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The Impact of Racial Segregation on College Attainment in Spatial Equilibrium*

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Abstract

This paper seeks to understand the forces that maintain racial segregation and the Black-White gap in college attainment, as well as their interactions with place-based policy interventions. We incorporate race into an overlapping-generations spatial-equilibrium model with parental investment and neighborhood spillovers. Race matters due to: (i) a Black-White wage gap, (ii) amenity externalities—households care about their neighborhood's racial composition—and (iii) additional barriers to moving for Black households. We find that these forces account for 71% of the racial segregation and 64% of the Black-White gap in college attainment for the St. Louis metro area. The presence of spillovers and externalities generates multiple equilibria. Although St. Louis is in a segregated equilibrium, there also exists an integrated equilibrium with a lower college gap. We compare various place-based policy interventions to evaluate their effectiveness in reducing segregation and destabilizing the segregated equilibrium.

JEL Classification: J15, J24, O18

Keywords: Racial disparities, neighborhood segregation, education, income inequality.

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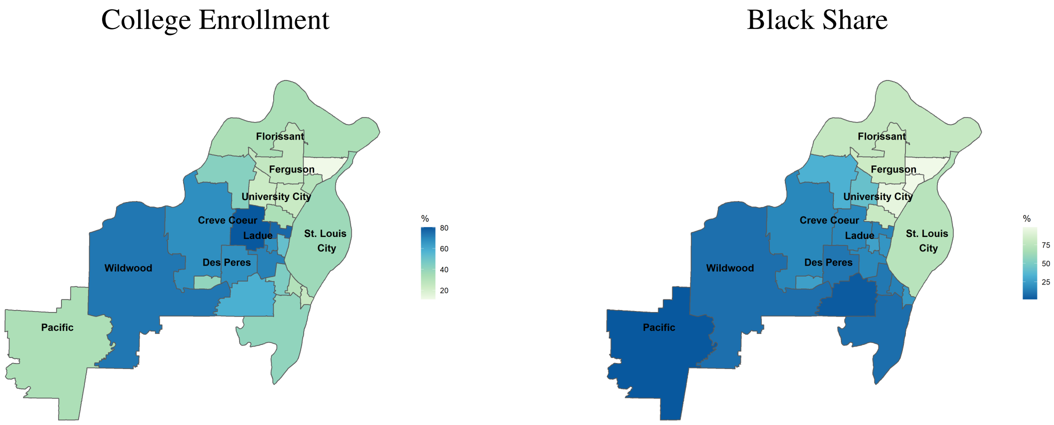
1 Introduction

There is a growing body of research showing that the neighborhood where a child grows up profoundly impacts their adult outcomes, such as college attainment, employment, and intergenerational mobility (e.g., Chetty et al., 2018; Chetty and Hendren, 2018; Chyn, 2018). However, segregation by race is a predominant feature of American cities, and, as a result, there is substantial racial inequality in exposure to advantageous neighborhoods (e.g., Bayer et al., 2021). In this paper, we first explore the mechanisms behind racial segregation and the Black-White gap in college attainment. We then study place-based interventions designed to reduce the college gap and racial segregation.

In St. Louis, one of the most segregated cities in the country and the focus of this paper, there is a Black-White gap in college attainment of 28 percentage points. Of the White children who grow up in St. Louis, 47 percent of them will earn a college degree, while only 19 percent of the Black children will (Chetty et al., 2018). At the same time, there is substantial neighborhood segregation by race. Figure 1 presents two maps of the school districts in St. Louis city and county. The left panel shows the proportion of the districts' students who enroll in a four-year college degree program, while the right panel shows the share of the districts' students who are Black. The maps show a striking link between the two, with a correlation of -0.63, suggesting a strong relationship between the city's segregation and its racial gap in college attainment. While previous authors have empirically demonstrated a causal relationship between segregation and college attainment (Ananat, 2011; Chyn et al., 2022; Cutler and Glaeser, 1997), the underlying mechanisms that generate this relationship are not yet fully understood.

This paper builds an overlapping-generations spatial-equilibrium model to study the mechanisms behind racial segregation and the racial gap in college attainment. The framework incorporates three channels through which race impacts household outcomes and neighborhood choices. Race matters due to: (i) the Black-White wage gap, (ii) *amenity externalities*—households care about the racial composition of their neighbors, and (iii) additional barriers to moving faced by Black households. Our first result is that these three channels account for 71 percent of the racial segregation and 64 percent of the college gap in the data. Importantly, neither the level of segregation nor the college gap are targeted in the calibration. Second, we find that both the Black-White wage gap and the amenity externalities are crucial for generating the level of racial segregation and the college gap observed in the data. In contrast, we find that

Figure 1: Neighborhood Segregation in St. Louis County



Notes: The left panel shows the share of students who go on to attend a 4-year college in each school district. The right panel shows the share of Black students who attend that school district. Source: School-district level data for Missouri in 2020 from the National Center for Education Statistics.

the additional barriers to moving faced by Black households do not seem to be quantitatively important. Third, we show that due to the presence of spillovers and externalities, the model has multiple equilibria. The quantitative exploration suggests that St. Louis is in the segregated equilibrium, likely due to the history of de jure racial segregation that shaped the current neighborhoods of St. Louis. However, the quantitative analysis also suggests that, even with the same calibration of the racial differences, there exists a more integrated equilibrium with a lower college gap. Finally, we study alternative place-based policy interventions in general equilibrium. We show that some interventions can destabilize the segregated equilibrium, and we compare the welfare implications among our proposed interventions.

Section 2 extends a standard overlapping-generations spatial-equilibrium model of a city with spillovers to include race. As in standard models, families choose the neighborhood where they live, taking into consideration local spillovers, which, in addition to parental investment, affect their child's skill. The child's skill then determines the probability they go to college and their future income. Local spillovers are a function of the share of adults with a college education in the neighborhood. The model extends this classic framework to incorporate race in three different ways. First, race affects workers' wages, with Black workers earning less than White workers conditional on education and skills—the Black-White wage gap. Second, race affects household preferences over the racial composition of their neighborhood, which we model as *amenity externalities*.[1] This captures a number of forces, including fear of discrimination in all-White neighborhoods, White flight, or homophily.[2] Third, Black households face an additional moving cost. This cost is a reduced-form way to capture a range of barriers to moving faced by Black households, which disproportionately impacts the neighborhood choice of Black families.[3] We incorporate these three aspects because together they capture a broad range of mechanisms supported by a substantial body of empirical research. The equilibrium features racial segregation, which leads to Black households experiencing lower neighborhood spillovers than White children, thereby contributing to gaps in college attainment.

Section 3 takes the model to the data. First, we calibrate the model using a rich set of data moments. To discipline the three differences between Black and White households, we (i) estimate the Black-White wage gap from Mincer regressions, (ii) target the the causal effect of a neighborhood's racial composition on neighborhood choice, as in Caetano and Maheshri (2021), and (iii) target the different propensity to move across neighborhoods by Black and White households. To map the St. Louis MSA Census tracts into three parsimonious neighborhoods, we use a k-means clustering algorithm. These neighborhoods represent: (i) a predominantly Black and low-income neighborhood, (ii) a predominantly White and middle-income neighborhood, and (iii) a predominantly White and high-income neighborhood. To discipline the skill formation process, college attendance decisions, and the importance of local spillovers, we target the relation between test scores, parental investment, and neighborhood educational attainment in the National Longitudinal Survey of Youth (NLSY) data. We conduct three validation tests to assess the key mechanisms in our model. First, we compare the model's predictions to established estimates from the literature on the causal effects of neighborhoods on college attainment, as estimated by Chetty et al. (2016), and segregation on educational attainment, as estimated by Ananat (2011). In both cases, our model aligns closely with these empirical estimates. Furthermore, we demonstrate that the model accurately captures the empirical relationship between college attainment and skill, including the differences in these

[1] We do not refer to the amenity externality as homophily because homophily typically refers to the preference for living near individuals who share similar characteristics, rather than the avoidance of those with different characteristics. The amenity externality in our model can encompass both forces.

[2] There is a substantial body of empirical work that shows that location choice depends on the racial composition of the neighborhood for both Black and White households, including Aliprantis et al. (2022); Almagro et al. (2023); Bayer et al. (2017, 2022); Bayer and McMillan (2005); Bayer et al. (2004); Boustan (2013); Caetano and Maheshri (2021); Card and Rothstein (2007); Davis et al. (2023); Galiani et al. (2015).

[3] See Turner et al. (2013) for a review of the ways in which minorities experience discrimination in housing markets.

relationships by race.

Section 4 presents the main quantitative results. First, we show that the model's three racial differences provide a good explanation of the college gap and racial segregation, which are not targets of the calibration. The model generates a racial gap in college attendance of 18 percentage points, explaining about 64 percent of the college gap in the data. The other 36 percent that the model does not capture is likely coming from other forces that are not present in the model. Similarly, the model generates 71 percent of the racial segregation in the data as measured by a dissimilarity index. In the model the index is equal to 0.43, while it is 0.61 in the data.

Next, we study the contribution of each of the three racial differences in explaining the segregation index and the college gap. We find that removing the wage gap increases the education of Black children for two main reasons. First, there is a direct effect: Black households have more resources and use them to increase their private investment in their children's education. Second, there is a general equilibrium effect: As the education of Black children increases, the spillover in the predominately Black neighborhood goes up, amplifying the initial effect of investment. However, due to the amenity externalities and the barriers to moving, racial segregation is not substantially reduced. As a result, there is still a racial gap in educational attainment because the neighborhood spillovers remain lower in the Black neighborhood than in the higher-income White neighborhoods.

When we remove the amenity externalities we also find a reduction of the racial college gap, but for different reasons. Without the amenity externalities, households adjust their neighborhood choice, which generates a large decrease in segregation. As a consequence, both White and Black households are exposed to similar local spillovers, which contributes to the reduction of the college gap. This effect is amplified by an increase in private investment by Black parents. Finally, we find that equalizing the mobility costs has a minimal effect on both the Black-White gap in college attainment and segregation.

Section 5 shows that the presence of spillovers and externalities generates multiple equilibria. The quantitative exploration suggests that although St. Louis is in a segregated equilibrium, there also exists a more integrated equilibrium with a lower college gap. In the history of St. Louis, racial covenants, redlining, and other de jure forms of segregation are no doubt important for generating the level of observed segregation (Johnson, 2020). Our analysis shows that this segregated equilibrium can be maintained even when these legalized forms of segregation are removed. We argue that if agents could coordinate, a transition from the segregated to the integrated equilibrium is possible. The quantitative analysis suggests that such a transition would be fast, with the bulk of the changes occurring within the first generation.

Finally, we use the model to compare two place-based government interventions that are being discussed by policymakers. First, Moving to Opportunity (MTO) focuses on subsidizing low-income households to relocate to high-education neighborhoods. In contrast, Opportunity Zones (OZ) incentivizes high-education households to move to low-education neighborhoods, aiming to improve local economic conditions in disadvantaged areas.[4] We find that both interventions effectively reduce racial segregation and the college gap. However, the main difference is that only the OZ intervention is able to destabilize the segregated equilibrium so that the economy converges to the integrated equilibrium. We find that the OZ intervention proves more succesfull in reducing both racial segregation and the college attainment gap and provides larger welfare gains than the MTO intervention.

Related literature. This paper builds on two separate strands of structural literature.[5] First, there is literature examining racial segregation in spatial equilibrium models, pioneered in Schelling (1969, 1971). Several papers (e.g. Banzhaf and Walsh, 2013; Bayer and McMillan, 2005; Bayer et al., 2004; Caetano and Maheshri, 2021; Christensen and Timmins, 2023; Sethi and Somanathan, 2004) examine racial segregation in models with homophily, Black-White wage gaps, exogenous neighborhood amenities, and housing market discrimination but do not consider the impact on human capital accumulation.[6]

Second, several papers (e.g. Aliprantis and Carroll, 2018; Chyn and Daruich, 2022; Eckert and Kleineberg, 2019; Fogli et al., 2023; Gilraine et al., 2023; Zheng and Graham, 2022) examine human-capital spillovers in quantitative spatial equilibrium models, and several papers (e.g. Almagro and Domínguez-Iino, 2024; Couture et al., 2023; Hoelzlein, 2020) examine the inter-

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[4] For references on how OZ works in the real world, visit, for example, https://eig.org/opportunity-zones/.

