kirsten Delegard, Kevin Ehrman-Solberg, and Penny Petersen, for sharing their covenants data and insights as well as the Urban Transition Historical GIS Project and John R. Logan for sharing their 1940 street grid for Minneapolis. We thank Dan Aaronson, Jason Abaluck, Nikhil Agarwal, Abi Adams-Prassl, Sara Bagagli, Pat Bayer, Giovanni Compiani, Mike Dinerstein, James Feigenbaum, Ed Glaeser, Rick Hornbeck, Samuel Myers Jr., Paulo Somaini, Dan Waldinger, Laura Weiwu, and seminar participants at the AREUEA National Meetings, AREUEA Virtual Seminar, Federal Reserve Banks of Chicago and Minneapolis, Junior Spatial Economics Conference at Sciences Po, NYU IO day, Midwest IO Conference, NBER SI (Urban), NBER IO of Housing Markets Conference (Stanford), OSUS, Russell Sage Foundation Emerging Scholars Conference, Southern Economic Association, UoT/UBC/UQAM Canadian Real Estate Conference, UQAM, and Urban Economics Association Conference for their helpful discussions and comments. This research is supported by the Russell Sage Foundation and Gates Foundation. Ben Couillard, Ben Fraser, Nanxi Fu, Jason Hong, Sarah Ji, Xiaofeng Liu, Jonathan Potter, Sriram Tolety, and Elias van Emmerick provided excellent research assistance. Emails: milena.almagro@chicagobooth.edu and aradhya.sood@rotman.utoronto.ca.

1. Introduction

In urban markets, non-price rationing is common. There is explicit rationing of affordable housing (Waldinger, 2021), landlords screen prospective tenants (Christensen and Timmins, 2023; Gold et al., 2025), and homebuyers experience both real estate broker steering and sellers' selectivity and preferences (Christensen and Timmins, 2022). An empirical challenge arises because we typically observe only finalized choices in the data, not the choice sets households face when making their residential decisions. If a household doesn't live somewhere, did they not want to, or was it not available? The literature mostly assumes the issue away or, in rare cases, explicitly observes the choice sets (Berry et al., 2004; Conlon and Mortimer, 2013). In this paper, we study restrictions on households' choice sets for two primary reasons. First, from a methodological perspective, existing models assume away supply-side restrictions, failing to account for the reality that certain neighborhoods are unavailable to some population subgroups, leading to biased estimates and welfare calculations (Christensen and Timmins, 2023). Second, a significant yet unanswered question in urban and spatial economics is how making a portion of housing units off-limits to certain population subgroups affects prices, location choices, and overall welfare. In this paper, we address this question in a historical context, considering how both household preferences and restrictions on household choice sets—whether *implicit* or policy-driven, *explicit* discrimination—affect the observed prices, sorting of households, and welfare across space.

Specifically, we examine how much restrictions on neighborhood choice sets versus households' preferences contribute to price differentials and shape the spatial sorting of households in the 1940 Minneapolis metro area. To achieve this, we construct a novel dataset that links households from the 1940 individual-count US census data and real-estate developments (neighborhoods) in the 1940 Minneapolis metro area to the street grid of that time. To our knowledge, this is the first dataset compiled at the development-household level in a historical context. Additionally, we can link data on the *explicit* instrument of housing discrimination, namely, racial covenants. These covenants, added to property deeds, explicitly prohibited certain racial and ethnic minorities from residing in covenanted homes and served as the primary *explicit* tool of housing discrimination in urban and suburban neighborhoods in the early to mid-20th century in the US.

The historical setting of the Minneapolis metro area is particularly useful for our analysis. First, during this period, the city experienced rapid urban expansion driven by real estate developers converting farmland into suburban developments with standardized housing and clearly defined boundaries. As a result, neighborhood access was determined at the development level rather than by individual sellers, providing a clean setting to study supply-side restrictions in the housing market. Secondly, racial covenants played a dual role: while non-minority households may have preferred living in areas with such restrictions, these covenants simultaneously limited residential options for minority households. This dual role also highlights the importance of distinguishing between preferences and restrictions when examining how choice-set restrictions arising from either discrimination or neighborhood design policies influence spatial sorting and inequality. This is relevant not only in a historical context but also in relation to current debates about zoning regulations, as, for example, single-family zoning not only reflects household preferences but can also raise housing prices, making neighborhoods less accessible to other households.

We start by providing empirical evidence that a subset of the city's population—minority households—faced restrictions on their neighborhood choices. We do this by using an *explicit* source of choice set restrictions: racial covenants. To account for the non-random placement of these covenants, we developed an urbanization frontier index to instrument for racial covenants, measuring land available for housing development at the metro area's frontier in 1940. The relevance condition primarily relies on the correlation between the outward expansion of development in the metro area into virgin and agricultural land and the rise in developers adding racial covenants to new real estate developments over time. Consequently, developments closer to the urbanized frontier of the metro area were more likely to include racial covenants in 1940 than those located nearer to the city center. The exclusion restriction relies on the idea that, conditional on building along the frontier, the precise location of development was as good as random. In this setting, where farmland was being converted into urban areas, land available for development often arose from farm turnover and the completion of projects driven by idiosyncratic financial shocks to developers. Using this instrumental variable approach, we find that living in a fully covenanted neighborhood decreases the likelihood of a non-White household by 10 percentage points. Additionally, we show that the impact of these covenants extended to White ethnic minorities. Specifically, living in a fully covenanted neighborhood reduced the probability of a White Eastern and Southern European immigrant household living there by 2.8 percentage points. These results highlight how *explicit* discrimination affected household sorting in 1940, restricting neighborhood choices for both non-White and White ethnic households, which we collectively refer to as minority households.

Next, we demonstrate the importance of accounting for restrictions on choice sets in residential choice models, both theoretically and through Monte Carlo simulations. Using a simplified discrete-choice model, we show that assuming all households consider every option—common in housing models—can lead to biased preference estimates if some households face restricted choices. Our theoretical findings indicate that this bias correlates with differences between the unobserved or *latent choice set* characteristics and those in the complete neighborhood set. If restricted neighborhoods exhibit lower (or higher) values for a certain characteristic than the full set of neighborhoods, then the model that ignores these restrictions will produce downward (or upward) biased estimates. Intuitively, if a researcher wrongly assumes that all households can choose from all neighborhoods, but in reality some households only consider options with lower (or higher) values for a given feature, the estimates will wrongly show that households sort more negatively (positively) on this characteristic than under their true preferences. Monte Carlo simulations reveal that the gap between true and estimated parameters widens as the proportion of restricted neighborhoods for minority households increases.

To account for the role of choice set restrictions in discrete choice models, we propose a two-sided matching housing market model that allows for differences in neighborhood choice sets across demographic groups, following the literature on selective admissions and latent choice sets (Goeree, 2008; Gandhi, 2019; Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2025). Our two-sided matching housing market model accounts for observable discrimination, such as that from racial covenants, as well as *implicit* restrictions limiting the choices available to minority groups, which are often harder to quantify. Concretely, to incorporate differences across latent choice sets, we model real-estate developers who have preferences for the households they "accept" into their neighborhood, according to an admission rule. This admission rule depends on the household's race or ethnicity and captures the likelihood of a neighborhood being included in different demographic groups' choice sets. These admission preferences, in turn, generate differences in the household's latent choice sets, which are explicitly linked to race or ethnicity. On the demand side, heterogeneous households from different demographic groups choose their most preferred neighborhood from the set of neighborhoods to which they are admitted. These choices depend on the household's preferences over rents, the neighborhood's demographic composition, and other neighborhood and location characteristics.

We estimate our model parameters following Goolsbee and Petrin (2004) and Bayer et al. (2007), which allow for heterogeneous preferences across different demographic groups. Specifically, we categorize households into two demographic groups: *minority* and *non-minority*, based on our reduced-form results. We further extend their approach to allow for the estimation of latent choice sets.

To estimate our model parameters, we face two types of identification challenges. First, to separately identify the parameters of the admission rules from household preferences, we follow Goeree (2008); Agarwal and Somaini (2025) and use an excluded shifter that affects the formation of choice sets but does not enter the household's utility. Specifically, we assume that racial covenants influence which neighborhoods are available to households but do not affect utility directly, once we control for rents and the neighborhood's demographic composition. Intuitively, we treat racial covenants as a means to control neighborhood demographics rather than as a feature that directly affects household utility. Second, we face several endogeneity concerns when estimating preferences, as house rents and demographic composition within a neighborhood are equilibrium outcomes and can thus be functions of unobservable demand shocks. To address these endogeneity concerns, we construct two instruments: one based on steep land slopes that affect construction costs and, therefore, house rents (Saiz, 2010); and another using a shift-share migration instrument to instrument for the share of minorities within a neighborhood

(Card, 2001; Tabellini, 2020).

Our results indicate that minority households faced substantial restrictions in choice sets and those restrictions increased with the presence of covenants. By contrast, we observe that covenanted neighborhoods favored the admission of non-minority households. Moreover, our admission rule estimates also show that non-minority households were less likely to be admitted in more expensive neighborhoods, although we do not see that rents play a role in admission for minority households. We interpret these results as capturing potential financial constraints for non-minority households. Finally, after controlling for the role of rents and covenants, minorities were 8 percentage points less likely to have the option of living in the average neighborhood, capturing other implicit forms of discrimination against minorities common to all neighborhoods.

On the demand side, we find that minority households are more sensitive to rents compared with non-minority households. Our demand estimates also show negative preferences for living with minority households and a strong homophily bias for non-minorities. Notably, when we estimate a model that ignores differences in neighborhood choice sets across demographic groups, we find that the rent coefficient for non-minority households is roughly 11.7% larger compared to our two-sided matching model, overstating the role that household preferences play in the observed equilibrium.

We develop two equilibrium counterfactual scenarios that remove the mechanisms generating the observed rent differentials and segregation: namely, choice set restrictions from the supply-side and distaste for minority households. In both simulations, rents adjust to clear the housing market which has an inelastic housing supply.[1] In the first scenario, we eliminate supply-side neighborhood choice set restrictions for both minority and non-minority households. The relaxation of these constraints increases demand, leading to higher rents. Despite the rent increase, the metro-wide minority population rises by 2 percentage points, reflecting that the original restrictions disproportionately limited their mobility. Segregation, as measured by the dissimilarity index (Cutler et al., 1999), falls by 16%.

[1]This is not a full spatial equilibrium counterfactual with endogenous demographic composition. Imposing such an equilibrium condition may amplify the role of preferences, as preferences over neighborhood demographics function like an agglomeration force.

In the second scenario, we remove households' distaste for living with minorities in addition to the restrictions in choice sets. Because households prefer to live with non-minorities, this leads to an increase in average neighborhood utility and a further upward shift in demand, driving rents even higher. Unlike the first scenario, the minority population declines slightly, as higher rents push some minority households out of the metro area. Nonetheless, segregation falls dramatically by 71%. These findings suggest that preferences over neighborhood demographic composition play a larger role in sustaining segregation than do choice set restrictions. Removing the latter accounts for only about one-fourth of the total reduction in segregation observed in 1940, compared to when both mechanisms are shut down.

Literature review: Our paper contributes to the literature on screening and restricted choice sets in discrete choice models, neighborhood segregation, and the role of policy instruments in shaping the distribution of households across space in several ways. .

First, non-price rationing and screening are widespread yet largely unexamined in choice models, particularly within urban and spatial economics (Waldinger, 2021; Christensen and Timmins, 2022, 2023). Our model and the estimation of the two-sided matching model of the housing market closely relate to the recent advances in estimating preference parameters amid unobserved choice set heterogeneity, primarily discussed in industrial organization literature (Goeree, 2008; Conlon and Mortimer, 2013; Gaynor et al., 2016; Gandhi, 2019; Ouazad and Rancière, 2019; Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2025).[2] In contrast to previous studies in urban and spatial literature that typically assume unrestricted choice sets, our approach estimates latent choice sets within the housing market context. Understanding of these restrictions is essential for determining the extent to which observed price differences and residential sorting stem from these constraints, rather than from preferences for homophily or housing prices. Additionally, while existing literature on latent choice sets, which primarily originates in the industrial organization literature (Conlon and Mortimer, 2013; Gandhi, 2019; Agarwal and Somaini, 2025), does not model endogenous characteristics. In contrast, our counterfactuals incorporate how equilibrium prices may respond to these restrictions as well as the role of

[2]See Crawford et al. (2021) for an extensive survey on this topic.

endogenous neighborhood amenities, specifically focusing on the share of minority households in a neighborhood, which is crucial in a spatial context (Diamond, 2016; Almagro and Domínguez-Iino, 2025).

Second, we contribute to the residential choice literature by distinguishing between preferences and choice set restrictions in driving household sorting. Understanding the causes of segregation is vital for addressing economic and policy-related questions, such as children's outcomes, upward mobility, and consumption inequality between public and private goods (Collins and Margo, 2000; Durlauf, 2004; Chetty et al., 2016; Chyn and Katz, 2021; Trounstine, 2018; Couture et al., 2024). While much of the existing research often attributes racial and ethnic segregation to preferences for cohabitation among similar races or neighborhood design policies (Fischel, 2002; Bayer et al., 2007; Caetano and Maheshri, 2021; Bayer et al., 2022), recent studies reveal that discrimination—both *explicit* and *implicit*—as well as financial or informational barriers significantly influence neighborhood sorting (Aaronson et al., 2021; Christensen and Timmins, 2022; Bergman et al., 2024; Sood and Ehrman-Solberg, 2026). A key challenge in this literature is disentangling the effects of choice set limitations from household preferences, both of which affect segregation. This paper explores the extent to which restrictions in neighborhood choice sets versus household preferences shape equilibrium outcomes such as the spatial distribution of households and prices.[3]

Third, our paper contributes to a substantial body of literature on how policy design influences spatial sorting and housing price differentials. While much literature focuses on localized treatment effects using regression discontinuity methods (Myers Jr, 1995; Shertzer et al., 2016; Rothstein, 2017; Trounstine, 2018; Fishback et al., 2020; Aaronson et al., 2021; Song, 2021; Hynsjö and Perdoni, 2022; Sood and Ehrman-Solberg, 2026), our study examines the impact across the entire metro area, allowing us to assess the aggregate effects of factors contributing to sorting and price differentials across space. Two exceptions are Bagagli (2023) and Weiwu (2023), who study segregation resulting from the US Interstate

[3]Related work by Li (2023) employs a differentiation approach to examine choice set restrictions, assuming no selection in their formation. In contrast, we model and estimate admission rules in which a household's demographics and neighborhood characteristics influence its acceptance probability within a neighborhood, thereby establishing a link between these characteristics and admission likelihood.

Highway System in a spatial equilibrium model. We advance this literature by explicitly incorporating restrictions in choice sets that differ across demographic groups using our novel data and a two-sided matching model. In doing so, we not only quantify the role of *explicit* discrimination policy instruments via racial covenants, but also that of other forms of *implicit* restrictions, which are more difficult to measure and are captured by differences in admission rules across demographic groups. Additionally, policy design literature often overstates the impact of design policies on observed equilibrium outcomes, neglecting the significant role of preferences. Therefore, it's crucial to examine both preferences and restrictions together.

2. Background, Data, and Empirical Evidence

Our focus on the 1940 Minneapolis metro area is based on two key reasons. This period was characterized by rapid urban expansion, during which developers, rather than individual sellers, often admitted households into neighborhoods. This allows us to construct housing restrictions for entire neighborhoods that will later shape choice sets. Additionally, 1940 marked the peak use of racial covenants, providing a measure of *explicit* restrictions, in addition to the implicit restrictions on households' choices.

2.1 Historical Background on Housing Restrictions

In 1940, various subgroups within populations faced both implicit and explicit restrictions in the housing market, which restricted their choices of neighborhoods. Implicit restrictions could take the form of uncoordinated actions by developers, real estate agents, and house sellers, which likely steered households away from certain neighborhoods (Massey, 1990; Rothstein, 2017; Christensen and Timmins, 2022). There were also instances of collective group action, such as threats of violence (Albright et al., 2021), that made some developments unwelcoming to racial and ethnic minorities during that time.

In addition to the implicit restrictions, the first half of the 20th century in the US also saw explicit restrictions in housing markets through racial covenants, which were used to limit the presence of minority households and shape neighborhood demographics. These private agreements, between real estate developers, homeowners, and neighbors, prohibited racial, ethnic, and religious minorities from living in certain areas across urban and suburban America (see Appendix Figure F.1). In US metro areas that were largely urbanizing during the first half of the twentieth century, including the Minneapolis metro area, developers added almost all racial covenants at the subdivision stage of new developments and widely advertised the presence of racial covenants in their developments (see Appendix Figure F.2 for an example of such an advertisement). The enforcement of these covenants depended on "injured parties" (usually neighbors) suing those who violated them, along with real estate agents and developers discouraging minorities from moving into covenanted neighborhoods.[4]

Four key historical events established racial covenants as a primary tool for neighborhood design in the US during the early 20th century making them increasingly popular over time. First, the 1917 *Buchanan v. Warley* US Supreme Court ruling prohibited racially segregated neighborhoods through zoning, making private racial covenants more appealing. Second, the National Association of Real Estate Boards amended its charter in 1924 to promote the use of these covenants. Third, the Supreme Court reaffirmed their legal enforceability in the 1926 *Corrigan v. Buckley* case, leading to widespread adoption. Finally, the 1938 Federal Housing Administration's underwriting manual favored mortgages linked with racial covenants. However, the 1948 *Shelley v. Kraemer* ruling declared these covenants unenforceable, effectively ending the use of racial covenants to design segregated neighborhoods.

2.2 Data

We combine data on historic real estate developments, the historical street grid, racial covenants, the 1940 US individual count decennial census, and housing characteristics with other geographic data, which allows us to map households and racial covenants to the real estate developments and geography of the 1940 Minneapolis metro area.

In our study, we define neighborhoods as real estate developments. During our study period of significant urban expansion, developers typically constructed a group of similar houses within their projects and decided whether to include covenants in property deeds. The size of these developments varied, with some having as few as 4 units (in the 25th percentile) and others as many as 48 (in the 75th percentile), with an average of 52.2

[4]See Sood and Ehrman-Solberg (2026) for a list of court cases related to racial covenants in the US.

units per development. On average, a development comprises 13.8% of the area of an enumeration district (ED), which is comparable to modern census tracts, with about 8.4 developments per ED (see Appendix Table A.3). Thus, defining neighborhoods at the development level provides the most relevant unit of choice for both household location demand decisions as well as admission rules. More detailed information about how we construct our dataset can be found in Appendix A.

Data on Historic Real-Estate Developments: Data on historic developments that have survived is available from the Hennepin County Assessor's Office in Minnesota, where the Minneapolis metro area is located. However, relying solely on available data for existing developments ignores those that were demolished or altered between 1940 and the present, leaving some 1940 households in the sample unmatched to any development. To address this issue, we gather information from historical city atlases for the municipalities of Minneapolis (1940), St. Louis Park (1939), Edina (1940), Richfield (1941), Hopkins (1954), and Robbinsdale (1941). These atlases contain to-scale maps of each development within these municipalities (see Figure F.3 for an example page). We then digitize and geocode the historical atlases to create a geo-located map of each missing development from the 1940s. There are a total of 3,158 developments in the Minneapolis metro area in 1940.

Historic Street Grids and Boundaries: Linking households, developments, and covenants to the present-day street grid results in fewer than 41% successful matches. This low match rate is largely due to changes in the historic street grid over the past 80 years, driven by highway construction and new residential and non-residential developments. To overcome this problem, we digitize and geocode the 1940 street grids for Minneapolis and five neighboring suburban municipalities—St. Louis Park, Edina, Richfield, Hopkins, and Robbinsdale — using city atlases and the Sanborn Insurance maps from around 1940. Together, these six municipalities form a contiguous part of the Minneapolis metro area and represent approximately 93% of Hennepin County's 1940 population. Additionally, we geocode and digitize the 1940 ED boundaries for Hennepin County.

Data on Racial Covenants: The data on racial covenants comes from the Mapping Prejudice Project, which provides a complete census of all covenanted sales deeds and development maps in Hennepin County. We combine data from sales deeds and development maps to determine the share of real estate development that was covenanted. In addition to the location of 24,642 racial covenants, Mapping Prejudice also provides information on the date of covenant execution.[5]

Individual-Count US Census Data: We use the individual count data from the 1940 US decennial census for the six municipalities in the Minneapolis metro area in our sample. The data include information on an individual's address, enumeration district, race, country of birth (to determine ethnicity), occupation, marital and ownership status, number of household members, and head of household. Since we conduct our analysis at the household-development level, we assume that the race and ethnicity of the head of household represents the entire household. We believe this assumption is reasonable, given that endogamy (marriage within the same race or ethnicity) was common in 1940. We also confirm this trend using the individual count data.[6] There are 164,674 households in the six Minneapolis metro area municipalities in 1940.