[5] This paper also builds on results from several strands of empirical literature. This includes work on the underlying causes of segregation (Boustan, 2013; Card et al., 2008; Cutler et al., 1999; Dawkins, 2005; Echenique and Fryer, 2007; Monarrez and Schönholzer, nd; Sethi and Somanathan, 2009) and the consequences of segregation (Ananat, 2011; Andrews et al., 2017b; Billings et al., 2013; Chyn et al., 2022; Cutler and Glaeser, 1997; Derenoncourt, 2022; Johnson, 2011).

[6] More generally, there is a recent effort to incorporate race into macroeconomic analysis (Aliprantis and Carroll, 2019; Boerma and Karabarbounis, 2023; Brouillette et al., 2021; Hsieh et al., 2019; Nakajima, 2023).

action between endogenous amenities and sorting by income but do not consider race.[7] This second set of papers is built on the literature on discrete choice models with local spillovers (e.g., Benabou, 1996; Brock and Durlauf, 1995; Fernandez and Rogerson, 1996), which, while seemingly motivated by racial inequalities, do not specifically model race. One exception is Badel (2015) who presents a model of racial segregation and human capital accumulation. He shows that the model has multiple equilibria, including an equilibrium in which White households earn more than Black ones due to differences in human capital accumulation.

Our model builds on previous work in two ways. First, we incorporate three ways in which race affects neighborhood segregation: inequalities in the labor market, amenity externalities, and barriers to moving. Second, we incorporate local spillovers, and, as a consequence, segregation endogenously affects educational attainment and intergenerational mobility. Our quantitative analysis shows that capturing each of these mechanisms and their interactions is important for studying the interplay between racial segregation, income segregation, and human capital accumulation.

The rest of this paper proceeds as follows. Section 2 presents the model. Section 3 shows how we take the model to the data. Section 4 presents the main counterfactual exercises closing the Black-White wage gap, removing the amenity externalities, and removing the barriers to moving. Section 5 analyzes the multiple equilibria feature of the model and the place-based interventions. Finally, Section 6 concludes.

2 Model

We extend a standard overlapping-generation spatial-equilibrium model to incorporate race. We model a single metro area. Families choose a neighborhood to live in while considering differences in local spillovers that affect their children's future income and education. The model incorporates three mechanisms through which race affects choices and outcomes: (i) racial disparities in the labor market, which are reflected in income, (ii) preferences over the racial composition of the neighborhood, which we call *amenity externalities*, and (iii) racial differences in barriers to moving across neighborhoods. We formally describe the model in detail below.

[7] Relatedly, Bilal and Rossi-Hansberg (2021) and De la Roca et al. (2022) consider spatial equilibrium models where location impacts future income growth.

2.1 Environment

The economy is populated by overlapping generations of agents who live for two periods. Agents are of race Black or White, denoted by $r \in \{B, W\}$. Race is a permanent characteristic of each dynasty. In the first period, the agent is young and acquires education. In the second period, the agent is an adult with an income that depends on their education, skill, and race.[8] Labor is perfectly mobile across neighborhoods, so wages do not depend on the neighborhood in which a household lives.

There are 3 neighborhoods, denoted by $n \in \{A, B, C\}$. All houses are of the same size and quality, and the rent in neighborhood n is denoted by p_n.[9] Housing is supplied elastically according to $S_n = \eta_n p_n^{\psi}$, where $\psi > 0$ is the price elasticity of housing supply and η_n reflects land availability in the neighborhood.

There are two educational levels, $e \in \left\{e^L, e^H\right\}$, corresponding to low (equivalent to non-college graduates) and high (equivalent to college graduates), respectively. Agents choose this education level before they enter the second period of their life. Four key characteristics shape the education choice. First, the education choice depends on the agent's race r, as wages are race-specific. Second, two individual inputs affect the cost of education: the skill s of the agent and the level of parental investment i. Finally, the neighborhood where the agent grows up has an impact on their education level as an adult through the local spillover. As in Fogli et al. (2023), this local spillover is meant to summarize a variety of neighborhood factors that we do not explicitly model. These may be peer effects (Agostinelli, 2018), quality of the local schools (Hyman, 2017), and networks (Rothstein, 2019), all of which have been shown to impact long-term outcomes of children. We model the local spillover effect in neighborhood n as a function of the share of households with parents with high education in that neighborhood, X_n. We do not model differences in school expenditures across neighborhoods because they are remarkably similar in the St. Louis Metro area. Using data from the National Center for Education Statistics (NCES), as of the 1999-2000 school year (the year we use to calibrate the

[8] The second period represents the entire working life, which means that there are complete markets in this stage. Hence, the paper abstracts from the influence of borrowing constraints on neighborhood choice. It is possible that the borrowing constraints affect Black households more than White households due to racial differences in parental wealth and bequests. As we explain below, the differential mobility cost by race captures some of these differences in wealth at the time of choosing their location.

[9] Following Couture et al. (2023) our utility function includes unit-demand for housing. This generates a non-homotheticity such that high-income households spend a lower share of their income on housing and, therefore, are more willing to pay for neighborhood amenities.

neighborhood characteristics in our model), expenditures per student were \$4842 in cluster A, \$4891 in cluster B, and \$4547 in cluster C. Furthermore, the average expenditures per student were \$4837 for Black students and \$4139 for White students.[10] In the absence of differences in monetary expenditures, we leave intangible differences in quality as part of the X_n.

2.2 Adult's Problem

For an adult of race r, skill s, and education level e who was born in neighborhood n_0, the value of living in neighborhood n is

$$V(r,s,e,n_0,n) = \max_{c,i} \log(c) + \log(A_{r,n}) + \beta\mathbb{E}\left[\mathcal{V}\left(r,s',e',n\right)\right]$$

subject to

$$\begin{aligned} c + i + p_n + m(r,n_0,n) &= y(r,e,s) \\ \log s' &= F^s(i,X_n) + \varepsilon_s \qquad \text{where } \varepsilon_s \sim N(0,\sigma_s) \\ P(e' = e^H) &= G^e\left(r,s',n\right) \end{aligned}$$

where β is the altruistic discount factor—that is, the extent to which parents care about the utility of their offspring. The cash-on-hand available for adults to spend is comprised solely of their labor income, $y(r,e,s)$. Income is a function of race, r, education, e, and skill s. They split their budget between consumption, investments into their children, rent, and moving costs. Investments in our model are inter-vivos transfers from parents to children that specifically support the development of the child's human capital. In order to live in a neighborhood, agents must consume one unit of housing services at rental price p_n. Finally, $m(r,n_0,n)$ captures moving costs that depend on race, the origin neighborhood n_0, and the destination neighborhood n. Note that this is not a moving cost as in a typical spatial equilibrium model. Instead, ours captures additional mobility frictions to intergenerational moves across neighborhoods of different qualities. We allow these frictions to depend on the race of the household. Specifically, in our calibration this moving cost is positive only for Black households that are moving out

[10] Missouri was forced to equalize funding across districts after a 1993 lawsuit Committee for Educational Equality v. State of Missouri found the existing funding disparities to be unconstitutional. The funding formula was updated again in 2005 to further account for differences in student need based on the share of students with IEPs, free and reduced lunch, or english as a second language.

of the majority-Black neighborhood. This is designed to capture additional barriers to moving faced by Black households, which are not present in the model. These barriers can include differences in financial constraints (Gupta et al., 2024) or discrimination in housing markets, which makes Black households face higher search frictions than White households in finding the same unit of housing.[11]

The skill of the child depends on a production function F^s and a shock ε_s, which is independently and identically distributed. The function F^s depends on the parent's investment and the neighborhood characteristics in which the child grows up, summarized by the spillovers X_n. We describe more about its calibration and functional form in Section 3.5. The probability that the child chooses high education, $(e' = e^H)$, depends on the outcome of the child's optimization problem. We summarize this by the policy function G^e, which depends on certain state variables that are relevant for the child. This will be further detailed in Section 2.3.

Finally, we model the amenity externalities as adults receiving utility from a neighborhood amenity, $A_{r,n}$, which depends on the race of the agent and the racial composition of their neighborhood. This racial composition is summarized by $S_{r,n}$, which is the share of households of race r in neighborhood n. The amenity externalities incorporate any motivation for location choice that is related to the neighborhood's racial composition. These can include fear of discrimination in an all-White neighborhood for Black households, White flight, or homophily. We describe in detail the empirical evidence surrounding the amenity externalities, as well as its functional form and calibration in Section 3.1. Although we do not explicitly model homophily based on income or education groups, the mechanisms in the model still generate several reasons for households to sort across neighborhoods by income, including rents, amenities, and education spillovers.

Given the value from living in each neighborhood, an adult of race r, skill s, education e, and initial neighborhood n_0 chooses a neighborhood in which to live during adulthood according to

$$\mathscr{V}\left(r,s,e,n_0\right) = \mathbb{E}_{\varepsilon}\left[\max_{n}\left\{V\left(r,s,e,n_0,n\right)+\varepsilon^{n}\right\}\right],$$

where ε^n are preference shocks that are independently and identically distributed, and drawn

[11] For example, Christensen and Timmins (2022) show that minority households are systematically shown housing in neighborhoods with higher poverty rates and in school districts with lower test scores. Quillian et al. (2020) document persistent racial gaps in mortgage costs and loan denials. Christensen et al. (2021) show that rental agents are less likely to respond to inquiries from applicants with racial or ethnic names.

from an extreme value distribution with shape parameter κ. This distributional assumption allows us to write the probability that a household of type (r,s,e,n_0) chooses to live in neighborhood n as

$$\lambda(r,s,e,n_0,n) = \frac{\exp\left(\frac{1}{\kappa}V(r,s,e,n_0,n)\right)}{\sum_{n\in N}\exp\left(\frac{1}{\kappa}V(r,s,e,n_0,n)\right)},$$

and the expected value function is

$$\mathscr{V}(r,s,e,n_0) = \kappa \ln\left(\sum_{n\in N}\exp\left(\frac{1}{\kappa}V(r,s,e,n_0,n)\right)\right).$$

2.3 Child's Problem

A child growing up in neighborhood n, of race r, and skill s chooses their education level $e \in \{e^L, e^H\}$ such that

$$e = \underset{\{e^L,e^H\}}{\operatorname{argmax}}\{\mathscr{V}\left(r,s,e^L,n\right)+\sigma^L, \mathscr{V}\left(r,s,e^H,n\right)-C(s)+\sigma^H\}$$

where σ^L and σ^H are preference shocks for education, which are independently and identically distributed, and drawn from an extreme value distribution with shape parameter σ. $C(s)$ is a utility cost of acquiring the high level of education, which is decreasing in the skills of the child. Taking into account these costs and their realized preference shocks, children choose the level of education that maximizes their expected value when entering adulthood. Applying the properties of the extreme value distribution, the probability that the child chooses high education can be written as

$$G^e(r,s,n) = \frac{1}{1+exp\left(-\frac{1}{\sigma}\left[\mathscr{V}(r,s,e^H,n)-C(s)-\mathscr{V}(r,s,e^L,n)\right]\right)}.$$

2.4 General Equilibrium

We now aggregate the economy to define the general equilibrium. The key general equilibrium objects of the model are $\{S_n, X_n, S_{r,n}\}_{n=1}^N$.