From this data, we also obtain the household's tenure status—owner-occupied, renter-occupied, or group quarters. We observe monthly rental prices and housing values for renter-occupied and owner-occupied households, respectively; however, no housing price data are available for households in group quarters. To enable a comparison between rents and housing values, we impute the monthly rental value of owner-occupied housing using the methodology following Katz (2017). The imputed rental value of owner-occupied housing, combined with rental price data, yields the mean monthly rental value for 98.2% of the developments in our sample.[7]

Data on Housing Characteristics: We use lot size to measure housing quality and build year to assess the newness of a development. For extant houses, we obtain lot sizes from the county's assessor's office. For historical developments or destroyed houses, we refer to scaled city atlases, which provide detailed information on lot shape and size (see Figure F.3). For 5 developments lacking lot size data, we impute the missing values using the mean log lot size from their respective EDs. Build years are also sourced from the county

[5]Mapping Prejudice Project analyzed roughly three million pages of sales deeds and development maps in Hennepin County, covering the period 1900-1960. Five people double-checked the existence and date of the covenant execution for each deed and map, limiting the scope of error in data collection.

[6]99.8% of households in our sample marry within their own race or ethnicity.

[7]See Appendix Section A.2 and Appendix Figure A.1 for details on this imputation process.

assessor for the extant houses to date. For 1,079 developments with missing build years and 19,185 households, we impute missing years with the mean build year of their ED . If that is also missing, we use the municipality's mean build year.

Other Geographic Data: We digitize an 1899 map of Hennepin County to highlight wetlands and semi-submerged areas, enabling us to assess the underlying land quality in the region's lake geography. Additionally, we obtain slope data from the Natural Resources Conservation Service's comprehensive survey of Hennepin County conducted in 1953. We also digitize a 1940 map highlighting the locations of heavy and light industries zoned areas, as well as commercial zoned areas in the city of Minneapolis. Last, we digitize the 1913 streetcar map of the Minneapolis metro area. See Appendix Table A.3 for summary statistics at the household, development, and enumeration district level.

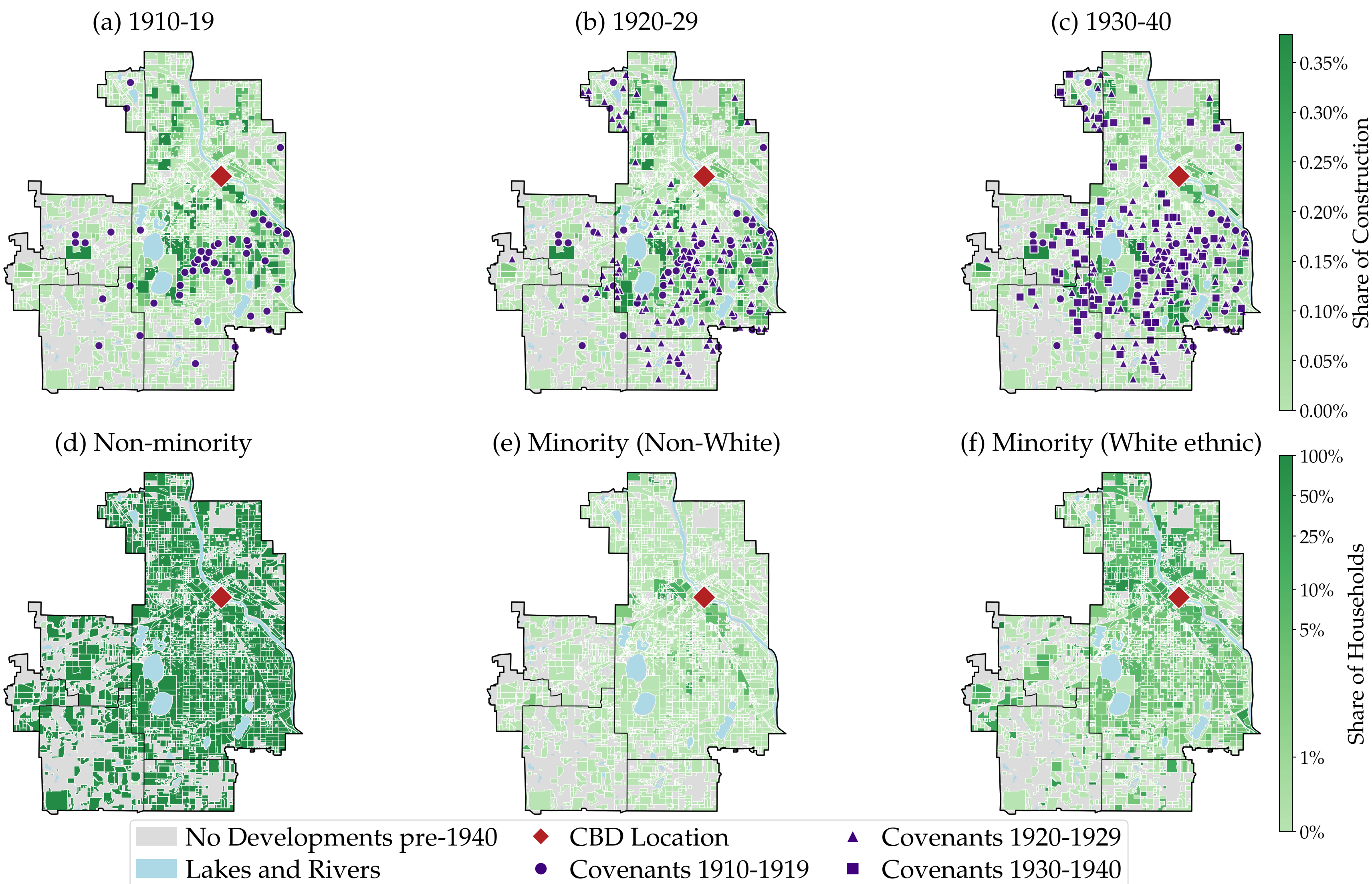
2.3 Construction of Household-Development Level Dataset

For our analysis, we need to link households, racial covenants, and other geographic data to geolocated developments in 1940. In the 1940 census, we have complete addresses for 75.1% of households. For the 24.9% of households with incomplete addresses, we impute missing street names and house numbers based on the enumeration order, as enumerators collected the census data on the same side of the street in order (Logan and Parman, 2017). Since this order is preserved in the census, we are largely able to impute missing house numbers and street names (see Appendix Table A.2), giving us complete addresses for 96.1% of the 1940 households in the Minneapolis metro area. We match these households with complete addresses to the geolocated historical developments. For the remaining 3.9% of households with missing addresses, we randomly assign these unmatched households across developments within their respective EDs.[8] Additionally, we link racial covenants and other geographic data to the historical developments. Further details on the geo-linking across datasets used to construct the final household-development dataset can be found in Appendix A.

Figure 1 a)–c) plot the distribution of new housing construction by development in three different periods–1910-19, 1920-29, 1930-40. The percentage of new construction within a

[8] In Section 2.4, we show that our findings are not determined by the random placement of these 3.9% of households.

Figure 1: Expansion of Housing Construction and Racial Covenants over Time



Note: This figure plots the percentage of a decade's overall housing construction which took place in each development in green. The purple circles, triangles, and squares indicate where a racial covenant is present in a development from the 1910s, 1920s, and 1930s respectively. The city boundary of Minneapolis, St. Louis Park, Edina, Robbinsdale, Richfield, and Hopkins is marked in black. Grey areas represent developments with no housing construction by 1940. The red diamond is the location of the central business district (CBD). Lakes and rivers are marked in blue.

development by decade is color-coded in green. As the figure shows, the construction is expanding radially outwards over time from the central business district (CBD), indicated by the red diamond. Additionally, the figure shows the introduction of racial covenants by decade, represented in purple. As demonstrated, the use of racial covenants began to spread continuously after 1910, the year when the first racial covenant was established, with a notable increase after 1930.

2.4 Empirical Evidence on Neighborhood Choice Set Restrictions

This section presents empirical evidence on how racial covenants influenced the racial and ethnic composition of the Minneapolis metropolitan housing market in 1940. These results play several roles in our analysis.

First, we interpret them as suggestive evidence that households belonging to certain racial or ethnic groups faced restrictions in the set of neighborhoods available to them. Second, we show that the groups affected by these restrictions included not only non-White households but also many "White" ethnic minorities, such as immigrants from Eastern and Southern Europe. This distinction allows us to classify households into minority and non-minority groups based on their racial and ethnic background, which we use to estimate heterogeneity in structural parameters across groups.

Finally, these findings motivate our structural analysis, as reduced-form evidence alone cannot disentangle households' direct preferences for neighborhood characteristics from the constraints imposed by factors such as racial covenants, prices, or other implicit restrictions on the set of neighborhoods available to minority households.

2.4.1 Reduced-Form Model

To study the effects of racial covenants on neighborhood demographics, we estimate the following model, where i indicates a household and j indicates a development in 1940:

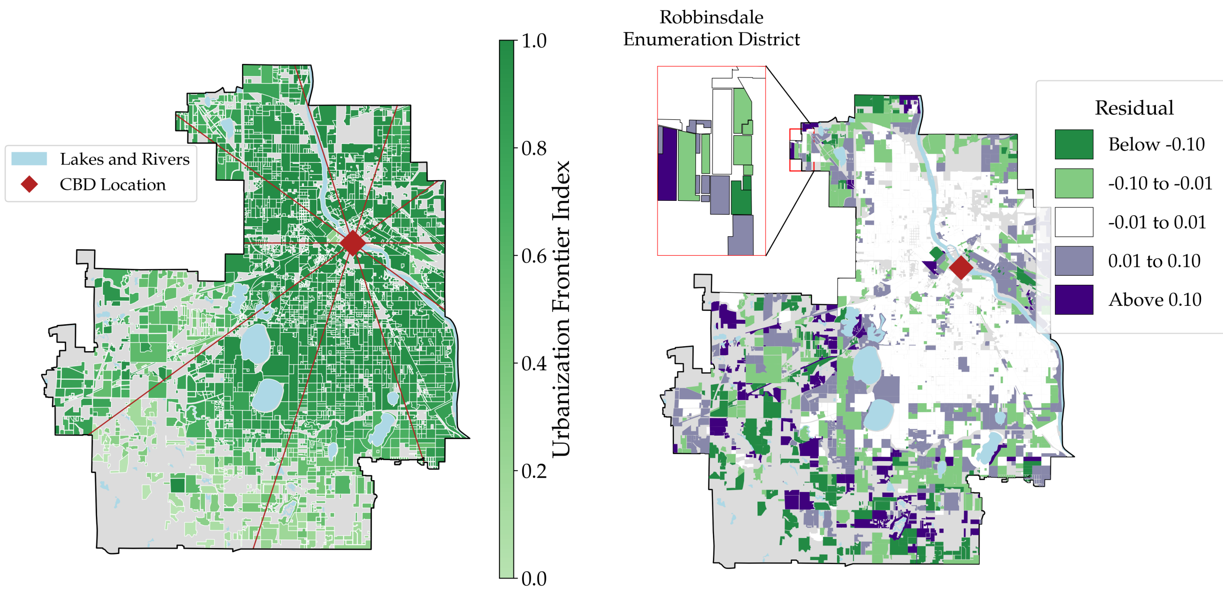
$$y_{ij} = \beta_0 + \beta_1 \text{Cov-Share}_{j(i)} + \beta_2 X_j + \eta_k(i) + \epsilon_{ij} \tag{1}$$

In this model, y is an indicator for a household's race or ethnicity in development j. $\text{Cov-Share}_{j(i)}$ is the share of the development j that had racial covenants.[9] X_j represents

[9] As illustrated in Appendix Figure B.2, usually, developments either have no covenants—of which there are many—or all houses within a development have covenants. However, there are a few developments

development level quality variables including the mean log of lot size, mean build year, the proportion with wetlands and the log of distance to each of a heavy industry zoned area, a commercially zoned area, the nearest lake, the streetcar, and the metro area's CBD.[10] $\eta_k(i)$ indicates the enumeration district k fixed effects within which household i is located.

Figure 2: Urbanization Frontier Index and Residual Patterns



Note: The left panel displays the urbanization frontier index across the ten radian sectors of 36° radiating from the central business district (CBD), which is displayed with a red diamond. The right panel shows the residuals from regressing the urbanization frontier index on the set of controls from Equation 2 and enumeration district (ED) fixed effects. To highlight the spatial variation, we provide a zoomed-in image of an ED in Robbinsdale.

Given that the decision to add covenants is strategic, it is important to account for the non-random placement of racial covenants across space. Moreover, Sood and Ehrman-Solberg (2026) show that racial covenants were more prevalent in lower-middle and middle-income neighborhoods, serving as a marginal dissuasive factor in areas more likely to undergo demographic transitions in the future. While we control for enumeration district fixed effects, the placement of covenants may still be correlated with unobservable factors even within an enumeration district. To address this concern, we construct an instrument for the share of covenanted development.

that fall within the 1% to 99% range for covenant share. This variation is why the key independent variable is a share rather than a binary indicator.

[10]Racial covenant clauses may be correlated with unobserved other types of covenants or housing characteristics. Thus, controlling for the lot size helps control for building quality, while controlling for the building year controls for the development's "newness."

To construct the instrument, we note three key facts: First, there is a clear radial outward expansion of new development away from the CBD, as shown in Figure 1 a-c. Second, racial covenants gained popularity nationwide between 1910 and 1940, as discussed in Section 2.1. Third, 94% of the racial covenants were added by developers on new housing and developments. Together, these imply that developments closer to the metro area's urbanizing frontier, or further from the CBD, were more likely to include racial covenants. Therefore, our instrument leverages the notion that developers between 1930 and 1940 were both likely to build along the 1930 urban frontier and also more inclined to use racial covenants.

We construct the instrument using the share of built-up area from previous periods in neighboring developments nearer to the city center. This instrument, *urbanization frontier index* denoted as f_j, captures the direction and momentum of urban expansion. To construct the index in 1940, we first divide the city from the CBD into r radian sectors of equal size. Within a sector r, we define $f_j \equiv \frac{\text{Built}_{r,1930}(z_j)}{\text{Lots}_{r,1930}(z_j)}$, where $\text{Built}_{r,1930}(z_j)$ is the number of houses built by 1930, and $\text{Lots}_{r,1930}(z_j)$ is the total number of buildable lots by 1930 within a given buffer zone z_j. Our preferred specification uses $r = 10$ and a buffer size of $z_j = 1000$ meters. Note that f_j ranges from 0 to 1. Figure 2 (left panel) plots the urbanization frontier index as well as the radian sectors for all developments in the Minneapolis metro area for 1940, where the pre-period is 1930.[11]

The relevance condition is based on the radial outward expansion of construction seen in Figure 1. As racial covenants became more widespread in the first half of the 20th century, our hypothesis posits that areas closer to this 1930 urbanized frontier were more likely to include them. In other words, our frontier index is a predictor of new housing construction during times when racial covenants are popular. Importantly, because we control for build year, the instrument does not simply capture new construction; rather, it predicts construction occurs during a decade when racial covenants were at the height of their popularity.

The exclusion restriction requires that, conditional on enumeration district fixed effects and development and location controls, the share of land developed by 1930 was as

[11] The ten-year interval (1930-40) allows for sufficient time for housing construction to occur.

good as random. In this context, both land availability as well as idiosyncratic changes in the fortunes of developers and builders who had purchased land from farmers and other landowners provide the underlying source of quasi-random variation.[12] To see the variation that our identification strategy is capturing, we plot the residuals from regressing the urbanization frontier index instrument, f_j, on development and location controls as well as enumeration district fixed effects. Figure 2 (right panel) plots the residuals for all developments, providing a closer view of the variation within a specific ED in Robbinsdale. As can be seen from the figure, there is random variation across developments, even within an ED. This variation shows that, conditional on the segment of the urban frontier, the exact location of real-estate development was random.

The first stage is given by the following model:

$$\text{Cov-Share}_{j(i)} = \alpha_0 + \alpha_1 f_j + \alpha_2 X_j + \eta_{k(i)} + \varepsilon_{j(i)}. \tag{2}$$

Observe that the instrument exploits temporal variation in the addition of covenants and ensures that development demographic differences within an enumeration district operate only through the addition of racial covenants at the frontier of the new development.

2.4.2 Reduced-Form Results

Table 1 reports the parameter estimates α_1 and β_1 from Equations 2 and 1 with Panels B and C showing OLS and instrumental variable (IV 2SLS) estimates, respectively. The first-stage estimates in Panel A indicate that the instrument functions as intended; as the urbanized built-up area increases, the likelihood of adding covenants in development j also rises. Specifically, moving from the minimum to the maximum value of the urbanization index (0 to 1) is associated with a 16.4 percentage point increase in the share of the development being covenanted. The first-stage F-Stat is 89.9.

In a fully covenanted development, an increase in $\text{Cov-Share}_{j(i)}$ from 0 to 1 results in a 10 percentage point decrease in the probability of a non-White household (column 2,

[12] Until the mid-1910s, the Minneapolis metro area concentrated commercial and residential development near the CBD. However, as the milling district declined in the early 1920s, development shifted outward (Danbom, 2003). This period was also difficult for U.S. farmers, who faced rising debt and falling commodity prices following World War I, leading to financial distress and farmland sales (Irwin, 2017). Using survey data from the 1960s and 1970s in neighboring Olmsted County, Minnesota, Pyle (1985) finds that the most common reason for farm sales for housing development was idiosyncratic personal shocks related to health and finances.

Panel C).[13] This finding holds true after controlling for development characteristics, such as build year and lot size, as well as ED fixed effects that capture broader neighborhood factors like racial and immigrant concentration, housing quality, and local amenities at the ED level.

In 1940, the groups of households facing discrimination were not only racial minorities but also certain White ethnic groups. In his 1933 book, real estate economist Homer Hoyt ranked ethnicities (Hoyt, 2000), categorizing them from "most favorable" to "least favorable" (see Figure B.1). Based on Hoyt's classification, we divide White households born outside the US into ointo four groups: Northern Europe (including Canada, Australia, and New Zealand) and Western Europe were deemed "more favorable", while Eastern and Southern Europe, along with others (White immigrant households from all other regions), were considered "less favorable" (see Appendix B for details).

Our analysis shows that fully covenanted developments increased the likelihood of Western European White households by 4.8 percentage points (column 4, Panel C), indicating they were preferred residents and faced no discrimination. We did not find any statistically significant effects for White households from Northern Europe. In contrast, covenants reduced the likelihood of Eastern and Southern European households by 2.8 percentage points (column 5, Panel C), highlighting that these covenants were a tool for discrimination not only against racial minorities but also against specific White ethnic groups during the early-to-mid 20th century.

The IV estimates (Panel C) are larger in absolute terms than the OLS estimates (Panel B), which may reflect two sources of bias in the OLS estimates. First, unobserved neighborhood characteristics may be positively correlated with both the adoption of covenants and the presence of households that did not face neighborhood restrictions, biasing the OLS coefficients toward zero. Second, endogenous residential sorting may also attenuate the OLS estimates if households with stronger preferences for segregated neighborhoods disproportionately select neighborhoods more likely to adopt covenants, even if those neighborhoods ultimately did not adopt these covenants.

[13] Non-White households include Black, Asian, and Native American households, as defined by the census, regardless of their country of birth.