Definition: A *Recursive Competitive Equilibrium* is characterized by policy functions for the neighborhood choice $n(r,s,e,n_0)$, consumption $c(r,s,e,n_0,n)$, and investment $i(r,s,e,n_0,n)$ decisions of the parent; the education choice $e'(r,s,e,n)$ of the child; value functions $V(r,s,e,n_0,n)$;

house prices $\{p_n\}_{n=1}^{N}$; local spillovers $\{X_n\}_{n=1}^{N}$; neighborhood racial shares $\{S_{r,n}\}_{n=1}^{N} \forall r \in \{B,W\}$; and an ergodic distribution $F(r,s,e,n_0,n)$ over race, skill, education, birth neighborhood, and adult neighborhood, which satisfy the following:

(i) Household optimization: The policy functions n, e', c, i solve both the adult's and child's problem.

(ii) Housing market clearing:

$$S_n = \eta_n p_n^{\psi} = \int F(dr, ds, de, dn_0, n) \qquad \forall\, n = 1, \ldots, N$$

(iii) Spillover consistency:

$$X_n = \frac{\int F\left(dr, ds, e^H, dn_0, n\right)}{S_n} \qquad \forall\, n = 1, \ldots, N$$

(iv) Location consistency:

$$S_{r,n} = \frac{\int F(r, ds, de, dn_0, n)}{S_n} \qquad \forall\, n = 1, \ldots, N \text{ and } r \in \{B, W\}.$$

The model has three general equilibrium forces. First, the housing market has to clear, with the demand for housing summarized by the population of each neighborhood, S_n. The demand comes from all the adults that choose to live in n, which is given by $\int F(dr, ds, de, dn_0, n)$. In equilibrium, demand and supply of housing are equalized: $S_n = \eta_n p_n^{\psi} = \int F(dr, ds, de, dn_0, n)$.

Second, the local spillovers are the share of households with parents with high education in that neighborhood, X_n. The number of households with parents with high education in n is $\int F\left(dr, ds, e^H, dn_0, n\right)$. Therefore, the share of parents with high education is $X_n = \frac{\int F\left(dr, ds, e^H, dn_0, n\right)}{S_n}$.

Third, there are amenity externalities, summarized by the racial composition of each neighborhood $S_{r,n}$. The number of households of race r in n is $\int F(r, ds, de, dn_0, n)$. Therefore, the share of households of race r is $S_{r,n} = \frac{\int F(r, ds, de, dn_0, n)}{S_n}$.

The presence of spillovers and amenity externalities imply that the model can have multiple equilibria. We tackle the equilibrium multiplicity in Section 5. In the next section, we calibrate the model assuming the economy is always in the same equilibrium.[12]

Intergenerational transmission The model captures two channels of intergenerational linkages. First, we explicitly model investment as inter-vivos transfers between parents and children. Investment by parents leads to higher-skilled children, which implies higher incomes and higher education probabilities. The second intergenerational linkage is through the neighborhood in which a child is born. The neighborhood captures two forces. On the one hand, living in a high-quality neighborhood is a complementary way of investing in the skills of a child, increasing income and educational attainment. On the other hand, there is persistence in neighborhood choice across generations due to the moving cost. A child who is born in a high-quality neighborhood does not need to pay the moving cost to live there as an adult, while a child born in a low-quality neighborhood will face an additional barrier to upgrading their neighborhood quality. While we do not explicitly model an inherited-wealth gap, we do model the intergenerational persistence of income and education through these other channels.

3 Quantitative Evaluation

In this section, we describe how we take the model to the data. Then, we perform validation exercises to show that the model replicates several non-targeted causal estimates from the literature.

We calibrate the model to represent key features of the St. Louis MSA. Besides being one of the most segregated cities in the U.S., St. Louis has two features that are convenient for our analysis. First, 95 percent of households are either White or Black. Given the small share of other races, it is reasonable to focus on just White and Black households. Second, the labor market is well integrated, with low commuting costs across neighborhoods. This is in line with our model's assumption of a single, city-wide labor market.

Our calibration strategy requires some parameters to be set externally, while others are calibrated internally so that the model best matches a rich set of moments in the data. In both cases, some moments and estimates are taken from the literature, while for others, we compute the moment ourselves in the data. Table 1 shows the parameters that were set externally, based on the literature or our own estimates. Table 2 shows the parameter values and the correspond-

[12] Specifically, we have nine general equilibrium variables, $\{S_n, X_n, S_{r,n}\}$ for $n = A, B, C$, for which we can observe the data counterparts. The calibration routine always starts with their data counterparts as the initial guesses for these variables.

Table 1: Externally Calibrated Parameters

Parameter	Description	Value	Source
β	Discount factor	0.97^{40}	
γ_B	Bliss points for Black	0.50	Banzhaf and Walsh (2013)
γ_W	Bliss points for White	0.90	Banzhaf and Walsh (2013)
$w(B,L)$	Relative wage of Black, low education	0.92	Mincer regressions
$w(B,H)$	Relative wage of Black, high education	1.57	Mincer regressions
$w(W,H)$	Relative wage of White, high education	1.71	Mincer regressions
χ	Return to skill	0.18	Mincer regressions
ψ	Housing supply elasticity	2.36	Saiz (2010)

Table 2: Internally Calibrated Parameters

Parameter	Description	Value	Moment	Data	Model
Neighborhoods					
A_A	Amenity in A	1.0000	Population neighborhood A	0.1700	0.1150
A_B	Amenity in B	1.1894	Population neighborhood B	0.6200	0.6676
A_C	Amenity in C	1.2752	Population neighborhood C	0.2100	0.2174
η_A	Housing supply in A	25.3023	Rent neighborhood A	0.1200	0.1017
η_B	Housing supply in B	22.6165	Rent neighborhood B	0.2178	0.2248
η_C	Housing supply in C	1.4118	Rent neighborhood C	0.4460	0.4526
κ	Shape parameter for location	0.1232	Neighborhood flows	0.4600	0.4200
$m_s b$	Migration cost for Black HHs	0.0200	Diff in moving prob for Black HHs	-0.4550	-0.4853
Disamenities: Importance of bliss point					
φ_W	White	0.5492	Migration response to Black share, Black non-college	0.0241	0.0267
φ_B	Black	0.8740	Migration response to Black share, Black college	0.0345	0.0274
			Migration response to Black share, White non-college	-0.0225	-0.0280
			Migration response to Black share, White college	-0.0283	-0.0278
Skill production					
θ_c	Constant term	0.7884	Mean skills	1.0000	0.9669
θ_i	Investment	0.1579	Reg S on x and i	0.1510	0.1588
θ_X	Spillovers	0.3081	Reg S on x and i	0.2984	0.3053
σ_s	Std. skill shock	0.1916	Rank-rank correlation	0.4130	0.4143
Education					
$\bar{c}$	Education cost level	1.7879	Educational probability	0.4166	0.4624
σ	Shape parameter education	0.2572	R^2 education choice	0.1570	0.1712

ing moments that are targeted in our internal calibration routine. Although the calibration of all the parameters is done jointly, some moments are more informative than others for a given parameter of interest. See Appendix B.1 for more details on identification. Next, we further discuss each aspect of the model, the associated parameters, and the empirical estimates we use to discipline them.

First, as agents live for two periods, we set each period length equal to 40 years. Accordingly, the discount factor $\beta = 0.97^{40}$.

3.1 Amenity externalities

Our model includes local amenities that depend on the racial composition of the neighborhood, as suggested by Becker and Murphy (2000). In the data, there is abundant evidence that households care about the racial composition of a neighborhood when moving.[13] The amenity externalities capture many different forces that could lead to this empirical regularity. For example, the externalities can be interpreted as homophily, that is, the preference to live with neighbors of your own race. They can also capture the White flight phenomenon in which White households migrate away from more racially-diverse areas. An additional interpretation is that agents fear being discriminated against when living in a neighborhood in which the neighborhood racial composition deviates from some ideal mixture. For example, if an agent worries about facing discrimination in a public park, they enjoy the amenity less than an individual who does not worry about discrimination. We do not need to take a specific stand on its interpretation, but we let the data determine its empirical relevance.

We follow Banzhaf and Walsh (2013) and assume the amenity an individual enjoys takes the following functional form:

$$A_{r,n} = A_n \left(1 - \varphi_r \left(S_{r,n} - \gamma_r\right)^2\right).$$

The amenity, $A_{r,n}$, has two components. The first is an exogenous component, A_n, representing the traditional amenities that affect the valuation of a neighborhood: These could reflect proximity to a downtown, access to parks or a waterfront, etc. Second, the amenity includes an endogenous component that depends on the neighborhood's racial composition, $S_{r,n}$. Following Banzhaf and Walsh (2013), households have a "bliss point" for the degree of racial integration in their neighborhoods. The "bliss point" γ_r depends on the race of the household. The parameter φ_r controls the strength of the amenity externalities, which also differs by race. As the racial composition of the neighborhood deviates from the household's bliss point, it benefits less from the exogenous amenity by a factor $\varphi_r \left(S_{r,n} - \gamma_r\right)^2$. The higher the φ_r, the more the household's utility declines when the neighborhood's racial composition deviates from the bliss point.

We draw on two sources of empirical evidence to help us discipline $A_{r,n}$. First, we follow Banzhaf and Walsh (2013) and set $\gamma_W = 0.9$ and $\gamma_B = 0.5$. In turn, Banzhaf and Walsh (2013) draw on survey evidence from Krysan and Farley (2002) showing that Black households prefer a neighborhood mix that is about 50 percent White and 50 percent Black, while White

[13] For example, see Aliprantis et al. (2022); Almagro et al. (2023); Bayer et al. (2017, 2022); Bayer and McMillan (2005); Bayer et al. (2004); Boustan (2013); Caetano and Maheshri (2021); Card and Rothstein (2007); Davis et al. (2023); Galiani et al. (2015).

households prefer a mix that is about 90 percent White and 10 percent Black.[14] Interestingly, the survey evidence also shows that the main reasons for these choices are based on the racial characteristics of the other residents, independent of other neighborhood characteristics and amenities.

Second, Caetano and Maheshri (2021) isolate the causal effect of a neighborhood's racial composition on neighborhood choice from other local characteristics. They build a dynamic discrete neighborhood choice model and estimate the marginal effect of an increase in a neighborhood's Black share on the valuation of the neighborhood for Black and White households. In particular, their paper finds that the responses of neighborhood choice probabilities to the neighborhood's racial composition are larger than the responses to its income composition, consistent with the survey evidence mentioned above. We use their moments as targets in our calibration in order to identify φ_B and φ_W, the intensity of the amenity externalities for Black and White households, respectively. Specifically, we calculate the change in the probability that group g (i.e., Black or White, and college or non-college graduates) chooses neighborhood j (conditional on moving) in response to a 1-percentage-point increase in the Black share in both the model and the data.[15]

Table 2 shows that the model is consistent with the causal effects of the Black share on neighborhood choice. In both the data and the model, the response of White households, both college and non-college, to a 1-percentage-point increase in the Black share is between -2 and -3 percentage points. For Black households, the response is between 2 and 3.5 percentage points. Importantly, we do not target the level of the racial composition of each neighborhood, but the causal effect of a neighborhood's racial composition on neighborhood choice. Instead, we show later that the model does a good job in replicating those non-targeted moments.

[14] In Appendix B.4, we perform some robustness checks of our main results with respect to these bliss points γ_B and γ_W.

[15] We compute the data target following Caetano and Maheshri (2021). The marginal effect of the Black share is given by $\frac{\partial P_{gj}}{\partial s_j} = \beta_g P_{gj}(1-P_{gj})$. We use their estimates of β_g combined with the neighborhood choice probabilities (for movers) for each neighborhood from our model, P_{gj}. In the model, we exogenously increase the Black share in neighborhood j by 1 percentage point; re-solve the value functions holding spillover and rents constant; compute the change in the probability that a mover chooses neighborhood j; and repeat for each neighborhood, 1 at a time. The model moment corresponds to the average over the three neighborhoods. In robustness exercises, we study the model's asymmetries and non-linearities by increasing or decreasing the Black share by different amounts.

Table 3: Neighborhood Characteristics in St. Louis

	All	Cluster A	Cluster B	Cluster C
Population Share	1.00	0.17	0.62	0.21
Black Share	0.20	0.78	0.09	0.07
College Share of Adults	0.28	0.15	0.23	0.53
Income ($)	57,835	33,273	55,405	84,749
Median House Price ($)	171,749	82,699	150,060	307,244

Notes: k-means clustering results for the St. Louis MSA. Data from 2000 Census and Chetty et al. (2018)

3.2 Neighborhood Characteristics

We use data on neighborhood characteristics to create a parsimonious representation of neighborhoods in the St. Louis MSA that can be mapped to the model. In addition, the exercise shows that assuming three neighborhoods is reasonable. We use data on Census tracts from the 2000 Census, compiled by Chetty et al. (2018). Our goal is to stratify the St. Louis Census tracts according to their socioeconomic characteristics. Specifically, we use a *k*-means clustering algorithm to group Census tracts by four different attributes: the median household income, the fraction of adults over 25 years with at least a bachelor's degree, the Black share of the population, and the median house price.[16] Note that each of these characteristics has a counterpart in our model that we will use to discipline the model.

Table 3 shows our results for the St. Louis MSA. In the entire MSA, the share of Black households is 20 percent. The clustering algorithm creates two predominantly White neighborhoods, B and C, which have 9 and 7 percent Black households, respectively. Neighborhood C has the highest income, house prices, and share of college graduates. In neighborhood A 78 percent of households are Black, making it a predominantly Black neighborhood. It also is relatively low-income, has the cheapest houses, and has the lowest share of college graduates. Hence, a good description of the data is that there is one predominantly White and high-income cluster, one predominantly White and middle-income cluster, and one predominantly Black and low-income cluster.[17]

One might be concerned about how sensitive the results are to using three clusters instead of more. In Appendix A.1, we perform robustness exercises by extending the analysis to four

[16]To compare different variables, we normalize each variable by the z-score. We exclude Census tracts with missing values in characteristics.

[17]See Appendix A.1 for a map of how the *k*-means clustering algorithm sorted the Census tracts into three neighborhoods.

or five clusters. With four clusters, the neighborhoods look similar, but cluster B, the predominately White and low-income cluster, is split into two groups. With five clusters, neighborhood C, the predominately White and high-income cluster, is also split in two. We interpret this to mean that with more clusters, the algorithm would like to even further stratify the White neighborhoods by income level but leave the predominately Black neighborhood unchanged. Therefore, with three neighborhoods, we are able to capture the stratification by both race and income. In light of this, we believe that focusing on three clusters is enough to capture the features of the data relevant to this paper while also helping to keep the model quantitatively tractable.[18]

We target some of the features in Table 3 and leave others as untargeted moments. We target the population shares, which identify the exogenous amenities of each neighborhood, A_n. We also target the relative differences in house prices, described below. On the other hand, we leave the racial compositions untargeted in order to learn how well the forces in our model can generate the level of segregation seen in the data.[19]

Finally, we externally set the housing supply elasticity using the estimate for St. Louis from Saiz (2010): $\psi = 2.36$. We internally calibrate the housing supply shifters, η_A, η_B, and η_C, to match the rent in each neighborhood from Table 3. We convert housing values to rents following Ganong and Shoag (2017) and impute a rental value of 5 percent of the housing price.[20]

3.3 Moving Across Neighborhoods

Our model contains mobility costs, $m(r,n_0,n)$, which depend on race, the origin neighborhood, and the destination neighborhood. In practice, we parameterize this in the following way:

$$m(r,n_0,n) = m^B \mathbb{1}(r = B, n_0 = A, n \neq A)$$

In other words, the mobility cost m^B applies only to Black households moving from the majority Black neighborhood ($n_0 = A$) to either of the other two neighborhoods. This is meant to be a

[18] Another concern is how stable the estimation is across time. The benchmark results use the 2000 Census. We also did the estimation with the Census of 1990, 2010, and 2020 and found similar results. This suggests that it is reasonable to assume that we are at a steady state in terms of neighborhood segregation.

[19] However, we do impose that the city-wide share of Black households is the same as in the data, 20 percent.

[20] In the model we normalize the average life-time earnings of a White low-educated worker to 1, i.e. $w(W,L) = 1$. Hence, 1 is equivalent to $\frac{\$34{,}444(1-\beta^{40})}{1-\beta}$ dollars.

reduced-form way of capturing a range of barriers to moving faced by Black households and, in particular, the ones who move into predominantly White areas. Some potential sources of these barriers may be discrimination in housing markets or difficulties in obtaining a mortgage in these neighborhoods. For specific examples, see Christensen and Timmins (2022), Quillian et al. (2020), and Christensen et al. (2021).

To discipline the parameter m_b, we draw on data to calculate the racial differences with respect to moving out of the majority Black neighborhood. Note that the notion of "moving" in our model corresponds to a child living in a different neighborhood type from that of their parents. We combine data from the 1997 National Longitudinal Survey of Youth (NLSY-97), containing county of residence for both parents and children, with the Census data used in our neighborhood clustering exercise. To map counties to neighborhood types in the NLSY-97, we do the same clustering exercise as we did in St. Louis, applied to the national level (see Appendix A.2 for details). Knowing the neighborhood types of parents and their children, we create transition matrices between them for both Black and White households. These matrices are presented in Table 13 in Appendix A.2. We find that Black children who are born in Neighborhood A are 45.5 percentage points less likely to live in B or C as adults, compared with their White counterparts. Table 14 shows that this 45.5 percentage point gap remains stable when controlling for characteristics of the child and the child's household, including parental income and education and the child's educational attainment. We choose m^B in the model to target this number. Our calibrated value of m^B is 0.02, which is 2 percent of the average life-time earnings of White, low-educated workers.

The moving decision in the model also comes with a taste shock that has shape parameter κ. Intuitively, the size of the shock is informative about how many people live in different neighborhoods than their parents. The higher the variance of the shocks, the less intergenerational persistence there will be in neighborhood choice. Thus, using the same notion of moving as above, we internally calibrate κ to match the 46 percent of people who live in a different neighborhood type than where they were born (see Appendix A.2 for the estimation).

3.4 Black-White Wage Gap

Household income in our model, $y(r,e,s)$, depends on race, education, and skill. To discipline how income varies with its inputs, we estimate versions of the Mincer (1974) equation in the NLSY-97. We use individuals' total wage and salary income at age 34 or 35.[21] We incorporate skills into our measurement via the Armed Services Vocational Aptitude Battery (ASVAB) test score. The ASVAB score maps well to the notion of skill in our model, as both are outcomes measured after childhood inputs, such as parental investment and neighborhood spillovers, are taken into account. We estimate earning regressions of the type

$$\log(\text{earnings}_i) = \beta_0 + \beta_1 \text{ race}_i + \beta_2 \text{ college}_i + \beta_3 \log(\text{ASVAB}_i) + \beta_4 \mathbf{X}_i + \varepsilon_i,$$

where race is an indicator for White; college indicates if the education level is bachelor's degree or above; ASVAB is the Armed Services Vocational Aptitude Battery score, which we normalize to have a mean and standard deviation of one; and $\mathbf{X}_i$ is a control for gender. Table 15 in Appendix A.3 shows the estimated coefficients and their standard errors.

For the model, we parameterize $y(r,e,s) = w(r,e)\, s^{\chi}$ and use our Mincer estimates to infer each component. To back out $w(r,e)$, the wage conditional on race and education per unit of skills, we first normalize it to one for White households with no college: $w(W,e_L) = 1$. Then, for example, for Black college households, the wage is equal to:

$$w(B,e_H) = \frac{\exp(\beta_0+\beta_2)}{\exp(\beta_0+\beta_1)} = 1.58.$$

We do the same calculation for each education and race combination. As listed in Table 1, the wages for low and high education for White households are 1.00 and 1.71, respectively, while those for Black households are 0.92 and 1.58, respectively. Note that, by assumption, the skill premium for both Black and White households is equal to 71 percent. Finally, the return to skills, χ, equals 0.18. These estimates are in line with the empirical estimates in the literature (e.g., Heckman et al., 2006; Neal and Johnson, 1996).

3.5 Skills and Educational Attainment

To inform the calibration of the skill production function, F^s, and the way skills map into college choice, we study the relationships between college attainment, skill, neighborhood characteristics, and parental investment in the NLSY-97. We first need to map various objects in the model to the data. We measure skill using the ASVAB score, as we do in the Mincer regressions. To measure parental investments, we use data on parent-to-child transfers from

[21] Respondents in the NLSY-97 are interviewed every two years, which is why we cannot focus on a single age.

Abbott et al. (2019). Their methodology constructs these transfers from questions on income transfers and allowances from parents from the NLSY-97.

We assume the following functional form for the skill production function:

$$\log s = F^s(i, X_n) + \varepsilon_s = \theta_c + \theta_i \log(i) + \theta_X \log(X_n) + \varepsilon_s$$

There are two endogenous inputs into skill: one at the individual level and one at the neighborhood level. First, skill is increasing in parental investment i, with elasticity θ_i. Second, skill is increasing with neighborhood spillovers X_n, with elasticity θ_X. There is also an independently and identically distributed shock, ε_s, which has distribution $N(0, \sigma_s)$. This allows for additional randomness in income across generations, which will help in matching the data. This closely follows the approach of Fogli et al. (2023), who assume that the production function (of the child's wage) is Cobb-Douglas over the neighborhood spillover and parental wage.

We calibrate θ_c such that the mean level of skill equals one. We perform this normalization to align with the estimation of wages by education and race in the data. For θ_i and θ_X, we run a regression of log(ASVAB) on the log(parental investments) and the log(college share) of the county where each respondent grew up. We do not claim that these coefficients represent the causal effect of neighborhood spillovers or parental investment on skill, but we use them as inputs in our indirect inference exercise. We run the same regression in the model using a random sample of 100,000 simulated households drawn from the model's steady state distribution. We target the coefficients on parental investments and the college share. The regression results are presented in Table 16 in Appendix A.4. We assume that the parameters of the skill production function, $(\theta_c, \theta_i, \theta_x)$, are the same for both races. In Appendix A.4, we show that we do not find empirical support for allowing them to differ by race.

To calibrate σ_s, the standard deviation of the shock to skill production, we target the rank-rank correlation of income in St. Louis, which is equal to 0.41 according to Chetty et al. (2014). The calibrated parameters, as well as the associated model and data moments, are summarized in the "Skill production" panel of Table 2.

The education decision also depends on the cost of attaining education. We assume that the cost of education has the following functional form: $C(s) = \bar{c} - s$, where $\bar{c}$ is a parameter that determines the level of the education costs. Aside from skill, the education choice also depends on the realization of taste shocks with shape parameter σ. We calibrate $\bar{c}$ to target the aggregate education level of 42 percent—the share of children born between 1978-1983 who grew up in St. Louis and completed at least a bachelor's degree in Chetty et al. (2018). This number is distinct from the 28 percent of *adults* living in St. Louis who have completed a college degree (Column 1 of Table 3). These numbers differ for two reasons: First, college attainment is higher for the younger cohort of adults than previous cohorts; second, the share of adults with a college degree is affected by in- and out-migration.[22] Because we solve our model in the steady state, we impose that the share of children who go to college is equal to that of adults with high education. In the data, we scale up the college share of adults so that the aggregate level of college attainment is equal to 42 percent; this amounts to multiplying the college share from Table 3 by a factor of 1.49. Thus, neighborhoods A, B, and C in our targets have a college share of 22, 34, and 79 percent, respectively.

Finally, to calibrate the shape parameter σ, we target the R-squared from a regression of education on skill (for details, see Appendix A.4). Like the shape parameter, the R-squared is indicative of how much "randomness" there is in the pattern of college attainment as a function of skill.

3.6 Validation: Causal Estimates in the Data and Model

Next, we perform three validation exercises demonstrating that the model is consistent with several non-targeted moments that form the basis for the key mechanisms of the model. We show the model can replicate the causal effect of segregation and childhood neighborhood on adult outcomes. Then we show that the model can also match the reduced form relationship in the data between college attainment and skill, and the differences in this relationship by race.