Table 1: Racial Covenants and Sorting in the Housing Market

	First Stage	Non-White	White Northern European Imm.	White Western European Imm.	White Eastern & Southern European Imm.	White Other Imm.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First Stage						
Urbanization Index	0.164***					
	(0.017)					
Panel B: OLS						
Share Covenanted		−0.006***	0.022*	−0.002	−0.001	−0.012**
		(0.001)	(0.011)	(0.002)	(0.001)	(0.005)
Panel C: IV 2SLS						
Share Covenanted		−0.100***	−0.051	0.048**	−0.028**	−0.004
		(0.034)	(0.149)	(0.023)	(0.013)	(0.083)
Location controls	✓	✓	✓	✓	✓	✓
ED FEs	✓	✓	✓	✓	✓	✓
Mean log lot size	✓	✓	✓	✓	✓	✓
Mean build year	✓	✓	✓	✓	✓	✓
Observations	164,673	164,673	164,673	164,673	164,673	164,673
Mean dependent variable	0.012	0.010	0.151	0.005	0.003	0.064
First-Stage F-Stat	89.9	89.9	89.9	89.9	89.9	89.9

Note: This table plot the first stage, OLS, and instrumental variable (IV 2SLS) parameter estimates from Equations 1 and 2. Non-White refers to households identified as Black, Asian, or Native American, regardless of their country of birth. White Northern European, Western European, Eastern and Southern European, and Other Immigrants (Imm.) denotes households identified as White and birthplace in these regions. Refer to Appendix B to see which countries are in each of these four categories. Panel A reports the first-stage parameter estimate of the urbanization frontier index (instrument) on share covenanted, where share covenanted is the fraction of lots in a development with racial covenants. Panels B and C show the OLS and IV 2SLS parameter estimates, respectively. Robust standard errors in parentheses. Location controls include log slope, wetlands share, and log distances to the central business district, heavy-industry zoning, commercial zoning, the nearest lake, and the streetcar. ED FEs are enumeration-district (ED) fixed effects. Mean log lot size and build year control for the development-level means of these variables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Robustness: The baseline results in Table 1 use radian sectors of $r = 10$, $z_j = 1000$ meters, and the number of houses built by 1930 as a measure of the 1940 urbanization index. These findings remain robust when considering a longer time period (houses built by 1910; Appendix Table B.1, Panel A) and a varying buffer zone that decreases as the distance from the CBD increases ($z_j = 500 - 2000$ meters; see Appendix Table B.1, Panel B). There is also a concern that our findings might be influenced by the Home Owners' Loan Corporation (HOLC) redlining (Aaronson et al., 2021). However, we believe this is unlikely because the covenants predate HOLC, and HOLC only covered parts of Minneapolis, not the entire metro area. To ensure that HOLC redlining does not affect our results, we control for the share of D-graded areas in developments, and the baseline results remain unchanged (Appendix Table B.1, Panel C). Furthermore, there may be a concern that our results are driven by the 3.89% of households we could not match to specific developments. When we make alternative assumptions about matching these households to different developments, the estimated results remain consistent with the baseline findings (see Appendix Table B.1, Panel D). Finally, in the baseline analysis, we do not control for household characteristics because they could be endogenously correlated with racial covenants. However, controlling for the head of household's occupation, ownership status (owner, renter, or living in group quarters), marital status, or the number of total and working members in the household, does not alter the baseline effects of covenants on racial and ethnic sorting (see Appendix Table B.1, Panel E).[14]

2.4.3 Taking Stock

Taking stock, the reduced-form evidence indicates that racial covenants had a first-order effect on the sorting of households, negatively affecting non-White households as well as some White ethnic households. However, like prices and other neighborhood design policies such as zoning, racial covenants can shape observed sorting patterns through multiple channels: by restricting households' choice sets—either explicitly, as with covenants, or implicitly—and/or by influencing household preferences. In addition, such restrictions can affect equilibrium prices, which in turn shape sorting when demographic groups differ in their price sensitivity. A reduced-form approach cannot disentangle these mechanisms, a limitation we address by building, estimating, and conducting counterfactual analyses using a two-sided matching model in Section 3.

[14]We do not control for housing prices or rents in our reduced-form specifications because these prices are themselves influenced by racial covenants and neighborhood composition making them an endogenous control; controlling for them could introduce bias. Additionally, since census only collected income data from a 5% sample, we use the occupation indicator as a proxy for household income and wealth. For further details, see Appendix B.1.

Based on the results from Table 1, we define minority households as non-White households, regardless of the birthplace, along with White households from Eastern and Southern Europe, and those from "other" countries. All remaining households are labeled non-minority. Using this classification, minority households accounted for 7.61% of households in the Minneapolis metro area in 1940. Figure 1 d-f plot the share of non-minority, non-White, and White ethnic households in developments across the metro area.[15]

3. Model

3.1 Ignoring Restrictions on Choice Sets

We first show how ignoring restrictions on the household's neighborhood choice sets can bias household preference estimates. To do so, we rely on a simplified economy where minority or non-minority households face restrictions in their choice sets and can only choose to live in a restricted set of neighborhoods.

We start by proving a general result that holds under mild assumptions and helps us quantify the sign of the bias of a mis-specified residential choice model. Concretely, consider the following model:

$$V_j^{k,i} = \beta^k X_j + \epsilon_j^i$$

where $V_j^{k,i}$, is the utility of household i of demographic type $k \in \{m, nm\}$, which stands for minority and non-minority, respectively, living in neighborhood j. Utility depends on neighborhood j's characteristics X_j such as average rent, share of covenants, or house size, and an idiosyncratic component that is drawn from Type-I extreme value distribution ϵ_j^i. Each household chooses the neighborhood that gives her the highest positive utility. We denote $\mathcal{J}$ as the set of all possible neighborhoods. We denote the choice set of type-k households (the latent choice set) as $\mathcal{J}_0^k$. $\mathcal{J}_1^k$ is the set of restricted neighborhoods that are not available to type k groups, so $\mathcal{J} = \mathcal{J}_0^k \cup \mathcal{J}_1^k \; \forall k$.

We use maximum likelihood (MLE) to estimate β^k. If the choice set of the type k group is correctly specified, given our distributional assumption on idiosyncratic shocks, the

[15] Appendix Figure B.3 plots the distribution of minority shares across developments.

probability of choosing neighborhood j is:

$$\mathbb{P}_j^k(\beta^k) = \frac{\exp(\beta^k X_j)}{\sum_{l \in \mathcal{J}_0^k} \exp(\beta^k X_l)}.$$

The log-likelihood of the type k group is given by:

$$L^k(\beta^k) = \sum_{j \in \mathcal{J}_0^k} N_j^k \log \mathbb{P}_j^k(\beta^k),$$

where N_j^k is the number of type k households living in the j neighborhood in the data. Denote $\hat{\beta}^k \equiv \arg\max L^k(\beta)$ as the solution of the correctly specified choice set.

On the other hand, if the econometrician wrongly assumes that the choice set for type k households is given by $\mathcal{J}$ instead of $\mathcal{J}_0^k$, the choice probabilities are given by:

$$\tilde{\mathbb{P}}_j^k(\beta^k) = \frac{\exp(\beta^k X_j)}{\sum_{l \in \mathcal{J}} \exp(\beta^k X_l)}.$$

In the case where the choice set is wrongly given by $\mathcal{J}$, the log-likelihood is given by:

$$\tilde{L}^k(\beta^k) = \sum_{j \in \mathcal{J}} N_j^k \log \tilde{\mathbb{P}}_j(\beta^k) = \sum_{j \in \mathcal{J}_0^k} N_j^k \log \tilde{\mathbb{P}}_j(\beta^k),$$

where the second equality follows as the empirical $N_j^k = 0$ for all $j \in \mathcal{J}_1^k$. Denote $\tilde{\beta}^k \equiv \arg\max \tilde{L}^k(\beta)$ as the solution of the problem with the mis-specified choice set.

Next, we assume differences in neighborhood characteristics X_j across choice sets. We assume that neighborhoods that are not in the choice set of type k, $\mathcal{J}_1^k$, have larger X_j, on average. For example, house size can be larger in neighborhoods belonging to $\mathcal{J}_1^k$.

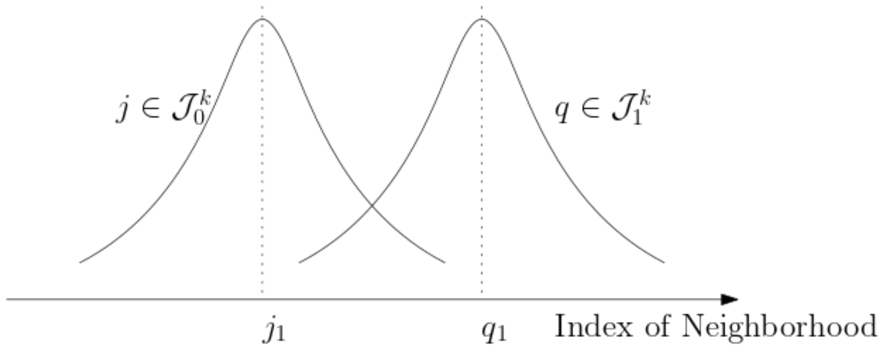
Assumption 1. *Neighborhoods in the choice set for type-k household have smaller X_j, on average:*

$$\frac{1}{N_0^k} \sum_{j \in \mathcal{J}_0^k} X_j \leq \frac{1}{N_1^k} \sum_{j \in \mathcal{J}_1^k} X_j,$$

where N_0^k and N_1^k are the number of type k households in $\mathcal{J}_0^k$ and $\mathcal{J}_1^k$, respectively.

We allow for the range of the conditional X_j distributions to have a non-empty inter-

Figure 3: Overlapping Neighborhood Characteristics X_j Distributions



Note: This figure plots the conditional distributions for neighborhood characteristics X_j for the neighborhoods in the latent choice set, $\mathcal{J}_0^k$, and the set of restricted neighborhoods that are not available to demographic type k, $\mathcal{J}_1^k$. $[j_1, q_1]$ denote the interval where the range of the X_j distributions for $\mathcal{J}_0^k$ and $\mathcal{J}_1^k$ intersect.

section, namely that they do not have a disjoint support, but this overlap cannot be too large (see Figure 3). Concretely, let's denote $[j_1, q_1]$ the interval where the range of the X_j distributions for $\mathcal{J}_0^k$ and $\mathcal{J}_1^k$ intersect. Namely, $X_j \leq X_{q_1}, \forall j \in \mathcal{J}_0^k$ and $X_{j'} \geq X_{j_1}, \forall j' \in \mathcal{J}_1^k$. We assume that the mass of households in the restricted choice set $\mathcal{J}_1^k$ inside $[j_1, q_1]$ is smaller than the mass of households in the set $\mathcal{J}_0^k$ inside $[j_1, q_1]$:

Assumption 2. *Let $N_0^{k,s}$ and $N_1^{k,s}$ denote the number of observations of the distribution of X_j inside the range $[j_1, q_1]$, conditional on choice sets $\mathcal{J}_0^k$ and $\mathcal{J}_1^k$, respectively. We assume that $\frac{N_0^{k,s}}{N_0^k} \geq \frac{N_1^{k,s}}{N_1^k}$.*

Denote the minimum and maximum values of X_j in the constrained choice set $\mathcal{J}_1^k$ as X_q^{min} and X_q^{max}, respectively. Denote the minimum and maximum values of X_j in the latent choice set $\mathcal{J}_0^k$ as X_j^{min} and X_j^{max}, respectively. Define $\underline{\beta}^k \equiv \frac{\log \frac{N_0^{k,s}}{N_0^k} \frac{N_1^k}{N_1^{k,s}}}{\log \frac{X_{q_1}}{X_q^{min}} \frac{X_j^{max}}{X_j^{min}}}$, $\overline{\beta}^k \equiv \frac{\log \frac{N_0^{k,s}}{N_0^k} \frac{N_1^k}{N_1^{k,s}}}{\log \frac{X_q^{min}}{X_q^{max}} \frac{X_j^{min}}{X_{j_1}}}$. It is easy to see that under assumption 2, $\underline{\beta}^k < 0$ and $\overline{\beta}^k > 0$.

Theorem 1. *For $\beta \in (\underline{\beta}^k, \overline{\beta}^k)$, under assumptions 1 and 2, $\tilde{\beta}^k < \hat{\beta}^k$. In other words, with misspecified choice sets, the MLE estimate of demand sensitivity to the neighborhood characteristics for the type k group has a downward bias.*

Proof. See proof in Appendix C.1.1. □

The intuition for the result above is straightforward. If the econometrician wrongly assumes that type-k households can choose from all neighborhoods but only observes choices from a restricted choice set whose conditional mean of the observable characteristic is lower, the MLE estimator will wrongly infer that type k households dislike neighborhoods with higher X_j more than they actually do, hence, producing an estimate of β that is downward biased. We also obtain the opposite result if we instead assume that neighborhoods in the choice set of type-k household have *higher* X_j:

Theorem 2. *Assume that houses in the choice set for type k have higher X_j, on average:*

$$\frac{1}{N_0^k}\sum_{j\in\mathcal{J}_0^k} X_j \geq \frac{1}{N_1^k}\sum_{j\in\mathcal{J}_1^k} X_j,$$

and that the mass of the overlap between distributions is not too large:

$$\frac{N_0^{k,s}}{N_0^k} \leq \frac{N_1^{k,s}}{N_1^k}.$$

Then, for $\beta \in (\underline{\beta}^k, \overline{\beta}^k)$, it follows that $\tilde{\beta}^k > \hat{\beta}^k$. In other words, under mis-specified choice sets, the MLE estimate of the demand sensitivity to the neighborhood characteristics for the type k group has an upward bias.

3.1.1 Monte Carlo Simulations

We can also quantify how the size of the bias in the mis-specified model increases as the share of neighborhoods that are restricted to the type k households within the metro area increases. To do so, we rely on Monte Carlo simulations designed as follows. First, we simulate a residential choice model with type k group that has preferences for housing characteristics. In the neighborhoods that are accessible to type k households, we simulate that the housing characteristic X_j is 50% lower, on average. For each data draw, we estimate coefficients for type k households for a mis-specified model with an unrestricted choice set as well as a correctly specified model with the correct choice set. Appendix Figure C.1 plots the distribution of estimates for type-k households. When the true value of β^k is 0.46, the unrestricted model estimates are lower than the true value, i.e., the mis-specified unrestricted model delivers estimates with a downward bias, which will in turn imply that type-k households have a lower willingness-to-pay for characteristic X_j than they actually do. Additionally, note that the difference between the true and estimated β^k increases as we increase the share of restricted neighborhoods for type-k households.[16]

3.2 A Two-Sided Matching Model of the Housing Market

Having established the importance of correctly specifying choice-sets, we now proceed to present a two-sided matching model with selective admissions of households into neighborhoods. Households in our model belong to different demographic types, namely, minorities and non-minorities, with heterogeneous preferences for neighborhood characteristics across types. To model real estate developments' admission rules, we follow a reduced form model based on the demographics of the household as well as development characteristics that determines which household is admitted into a development. Importantly, we assume that this admission rule is a function of household's race or ethnicity. This model of selective admissions introduces variation, and thus, restriction in the neighborhoods that can be accessed by different demographic groups. The household demand model for neighborhoods also allows for heterogeneous preferences for neighborhood characteristics across types.

3.2.1 Demand Model

Households, indexed by i, belong to two types k: minorities m and non-minorities nm. In what follows, we fix the non-minority group as our baseline group and denote with indicator $m(i)$ if i belongs to the minority group. The indirect utility for household i from residing in development j is given by:[17]

$$U_{ij} = (\beta^{nm} + \beta^{m}\mathbb{1}\{k(i) = m\})X_j^d + \xi_j + \epsilon_{ij} \quad (3)$$

$$= \delta_j + \beta^{m(i)}X_j^d + \epsilon_{ij}, \quad (4)$$

[16] Crawford et al. (2021) perform a similar simulation exercise.

[17] This model requires the definition of a baseline group. If not, observe that the combination;

$$\tilde{\delta}_j = \delta_j + cX_j, \qquad \tilde{\beta}^{nm} = \beta^{nm} + c, \qquad \tilde{\beta}^{m} = \beta^{m} + c,$$

gives observationally equivalent outcomes.

where X_j^d are observable characteristics of development j that enter the demand function, ξ_j are unobservable demand shocks, $\beta^{m(i)} = \beta^m \mathbb{1}\{k(i) = m\}$, and $\delta_j = \beta^{nm} X_j^d + \xi_j$. In other words, δ_j represents the average utility of the non-minority group and β^m are the deviations in preferences of the minority group relative to the non-minority group. The characteristics of development j that enter demand, X_j^d, include development monthly rent p_j, the share of minority households m_j, indicating that households can have preferences on the racial and ethnic makeup of their neighbors, the share of home ownership,[18] as well as the distance to the CBD, heavy industry zoned area, commercial area, and the nearest streetcar and lake. ϵ_{ij} is an idiosyncratic shock associated with household i's choice for development j. If ϵ_{ij} is an i.i.d. type-I extreme value error, the choice probability for development $j \in \mathcal{O}$ conditional on choice set $\mathcal{O}$ for type k is given by:

$$\mathbb{P}_j^k(\boldsymbol{\delta}, \boldsymbol{\beta} | \mathcal{O}) = \frac{\exp(v_j^k(\boldsymbol{\delta}, \boldsymbol{\beta}))}{1 + \sum_{j' \in \mathcal{O}} \exp(v_{j'}^k(\boldsymbol{\delta}, \boldsymbol{\beta}))},$$

where (δ, β) is the vector of demand parameters and $v_{ij}(\boldsymbol{\delta}, \boldsymbol{\beta}) \equiv \delta_j + \beta^{m(i)} X_j^d$. Importantly, $\mathbb{P}_j(\boldsymbol{\delta}, \boldsymbol{\beta} | \mathcal{O}) = 0$ if $j \notin \mathcal{O}$. We also assume that the outside option is always in the choice set of every household, regardless of demographic type.

3.2.2 Development Admission Rule

We introduce heterogeneity in the choice sets as development admission rules, following Gandhi (2019) and Agarwal and Somaini (2025). Household i is admitted to development j according to the following rule:

$$\eta_i \geq \alpha X_j^s + \alpha^{m(i)} X_j^s, \tag{5}$$

where X_j^s are the development characteristics that enter in the admission rule and η_i is household i's unobservable idiosyncratic component related to her admission. Note that this rule allows for differences in admission across demographic types for all developments by setting $X_j = 1$ for all j, but also through interactions with development characteristics as mediated by $\alpha_1^{m(i)} X_j^s$. X_j^s includes a constant which measures the general distaste for

[18] We control for the homeownership rate as there is variation in this across types (Appendix Table A.1).

minority households, the development monthly rent p_j, and the share of covenants in a development Cov-Share$_j$.[19]

From equation (5), we can see that if i is admitted into development j and $\alpha X_j^s + \alpha^{m(i)} X_j^s \geq \alpha X_{j'}^s + \alpha^{m(i)} X_{j'}^s$, then household i must also be admitted into development j'. This transitivity result implies we only have to consider $J+1$ potential choice sets for each demographic group k that can be ordered as follows:[20]

$$\{0\}, \{0, 1^{k(i)}\}, \ldots, \{0, 1^{k(i)}, ..., J^{k(i)}\}$$

where we order developments according to:

$$\alpha X_{J^{k(i)}}^s + \alpha^{m(i)} X_{J^{k(i)}}^s \geq \alpha X_{J^{k(i)}-1}^s + \alpha^{m(i)} X_{J^{k(i)}-1}^s \geq ... \geq \alpha X_{1^{k(i)}}^s + \alpha^{m(i)} X_{1^{k(i)}}^s.$$

Intuitively, the larger j is, the larger $\alpha X_{j^{k(i)}}^s + \alpha^{k(i)} X_{j^{k(i)}}^s$ and the stricter the admission rule. Therefore, for household i the probability that the set $[j^{k(i)}] \equiv \{0, 1^{k(i)}, ..., j^{k(i)}\}$ is her choice set, $\boldsymbol{O}^i$, is given by:

$$\begin{aligned}\mathbb{P}(\boldsymbol{O}^i = [j^{k(i)}] | \boldsymbol{\alpha}) &= \mathbb{P}(\alpha X_{j+1}^s + \alpha^{m(i)} X_{j+1}^s > \eta_i \geq \alpha X_j^s + \alpha^{m(i)} X_j^s) \\ &= F_\eta\left(\alpha X_{j+1}^s + \alpha^{m(i)} X_{j+1}^s\right) - F_\eta\left(\alpha X_j^s + \alpha^{m(i)} X_j^s\right),\end{aligned}$$

where F_η is the cumulative distribution function of the idiosyncratic payoff error term η_i.

[19] We do not model rent differences by race or ethnicity as we do not find that minority households, which includes both racial minorities and some White ethnic groups, pay a significant premium above non-minority households (see Appendix Figure A.2) unlike most of the literature that focuses primarily on premiums paid by Black households Kain and Quigley (1975) and Cutler et al. (1999). See Appendix Section A.2 for details.

[20] Observe that this transitivity result relies on the assumption that the unobservable component that enters into admission rules, η_i, is common across developments. This assumption may fail if households of a group are favored differently by different developments in a way that is unobservable to the econometrician. One example of this could be family ties between households and developers. While we can relax this assumption, it is helpful for computational reasons as otherwise, we would have to consider the full power set of $\{0, 1, ..., J\}$, which has 2^J elements. However, we believe that this unobservable match-specific component does not play a big role given that our model already allows developments to have different preferences over households based on observable components, such as race or ethnicity and the interaction of race or ethnicity with characteristics of the development.