Moving to Opportunity: First, we validate the model using estimates from the literature on the causal effect of childhood neighborhood on college attainment. Chetty et al. (2016) studied the Moving to Opportunity (MTO) experiment, which provided housing vouchers to low-income families living in public housing in low-income neighborhoods in Baltimore, Boston, Chicago, Los Angeles, and New York. Families were randomized into two groups. Those in the experimental group received housing vouchers that could be used to subsidize rent for private

[22] Out-migration is very similar by race conditional on parental income. For example, according to Chetty et al. (2018), at the 25th percentile of parental income, the probability of staying in St. Louis is 82 percent and 80 percent for Black and White children, respectively. At the 75th percentile, these probabilities are 73 and 75 percent.

market housing units located in Census tracts with poverty rates below 10 percent. Members of the control group received no vouchers through this experiment. Chetty et al. (2016) found that moving through the MTO program increased college attainment and earnings.

We simulate a policy similar to the MTO voucher program in our model. From the steady state, we evaluate a scenario in which the government provides low-education families that live in the lowest-income neighborhood (neighborhood A) with a voucher that subsidizes rent for housing if they move to either B or C. We replicate the design of the transfer. First, the eligibility criteria states that the household's income has to be below 30 percent of the median household income. Second, the amount of the transfer is such that households pay up to 30 percent of their labor income as a rental contribution, so the effective rental price for those in the program is the minimum between the actual rental price and 30 percent of their labor income.

Note that this validation exercise also assumes that rental prices and other equilibrium quantities (such as neighborhood spillovers) do not change. These assumptions align with the idea that relatively few families move in a small-scale randomized control trial, such as MTO, implying that neighborhood characteristics are unaffected.

Voucher-eligible families make several critical choices in our model. First, they must decide whether to take up the voucher and relocate to a more advantageous neighborhood. Panel I of Table 4 shows that 44 percent of households opt for the voucher in our simulation, similar to the data counterpart, whose 95% confidence interval is between 44 and 51 percent. Second, households also change their investment and education choice. We find that for college graduation, the treatment-on-the-treated (TOT) estimate is 13.4 percentage points, while the intent-to-treat (ITT) estimate is 5.9 percentage points, meaning that college attainment increases by 5.9 percentage points for families offered the voucher regardless of whether they used it. Both the TOT and the ITT are a bit over the upper bounds of the 95 percent confidence intervals of the data estimates, but overall, we see that the model's simulation of the MTO experiment gives reasonable outcomes compared with the results from Chetty et al. (2016).

Segregation: Second, we validate the model with estimates of the causal effect of segregation on educational attainment. Ananat (2011) uses exogenous variation in a city's susceptibility to segregation from the historical layout of train tracks to measure the causal impact of segregation

Table 4: Validation: Replicating Empirical Causal Effects

	Data	Model
I. Moving to Opportunity		
Takeup rate (%)	[44.4 , 50.9]	44.3
Δ College attainment, treatment-on-the-treated (%)	[0.6 , 9.9]	13.4
Δ College attainment, intent-to-treat (%)	[0.3 , 4.7]	5.9
II. Segregation		
Δ College attainment, White	[-0.4, 0.2]	-0.1
Δ College attainment, Black	[-0.7, -0.1]	-0.4

Notes: Data estimates from Ananat (2011); Chetty et al. (2016). Data shows 95 percent confidence intervals.

on college attainment. A useful way of summarizing the segregation is with the dissimilarity index:

$$\text{Dissimilarity index} = \frac{1}{2}\sum_{i}^{N}\left|\frac{Black_i}{Black_{total}} - \frac{White_i}{White_{total}}\right|$$

where N is the number of neighborhoods and $Black_{total}$ and $White_{total}$ are the total mass of Black and White households, respectively. As explained in Ananat (2011), this measures the percent of Black (or White) households that would have to move to a different neighborhood in order for the proportion of Black households in each neighborhood to equal the proportion of Black households in the city as a whole.

In the model, we examine the impact of segregation by introducing an exogenous change in amenities and resolving for the general equilibrium. Specifically, we increase the exogenous component of amenities in neighborhood A, A_A, by 1%. Starting from the segregated equilibrium, this change increases the level of segregation as Black households are now even more willing to live in the neighborhood A, while White households discount the exogenous change in amenities due to the racial composition of the neighborhood. Then, we calculate the change in educational attainment per change in the dissimilarity index, as in the data.

Panel II of Table 4 shows the results. The model implies that more segregation is associated with lower educational attainment for both Black and White children, though as in the data, the response is larger for Black children than White Children. The magnitude of the impact falls within the 95% confidence interval derived from the data.

Table 5: College Attainment and Skills

	All		Black		White	
	Data	Model	Data	Model	Data	Model
log(skills)	0.191***	0.207***	0.127***	0.177***	0.223***	0.213***
	(0.0059)	(0.0014)	(0.0077)	(0.0030)	(0.0095)	(0.0017)
Constant	0.420***	0.454***	0.364***	0.426***	0.421***	0.456***
	(0.0075)	(0.0015)	(0.0170)	(0.0033)	(0.0081)	(0.0017)
Obs.	4,997	100,000	1,600	20,021	3,397	79,979
R2	0.157	0.171	0.143	0.150	0.152	0.157

*Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Education and skill: Though we do not target it directly, the model can match the extent to which college attainment increases with skill in the data, as shown in Table 5. In the data, children with 1% higher ASVAB scores have a 0.19 percentage point higher probability of obtaining a college degree. Column 2 shows that this relationship is similar in the model.[23]

Moreover, although the model does not allow for differences in the skill production function by race, it successfully matches the observed weaker correlation between skill and college attainment for Black children compared to White children. Columns 3 to 6 present regression results of college attainment on skill, separately for Black and White children in both the data and the model. In the data, the semi-elasticity of college attainment relative to skill is 0.127 for Black children, which is notably lower than the 0.223 observed for White children. Likewise, the model shows a lower semi-elasticity for Black children than for White children.

4 Sources of Segregation and College Attainment Gap

What are the sources of segregation and the college attainment gap? In this section, we first show that the calibrated model generates a sizable amount of the observed college gap and segregation in the data despite neither being targeted in the calibration routine. Then, in Section 4.2, we discuss the sources of neighborhood heterogeneity that are most important in generating the gaps in college attainment and neighborhood choice. Finally, in Sections 4.3 to 4.5, we perform a series of counterfactuals removing each source of racial differences in the model: the Black-White wage gap, amenity externalities, and the differences in mobility costs.[24] We

[23] We normalize the standard deviation of log(skills) to be 1 in both the model and the data so that the coefficients are directly comparable.

[24] To avoid switching between equilibria in the counterfactual exercises, we always start from the initial steady-state equilibrium and use a high degree of dampening in our numerical routine. We analyze the equilibrium multiplicity in Section 5.

find that removing the Black-White wage gap substantially reduces the college attainment gap while maintaining a similar level of segregation. Removing the amenity externalities closes the college attainment gap, primarily by reducing segregation. Differential mobility costs are quantitatively unimportant, having minimal impact on both the college gap and segregation.[25]

4.1 The College Gap and Segregation in the Baseline Model

The calibration targets the unconditional education probability, but not its cross-sectional dispersion by race. The first result is that the model generates a college gap of 18 percentage points, explaining 64.3 percent of the college gap in the data (see Table 6). In the model, college attainment is 50 and 32 percent for White and Black households, respectively. In the data, college attainment is 47 and 19 percent for White and Black households, respectively. The remaining 35.7 percent that the model does not capture is likely coming from other forces that are not present in the model (e.g., credit constraints for education, Lochner and Monge-Naranjo, 2011). In Appendix B.2 we explain how different households choose education and neighborhood in the benchmark model, which generates the college gap and racial segregation in equilibrium.

Regarding the neighborhood composition, the calibration targets the migration responses to changes in the Black share, but not the racial composition of the neighborhoods. The second result is that the model generates a similar racial distribution as in the data. In particular, the model predicts a Black share of 79 percent in neighborhood A, while it is 78 percent in the data. Using the dissimilarity index as our baseline measure of segregation, the model is able to generate 70.5 percent of the level of segregation in the data: The dissimilarity index is 0.43 in the model versus 0.61 in the data.

We conclude that the combination of (i) racial disparities in the labor market, (ii) preferences over the racial composition of the neighborhood, and (iii) racial differences in barriers to moving across neighborhoods does a good job in explaining segregation and the college attainment gap. Next, we discuss the role of neighborhood heterogeneity before examining the importance of each of the three racial differences through a series of counterfactual exercises.

[25] In Appendix B.4, we perform some sensitivity analyses to assess the robustness of our counterfactual exercises with respect to different parameter values.

Table 6: College Attainment and Segregation

	Data	Model
College Attainment:		
All	0.42	0.46
White	0.47	0.50
Black	0.19	0.32
College gap	0.28	0.18
Black Share:		
Neighborhood A	0.78	0.79
Neighborhood B	0.09	0.14
Neighborhood C	0.07	0.06
Segregation Index	0.61	0.43

4.2 Neighborhood Heterogeneity Matters

The model has three general equilibrium forces that vary across neighborhoods: (i) spillovers, X_n, (ii) racial composition, $S_{r,n}$, and (iii) rents, p_n. We now evaluate how important it is to have each of these three forces determined in equilibrium at the neighborhood level, instead of them being determined at the city level.

The first row of Table 7 shows the benchmark economy; i.e., we include all three sources of neighborhood heterogeneity. In the second row, we consider a counterfactual model in which we remove the neighborhood heterogeneity in spillovers, but we keep the heterogeneity in the racial shares and rents. Specifically, we assume that the production of skills takes into account the aggregate X instead of the local X_n so that every child receives the same spillover regardless of where they live. In this setting, the college gap reduces by 15 percentage points from 0.18 to 0.03. However, the dissimilarity index remains essentially unchanged. This result shows that modeling the heterogeneity in spillovers across neighborhoods is not important for generating racial segregation, but it is important for accounting for the college gap.

The third row of Table 7 considers a counterfactual that removes neighborhood heterogeneity in the amenity externalities. We set the racial composition for amenities to the city-wide Black share of 20 percent instead of the neighborhood Black share. This means that households assume that each neighborhood will have 20 percent Black households when making their location choices. This equalization leads to a much lower segregation index. With equal racial shares, households agree on the relative amenities provided by each neighborhood. Therefore, neighborhood choices are more similar, decreasing the segregation index. Due to the reduction in segregation, White and Black children are exposed to more similar neighborhood spillovers, which reduces the college gap.

The fourth row of Table 7 considers a counterfactual that removes neighborhood heterogeneity in rents. We set rents to the city-wide average instead of the neighborhood market-clearing rental rate, removing house price differences across neighborhoods. This leads to a lower segregation index, as the previous exercise, but it is due to different forces. The racial wage gap and the non-homotheticity in housing imply that Black households are more likely to live in neighborhood A due to the low rents. This initial racial sorting based on rents then gets amplified by the amenity externalities. When rents are equalized across neighborhoods, Black households are less likely to live in neighborhood A. In turn, this equalizes the racial shares across neighborhoods, reducing the role of the amenity externalities and leading to more integration. Therefore, not modeling the price differences across neighborhoods has similar effects to not modeling differences in race shares. As a result, White and Black children are exposed to more similar neighborhood spillovers, which reduces the college gap. Finally, equalizing all three sources of heterogeneity combines all of the forces above. As a consequence, the model does not generate a college gap at all, but some segregation remains because White households still earn more on average, meaning they are better able to afford the higher exogenous amenities in neighborhoods B and C.

We conclude from this exercise that the three dimensions of heterogeneity we model for neighborhoods are crucial for generating a college gap and dissimilarity index in line with the data. It also illustrates how it is possible to have a small college gap alongside a high level of segregation. On the other hand, the exercise found that reduced segregation appears to be associated with a small college gap. In the next sections, we will examine how the racial differences we model connect to these two scenarios.