3.2.3 Match probabilities

Putting everything together, the probability of an observed match s_{ij} for individual i is given by:

$$\begin{aligned}
\mathbb{P}(s_{ij}=1|\boldsymbol{\delta},\boldsymbol{\beta},\boldsymbol{\alpha}) &= \sum_{O\in 2^{|J|}} \mathbb{P}^{k(i)}(O|\boldsymbol{\alpha})\mathbb{P}_j^{k(i)}(\boldsymbol{\delta},\boldsymbol{\beta}|O) \\
&= \sum_{n=1}^{J} \mathbb{P}([n^{k(i)}]|\boldsymbol{\alpha})\mathbb{P}_j^{k(i)}(\boldsymbol{\delta},\boldsymbol{\beta}|[n]) \\
&= \sum_{n\geq j^{k(i)}}^{J^{k(i)}} \mathbb{P}([n^{k(i)}]|\boldsymbol{\alpha})\mathbb{P}_j^{k(i)}(\boldsymbol{\delta},\boldsymbol{\beta}|[n]) \\
&= \sum_{n\geq j^{k(i)}}^{J^{k(i)}} \left(F_\eta\left(\alpha X_{n+1}^s + \alpha^{m(i)} X_{n+1}^s\right) - F_\eta\left(\alpha X_n^s + \alpha^{m(i)} X_n^s\right)\right) \frac{\exp(v_j^{k(i)}(\boldsymbol{\delta},\boldsymbol{\beta}))}{\sum_{j'=1}^{n}\exp(v_{j'}^{k(i)}(\boldsymbol{\delta},\boldsymbol{\beta})+1},
\end{aligned} \tag{6}$$

where the third equality follows from the fact that $j^{k(i)} \notin [n^{k(i)}]$ if $j^{k(i)} > n^{k(i)}$.

4. Estimation and Results of the Two-sided Matching Model

4.1 Estimation Procedure

The estimation relies on a first-step and a second step following Goolsbee and Petrin (2004) and Bayer et al. (2007). We extend their procedures to allow for the estimation of the latent choice sets. The estimation algorithm proceeds as follows:

First Step For given (α, β), we construct the Maximum Likelihood function following these steps:

1. Order developments for each $k \in \{m, nm\}$ according to admission rules :

$$\Pi_{1^k}(\alpha) \leq \ldots \leq \Pi_{J^k}(\alpha),$$

   where $\Pi_j(\alpha; k) \equiv \alpha X_j^s + \alpha^k X_j^s$.

2. Given the previous ordering, for each choice set $[n]$, construct choice set probabilities:

$$\mathbb{P}(\mathcal{O} = [n^k] | \alpha; k) = F_\eta\Big(\Pi_{n+1}(\alpha; k)\Big) - F_\eta\Big(\Pi_n(\alpha; k)\Big).$$

3. Compute the probability of a match following a modified version of the contraction mapping in Berry et al. (1995), Goolsbee and Petrin (2004), and Bayer et al. (2007) to recover δ_j:[21]

   (a) Start with a guess of δ_j, say δ_j^0.

   (b) For every step, s, compute match probabilities for all minority and non-minority households given α, β, and δ_j^s:

$$\mathbb{S}_j(\alpha, \beta, \delta^s; k) = \sum_{n \geq j^k}^{J^k} \mathbb{P}(\mathcal{O} = [n^k] | \alpha; k) \cdot \frac{\exp(v_j^k(\beta, \delta_j^s))}{\sum_{j'=1}^{n} \exp(v_{j'}^k(\beta, \delta_j^s)) + 1}.$$

   (c) Compute the model-predicted match probability for development j by summing across groups:

$$\mathbb{S}_j(\alpha, \beta, \delta^s) = \sum_k \mathbb{S}_j(\alpha, \beta, \delta^s; k) \cdot \frac{N^k}{N}.$$

   (d) Update δ_j^s using:

$$\delta_j^{s+1} = \delta_j^s + \log s_j - \log \mathbb{S}_j(\alpha, \beta, \delta^s).$$

   (e) Repeat until convergence.

4. Given α, β, and the resulting $\delta_j(\alpha, \beta)$, compute the log-likelihood:

$$\mathcal{L}(\alpha, \beta) = \sum_i \sum_j s_{ij} \log \mathbb{S}_j(\alpha, \beta; k(i)).$$

Second Step For every evaluation of the second step, we proceed as follows:

[21] Berry et al. (1995) show that for given observed shares $s_j \equiv \frac{1}{N} \sum_i s_{ij}$ and $\beta^{m(i)}$, there is a unique vector of δ_js that makes choice probabilities equal to s_j and that these δ_j's can be recovered using a contraction mapping.

1. Maximize the log-likelihood function to estimate α, β and the resulting δ_j.
2. We estimate the remaining β^{nm} by GMM using the following moments:

$$\mathbb{E}[G(\alpha, \beta)] = \mathbb{E}[\xi_j \cdot z_j] = 0,$$

where z_j are either instruments for the endogenous variables or the variables that are assumed to be orthogonal to ξ_j. Concretely, we maximize the following objective function:

$$\max_{\alpha,\beta} G(\alpha, \beta)' W G(\alpha, \beta),$$

where $G(\alpha, \beta)$ is the vector of empirical moments and W is a weighting matrix.

4.2 Identification

In this section, we explain the sources of variation that identify our parameters. We do so step by step. Recall that in the first step we estimate the parameters governing the admission rule α, the differences in preference parameters for minority households β as well as the utility levels δ_j of the non-minority group. In the second step, after recovering δ_j in the first step, we identify the parameters of the non-minority households using an instrumental variable approach.[22]

4.2.1 Identification of the First Step: Admission Rules versus Preferences

We now discuss the variation in the data that allows us to separately identify admission-rule parameters $\boldsymbol{\alpha}$ from demand parameters $\boldsymbol{\beta}$ in our model. To make progress, we first need to make several normalizations. First, as pointed out by Train (2009), the level of utility is not identified. Thus, we normalize the value of the outside option equal to zero ($\delta_j = 0$) for all demographic groups. Because the scale of a logit model is not identified, we also normalize the variance of idiosyncratic shocks ϵ_{ij} to be equal to $\frac{\pi^2}{3}$. On the side of the admission rule, we also need to normalize the variance of η and fix $\sigma_\eta^2 = 1$.

Next, to separate parameters that enter into the admission rule from preferences, we

[22]A feature of our data and setting is that, because neighborhoods are defined as developments, a development can span more than one ED, unlike census blocks or block groups, which are confined to a single census tract. Approximately 500 developments contain households across different EDs (usually 2 EDs). We therefore perform our structural estimation at the unit of the intersection of developments and EDs, of which there are around 4000, so that when we take ED fixed effects in the second step of estimation, our estimates are unbiased and efficient. See Appendix Section D.1 for details.

rely on the exclusion shifter argument (Goeree, 2008; Agarwal and Somaini, 2025). That is, we assume the existence of a variable that shifts the formation of choice sets but not household utility, conditional on the rest of the covariates. Concretely, we assume that racial covenants do not enter utility after conditioning for rents and the share of minority households.[23] Finally, we show that the estimated effect of racial covenants on utility is not statistically significant, providing suggestive support for our excluded shifter assumption. While it is possible to identify the model using its structural and parametric features alone, as we show in Appendix D.2, we prefer that our identification argument relies on exclusion restriction arguments, as it is a more transparent, robust, and credible strategy.

4.2.2 Identification of the Second Step

To recover the preferences for the non-minority group β^{nm}, we project δ_j on X_j^d. Note that the unobservable component of utility ξ_j enters additively in δ_j. Therefore, the identification assumptions required by the OLS would give biased estimates if there are observable characteristics (X_j^{nm}) that are potentially correlated with ξ_j. In our case, there are two potentially endogenous variables that are part of household's utility. These characteristics are monthly rents and the development's minority share, which are equilibrium objects.To overcome this endogeneity challenge, we construct moments based on instruments orthogonal to ξ_j.

First, we instrument the log of monthly rents using the log of slope within development j, following Saiz (2010), who documents significant increase in construction costs as land lot's slope increases. The identifying assumption is that the steeper slope instrument shifts the housing supply by affecting construction costs, and thus prices, but does not affect the demand for housing, especially in the relatively flat lake geography of the Minneapolis metro area.

Second, we instrument development level minority share m_j by constructing a shift-share IV following Card (2001); Tabellini (2020). We construct the municipality c level shift share instrument $Z_{c,1940}$ for the six municipalities in our sample as:

[23] We also assume that geographic characteristics of a development–such as distance to the city center or access to transportation–enter utility but not the admission rule. The presence of both types of excluded shifters enables the identification of more general and less parametric two-sided matching models with latent choice sets, as in Agarwal and Somaini (2025). However, given the structural and parametric assumptions we impose, identification in our setting does not require the presence of both shifters.

$$Z_{c,1940} = \frac{M_{c,1930} + \sum_r w_{cr}(1930) O^Q_{r,1930-38}}{\hat{P}_{c,1940}} \tag{7}$$

where w_{cr} is the share of households from foreign country r living in c in the baseline year of 1930. $M_{c,1930}$ denotes the 1930 stock of minority households in municipality c. $O^Q_{r,1930-38}$ refers to the total yearly immigration quota assigned to country r under the US Immigration Act of 1924, multiplied by 9 to cover the 1930–1938 period, as specified by the US Immigration Act of 1924. This act provides an exogenous national-level variation in the influx of households from various countries.[24] We also weight the shift-share instrument using $\hat{P}_{c,1940}$, which is the predicted population of city c in 1940. Given that our estimation in the second step employs ED-level fixed effects to control for the underlying broader location quality, to get variation in the municipality-level shift share instrument within an ED, we weight $Z_{c,1940}$ by the household's relative size within the metro area. Refer to Appendix D.3 for more details on the construction of this instrument.

The first identifying assumption for the shift-share instrument is that the lagged shares of each municipality in 1930 are not correlated with any unobservable factors from the municipality's past. This is likely because all six municipalities are situated in the same metropolitan area, where similar local macroeconomic trends are likely to affect them. The second identifying assumption is that the national shifter, represented by the 1924 immigration quotas, is exogenous to local metro-level shocks, as argued by Tabellini (2020).

We can test whether our instruments are relevant and correlated with our endogenous variables in the direction that we would expect. Results for the first-stage regression are shown in Table 2. We can see that the log slope is positively correlated with the log of rents, suggesting that larger slopes is positively correlated with higher construction costs, and a higher value of the shift share instrument is positively correlated with a higher minority share in the development. This relationship holds true even after controlling for the remainder instrument, as shown in columns 2 and 4. We can also see that the first stage models have an F-stat of at least 14, usually higher.

[24]Since at least 87% of the households in the minority group are White ethnic, and hence foreign-born, we focus on a shifter that exogenously affects the foreign-born population rather than the US-born population.

Table 2: First-Stage for Second Step of Estimation

	(A) Monthly Rents		(B) Minority Share	
	(1)	(2)	(3)	(4)
Main instrument				
Log slope	0.132***	0.129***	—	—
	(0.015)	(0.016)		
Shift–Share	—	—	100.100***	22.500***
			(10.973)	(2.443)
Other Instruments as Controls		✓		✓
Observations	150,686	149,970	164,637	163,524
F-statistic	33.1	105.7	13.9	19.2
ED fixed effects	✓	✓	✓	✓
Location controls	✓	✓	✓	✓

Notes: This table shows the first stage regression estimates for the instruments used in the second step of the two-sided matching model's estimation. Robust standard errors in parentheses. All specifications include enumeration district (ED) fixed effects and controls for logged distances to the central business district, nearest lake, commercial area, heavy industrial zone, and nearest streetcar, as well as the wetland percentage within the development. Columns 2 and 4 also include the other instrument as a control. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.3 Results

In this section, we present estimation results of the two-sided housing market model with selective admissions. Table 3 presents the parameter estimates for both the admissions rule (α) from Equation 5 and demand preferences (β) from Equation 3. Column 1 presents a model that only estimates demand preferences without accounting for selective admission, while Column 2 provides estimates that also account for selective admissions and restrictions on choice sets for each demographic group. It is important to note that since the parameter estimates for the admission rule in Equation 5 are less than or equal to η_i, a positive parameter estimate indicates a lower probability of admission. Standard errors are provided in parentheses.

We find that the admission penalty for minority households, denoted as α^m, is 0.21. This indicates that minority households are less likely to be admitted to the developments relative to non-minority households. Specifically, we can calculate the difference in admission probabilities for minority versus non-minority households across developments. On average, a minority household is 8 percentage points less likely to be admitted compared to non-minority households, even after accounting for *explicit* discrimination from racial covenants and financial restrictions arising from higher rents.[25]

Table 3: Estimation Results Comparison - With and Without Choice Set Restrictions

	Location Demand Only Model (1)		Two-Sided Matching Model (2)	
Admission Rule Parameters:				
α^m			0.210***	(0.012)
α^m_{rent}			-0.002	(0.047)
$\alpha^{nm}_{\text{rent}}$			0.135***	(0.004)
$\alpha^m_{\text{covenant}}$			0.041*	(0.021)
$\alpha^{nm}_{\text{covenant}}$			-0.021***	(0.003)
Demand Side Parameters:				
β^m_{rent}	-1.515***	(0.069)	-1.521***	(0.104)
β^{nm}_{rent}	-1.342***	(0.067)	-1.201***	(0.066)
$\beta^m_{\text{minority}}$	-1.386***	(0.087)	-1.298***	(0.087)
$\beta^{nm}_{\text{minority}}$	-2.493***	(0.087)	-2.469***	(0.086)
$\beta^m_{\text{distance to CBD}}$	-0.762***	(0.044)	-0.809***	(0.044)
$\beta^{nm}_{\text{distance to CBD}}$	-0.733***	(0.042)	-0.708***	(0.042)
$\beta^m_{\text{distance to streetcar}}$	-0.025**	(0.011)	-0.157***	(0.012)
$\beta^{nm}_{\text{distance to streetcar}}$	-0.176***	(0.006)	-0.163***	(0.006)
Observations	163,865		163,865	
Log Likelihood	1481741.5		1481268.6	

Notes: This table presents results from location choice demand model without any choice set restrictions (column 1) and two-sided matching model (column 2). Admission rule parameters are from Equation 5 and demand side parameters are from Equation 3. Standard errors are in parenthesis. m refers to minority households; nm refers to non-minority households. CBD refers to central distance district. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

We also find that the estimate of $\alpha^{nm}_{covenant}$ is negative and statistically significant, in contrast to the positive and statistically significant estimate of $\alpha^m_{covenant}$. These estimates

[25] Note that $\Phi(0.21) \approx 0.58$ and the baseline average probability of admission for non-minority households is 0.5.

suggest that developments with a higher proportion of covenants are more likely to admit non-minority households, while they are less likely to admit minority households. This result reaffirms our earlier reduced-form findings that highly covenanted developments give more priority to non-minority households in their resident selection process. Although the admission restrictions related to racial covenants are significant for minority households, they account for only about 20% of the general admission restrictions faced by these households.

The parameter estimate of α^{m}_{rent} is not significantly different from zero, indicating that minority households do not experience additional high rents or financial constraints when seeking admission after controlling for general admission penalties and those associated with racial covenants. In contrast, the estimate for α^{nm}_{rent} is both positive and statistically significant. This suggests that higher rents and financial constraints serve as barriers to admission for non-minority households. In fact, the impact of rents and financial restrictions on non-minority households is substantial, nearly three times greater than the effect of covenant restrictions on minority households.

Moving on to the demand parameter estimates, we find that all households have a negative coefficient on rents. For all the specifications, we obtain a more negative β^{m}_{rent}, meaning that minority households are more price-sensitive than non-minority households. This result is in line with what previous studies have found (Bayer et al., 2007; Almagro et al., 2024).

Since development rents are a critical factor influencing the admission of non-minority households into housing developments, the location demand only model which does not account for choice set restrictions overestimates the price sensitivity for non-minority households (column 1). In fact, the rent coefficient for non-minority households is actually 11.7% larger in magnitude in the location demand-only model. In contrast, the rent coefficient remains relatively stable in both models for minority households, which we have already demonstrated, is not affected by rents after controlling for the general penalty and the racial covenants associated penalty. Thus, as indicated by Theorems 1 and 2, ignoring choice set restrictions affects the non-minority households' demand preference parameters and creates a downward bias.

Importantly, we find that both minority and non-minority households do not like living in developments with a higher minority share, but relative to minorities, non-minority households dislike living in these developments twice as much. In fact, for non-minority households, the share of minority households in the development is the most important factor in determining their location choice.

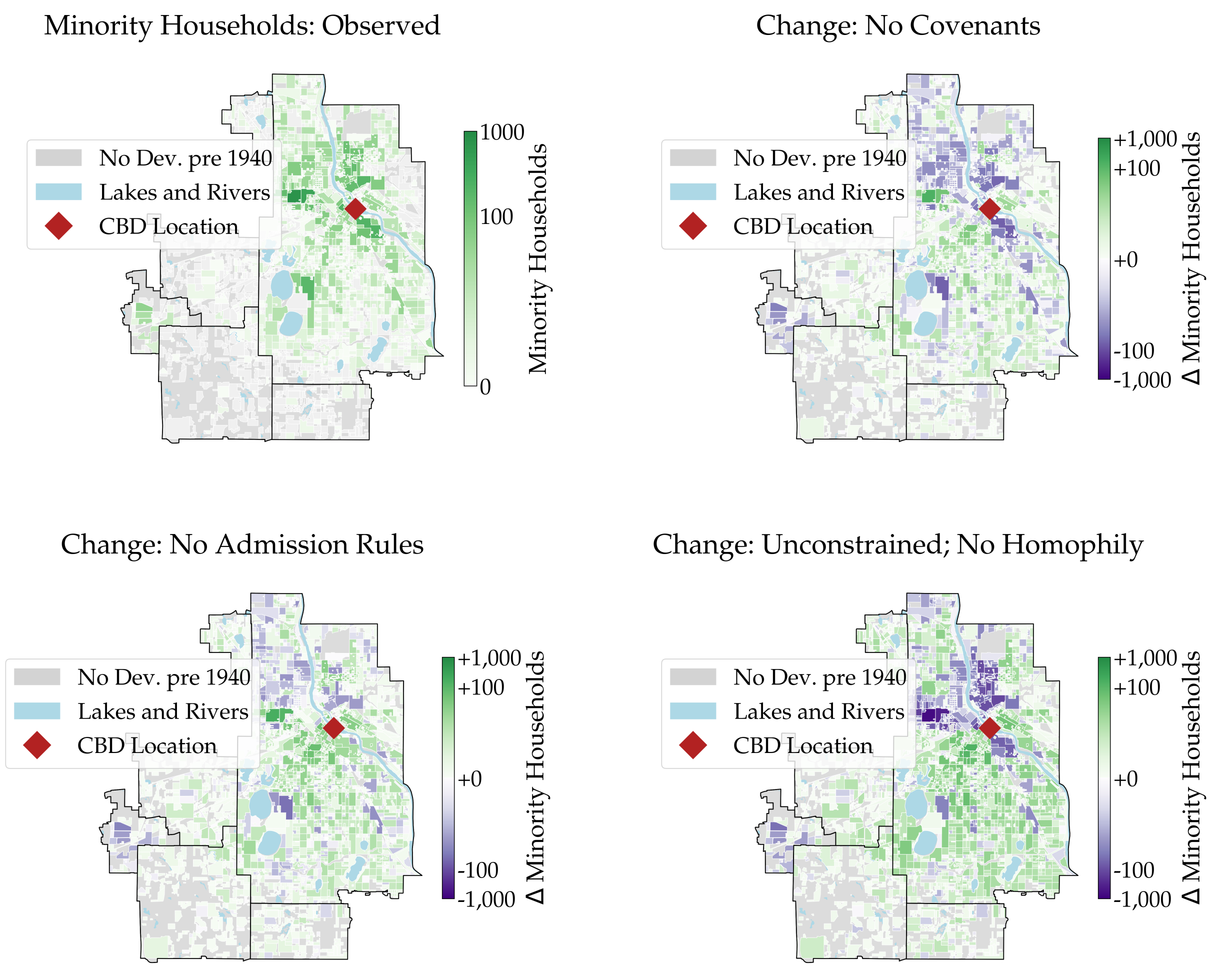
While we cannot provide direct evidence of our exclusion restriction that covenants do not enter utility after conditioning on development's rents and demographic composition, we can show empirical support in favor of it. Concretely, Appendix Table E.1 shows the estimation results of a specification where covenants also enter the utility function. In such model, we find non-significant estimates for racial covenants for both minority and non-minority households' utility. Moreover, the estimates for the other coefficients are not statistically different from those reported in our baseline specification as shown in column (2) of Table E.1.[26]

5. Counterfactual Analysis

This section presents our counterfactual analysis designed to quantify the contribution of different mechanisms to the observed segregation patterns. We simulate three equilibrium scenarios in which we sequentially remove key drivers of segregation: (i) racial covenants, (ii) neighborhood choice set restrictions, and (iii) preferences against residing near minority households in addition to the choice set restrictions. In all three scenarios, housing rents adjust to clear the market. We assume a fixed and perfectly inelastic housing supply curve. We compare outcomes from these simulations to the sorting patterns observed in the data. Following standard practice, we measure segregation using the dissimilarity index, which ranges from 0 to 1. A higher value of the index indicates greater levels of segregation in a metro area. The minority-non minority dissimilarity index for the Minneapolis metro area in 1940 is 0.494. This number is lower than both the national dissimilarity index and the city-wide dissimilarity index for the same year, as reported in

[26]While the identification of our baseline model relies on an excluded shifter, the identification of this model follows the arguments laid out in Appendix D.2. Intuitively, a model with full consideration and logit-based choice probabilities should satisfy the IIA property of log odds ratios. Deviations from IIA observed in the data are thus interpreted as evidence of limited consideration. This logic follows a similar approach to Abaluck and Adams-Prassl (2021).