4.3 Removing the Wage Gap

We now assess the role of the Black-White wage gap. We give low- and high-education Black households the same wage as their White counterparts, conditional on education and skill. Remember that income is a function of skill and wage, which in turn depends on race and education, $y(r,e,s) = w(r,e)\, s^{\chi}$. When we equalize wages by race, we set $w(B,e) = w(W,e)$ for each education level, low or high. This means average income y could still differ by race if the

Table 7: Neighborhood Heterogeneity Matters

	Heterogeneity in				
	Spillovers, X_n	Race, $S_{r,n}$	Rents, p_n	College Gap	Dissimilarity Index
Benchmark	$\surd$	$\surd$	$\surd$	0.18	0.43
Equal spillovers	$\times$	$\surd$	$\surd$	0.03	0.40
Equal race shares	$\surd$	$\times$	$\surd$	0.02	0.04
Equal rents	$\surd$	$\surd$	$\times$	0.00	0.15
All equal	$\times$	$\times$	$\times$	0.00	0.02

Notes: The table shows the college gap and the segregation index when we remove the neighborhood heterogeneity in spillovers, race, and/or rents. $\times$ indicates that we remove that source of neighborhood heterogeneity, while $\surd$ indicates that we keep it. For each case we solve for the new general equilibrium and compute the college gap and dissimilarity index.

average skill differs. Equalizing wages entails increasing wages, $w(B,l)$, for Black non-college workers from 0.92 to 1.00 and increasing wages, $w(B,h)$, from 1.57 to 1.71 for Black college workers. We compare the new equilibrium with the baseline in panel A of Table 8.

We start by evaluating the changes between the baseline steady state and the new counterfactual general equilibrium. The college gap reduces by 8 percentage points (from 18pp to 10pp) when we remove the wage gap. There is also a small reduction in segregation. The dissimilarity index declines from 0.43 to 0.37. Even without the wage gap, racial segregation across neighborhoods remains, and, as a result, the college gap is not fully closed.

The second row in panel A Table 8 considers the effect of equalizing wages in partial equilibrium. In this exercise, we keep the values of the endogenous forces, X_n, $S_{r,n}$, and p_n, constant at the benchmark values but allow households to re-optimize in response to the new wages. This exercise reveals that there are strong general equilibrium effects. The college gap reduces only 3 percentage points in partial equilibrium, while it reduces 8 percentage points in general equilibrium. Therefore, all of the effects are amplified in general equilibrium because the equilibrium changes in neighborhood spillovers, race shares, and rents further reinforce the more-educated and slightly more-integrated world that arises after removing the wage gap in partial equilibrium. Because the amenity externalities are still in place, allowing the race shares to adjust generates more segregation in equilibrium. Similarly, because the spillovers adjust in general equilibrium, their effects on the college gap are further reinforced.

Figure 2 shows who lives in each neighborhood under each counterfactual experiment. Equalizing wages affects the racial composition of the neighborhoods, with a decrease in the

Table 8: Sources of Segregation and College Attainment Gap

	College gap	Dissimilarity index
Benchmark	0.18	0.43
A. No Wage Gap Counterfactual		
General equilibrium	0.10	0.37
Partial equilibrium	0.15	0.38
B. Race-Blind Counterfactual		
General equilibrium	0.02	0.04
Partial equilibrium	0.02	0.05
C. Equal Mobility Cost Counterfactual		
General equilibrium	0.17	0.46
Partial equilibrium	0.17	0.41

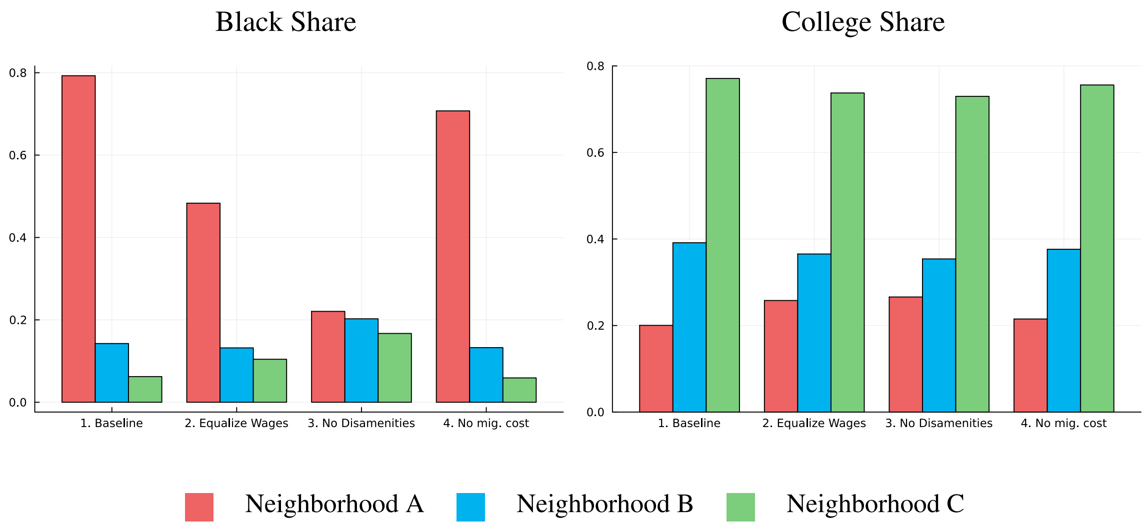
Notes: No wage gap means that the wage for Black and White workers are set equal conditional on education and skill. Race-blind means $\varphi_B = \varphi_W = 0$. Equal mobility cost means $m^B = 0$.

Black share of neighborhood A. It also reduces the differences in the college shares across neighborhoods, primarily by increasing the college share of neighborhood A. In the baseline model, the college share of adults in neighborhood C is 3.8 times the college share in neighborhood A (3.5 in the data), which closes to 2.8 when we remove the wage gap. This comes from the fact that more Black children go to college in the new equilibrium, many of whom still choose to remain in neighborhood A because of the barriers to moving and the amenity externalities. Thus, we find that, overall, removing the wage gap only mildly affects segregation by race.

If closing the wage gap has modest impacts on neighborhood choice, then what do Black households do with their higher wages? Instead of using them to move to more expensive neighborhoods, they invest the money into their children (see Appendix B.3 for further details). Along with the equalization of neighborhood spillovers, this increased investment drives the improved educational attainment for Black workers in this counterfactual.

Next, we study the effects on intergenerational mobility. Specifically, Table 9 shows how the relationship between parent and child education changes for different groups of households. The second column indicates considerable improvements in intergenerational mobility among Black children. For children of college-graduate parents, the racial gap in college attainment

Figure 2: Black and College Share: Comparison Among Counterfactual Economies



Notes: Black and college share by neighborhoods in the baseline and counterfactual economies.

decreases from 14 percentage points to 9 percentage points. Similarly, for children of non-college parents, the racial gap in college attainment decreases from 15 percentage points to 8 percentage points. Hence, we see an equalization of intergenerational mobility across races for children of both non-college and college graduates.

So far we have discussed the impact of completely closing the wage gap. Instead, Figure 3 shows the impacts of partially closing the wage gap on the college gap (left panel) and the segregation index (right panel).[26] There are substantial non-linearities. In particular, segregation falls when the wage gap is completely closed but rises when the wage gap is closed by only 50 percent. This is due to the general equilibrium effects shown in Table 8. As the wage gap closes, so does the college gap. At first, Black households continue to sort to neighborhood A, increasing the segregation index. As the wage gap closes further, the spillover in neighborhood A increases and more White and Black households choose to live there, equalizing the neighborhood racial compositions. The initial impact of closing the wage gap on the college gap is amplified as the neighborhood spillovers equalize. Once the wage gap is closed completely (the case considered in Table 8), the college gap closes by 8 percentage points, or about 45 percent of the baseline college gap.

[26]In the baseline calibration, Black workers face a wage penalty of 8 percent. Specifically, Figure 3 shows the impact of reducing this penalty between 0 and 100 percent. For example, when the wage gap is closed by 50 percent, Black households face a wage penalty of 4 percent.

Table 9: Cross-Sectional Education Probabilities

	Benchmark	No wage gap	Race blind	Equal mobility cost
All	0.46	0.43	0.42	0.44
White	0.50	0.45	0.42	0.48
Black	0.32	0.35	0.40	0.30
Gap	0.18	0.10	0.02	0.17
College parent	0.55	0.52	0.51	0.54
Non-college parent	0.39	0.36	0.35	0.37
Gap	0.17	0.16	0.16	0.17
Non-college parent, White	0.43	0.38	0.36	0.41
Non-college parent, Black	0.27	0.30	0.34	0.26
Gap	0.15	0.08	0.01	0.15
College parent, White	0.57	0.53	0.51	0.56
College parent, Black	0.43	0.45	0.50	0.41
Gap	0.14	0.09	0.01	0.15

Notes: Each column provides the education probability of different groups for the benchmark economy and each of the three main counterfactuals. No wage gap means that wages for Black and White are set equal conditional on education and skill. Race-blind means $\varphi_B = \varphi_W = 0$. Equal mobility costs means $m^B = 0$.

4.4 Race-Blind Counterfactual

The racial gap that remains when we equalize wages is a consequence of the differences in the migration costs and household preferences—White households, who tend to be college educated, cluster in neighborhoods B and C, resulting in lower spillovers in the majority Black neighborhood A. In this next counterfactual, we perform a "race-blind" counterfactual, in which households are unresponsive to the racial composition of their neighbors, but we leave both the Black-White wage gap and the different mobility costs in place. We remove the amenity externalities from preferences by setting $\varphi_B = \varphi_W = 0$. This makes the racial makeup of the neighborhood irrelevant in utility.

The college attainment gap reduces by 16 percentage points when both White and Black households are race-blind (panel B of Table 8, first row). This reduction results from both (i) White households reducing their education—from 50 to 42 percent and (ii) Black households increasing their education—from 32 to 40 percent percent. Interestingly, in the race-blind counterfactual, most of the effects are also present in partial equilibrium (panel B of Table 8, second row). By making households race-blind, even in partial equilibrium, households adjust their neighborhood choice. In fact, almost all of the change in the segregation index (from 0.43 to 0.04) occurs in partial equilibrium. This means that, quantitatively, the general equilibrium impacts such as the equalization of rents are not important determinants of household choices here, once households are race-blind. As a consequence, the college gap reduces to the same level as in the general equilibrium.

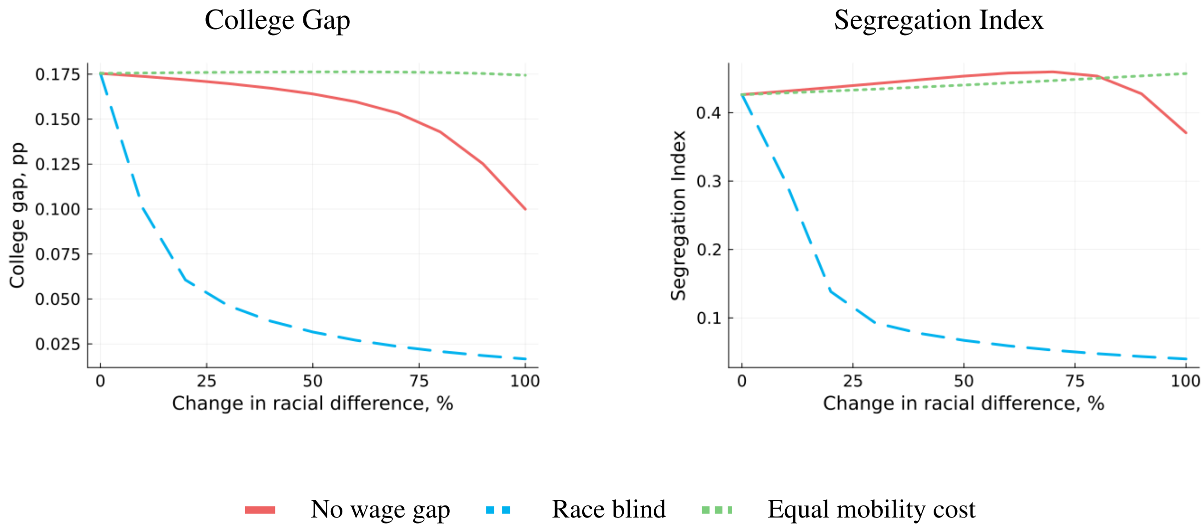
Figure 2 shows that without the amenity externalities, the neighborhoods become more similar, particularly in terms of racial composition. Nevertheless, some amount of segregation by race remains. The segregation index reduces from 0.65 to 0.04. This is due to households segregating themselves by income, which in turn differs by race, even when college attainment is equal, because of the wage gap. High-income households are more willing to pay for the exogenously given amenities that are unequal across neighborhoods. Since White households have higher incomes than Black households, they are more likely to choose to live in neighborhood C, the high-rent and high-amenity neighborhood.