Figure 4: Number of Minority Households and Differences under Counterfactuals



Note: This figure maps the distribution of minority households across developments under the 1940 observed equilibrium and the three counterfactual scenarios. CBD stands for central business district.

Cutler et al. (1999). However, it's important to note that Cutler et al. (1999), along with the broader literature, focuses on the Black-non-Black dissimilarity index, while we present the minority-non-majority dissimilarity index, where our definition of minority includes discriminated White ethnic households along with racial minorities.

In the first counterfactual, we remove racial covenants preference and distaste for non-minority and minority households, respectively. This would be equivalent to racial covenants being hypothetically outlawed in 1940. Removing the instrument of racial covenants reduces the dissimilarity index from 0.494 to 0.419 (Table 4, row 3). Figure 4 maps the number of minority households in the observed 1940 equilibrium (top left) and the differences between the actual minority household count and the three counterfactual scenarios across the developments in the Minneapolis metro area. In the first counterfactual scenario (top right), which removes racial covenants in the selective admission process, there is a decrease in the number of minority households in developments near the CBD. Conversely, the number of minority households increases slightly throughout the rest of the metropolitan area.

In the second counterfactual, we remove all neighborhood choice set restrictions for both minority and non-minority households. Removing selective admissions increases demand, pushing rents upward. Despite the higher rents, the minority household share within the metro rises from 7.3% to 9% (Table 4, row 5), indicating that the choice set restrictions were disproportionately limiting the entry of minority households into the metro area. The metro-wide dissimilarity index declines from 0.494 to 0.410. In the second counterfactual scenario (bottom left), which removes neighborhood choice set restrictions, the number of minority households increases across many developments (Figure 4). We observe a dispersion of minority households away from historically concentrated areas—especially near the city center—toward developments that previously had few or no minority households.

In the third scenario, we eliminate households' distaste for living near minority households in addition to eliminating all selective admissions. Because all households generally prefer neighborhoods with fewer minority households, this change increases the average neighborhood utility, generating a positive demand shock and pushing rents even higher. Unlike the second counterfactual, the metro-wide minority population declines slightly to 7.1%, as higher rents drive some minority households out of the metro area (Table 4, row 6 vs. row 7). Nevertheless, the spatial distribution of minority households becomes even more dispersed (Figure 4, bottom right), and the dissimilarity index drops sharply to 0.13, indicating a 71% reduction from the observed segregation.

These findings suggest that preferences over neighborhood demographic composition are a more important driver of segregation than the instrument of racial covenants or choice set restrictions. The removal of all choice set restrictions explains only about one-quarter of the total reduction in segregation achieved when both choice set restrictions

Table 4: Off-equilibrium Decomposition of Counterfactuals

	No covenants		No admission rules		No homophily		Equilibrium	Dissimilarity	Minority (%)
	nm	m	nm	m	nm	m			
(1)	×	×	×	×	×	×	✓	0.494	7.3
(2)	✓	×	×	×	×	×	×	0.421	7.3
(3)	✓	✓	×	×	×	×	×	0.419	7.3
(4)	✓	✓	✓	×	×	×	×	0.431	7.5
(5)	✓	✓	✓	✓	×	×	×	0.432	8.9
(6)	✓	✓	✓	✓	✓	✓	×	0.117	7.7
(7)	✓	✓	✓	✓	✓	✓	✓	0.130	7.0

Note: This table presents the off-equilibrium decomposition of the three counterfactuals–"no covenants", "no admission rules", and "no homophily" step-by-step. nm stands for non-minority households and m stands for minority households.

and preferences over neighborhood demographic mechanisms are eliminated. Note that the estimated distaste for minority households in 1940 could be shaped by past policy or people's worldviews, independent of those factors. We are unable to separate these influences. Additionally, these preferences reflect not only prejudice but also homophily from cultural and linguistic similarities. Again, we cannot differentiate between these two aspects.

6. Conclusion

In this paper, we study how both household preferences and restrictions on households' choice sets—whether *implicit* or policy-driven, *explicit* discrimination—affect the observed prices and sorting of households across space. To do this, we have created a novel dataset that links households from the 1940 individual-count US census data to real estate developments in the 1940 Minneapolis metro area, and to the racial covenants and street grid of that time. We provide evidence that racial covenants had a causal effect on racial and ethnic sorting in the Minneapolis metro area in 1940 and were a source of restrictions to the choice of minority households. We propose a two-sided version of the traditional discrete-choice models of residential choice, where we model restrictions arising from both *implicit* and *explicit* discrimination as selective admissions of households on the supply side. We use our newly collected data to estimate our model, finding that minority households had lower admission probabilities into developments, even after controlling for the share of covenants and rents. We also find that ignoring restrictions on choice results in biased estimates of the rent elasticities for non-minority households facing restrictions on their choice sets due to rent or financial constraints, a result that aligns with our theoretical predictions. Our counterfactuals suggest that removing restrictions on households' neighborhood choice sets accounts for only about one-quarter of the total reduction in observed segregation. The remaining decrease in segregation is attributed to the removal of distaste for minority neighbors.

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Choices or Constraints? Disentangling Preferences from Restrictions in Housing Markets

by Milena Almagro and Aradhya Sood

ONLINE APPENDIX

A. Data Appendix

A.1 1940 Individual Count US Census Data

We use the 1940 individual count census data for the state of Minnesota from Integrated Public Use Microdata Series (IPUMS). Using the county identifier, we arrive at 570,044 individual records in Hennepin County in 1940. Aggregating up to the head of household level, there are 179,923 households across the whole of Hennepin County, which we restrict to 164,674 households when we focus only on the six municipalities in the sample of the Minneapolis metro area.

A.2 Housing Tenure and Monthly Rental Value Data and Imputation

Table A.1: Housing Tenure Shares by Minority Status

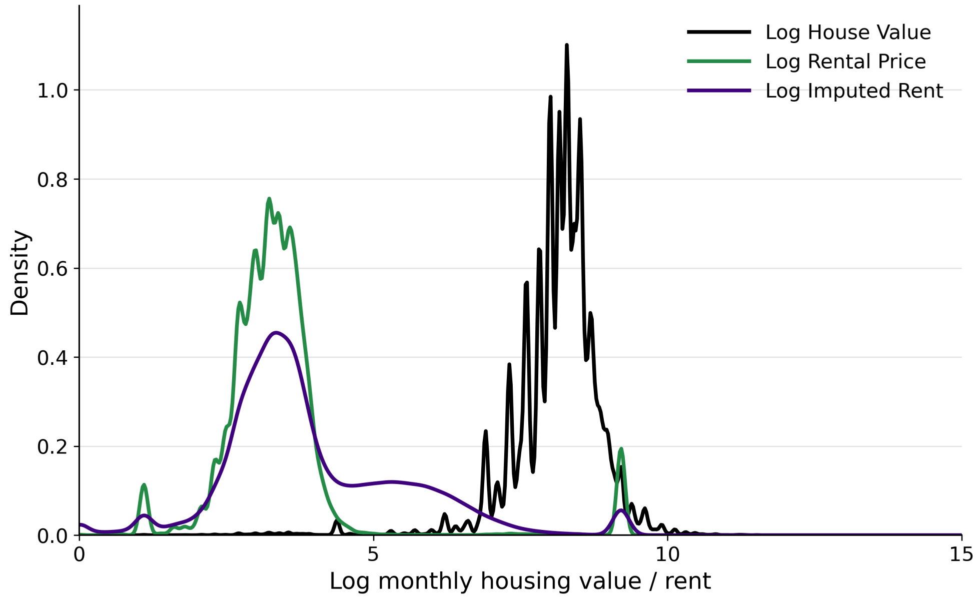
Group	Owner-Occupied	Renter-Occupied	Group Quarters
Non-Minority	0.39	0.54	0.07
Minority (Combined)	0.48	0.47	0.05
Minority (Non-White)	0.19	0.73	0.07
Minority (White Ethnic)	0.52	0.43	0.05

Note: This table shows housing tenure shares for owner-occupied, renter-occupied, and group quarter-occupied homes for non-minority and minority households. We also break down the housing tenure shares within the two minority household subgroups: non-White and White ethnic groups.

Table A.1 provides the housing tenure shares for owner-occupied, renter-occupied, and group quarter-occupied homes for non-minority and minority households. We also break down the housing tenure shares within the two minority household subgroups: non-White and White ethnic groups. As can be seen from the table, there is variation in home ownership rates across different demographic groups.

As noted in Section 2.2, we only observe monthly rental prices and housing values for renter-occupied and owner-occupied households, respectively. To enable a comparison

Figure A.1: House Value, Rental Price, and Imputed Rental Value Distributions

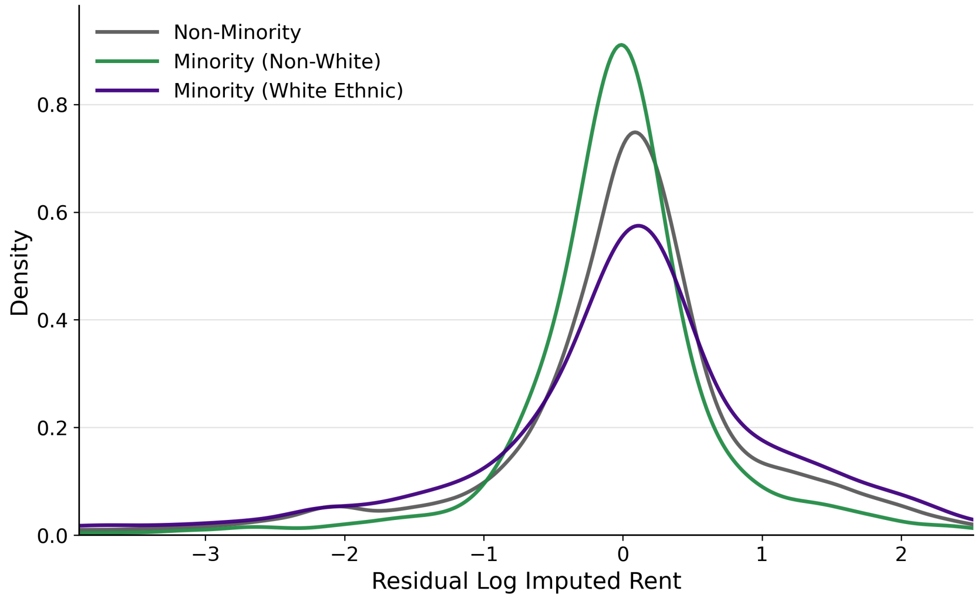


Note: This figure plots the log of house values for owner-occupied housing (in black) and the log of monthly rents for renter-occupied housing (in green) for the households in the analysis sample. In purple, it plots the combined log monthly rents for renter-occupied housing and the imputed monthly owner cost of housing for owner-occupied housing.

between monthly rents and housing values, we impute monthly rental values for owner-occupied housing units. Following Katz (2017), we use a gamma distribution with shape parameter 0.8 and scale parameter 1 to impute annual rental values, which we divide by 12 to obtain monthly rental values. The imputed rental value of owner-occupied housing, combined with rental price data, yields the mean development-level monthly rental value for 98.2x% of the developments in our sample. Figure A.1 plots the log of house values for owner-occupied housing (in black) and the log of monthly rents for renter-occupied housing (in green) for the households in the analysis sample. In purple, it plots the combined log monthly rents for renter-occupied housing and the imputed monthly owner cost of housing for owner-occupied housing.

Figure A.2 plots the residuals from a regression of the log of monthly rental values on development fixed effects interacted with housing tenure fixed effects, capturing the variation in rental value within developments. As noted in Section 3.2.2, we do not account for the differences in rental values paid by various demographic groups. This is because the figure illustrates that the rents paid by non-White minority households

Figure A.2: Distribution of Monthly Rental Value Residuals



Note: This figure plots the residuals from a regression of the log of monthly rental values on development fixed effects interacted with housing tenure fixed effects.

are only slightly lower within developments. In contrast, the rents paid by White ethnic minority households exhibit a distribution similar to that of non-minority households.

A.3 Data on Historic Real Estate Developments

To construct the geography of historic real estate developments, we begin with Hennepin County assessor parcel data and group parcels by development ID. This yields 5,843 present day development polygons in the Minneapolis metro area once we clean boundaries and split multipart geometries into contiguous pieces. We then add and revise geometries using digitised historical city atlases with development maps (see Figure F.3 for an example page from the city atlas) for places where current parcels are missing, destroyed, or inconsistent with historical development boundaries. After incorporating these historical supplements and replacements, the map contains 6,561 contiguous polygons. This process also includes grouping polygons with identical development names that are within 500 meters of each other. The 6,561 contiguous polygons collapse to 3,160 unique developments that contain at least one household in the 1940 census.

A.4 Data on Racial Covenants

The Mapping Prejudice Project searched every sales deed and development map from 1900 to 1960 in Hennepin County to identify those with racial covenants. There are 25,818 racial covenants at the lot level in Hennepin County, of which we identify 24,642 as unique covenant observations based on the following attributes: language used on covenants, development name, city, block, lot, grantor and grantee name, date of deed, and date of execution. Of those, there are 19,668 unique observations in the six municipalities to which we restrict our attention. We use the historical development-level dataset and Hennepin County assessor data to match racial covenants to developments. We match covenant information to parcels within each development to determine the share of covenants in each development. In addition, we also keep track of the date of the covenant execution.

A.5 Historic Street Grids

We use historic street network data to geocode addresses and developments. For the city of Minneapolis, our primary source is the Map USA Database from Brown University (Logan, 2017). To enhance this data, we also collect information from city atlas maps and Sanborn insurance maps for Minneapolis, as well as for five other municipalities: St. Louis Park, Edina, Richfield, Hopkins, and Robbinsdale, in and around 1940. The street grid files have been collected, digitized, geocoded, and cleaned to extract details such as street names, types (e.g., street, avenue, boulevard), and directional prefixes or suffixes. Additionally, these files include interpolated address number ranges for accurate geocoding.

A.6 Data on Enumeration District and Municipality Boundaries

To define broader neighborhoods within a municipality, we digitized and geocoded the 1940 census enumeration district (ED) boundary files for Hennepin County. We performed extensive data cleaning to standardize the ED numbering system and align the boundaries with other geographic datasets. These boundary files enable us to map the census household data accurately within each ED. Additionally, we use municipality boundary shapefiles to fill in any missing municipalities in household addresses. Because there is a direct association between an ED identifier and a municipality, there is no risk of mistakenly assigning a household to the wrong municipality.

A.7 Housing Characteristics and Other Geographic Data

The baseline lot size and build year data, as mentioned in Section 2.2, are obtained from the Hennepin County Assessor's Office. If either of these data points is missing, we supplement it with Zillow data. Please note that while Zillow's data was freely available under an academic license in 2019, it is no longer offered for free.

The slope data come from the Natural Resources Conservation Service. We use the mean elevation and slope at the development level. We digitize and geocode a 1899 map of Hennepin County to highlight wetlands and semi-submerged areas, and use this to create the share of development with wetlands measure. To assess proximity to commercial and industrial zones, we create a shapefile based on the 1940 Minneapolis city atlas (plate 84B), reflecting the 1923 zoning ordinance for the city of Minneapolis. We calculate the Euclidean distance from each development's edge to heavy industrial and commercial areas. We acknowledge that, while we don't consider commercial and industrial zones in five other suburban municipalities, Minneapolis was the metro area's primary commercial and industrial hub. We also assume that activities occur within their designated zones, as land use is generally adhered to in the US, including in the mid-20th century (Shertzer et al., 2016). We also digitize the 1913 streetcar map of the Minneapolis metro area and calculate the Euclidean distance from the edge of a development to the nearest point on the streetcar path. Lastly, we also calculate the Euclidean distance from each development to its nearest lake and to the central business district (CBD) of the metro area, St. Anthony Falls, where the commercial and industrial hub of the area resided in the mid-20th century.

A.8 Imputation of Missing Household Addresses

To enable household-development level analysis, we cleaned, geocoded, and matched a total of 164,674 households from six municipalities included in our sample. The initial step involved using raw addresses obtained from the census, which we meticulously cleaned to extract house numbers, directional prefixes, street names, and street types. Before any processing, we found that 95.6% of the addresses contained a usable street name, 78.1% included a house number, and 75.1% had both components (see Table A.2, Panel A). It is

Table A.2: House Address Imputation

Address Information	Count	%
Panel A: Raw		
Street Name	157,452	95.61
House Number	128,596	78.09
Full Addresses	123,721	75.13
Total	164,674	100.00
Panel B: After Imputation		
Street Name	159,536	96.88
House Number	161,911	98.32
Full Addresses	158,265	96.11
Total	164,674	100.00

Note: Panels A and B in the table display the counts and percentages (%) of households with address information in the raw 1940 census data and after the imputation process, respectively, in the six municipalities in the sample. "Street Name" indicates the availability of the street name, "House Number" indicates the presence of a house number, and "Full Addresses" indicates households with both street name and house number.

important to note that every household in the census is assigned an enumeration district (ED) ID, which also provides a link to the municipality. Following the methodology outlined by Logan and Parman (2017) as well as using string parsing, pattern matching, and fuzzy text matching with reference street-name files, we filled missing components using adjacent records. As a result of this multi-step cleaning and imputation process, coverage improved to 96.9% for street names, 98.3% for house numbers, and 96.1% for complete addresses (Table A.2 Panel B).

The cleaned addresses were then geolocated by matching them to Hennepin County parcel and street grid files. This matching process utilized the ED, house number, street name, street type, and directional information, resulting in 40.6% of addresses being successfully matched. The remaining addresses were matched manually using historical development shapefiles and the street grid. Of the 164,674 households, 96.1% were matched exactly to a development, while the remaining households were assigned randomly to a development within the same ED.

A.9 Combining Datasets

Table A.3: Statistics at the Household, Development, and Enumeration District Level

Variables	P_{25}	P_{50}	P_{75}	Mean	SD	N
Panel A: Household-Level						
No. of Household Members	2.00	3.00	4.00	3.17	2.00	164,674
No. of Working Household Members	2.00	2.00	2.00	1.79	0.41	164,674
Home Ownership Dummy	0.00	0.00	1.00	0.40	0.49	164,674
Married Dummy	0.00	1.00	1.00	0.71	0.45	164,674
Panel B: Development-Level						
Number of Households	4.00	14.00	48.00	52.15	128.70	3,158
Size (km^2)	0.02	0.11	0.39	0.92	8.44	3,158
Minority Share	0.00	0.00	0.07	0.07	0.16	3,158
Share Covenanted	0.00	0.00	0.00	0.05	0.20	3,158
Mean Build Year	1909	1918	1926	1918	11	3,158
Mean Log Lot Size	8.63	8.92	9.70	9.38	1.19	3,158
Distance to Commercial Area (m)	1	100	424	594	1224	3,158
Distance to CBD (m)	3375	5367	8414	6053	3385	3,158
Distance to Heavy Industry (m)	177	604	1586	1168	1487	3,158
Distance to Nearest Lake (m)	453	1002	1681	1193	944	3,158
Distance to Streetcar (m)	126	302	917	760	1057	3,158
Percent Wetlands	0.00	0.00	0.00	4.17	16.18	3,158
House Rental Values (USD Monthly)	49.58	123.42	228.20	200.15	349.19	3,101
Urbanization Index	0.09	0.31	0.64	0.37	0.29	3,158
Log Slope	0.72	1.06	1.20	1.02	0.61	3,158
Shift-Share Instrument	0.0004	0.0005	0.0006	0.0005	0.0003	3,158
Panel C: Enumeration District Level						
Number of Developments	4.00	7.00	10.00	8.42	7.48	468
Size (km^2)	1.71	2.40	4.54	6.18	22.01	468

Note: This table provides summary statistics at household level, development level, and enumeration district level. P_{25}, P_{50}, and P_{75} refer to the 25th, 50th, and 75th percentile, respectively. Size is measured in square kilometers (km^2), while distance is measured in meters (m). CBD stands for cental business district.

The final step in the data construction process involved spatially matching the various datasets together. The output is a household-development level dataset for the Minneapolis metro area. Table A.3 provides summary statistics for the analysis sample at the household, development, and enumeration district levels. P_{25}, P_{50}, and P_{75} refer to the 25th, 50th, and 75th percentile, respectively.

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B. Additional Empirical Evidence

As highlighted in Section 2.4, we group White immigrant households into four categories based on their listed birthplace from "most favorable" to "least favorable" following the ranking by Hyot (1935). Figure B.1 shows these rankings. Below we describe which country we place in which of the four White ethnic categories:

Figure B.1: Homer Hoyt's Ranking of Households Based on Race and Ethnicity

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most favorable come first in the list and those exerting the most detrimental effect appear last.[32]

1. English, Germans, Scotch, Irish, Scandinavians
2. North Italians
3. Bohemians or Czechoslovakians
4. Poles
5. Lithuanians
6. Greeks
7. Russian Jews of the lower class
8. South Italians
9. Negroes
10. Mexicans

Note: This figure is from "One hundred years of land values in Chicago: The relationship of the growth of Chicago to the rise of its land values, 1830-1933" by Homer Hoyt (1935).

Northern Europe & the Commonwealth: Denmark, Finland, Iceland, Norway, Sweden, the Netherlands, England, Scotland, Wales, the United Kingdom, and Ireland, as well as the British Commonwealth countries including Canada, Australia, and New Zealand.

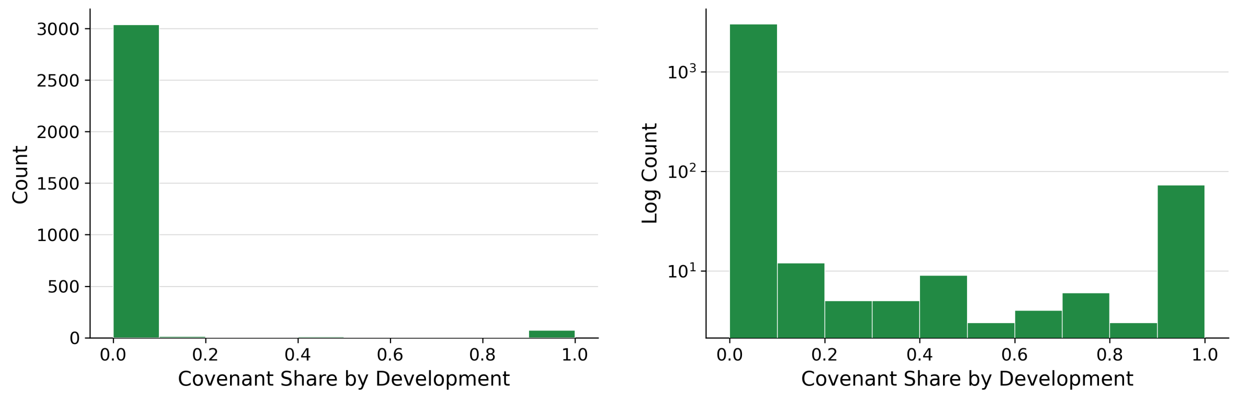
Western Europe: Belgium, France, Liechtenstein, Luxembourg, Monaco, Switzerland, and Italy.

Eastern and Southern Europe: Albania, Portugal, Spain, Bulgaria, Hungary, Yugoslavia, Central Europe, Estonia, Latvia.

Other Regions: Austria, Germany, Poland, Romania, Czechoslovakia, Other USSR/Russia, Turkey, Greece, Syria, Israel/Palestine, Lebanon, China, Japan, Korea, Indonesia, Philippines, India, Asia Minor, Asia (unspecified), Africa (unspecified), Puerto Rico, Mexico, Central America, Cuba, West Indies, South America, Unspecified.

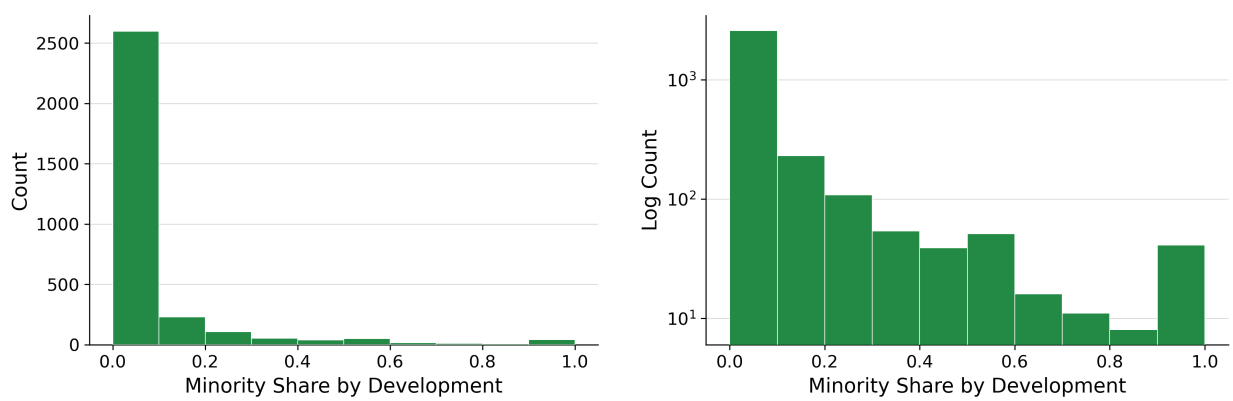
Figure B.2 plots the distribution of covenants shares across developments, presented as

Figure B.2: Distribution of Covenant Shares across Developments



Note: This figure illustrates the distribution of covenants shares across developments, presented as counts on the left and on a logarithmic scale on the right.

Figure B.3: Distribution of Minority Shares across Developments



Note: This figure illustrates the distribution of minority shares across developments, presented as counts on the left and on a logarithmic scale on the right.

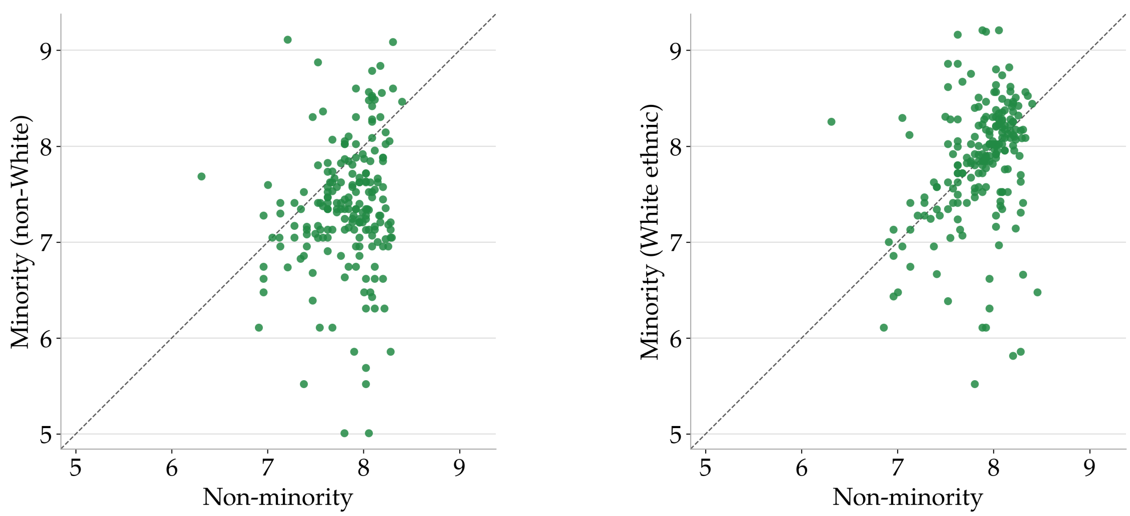
counts on the left and on a logarithmic scale on the right. Figure B.3 plots the distribution of minority shares across developments, presented as counts on the left and on a logarithmic scale on the right. Table B.1 provides the robustness tests for reduced form analysis.

B.1 Census Occupation Identifier and IPUMS Imputed Income

For our analysis, we use an indicator for occupation to account for income and wealth effects as the 1940 census did not record total income data for all individuals. However, the census provides a variable named *occscore* which represents the median total income for a given occupation in 1950, mapped to the 1940 individuals. A potential issue with using occupation fixed effects or *occscore* could be that variation within occupations could correlate with both race or ethnicity and sorting in the housing market.

To understand the extent of bias, we calculate *occscore* from the 1950 census and let it vary by race or ethnicity. This takes the median income by occupation from the 20% sample, for which income data were collected in 1950, and assigns it to the corresponding occupation code. In Figure B.4, we plot the log of *occscore* for non-minority individuals against that for non-White individuals (left panel) and for White ethnic individuals (right panel). The clustering around the 45-degree lines indicates that concern about income differentials within occupations by race or ethnicity is not widespread. Therefore, we continue to use an occupational indicator to account for income and wealth effects in our analysis.

Figure B.4: IPUMS Median Log Imputed Income by Occupation



Note: This figure plots the log of a reconstructed race/ethnicity-varying 1950 occscore, Integrated Public Use Microdata Series (IPUMS) income imputed using the median income by occupation from the 20% sample, for non-minority individuals against that for non-White individuals (left panel) and for White ethnic individuals (right panel).

Table B.1: Racial Covenants and Sorting: Robustness

	Non-White	White NE Imm.	White WE Imm.	White EE/SE Imm.	White Other Imm.
Panel A: 1910 - 1940 Timeframe					
Share Covenanted	-1.149***	0.065	0.419**	-0.092	-0.556
	(0.353)	(0.768)	(0.180)	(0.109)	(0.507)
Observations	164,673	164,673	164,673	164,673	164,673
First-Stage F-Stat	22.73	22.73	22.73	22.73	22.73
Panel B: Instrument with Shrinking Buffer Zone					
Share Covenanted	-0.133***	-0.087	0.066**	-0.026*	-0.046
	(0.041)	(0.165)	(0.027)	(0.015)	(0.093)
Observations	164,673	164,673	164,673	164,673	164,673
First-Stage F-Stat	94.44	94.44	94.44	94.44	94.44
Panel C: Baseline + Additional Control for Share with D-Grade Rating in HOLC					
Share Covenanted	-0.101***	-0.050	0.047**	-0.028**	-0.005
	(0.034)	(0.148)	(0.023)	(0.013)	(0.083)
Observations	164,673	164,673	164,673	164,673	164,673
First-Stage F-Stat	90.08	90.08	90.08	90.08	90.08
Panel D: Alternative Household to Development Matching					
Share Covenanted	-0.099***	-0.030	0.048**	-0.026**	-0.003
	(0.034)	(0.146)	(0.023)	(0.013)	(0.082)
Observations	164,673	164,673	164,673	164,673	164,673
First-Stage F-Stat	92.59	92.59	92.59	92.59	92.59
Panel E: Baseline + Additional Household-Level Controls					
Share Covenanted	-0.102***	-0.082	0.046**	-0.031**	-0.044
	(0.036)	(0.144)	(0.024)	(0.013)	(0.083)
Observations	164,670	164,670	164,670	164,670	164,670
First-Stage F-Stat	90.64	90.64	90.64	90.64	90.64
Mean Dep. Variable	0.010	0.151	0.005	0.003	0.064
Location controls	Yes	Yes	Yes	Yes	Yes
ED FEs	Yes	Yes	Yes	Yes	Yes

Note: This table plots the instrumental variable (IV 2SLS) parameter estimates from Equation 1. Non-White includes households identified as Black, Asian, or Native American, regardless of birth country. White Northern European (NE), Western European (WE), Eastern and Southern European (EE/SE), and Other Immigrants (Imm.) refer to White households from these regions (see Appendix B for details). Robust standard errors in parentheses. All panels control for location variables such as log slope, and log distances to the central business district (CBD), heavy-industry zoning, commercial zoning, the nearest lake, and the streetcar. Additionally, they control for development-level mean log lot size and mean build year. ED FEs are enumeration-district (ED) fixed effects. Panel A employs a longer pre-period (1910-1940) for the urban frontier instrument. Panel B constructs the instrument with a shrinking buffer zone based on distance to the CBD (from 2000 to 500 meters). Panel C adds a control for the share of development with D-grade rating in HOLC redlining. Panel D uses an alternative household-to-development matching for 3.89% of households. Panel E adds household controls of ownership tenure, occupation indicator, marital status, and number of household members and working members to the baseline specification. $^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

C. Model Details

C.1 Details on Ignoring Restrictions on Choice Sets

C.1.1 Proof of Theorem 1

Proof. By definition of $\tilde{\beta}$ and $\hat{\beta}$, we have the following inequalities:

$$\tilde{L}^m(\hat{\beta}^m) < \tilde{L}^m(\tilde{\beta}^m), \quad L^m(\tilde{\beta}^m) < L^m(\hat{\beta}^m)$$

Combining both inequalities, we get the following equivalence relations:

$$\begin{aligned}
&\tilde{L}^m(\hat{\beta}^m) - L^m(\hat{\beta}^m) < \tilde{L}^m(\tilde{\beta}^m) - L^m(\tilde{\beta}^m) \iff \\
&\sum_{j \in \mathcal{J}0} N_j \log\left(\frac{\tilde{\mathbb{P}}j(\hat{\beta}^m)}{\mathbb{P}j(\hat{\beta}^m)}\right) < \sum_{j \in \mathcal{J}0} N_j \log\left(\frac{\tilde{\mathbb{P}}j(\tilde{\beta}^m)}{\mathbb{P}j(\tilde{\beta}^m)}\right) \iff \\
&\sum_{j \in \mathcal{J}0} N_j \log\left(\frac{\sum_{k \in \mathcal{J}0} \exp(\hat{\beta}^m \log p_k)}{\sum_{k \in \mathcal{J}} \exp(\hat{\beta}^m \log p_k)}\right) < \sum_{j \in \mathcal{J}0} N_j \log\left(\frac{\sum_{k \in \mathcal{J}0} \exp(\tilde{\beta}^m \log p_k)}{\sum k \in \mathcal{J} \exp(\tilde{\beta}^m \log p_k)}\right) \iff \\
&\log\left(\frac{\sum_{k \in \mathcal{J}0} \exp(\hat{\beta}^m \log p_j)}{\sum_{k \in \mathcal{J}} \exp(\hat{\beta}^m \log p_k)}\right) < \log\left(\frac{\sum_{k \in \mathcal{J}0} \exp(\tilde{\beta}^m \log p_k)}{\sum_{k \in \mathcal{J}} \exp(\tilde{\beta}^m \log p_k)}\right) \iff \\
&\frac{\sum_{j \in \mathcal{J}_0} \exp(\hat{\beta}^m \log p_j)}{\sum_{j \in \mathcal{J}} \exp(\hat{\beta}^m \log p_j)} < \frac{\sum_{j \in \mathcal{J}_0} \exp(\tilde{\beta}^m \log p_j)}{\sum_{j \in \mathcal{J}} \exp(\tilde{\beta}^m \log p_j)}
\end{aligned}$$

Define the following function:

$$F(\beta) = \sum_{j \in \mathcal{J}_0} \tilde{\mathbb{P}}_j(\beta) = \frac{\sum_{j \in \mathcal{J}_0} \exp(\beta \log p_j)}{\sum_{j \in \mathcal{J}} \exp(\beta \log p_j)}.$$

Under this definition, the above inequalities can be written as:

$$F(\hat{\beta}) < F(\tilde{\beta}).$$

Taking derivatives of $F(\beta)$, we get:

$$\frac{\partial F(\beta)}{\partial \beta} = \sum_{j \in \mathcal{J}_0} \tilde{\mathbb{P}}_j(\beta) \Big\{ \log p_j - \sum_{j \in \mathcal{J}} \tilde{\mathbb{P}}_j(\beta) \log p_j \Big\}$$

$$= \sum_{j\in\mathcal{J}_0} \tilde{\mathbb{P}}_j(\beta)\log p_j - F(\beta)\sum_{j\in\mathcal{J}} \tilde{\mathbb{P}}_j(\beta)\log p_j.$$

From the last expression, it is easy to see that[1]

$$\frac{\partial F(\beta)}{\partial\beta} < 0 \iff \sum_{j\in\mathcal{J}_0} \mathbb{P}_j(\beta)\log p_j - \sum_{j\in\mathcal{J}} \tilde{\mathbb{P}}_j(\beta)\log p_j < 0$$

Observe that

$$\begin{aligned}
&\sum_{j\in\mathcal{J}_0} \mathbb{P}_j(\beta)\log p_j - \sum_{j\in\mathcal{J}} \tilde{\mathbb{P}}_j(\beta)\log p_j \\
=& \sum_{j\le j_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)]\log p_j + \sum_{j_1<j<q_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)]\log p_j \\
&- \sum_{j_1\le q\le q_1, q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)\log p_q - \sum_{q>q_1, q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)\log p_q \\
<& \sum_{j\le j_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)]\log p_j + \sum_{j_1<j<q_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)]\log p_j \\
&- \sum_{j_1\le q\le q_1, q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)\log p_{j_1} - \sum_{q>q_1, q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)\max_{j\in\mathcal{J}_0}\log p_j
\end{aligned}$$

The inequality follows from assumption 1.

The probability should satisfy

$$\sum_{j\le j_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)] + \sum_{j_1<j<q_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)] = \sum_{j_1\le q\le q_1, q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) + \sum_{q>q_1, q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)$$

Replace $\sum_{q>q_1, q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)$ in the above inequality, we get

$$\begin{aligned}
&\sum_{j\in\mathcal{J}_0} \mathbb{P}_j(\beta)\log p_j - \sum_{j\in\mathcal{J}} \tilde{\mathbb{P}}_j(\beta)\log p_j \\
<& \sum_{j\le j_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)][\log p_j - \max_{j\in\mathcal{J}_0}\log p_j] + \sum_{j_1<j<q_1, j\in\mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)][\log p_j - \max_{j\in\mathcal{J}_0}\log p_j]
\end{aligned}$$

[1]Notice that $\frac{\tilde{\mathbb{P}}_j(\beta)}{F(\beta)} = \frac{\tilde{\mathbb{P}}_j(\beta)}{\sum_{k\in\mathcal{J}_0}\tilde{\mathbb{P}}_k(\beta)} = \mathbb{P}_j(\beta)$.

$$
\begin{aligned}
&\quad - \sum_{j_1 \le q \le q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)[\log p_{j_1} - \max_{j \in \mathcal{J}_0} \log p_j] \\
&< \sum_{j_1 < j < q_1, j \in \mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)][\log p_j - \max_{j \in \mathcal{J}_0} \log p_j] \\
&\quad + \Big\{ \sum_{j \le j_1, j \in \mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)] - \sum_{j_1 \le q \le q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) \Big\} [\log p_{j_1} - \max_{j \in \mathcal{J}_0} \log p_j]
\end{aligned}
$$

The first term is negative[2]. If we show the terms in the brace is negative, then the above formula is negative.