The amenity externalities also affect educational attainment for Black children through an increase in investment of Black parents, as in the wage-gap counterfactual (see Appendix B.3). Black parents now expect their children to want to live in high-rent, high-amenity neighborhoods as adults. As such, they will want to be college graduates to afford the more-expensive rent while maintaining their level of consumption.

Moreover, because many Black households now live in better neighborhoods than before, their chances of going to college increase. The gap in intergenerational mobility closes for both non-college and college households. It goes from 14 percentage points to 1 percentage point for college households. For non-college households, the gap goes from 15 percentage points to 1 percentage point.

The closing of the intergenerational mobility gap in this experiment is also partially driven by a slight decline in the probability of going to college for White children, due to equilibrium changes in rents and spillovers. In the race-blind counterfactual, White households are more willing to live in neighborhood A that has lower rents, so they decrease their demand for college. Therefore, our takeaway from this experiment is that although there are considerable differences in neighborhood characteristics for both Black and White children, most of the gains from removing the amenity externalities accrue to Black children, particularly those whose parents do not have college degrees.

Figure 3: Sources of Segregation and College Attainment Gap



Note: The panels show the college gap and segregation index for each counterfactual: (i) no wage gap, (ii) race blind, and (iii) equal mobility cost. For each counterfactual we vary the difference between races from 0 percent (i.e., as in the benchmark) to 100 percent (i.e., fully close the difference).

As with closing the wage gap, the impact of the amenity externalities is non-linear in the extent to which they are removed. The main counterfactual, shown in Table 8, examines the impact of completely removing the amenity externalities by setting $\varphi_B = \varphi_W = 0$. Figure 3 shows the impact of partially removing the amenity externalities by lowering both φ_B and φ_W between 0 to 100 percent. Even a small decrease in the amenity externalities, φ_B and φ_W, has a large impact on the college gap and segregation. Most of the changes accrue with the amenities externalities being decreased by only 25 percent. This is because the amenity externalities are a primary driver of the racial differences in neighborhood sorting. As the neighborhood racial compositions equalize, Black and White children are exposed to more similar spillovers, closing the college gap. In turn, the neighborhood racial compositions equalize even more, making the amenities even less important. After 25 percent, the neighborhoods are similar enough such that further changes to φ_B and φ_W do not have significant impacts.

4.5 Equal Mobility Cost

Finally, we remove the differential mobility cost by setting $m^B = 0$. Overall, the impact of equalizing the mobility cost is quantitatively small. Panel C of Table 8 shows that in this counterfactual, the college gap closes by only 1 percentage point and the segregation index actually increases slightly from 0.43 to 0.46. This is due to the general equilibrium effect of the mobility cost on neighborhood choice for Black households. Because the mobility cost is only paid when they move out of neighborhood A to neighborhood B or C, Black households internalize the effect of this cost on the neighborhood choice of their children. In other words, they are less likely to choose neighborhood A because it will be costly for their children to move out of neighborhood A should they wish to do so. As a result, when this barrier is removed, they are more likely to choose to live in neighborhood A. In the baseline model, 46 percent of Black households choose to live in neighborhood A, which increases to 51 percent without the mobility cost.

5 Multiple Equilibrium and Place-Based Interventions

The presence of spillovers and amenity externalities imply that the model might have multiple equilibria. Intuitively, multiplicity arises when there are strong economic interactions coming from either (i) the endogenous spillovers in the production of skills and/or (ii) the amenity externalities.[27] In this section, we search for and compare the different equilibria of the model. Then, based on the multiplicity of equilibria, we study two different place-based policy interventions in general equilibrium. In particular, we ask if these placed-based policies can be used to "destabilize" certain equilibria with undesirable outcomes, such as segregation, rendering the integrated equilibrium the only solution to the model.

5.1 Multiple Equilibrium

We search for all possible equilibria of the model. Specifically, we consider 150,000 quasi-random initial guesses for the 9 general equilibrium values $(X_n, S_{r,n}, S_n)$ for $n = A, B, C$. For each of these values we solve for the general equilibrium of the model. We find that, depending on the initial guess, the model converges to one of the two equilibria described in Table 10 99.7% of the time.[28]

The first equilibrium is the one that matches the data, with a sum of squared errors (SSE) of 0.02. This equilibrium is the most *likely* one to occur from our quasi-random initial guesses: The economy converges to this equilibrium 58 percent of the time. This equilibrium has a relatively large segregation index, so we label it as the *segregated equilibrium*. All of the

[27] Allen et al. (2024) consider a broad class of spatial models and discuss the presence of multiple equilibria in these settings.

[28] The other 0.3% of the times (i.e., 450 out of 150,000 times) the economy converges to equilibria with very low aggregate education, below 5%. We do not believe that these equilibria are realistic, so we exclude them from our analysis, focusing instead on the segregated and integrated equilibrium. We also explored alternative ways to select initial guesses and always found the same set of equilibria.

Table 10: Multiple Equilibrium

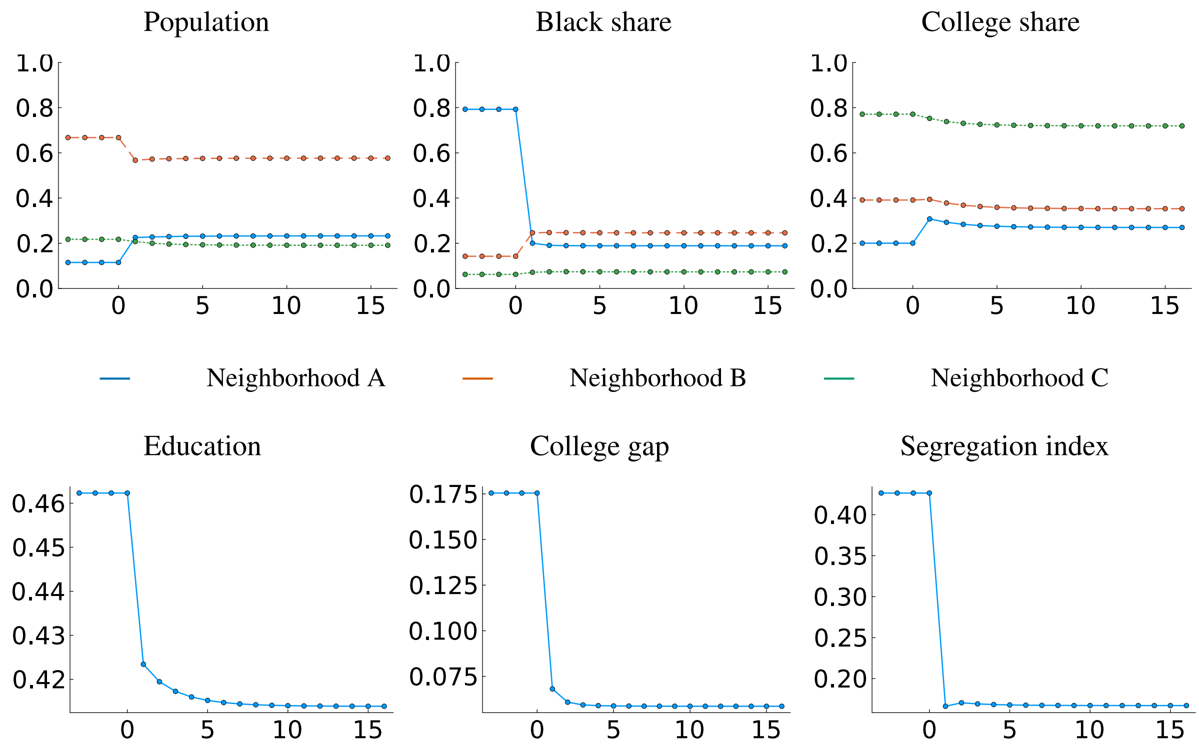
	Equilibrium 1 Segregated	Equilibrium 2 Integrated
Dissimilarity index	0.43	0.17
Population neighborhood A	0.12	0.23
Population neighborhood B	0.67	0.58
Population neighborhood C	0.22	0.19
Black share, neighborhood A	0.79	0.19
Black share, neighborhood B	0.14	0.25
Black share, neighborhood C	0.06	0.07
Neighborhood Flows	0.42	0.55
Education	0.46	0.41
College gap	0.18	0.06
Education, White	0.50	0.43
Education, Black	0.32	0.37
Education, neighborhood A	20.03	26.98
Education, neighborhood B	39.12	35.29
Education, neighborhood C	77.10	71.91
SSE	0.02	0.27
Occurrence, percent	57.84	41.86

Notes: SSE refers to the sum of squared errors of the target moments in the calibration.

analyses in the previous sections refer to this particular equilibrium.

We also find a second equilibrium, equilibrium two, which has a lower dissimilarity index, so we label it as the *integrated equilibrium*. This has a lower aggregate level of education (41 instead of 46 percent) but a much lower college gap of 6 percentage points, instead of 18 percentage points as in the segregated equilibrium. We emphasize that this integrated equilibrium exists even though households have the same racial preferences and face the same amount of racial discrimination in mobility and labor markets as in the segregated equilibrium. Note that this equilibrium is much further away from the data, with an SSE of 0.27 versus 0.02 for the baseline equilibrium. Moreover, this is the second most-likely equilibrium to occur: 42 percent of the initial points converge to this equilibrium. By comparing the initial guesses that converge to equilibrium one and two we find that the key difference is the level of segregation in the initial guess. When we start with a high level of segregation the economy converges to the segregated equilibrium. This suggests that St. Louis's history of de jure segregation established conditions that sustain a segregated city today, even though the same parameters could support a more integrated equilibrium.

Figure 4: Escaping the Segregation Trap



Notes: Transition path from the segregated to the integrated equilibrium. In period $t = 0$*, agents learn that in period* $T = 15$*, they will coordinate to be in the integrated equilibrium.*

Coordination The presence of multiple equilibria means that the economy can coordinate to be in any of the equilibria. We study what would happen if households could coordinate to move the economy from the segregated to the integrated equilibrium. We start the economy in the steady-state of the segregated equilibrium. In period $t = 0$, agents learn that in period $t = T$ they will coordinate to be in the integrated equilibrium. We then implement a shooting algorithm to study the transition path from the segregated to the integrated equilibrium.

Figure 4 shows the transition path when agents in period $t = 0$ learn that in period $T = 15$ they will coordinate to be in the integrated equilibrium. The figure shows that most of the changes occur upon impact of agents learning about the future coordination in period $t = 0$.[29]

This exercise demonstrates that spillovers and externalities lead to multiplicity of equilibria. The empirical evidence indicates that St. Louis is currently in a segregated equilibrium; nonetheless, an alternative equilibrium characterized by more racial integration and a lower college gap also exists. If households were able to coordinate their actions effectively, transitioning from one equilibrium to the other could be feasible. The quantitative analysis suggests

[29] We find similar results for different values of T.

that a transition from the segregated to the integrated equilibrium would be fast; while it takes 4 or 5 generations to converge to the new equilibrium, the bulk of the reduction in the college gap and segregation happens within one or two generations. In the next section we study two place-based and evaluate whether they can decrease segregation and the college gap.