Recall that $\mathbb{P}_j(\beta) = \frac{\exp(\beta \log p_j)}{\sum_{j \in \mathcal{J}_0} \exp(\beta \log p_j)}$ and $\tilde{\mathbb{P}}_j(\beta) = \frac{\exp(\beta \log p_j)}{\sum_{j \in \mathcal{J}} \exp(\beta \log p_j)}$, the terms in the brace can be written as:

$$
\begin{aligned}
&\sum_{j \le j_1, j \in \mathcal{J}_0} [\mathbb{P}_j(\beta) - \tilde{\mathbb{P}}_j(\beta)] - \sum_{j_1 \le q \le q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) \\
&= \sum_{j < j_1, j \in \mathcal{J}_0} \frac{\exp(\beta \log p_j)}{\sum_{j \in \mathcal{J}_0} \exp(\beta \log p_j)} - \sum_{j < j_1, j \in \mathcal{J}_0} \frac{\exp(\beta \log p_j)}{\sum_{j \in \mathcal{J}} \exp(\beta \log p_j)} - \sum_{j_1 \le q \le q_1, q \in \mathcal{J}_1} \frac{\exp(\beta \log p_q)}{\sum_{j \in \mathcal{J}} \exp(\beta \log p_j)} \\
&= \frac{\sum_{j < j_1, j \in \mathcal{J}_0} \exp(\beta \log p_j) \sum_{q \in \mathcal{J}_1} \exp(\beta \log p_q) - \sum_{j_1 \le q \le q_1, q \in \mathcal{J}_1} \exp(\beta \log p_q) \sum_{j \in \mathcal{J}_0} \exp(\beta \log p_j)}{\sum_{j \in \mathcal{J}_0} \exp(\beta \log p_j) \sum_{j \in \mathcal{J}} \exp(\beta \log p_j)} \\
&= \frac{\sum_{j < j_1, j \in \mathcal{J}_0} \exp(\beta \log p_j) \sum_{q > q_1, q \in \mathcal{J}_1} \exp(\beta \log p_q)}{\sum_{j \in \mathcal{J}_0} \exp(\beta \log p_j) \sum_{j \in \mathcal{J}} \exp(\beta \log p_j)} \\
&\quad - \frac{\sum_{j_1 \le q \le q_1, q \in \mathcal{J}_1} \exp(\beta \log p_q) \sum_{j_1 \le j \le q_1, j \in \mathcal{J}_0} \exp(\beta \log p_j)}{\sum_{j \in \mathcal{J}_0} \exp(\beta \log p_j) \sum_{j \in \mathcal{J}} \exp(\beta \log p_j)} \\
&= \sum_{j < j_1, j \in \mathcal{J}_0} \mathbb{P}_j(\beta) \sum_{q > q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) - \sum_{j_1 \le j \le q_1, j \in \mathcal{J}_0} \mathbb{P}_j(\beta) \sum_{j_1 \le q \le q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) \\
&= \sum_{q > q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) - \sum_{j_1 \le j \le q_1, j \in \mathcal{J}_0} \mathbb{P}_j(\beta) \sum_{q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)
\end{aligned}
$$

The last line can be written into:

$$
\begin{aligned}
&\sum_{q > q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_k(\beta) - \sum_{j_1 \le j \le q_1, j \in \mathcal{J}_0} \mathbb{P}_j(\beta) \sum_{q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) \\
&= \sum_{q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta) [\frac{\sum_{q > q_1, q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)}{\sum_{q \in \mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)} - \sum_{j_1 \le j \le q_1, j \in \mathcal{J}_0} \mathbb{P}_j(\beta)]
\end{aligned}
$$

[2]Note that for all $j \in \mathcal{J}_0$, $\mathbb{P}_j(\beta) > \tilde{\mathbb{P}}_j(\beta)$ for all β

$$= \sum_{q\in\mathcal{J}_1} \tilde{\mathbb{P}}_q(\beta)[\sum_{q>q_1,q\in\mathcal{J}_1} \overline{\mathbb{P}}_q(\beta) - \sum_{j_1\le j\le q_1, j\in\mathcal{J}_0} \mathbb{P}_j(\beta)]$$

where $\overline{\mathbb{P}}_q(\beta) = \frac{\exp(\beta\log p_q)}{\sum_{q'\in\mathcal{J}_1}\exp(\beta\log p_{q'})}$.

It is clear that:

$$\sum_{q>q_1,q\in\mathcal{J}_1} \overline{\mathbb{P}}_q(\beta) < \sum_{j_1\le j\le q_1,j\in\mathcal{J}_0} \mathbb{P}_j(\beta) \iff \sum_{j\in\mathcal{J}_0} \mathbb{P}_j(\beta)\log p_j - \sum_{j\in\mathcal{J}} \tilde{\mathbb{P}}_j(\beta)\log p_j < 0 \iff \tilde{\beta} < \hat{\beta}$$

For $\beta \in [0, \overline{\beta})$, we have:

$$\sum_{j_1\le q\le q_1,q\in\mathcal{J}_1} \overline{\mathbb{P}}_q(\beta) = \frac{\sum_{j_1\le q\le q_1,q\in\mathcal{J}_1}\exp(\beta\log p_q)}{\sum_{q\in\mathcal{J}_1}\exp(\beta\log p_q)} > \frac{N_1^s\exp(\beta\log p_q^{min})}{N_1\exp(\beta\log p_q^{max})}$$

$$\sum_{j<j_1,j\in\mathcal{J}_0} \mathbb{P}_j(\beta) = \frac{\sum_{j<j_1,j\in\mathcal{J}_0}\exp(\beta\log p_j)}{\sum_{j\in\mathcal{J}_0}\exp(\beta\log p_j)} < \frac{N_0^s\exp(\beta\log p_{j_1})}{N_0\exp(\beta\log p_j^{min})}$$

$$\begin{aligned}
\frac{N_1^s\exp(\beta\log p_q^{min})}{N_1\exp(\beta\log p_q^{max})} \Big/ \frac{N_0^s\exp(\beta\log p_{j_1})}{N_0\exp(\beta\log p_q^{min})} &= \frac{N_1^sN_0}{N_1N_0^s}\exp\Big(\beta\log\frac{p_q^{min}}{p_q^{max}}\frac{p_j^{min}}{p_{j_1}}\Big) \\
&> \frac{N_1^sN_0}{N_1N_0^s}\exp\Big(\frac{\log\frac{N_0^s}{N_0}\frac{N_1}{N_1^s}}{\log\frac{p_q^{min}}{p_q^{max}}\frac{p_j^{min}}{p_{j_1}}}\log\frac{p_q^{min}}{p_q^{max}}\frac{p_j^{min}}{p_{j_1}}\Big) \\
&> 1
\end{aligned}$$

So $\sum_{j_1\le q\le q_1,q\in\mathcal{J}_1}\overline{\mathbb{P}}_q(\beta) > \sum_{j<j_1,j\in\mathcal{J}_0}\mathbb{P}_j(\beta)$ for $\beta\in[0,\overline{\beta})$. This is equivalent to $\sum_{q>q_1,q\in\mathcal{J}_1}\overline{\mathbb{P}}_q(\beta) < \sum_{j_1\le j\le q_1,j\in\mathcal{J}_0}\mathbb{P}_j(\beta)$ for $\beta\in[0,\overline{\beta})$.

For $\beta \in (\underline{\beta}, 0)$, we have:

$$\sum_{j_1\le q\le q_1,q\in\mathcal{J}_1} \overline{\mathbb{P}}_q(\beta) = \frac{\sum_{j_1\le q\le q_1,q\in\mathcal{J}_1}\exp(\beta\log p_q)}{\sum_{q\in\mathcal{J}_1}\exp(\beta\log p_q)} > \frac{N_1^s\exp(\beta\log p_{q_1})}{N_1\exp(\beta\log p_q^{min})}$$

$$\sum_{j<j_1,j\in\mathcal{J}_0} \mathbb{P}_j(\beta) = \frac{\sum_{j<j_1,j\in\mathcal{J}_0}\exp(\beta\log p_j)}{\sum_{j\in\mathcal{J}_0}\exp(\beta\log p_j)} < \frac{N_0^s\exp(\beta\log p_j^{min})}{N_0\exp(\beta\log p_j^{max})}$$

$$\frac{N_1^s\exp(\beta\log p_{q_1})}{N_1\exp(\beta\log p_q^{min})} \Big/ \frac{N_0^s\exp(\beta\log p_j^{min})}{N_0\exp(\beta\log p_j^{max})} = \frac{N_1^sN_0}{N_1N_0^s}\exp\Big(\beta\log\frac{p_{q_1}}{p_q^{min}}\frac{p_j^{max}}{p_j^{min}}\Big)$$

$$> \frac{N_1^s N_0}{N_1 N_0^s} \exp\left(\frac{\log \frac{N_0^s}{N_0}\frac{N_1}{N_1^s}}{\log \frac{p_{q_1}}{p_q^{min}}\frac{p_j^{max}}{p_j^{min}}} \log \frac{p_{q_1}}{p_q^{min}}\frac{p_j^{max}}{p_j^{min}}\right)$$

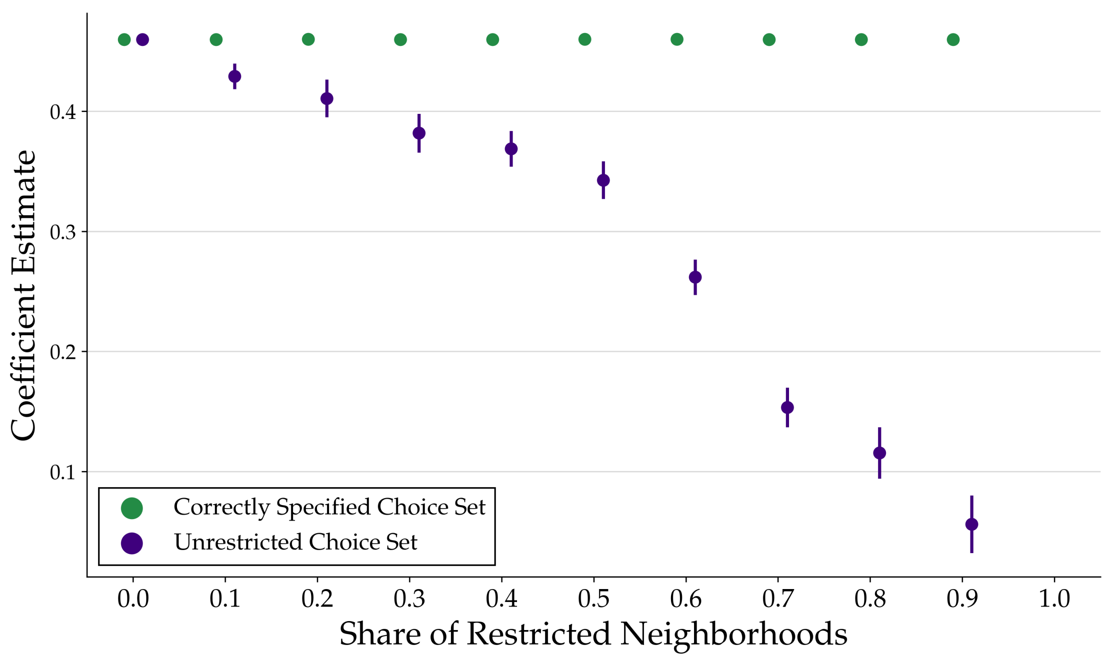
$$> 1$$

So $\sum_{q>q_1, q\in\mathcal{J}_1} \overline{\mathbb{P}}_q(\beta) < \sum_{j_1\leq j\leq q_1, j\in\mathcal{J}_0} \mathbb{P}_j(\beta)$ also holds for $\beta \in (\underline{\beta}, 0)$.

So within the range of $(\underline{\beta}, \overline{\beta})$, the inequality $\sum_{q>q_1, q\in\mathcal{J}_1} \overline{\mathbb{P}}_q(\beta) < \sum_{j_1\leq j\leq q_1, j\in\mathcal{J}_0} \mathbb{P}_j(\beta)$ holds, so we have $\tilde{\beta} < \hat{\beta}$. □

C.1.2 Details on Monte Carlo Simulations

Figure C.1: Estimated Coefficients under Correctly and Mis-Specified Models



Note: This figure plots the Monte-Carlo distribution of estimates for type k households for a mis-specified model with an unrestricted choice set (in purple) as well as a correctly specified model with the correct choice set (in green). Mean and 95% confidence intervals are reported. The true value of $\beta^k = 0.46$. The vertical axis plots the coefficient estimates while the horizontal axis plots the share of developments that are restricted to the type k households.

D. Identification and Estimation Details

D.1 Development–Enumeration District Correspondence

As highlighted in Section 4.2, the developments, our measure of neighborhoods, do not perfectly coincide with the enumeration districts (EDs) in the Census. Around 500 developments contain households belonging to different EDs, usually 2 different EDs. We, therefore, perform the structural estimation at the unit of the intersection of developments and EDs, of which there are around 4000. In this section, we show that our estimates are unbiased and efficient if we do so. In simple household-level model,

$$y_i = \beta D_{j(i)} + \gamma X_{j(i)} + \lambda_{e(i)} + u_i,$$

i indexes households, $j(i)$ denotes the development containing household i, and $e(i)$ denotes the ED containing household i. The treatment D_j and covariates X_j vary at the development level, while λ_e is an ED fixed effect.

As long as treatment and covariates vary only at the development level, the model can be aggregated without loss of information to the intersection of developments and EDs. Let N_{je} denote the number of households in the intersection of development j and ED e, and define the mean outcome at this level as:

$$\bar{y}_{je} \equiv \frac{1}{N_{je}} \sum_{i \in j \cap e} y_i.$$

Taking the mean of the household equation over all households in $j \cap e$ yields

$$\bar{y}_{je} = \beta D_j + \gamma X_j + \lambda_e + \bar{u}_{je},$$

where

$$\bar{u}_{je} = \frac{1}{N_{je}} \sum_{i \in j \cap e} u_i.$$

This expression shows that the household model aggregates exactly to the development–ED intersection level. The right-hand side variables remain unchanged because they are constant within each cell: D_j and X_j vary only by development, while λ_e varies only by ED.

To estimate this equation we can run a weighted regression at the (j, e) level with weights N_{je}. This aggregation is lossless in the sense that the weighted least squares objective function is identical to the household-level OLS objective. Specifically, household OLS minimizes

$$\sum_i \left(y_i - \beta D_{j(i)} - \gamma X_{j(i)} - \lambda_{e(i)}\right)^2 .$$

Grouping households by (j, e) cells, this objective can be written as

$$\sum_{j,e} \sum_{i \in j \cap e} \left(y_i - \beta D_j - \gamma X_j - \lambda_e\right)^2 .$$

Using the standard decomposition of squared deviations,

$$\sum_{i \in j \cap e} (y_i - \mu)^2 = \sum_{i \in j \cap e} (y_i - \bar{y}_{je})^2 + N_{je}(\bar{y}_{je} - \mu)^2,$$

the first term does not depend on the parameters $(\beta, \gamma, \lambda_e)$. The second term implies that minimizing the household objective is equivalent to minimizing

$$\sum_{j,e} N_{je} \left(\bar{y}_{je} - \beta D_j - \gamma X_j - \lambda_e\right)^2 .$$

This is exactly the weighted least squares problem obtained by estimating the aggregated equation at the (j, e) level with weights N_{je}. Therefore, the coefficient estimates from the two regressions coincide, implying that aggregation from households to development–ED cells is lossless.

This equivalence also implies that the estimate of β obtained from the aggregated regression is unbiased and efficient under the same conditions as the household regression. Unbiasedness follows because

$$E[\bar{u}_{je} \mid D_j, X_j, \lambda_e] = 0$$

whenever the household disturbances satisfy

$$E[u_i \mid D_{j(i)}, X_{j(i)}, \lambda_{e(i)}] = 0.$$

Efficiency follows because weighted least squares with weights N_{je} reproduces the same normal equations as household OLS, and therefore, uses all available information in the sample. Operationally, each development–ED intersection is treated as an observation weighted by the number of households in that cell, ensuring that estimation exactly replicates the household-level regression with ED fixed effects.

D.2 Identification under parametric restrictions

To show that a model with parametric restrictions without shifters is identified, we need to show that there's an injective mapping from the parameters to the data. In what follows, we show that such an injective mapping exists.

First, to build on intuition, note that in a model with full consideration where errors follow a logit distribution, the following equality holds:

$$s_j = \exp(\beta X_j^d - \beta X_{j'}^d) s_{j'}, \tag{D.1}$$

for all j and j', which follows from the independence of irrelevant alternatives property (IIA) implied by logit errors. In other words, under logit errors, the following moments should hold:

$$\mathbb{E}[\frac{s_j}{s_{j+1}}|\mathbf{X}_1,...,\mathbf{X}_J] = \mathbb{E}[\frac{s_j}{s_{j+1}}|X_j^d, X_{j+1}^d] \implies \mathbb{E}\left[\left(\frac{s_j}{s_{j+1}} - \mathbb{E}[\frac{s_j}{s_{j+1}} \mid X_j^d, X_{j+1}^d]\right) \cdot h(\mathbf{X}_1,...,\mathbf{X}_J)\right] = 0,$$

for all h such that $\mathbb{E}|h(\mathbf{X}_1, \mathbf{X}_2)| < \infty$, where $\mathbf{X}_j = (X_j^s, X_j^d)$.

We now consider a model without full consideration. We start with a simplified example to build on intuition, where we only have one demographic group, with utility given by $v_{ij} = \beta X_j^d + \epsilon_{ij}$, and an admission rule based on a scalar X_j^s:

$$\eta_i \geq \alpha X_j^s.$$

Let's assume $\alpha \geq 0$.[3] Under this monotonicity condition, we know that we can order developments according to increasing X_j^s:

$$X_1^s \leq \ldots \leq X_J^s.$$

Given this ordering, we know that:

$$\begin{aligned}
s_j &= \mathbb{P}(s_{ij} = 1|\boldsymbol{\delta}, \boldsymbol{\beta}, \boldsymbol{\alpha}) \\
&= \sum_{n \geq j}^{J} \left(F_\eta\left(\alpha X_{n+1}^s\right) - F_\eta\left(\alpha X_n^s\right)\right) \frac{\exp(\beta X_j^d)}{\sum_{j'=1}^{n} \exp(\beta X_{j'}^d) + 1} \\
&= \sum_{n \geq j+1}^{J} \left(F_\eta\left(\alpha X_{n+1}^s\right) - F_\eta\left(\alpha X_n^s\right)\right) \frac{\exp(\beta X_j^d))}{\sum_{j'=1}^{n} \exp(\beta X_{j'}^d) + 1} + \left(F_\eta\left(\alpha X_{j+1}^s\right) - F_\eta\left(\alpha X_j^s\right)\right) \frac{\exp(\beta X_j^d)}{\sum_{j'=1}^{j} \exp(\beta X_{j'}^d) + 1} \\
&= s_{j+1} \exp\left(\beta (X_j^d - X_{j+1}^d)\right) + \left(F_\eta\left(\alpha X_{j+1}^s\right) - F_\eta\left(\alpha X_j^s\right)\right) \frac{\exp(\beta X_j^d)}{\sum_{j'=1}^{j} \exp(\beta X_{j'}^d) + 1}. \qquad \text{(D.2)}
\end{aligned}$$

Because we assume that the outside is always included the choice set, we can also obtain the following expression for all $j = 1, \ldots, J$:

$$s_0 = s_j \exp(-\beta X_j^d) + \sum_{n=1}^{j-1} \left(F_\eta\left(\alpha X_{n+1}^s\right) - F_\eta\left(\alpha X_n^s\right)\right) \frac{1}{\sum_{j'=1}^{n} \exp(\beta X_{j'}^d) + 1}.$$

Comparing the previous expressions with (D.1), we see that, given our assumption of logit errors, any violations to IIA in the data arise because of lack of full consideration that is captured by the second summand of expression (D.1). By contrast, a model without full consideration with logit errors:

$$\mathbb{E}[\frac{s_j}{s_{j+1}}|\mathbf{X}_1, \ldots, \mathbf{X}_J] = \mathbb{E}[\frac{s_j}{s_{j+1}}|X_j^s, X_{j+1}^s, X_1^d, \ldots, X_{j+1}^d],$$

[3]It is straightforward to extend the argument when $\alpha \leq 0$.

which implies the following moments

$$\mathbb{E}\left[\left(\frac{s_j}{s_{j+1}} - \mathbb{E}[\frac{s_j}{s_{j+1}} \mid X_j^s, X_{j+1}^s, X_1^d, \dots, X_{j+1}^d]\right) \cdot h(\mathbf{X}_1, \dots, \mathbf{X}_J)\right] = 0$$

for all h such that $\mathbb{E}|h(\mathbf{X}_1, \dots, \mathbf{X}_J)| < \infty$.

Next, observe that that we can extend equation (D.2) to all j, forming a system of $J+1$ equations in the observed shares of matches $\{s_j\}_{j=1}^J$:

$$\begin{aligned}
s_0 &= s_1 \exp(-\beta X_1^d) + F_\eta\left(\alpha X_1^s\right) \\
&\vdots \\
s_j &= s_{j+1} \exp\left(\beta(X_j^d - X_{j+1}^d)\right) + \left(F_\eta\left(\alpha X_{j+1}^s\right) - F_\eta\left(\alpha X_j^s\right)\right) \frac{\exp(\beta X_j^d)}{\sum_{j'=1}^{j} \exp(\beta X_{j'}^d) + 1} \\
&\vdots \\
s_J &= \left(1 - F_\eta\left(\alpha X_J^s\right)\right) \frac{\exp(\beta X_J^d)}{\sum_{j'=1}^{J} \exp(\beta X_{j'}^d) + 1}.
\end{aligned}$$

The system above shows that, under a specific functional form assumption on F_η, we can identify the parameters α and β, as we have a system of $J+1$ equations and two unknown variables. In this simplified model with two parameters, having only one location and the outside option is enough. Generalizing this argument, we can identify up to $J+1$ parameters using the previous system of equations.

D.2.1 Adding match-specific admission rule unobserved heterogeneity.

Finally, we can write a similar system of equations when we add match-specific admission rule unobserved heterogeneity. Assume for simplicity our baseline model with only one group and one covariate entering in each side of the market. Assume that the admission rule is given by

$$\eta_{ij} \geq \alpha X_j^s.$$

In this more general model, we can write the probability of having choice set C as follows:

$$\mathbb{P}(C) = \prod_{j \in C} F_\eta(\alpha X_j^s) \prod_{j \notin C} (1 - F_\eta(\alpha X_j^s)),$$

where η_{ij} is i.i.d. distributed according to F_η. Following a similar argument as above, we have that for all j:

$$\begin{aligned} s_0 &= s_j \exp(-\beta(X_j^d)) + \sum_{\{C|j \notin C\}} \mathbb{P}(C) \frac{1}{1 + \sum_{k \in C} \exp(\beta X_k^d)} \\ &= s_j \exp(-\beta(X_j^d)) + \sum_{\{C|j \notin C\}} \prod_{j' \in C} F_\eta(\alpha X_{j'}^s) \prod_{j' \notin C} (1 - F_\eta(\alpha X_{j'}^s)) \frac{1}{1 + \sum_{k \in C} \exp(\beta X_k^d)}. \end{aligned}$$

Observe that under parametric assumptions of F_η, we have a system of J equations in two unknowns, α and β.

D.3 Shift-Share Instrument Construction

To address the potential endogeneity in minority household location decisions, we construct a shift-share instrument similar to Card (2001) and Tabellini (2020). The instrument combines three key components: predicted municipality growth rates from non-Minnesota metropolitan areas, historical migrant settlement patterns across the six municipalities in our sample, and immigration quotas from the US Immigration Act of 1924. We use the 1930 and 1940 IPUMS censuses to construct the instrument. First, we calculate the predicted 1940 population for each of the six municipalities in our sample, c, using the average growth rate of non-Minnesota metropolitan areas between 1930 and 1940:

$$\hat{P}_{c,1940} = P_{c,1930}(1 + g_{1930-1940}) \tag{D.3}$$

where $g_{1930-1940}$ represents the average population growth rate across all non-Minnesota metropolitan areas.

For each sending international region $r \in R$ and municipality c, we calculate historical settlement patterns using 1930 data:

$$\omega_{cr} = \frac{M_{cr,1930}}{\sum_{j \in C} M_{jr,1930}} \tag{D.4}$$

where $M_{cr,1930}$ represents the migrant population from region r in municipality c in 1930, and C denotes the set of six municipalities in our sample.

We then predict the number of new migrants in each municipality by combining these settlement patterns with immigration quotas:

$$\hat{M}_{c,1940} = \sum_{r} \omega_{cr} \cdot Q_r \cdot 9 \tag{D.5}$$

where Q_r represents the annual quota for region r under the US Immigration Act of 1924, multiplied by 9 to cover each year of the 1930–1938 period. We carry out this calculation separately for the set of sending regions included in each minority definition used in the paper. We then construct the municipality-level instrument as:

$$Z_{c,1940} = \frac{M_{c,1930} + \hat{M}_{c,1940}}{\hat{P}_{c,1940}} \tag{D.6}$$

where $M_{c,1930}$ represents the existing migrant population in municipality c in 1930 from the relevant set of sending regions.

For development-level analysis, we merge this municipality-level instrument to developments within municipality c. We scale the municipality-level instrument by the development's share of the estimation-sample population:

$$Z_{ac,1940} = Z_{c,1940} \cdot \frac{P_{ac,1940}}{\sum_{a,c} P_{ac,1940}} \tag{D.7}$$

where $P_{ac,1940}$ denotes the development-level population in the estimation sample. This instrument satisfies the exclusion restriction insofar as it relies on two plausibly exogenous components: national immigration quotas that were set without reference to local neighborhood or metro area economic and social conditions, and pre-period settlement patterns from 1930 that are unlikely to be correlated with subsequent development-level changes once development and location characteristics are controlled for.

References

Card, David, "Immigrant inflows, native outflows, and the local labor market impacts of higher immigration," Journal of Labor Economics, 2001, 19 (1), 22–64.

Tabellini, Marco, "Gifts of the immigrants, woes of the natives: Lessons from the age of mass migration," The Review of Economic Studies, 2020, 87 (1), 454–486.

E. Additional Results and Counterfactual Analysis

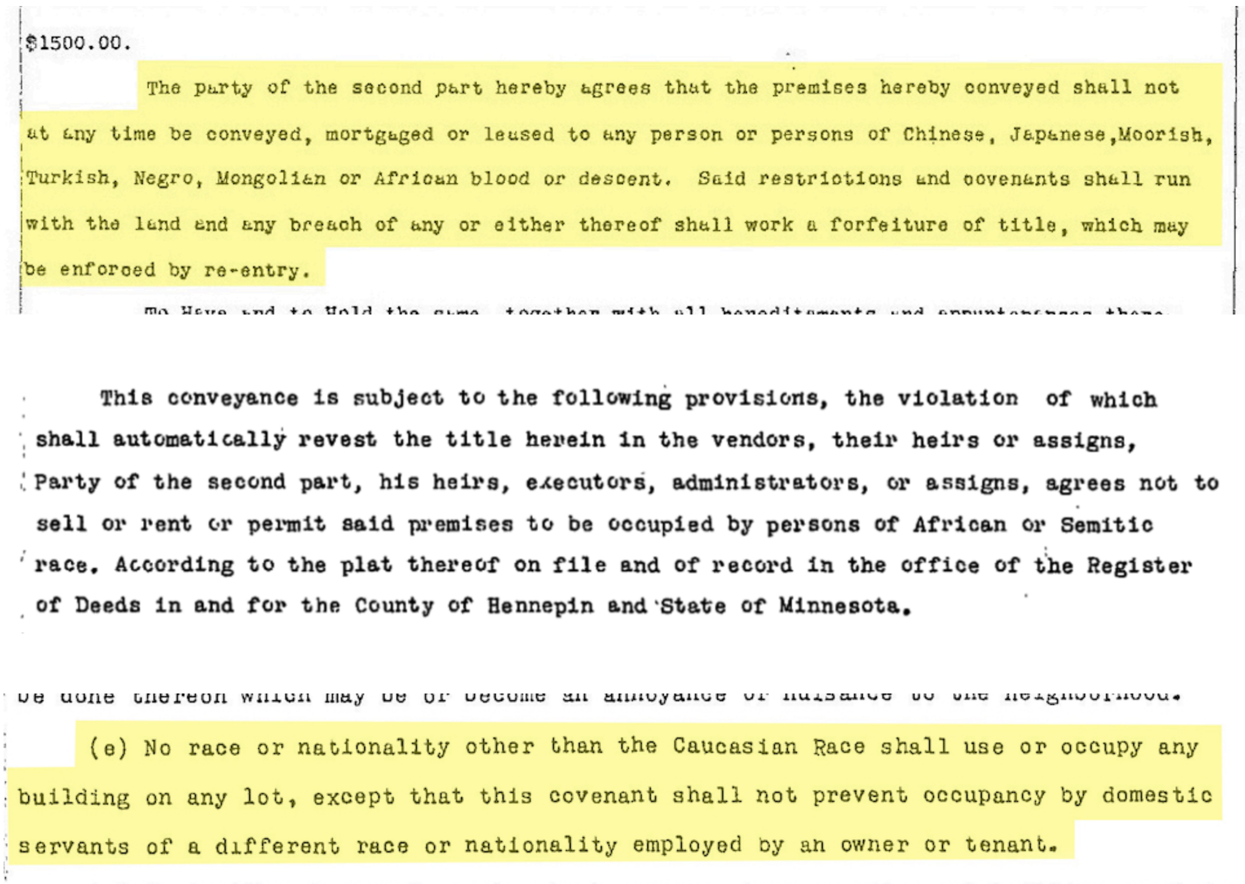
Table E.1: Estimation Results Comparison - With and Without Choice Set Restrictions

	Location Demand Only Model		Two-Sided Matching Model	
	(1)		(2)	
Admission Rule Parameters:				
α^{m}			0.222***	(0.031)
$\alpha^{m}_{\text{price}}$			-0.008	(0.054)
$\alpha^{nm}_{\text{price}}$			0.138***	(0.004)
$\alpha^{m}_{\text{covenant}}$			0.131	(0.226)
$\alpha^{nm}_{\text{covenant}}$			-0.028***	(0.003)
Demand Side Parameters:				
β^{m}_{price}	-1.456***	(0.074)	-1.474***	(0.115)
$\beta^{nm}_{\text{price}}$	-1.293***	(0.072)	-1.143***	(0.072)
$\beta^{m}_{\text{covenant}}$	-0.088	(0.070)	0.038	(0.314)
$\beta^{nm}_{\text{covenant}}$	-0.033	(0.069)	-0.078	(0.069)
$\beta^{m}_{\text{minority}}$	-1.481***	(0.106)	-1.413***	(0.106)
$\beta^{nm}_{\text{minority}}$	-2.586***	(0.106)	-2.583***	(0.106)
$\beta^{m}_{\text{distance to CBD}}$	-0.839***	(0.046)	-0.890***	(0.047)
$\beta^{nm}_{\text{distance to CBD}}$	-0.811***	(0.044)	-0.791***	(0.044)
$\beta^{m}_{\text{distance to streetcar}}$	-0.018	(0.011)	-0.155***	(0.013)
$\beta^{nm}_{\text{distance to streetcar}}$	-0.173***	(0.007)	-0.161***	(0.007)
Observations	162,772		162,772	
Log Likelihood	1,481,734.62		1,481,268.52	

Notes. Column 1 reports estimates from the location demand model without choice set restrictions. Column 2 includes admission rules. m refers to minority households; nm to non-minority. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

F. Additional Figures

Figure F.1: Examples of Racial Covenants



$1500.00.

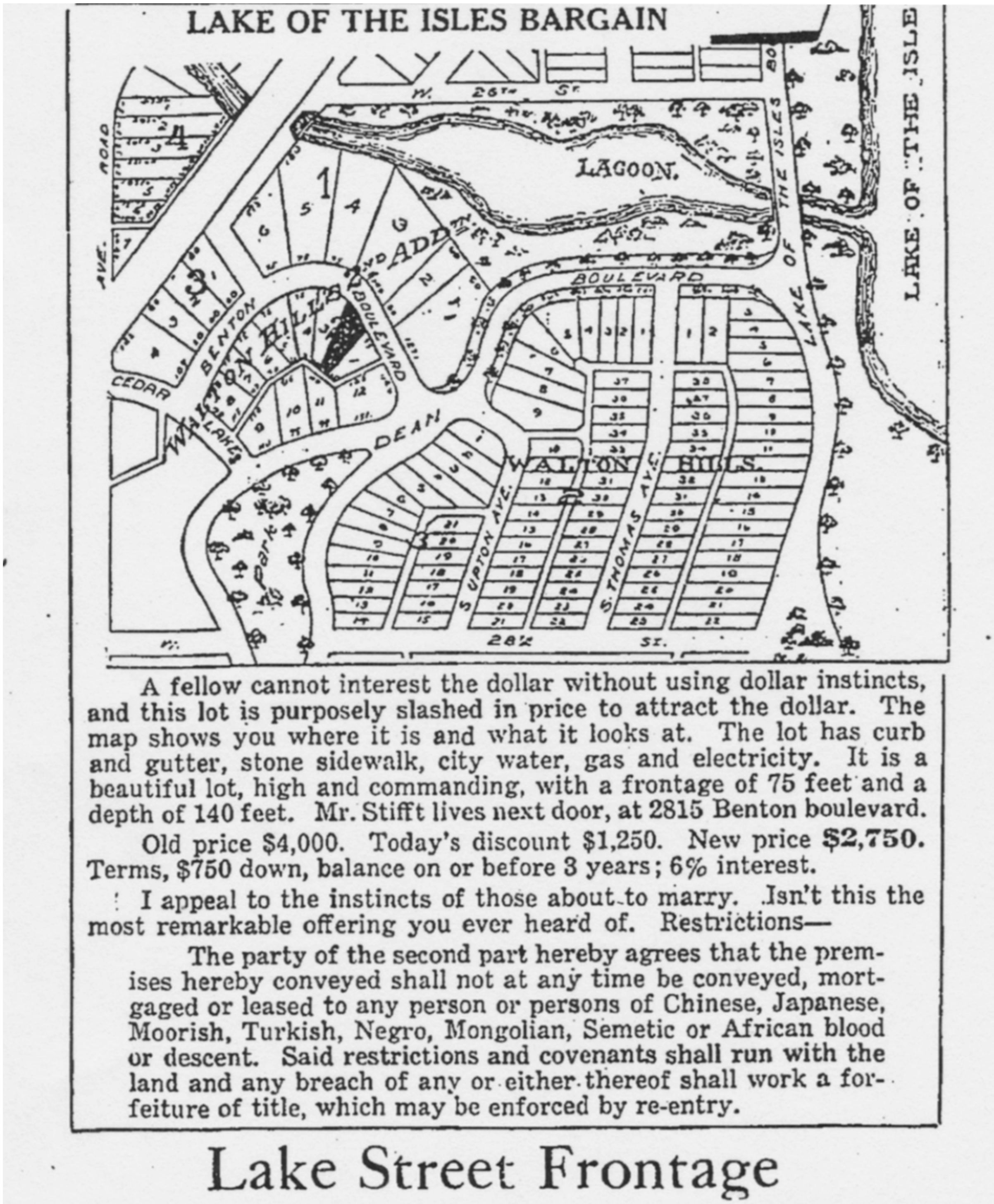
The party of the second part hereby agrees that the premises hereby conveyed shall not at any time be conveyed, mortgaged or leased to any person or persons of Chinese, Japanese, Moorish, Turkish, Negro, Mongolian or African blood or descent. Said restrictions and covenants shall run with the land and any breach of any or either thereof shall work a forfeiture of title, which may be enforced by re-entry.

This conveyance is subject to the following provisions, the violation of which shall automatically revest the title herein in the vendors, their heirs or assigns, Party of the second part, his heirs, executors, administrators, or assigns, agrees not to sell or rent or permit said premises to be occupied by persons of African or Semitic race. According to the plat thereof on file and of record in the office of the Register of Deeds in and for the County of Hennepin and State of Minnesota.

(e) No race or nationality other than the Caucasian Race shall use or occupy any building on any lot, except that this covenant shall not prevent occupancy by domestic servants of a different race or nationality employed by an owner or tenant.

Note: This figure provides three examples of racial covenants in sales deeds in Hennepin County, Minnesota.

Figure F.2: Newspaper Advertisement of Racial Covenants in a New Development



LAKE OF THE ISLES BARGAIN

A fellow cannot interest the dollar without using dollar instincts, and this lot is purposely slashed in price to attract the dollar. The map shows you where it is and what it looks at. The lot has curb and gutter, stone sidewalk, city water, gas and electricity. It is a beautiful lot, high and commanding, with a frontage of 75 feet and a depth of 140 feet. Mr. Stifft lives next door, at 2815 Benton boulevard.

Old price $4,000. Today's discount $1,250. New price **$2,750.** Terms, $750 down, balance on or before 3 years; 6% interest.

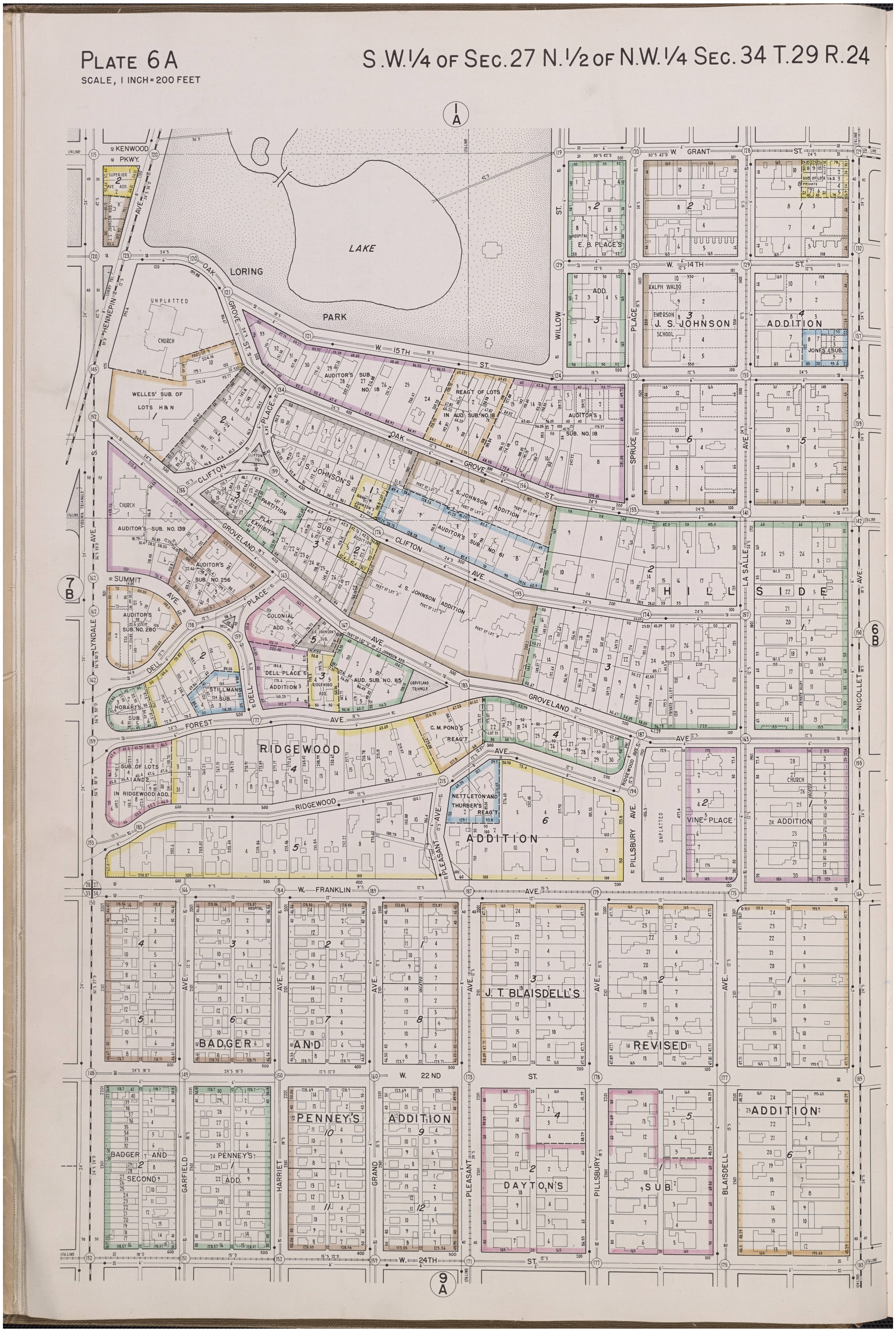
I appeal to the instincts of those about to marry. Isn't this the most remarkable offering you ever heard of. Restrictions—

The party of the second part hereby agrees that the premises hereby conveyed shall not at any time be conveyed, mortgaged or leased to any person or persons of Chinese, Japanese, Moorish, Turkish, Negro, Mongolian, Semetic or African blood or descent. Said restrictions and covenants shall run with the land and any breach of any or either thereof shall work a forfeiture of title, which may be enforced by re-entry.

Lake Street Frontage

Note: This figure provides an example of newspaper advertisement of racial covenants in the 'Walton Hills' development, *Minneapolis Morning Tribune, January 12, 1919*.

Figure F.3: Example Page from the 1940 Minneapolis City Atlas



Note: This figure provides an example page from the 1940 Minneapolis City Atlas, showing to-scale real estate development boundaries and development names.