5.2 Place-Based Policies

This section studies government policies that generate incentives for agents to move. In particular, we consider two alternative policies: (i) Moving to Opportunity (MTO) and (ii) Opportunity Zones (OZ).[30]

Moving to Opportunity First, we consider the MTO intervention described in Section 3.6. The main difference is that the exercise in the validation section was designed to replicate the results of the small-scale RCT. In the model, this is equivalent to analyzing the impact of the intervention in partial equilibrium. In this section, we are interested instead in the effects of scaling up the intervention, so we consider it in general equilibrium, as in Chyn and Daruich (2022) and Fogli et al. (2023). We parametrize the policy with two parameters, $\{p, s\}$. Households are eligible for a housing subsidy s if they live in neighborhoods B or C and their income is below the percentile p. To implement the policy in general equilibrium we set a tax on housing for all households to keep the government budget balanced. We search over programs $\{p, s\}$ that maximize steady state welfare (i.e., consumption equivalence under the veil of ignorance). The optimal intervention sets a subsidy of 10% for households with income below the 8th percentile. To finance it, we need a tax rate of 1%.

Opportunity Zones Second, we consider the *Opportunity Zones* (OZ) policy. This is a place-based intervention that can be used to rule out the segregated equilibrium so that the economy converges to the integrated equilibrium. Our consideration of this policy was inspired by a recent intervention in the U.S. The Tax Cuts and Jobs Act of 2017 (TCJA, Public Law No. 115-97) designated thousands of low-income neighborhoods as Qualified Opportunity Zones. This policy was designed to spur economic growth and job creation in low-income communities by providing tax benefits to investors. We can map the actual Qualified Opportunity Zones to the

[30] Another commonly considered policy is school vouchers or busing. However, because our model does not explicitly differentiate between schooling and neighborhood spillovers, it is unclear how to implement this policy within our framework.

three clusters of the St. Louis MSA analyzed in this paper. We find that most of the opportunity zones correspond to neighborhood A: 71 percent are in neighborhood A, 29 percent are in B, and there are no opportunity zones in C. The TCJA incentivizes businesses and developers to invest in Opportunity Zones (OZs) through tax benefits. However, our model does not account for business investment. Instead, within our framework, we represent OZs as a subsidy that encourages high-education households to move to neighborhood A.

The OZ intervention can facilitate the transition to the integrated equilibrium. If the incentives provided by the government are strong enough, it can destabilize the segregated equilibrium, causing it to no longer be an equilibrium of the model when the policy is implemented.

The OZ intervention is quite different from the MTO policy. OZ provides incentives for high-educated households to live in the low-educated neighborhood in order to improve the spillovers there. Instead, MTO subsidizes low-education households to live in the high-education neighborhoods.

The details of its implementation are as follows. The government provides a transfer τ to high-education households living in neighborhood A if the level of college attainment in neighborhood A is relatively low. Specifically, we set the threshold at 26 percent, which is just below the 27 percent college attainment rate in the integrated equilibrium. We solve the model starting from both the integrated and segregated equilibria.

First, when the economy starts in the integrated equilibrium, neighborhood A has an education level of 27 percent. Thus, the government transfer will never actually be paid, and the integrated equilibrium remains a stable equilibrium of the model for all values of τ.

Second, we start in the segregated equilibrium. We then solve the model for different values of τ. We find that when $\tau \leq \tau^* = 0.03$, the economy converges to a new equilibrium, similar to the segregated equilibrium, but with higher college attainment in neighborhood A and a lower level of segregation. When the transfer is larger than $\tau^* = 0.03$, we find that the segregated equilibrium is no longer an equilibrium of the model. Instead, the only possible equilibrium is the integrated equilibrium. Moreover, note that in equilibrium, the government is not making any transfers because the educational attainment in A is larger than 26 percent.

Comparison of MTO and OZ. The top panel of Table 11 compares the effectiveness of both policies. The OZ intervention proves more successful in reducing both racial segregation and the college attainment gap than the MTO. With OZ, the dissimilarity index drops from a benchmark of 0.43 to 0.17, whereas it only decreases to 0.40 with MTO. Similarly, the college attainment gap, initially at 0.18 in the benchmark, declines to 0.06 under OZ but only to 0.14 with MTO.

Following this, we calculate the welfare gains associated with moving from the benchmark equilibrium to either the MTO or OZ equilibrium. Welfare gains are measured in terms of consumption equivalence, representing the percentage change in consumption in the benchmark equilibrium that would leave agents indifferent between the segregated and new equilibrium (analogous to welfare under the veil of ignorance). These results are shown in the bottom panel of Table 11 for different population segments. Our findings indicate that both interventions yield welfare gains of similar magnitude: OZ delivers welfare gains that are 0.37 percentage points higher than MTO, with values of 1.63 percent for OZ and 1.26 percent for MTO.

Moreover, in both interventions, we find that Black households have larger gains than White households. Similarly, non-college households have larger gains than those with college. Note that neither of these interventions constitutes a Pareto improvement, as each creates both winners and losers. With the OZ intervention, 69% of individuals experience welfare gains, whereas the MTO intervention benefits 77%. The outcomes of these interventions reflect the fact that both are designed to decrease the inequality between Black and White households and between low- and high-education households. Finally, we find that under the OZ intervention, only the integrated equilibrium persists. In contrast, with the MTO intervention, the economy retains both the integrated and segregated equilibria. The policy reduces racial disparities within each equilibrium but fails to eliminate the segregated one. Therefore, the OZ intervention is the only one capable of destabilizing the segregated equilibrium.

6 Conclusion

There is growing empirical evidence that the neighborhood in which a child grows up substantially impacts a range of adult outcomes. At the same time, there is ample empirical evidence of a Black-White wage gap and the impact of race on neighborhood choice. These empirical patterns suggest that exposure to neighborhoods with large spillovers may systematically differ by race and drive the racial gap in adult outcomes.

To examine these issues, we develop a quantitative overlapping-generations spatial-equilibrium

Table 11: Place-based Policy Interventions

	Benchmark	**OZ**	**MTO**
Dissimilarity index	0.43	0.17	0.40
Population neighborhood A	0.12	0.23	0.20
Population neighborhood B	0.67	0.58	0.60
Population neighborhood C	0.22	0.19	0.20
Neighborhood Flows	0.42	0.55	0.50
Education	0.46	0.41	0.40
College gap	0.18	0.06	0.14
Education A	0.23	0.32	0.26
Education B	0.44	0.39	0.39
Education C	0.64	0.60	0.60
Welfare (C.E.), %			
Aggregate		1.63	1.26
Black		2.61	2.97
White		1.38	0.83
Non-college		1.93	1.79
College		1.26	0.61
Fraction with welfare gains		0.69	0.77

model that incorporates race. We find that the presence of the Black-White wage gap, the amenity externalities, and the barriers to moving generates a college gap of 18 percentage points—about 64 percent of the college gap in the data. We also find that removing the racial wage gap helps improve Black workers' educational attainment, but without substantially impacting racial segregation. In contrast, we find that removing amenity externalities is essential for reducing neighborhood segregation and improving access to neighborhoods with better spillovers, which increase future generations' skill and college attainment.

The presence of human capital spillovers and amenity externalities leads to the existence of multiple equilibria in the model. Even holding the racial preferences and the level of discrimination in labor and housing markets fixed, the economy could end up in an equilibrium with substantial segregation and a large Black-White gap in college attainment or in a more integrated equilibrium with a lower college gap. Finally, we explore two government interventions: (i) MTO and (ii) OZ. Both reduce racial segregation and educational disparities, but only OZ destabilizes the segregated equilibrium, leading to integrated equilibrium. Welfare gains are larger and less dispersed across households with OZ compared to MTO.

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Online Appendix

This material is for a separate, online appendix and not intended to be printed with the paper.

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A Data

A.1 Neighborhoods

Figure 5 shows how the k-means clustering algorithm sorts the Census tracts in three neighborhoods in St. Louis. Most of St. Louis city is in neighborhood A, the suburbs close to the city are in neighborhood C, and the rest of the MSA is in neighborhood B.

Figure 5: Neighborhoods in St. Louis

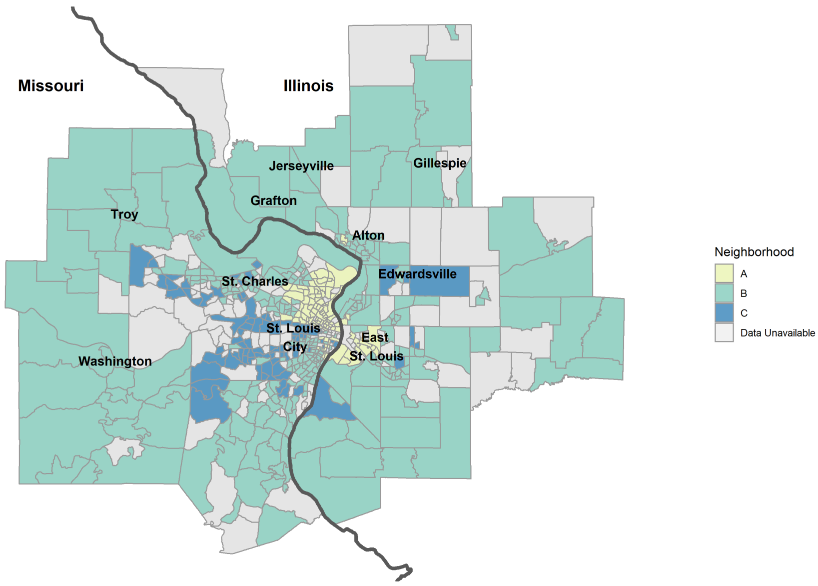


Table 12 shows how our Census tract grouping changes as we allow for four and five clusters instead of three as in the benchmark. With four clusters, the neighborhoods look similar, but cluster B, the predominately White and medium-income cluster, is split into two groups. With five clusters, neighborhood C, the predominately White and high-income cluster, is also split in two. We interpret this to mean that with more clusters, the algorithm would like to even further stratify the White neighborhoods by income level, but it leaves the predominately Black neighborhood unchanged. With three neighborhoods, we are able to capture both the stratification by race and income. In light of this, we believe that focusing on three clusters is enough to capture the features of the data relevant to this paper while also helping to keep the model quantitatively tractable.

Table 12: Neighborhood Characteristics: 3, 4, 5 Clusters

	Pop. Share	College Grads	Med. House Price	Income ($)	Black Share
3 Clusters					
1	0.17	0.15	82,700	33,273	0.78
2	0.62	0.23	150,060	55,405	0.09
3	0.21	0.53	307,244	84,749	0.07
4 Clusters					
1	0.16	0.15	81,340	33,075	0.80
2	0.41	0.17	128,066	49,345	0.09
3	0.32	0.36	205,442	69,510	0.09
4	0.11	0.62	364,776	91,104	0.07
5 Clusters					
1	0.16	0.15	80,269	33,008	0.80
2	0.07	0.48	236,963	54,115	0.26
3	0.42	0.17	129,813	49,650	0.09
4	0.27	0.36	212,970	74,640	0.05
5	0.07	0.64	394,385	99,220	0.05
Total	1.00	0.28	171,749	57,835	0.20

A.2 Neighborhood Flows

In this Appendix we describe how we derive the estimates for the share of people who live in a different neighborhood cluster as an adult, as well as the moving patterns of Black and White households.

First, we cluster Census tracts at the national level. We use a k-means clustering algorithm on the Census tracts using the same variables as we used for the St. Louis MSA: the Black share, house prices, median income, and the college share. This results in an assignment of one of three possible clusters for each Census tract.

Second, we go to the NLSY-97, where we observe county of residence, race, and education level (whether they have a college degree) and impute the probability an individual lives in each cluster at age 17 and at age 35. To make this imputation, we go back to the Census-tract level data and calculate the fraction of people in each county who live in each cluster type, conditional on education and race. We use these as the imputed probabilities for each person in the NLSY-97 because we observe their county, race, and education. Specifically, we know the probabilities that an individual of a given race and education is living in each cluster. If these probabilities are highly concentrated, meaning the probability of living in a specific cluster is high, then our estimates are more precise. However, the downside is that when we enforce a

Table 13: Parent-Child Neighborhood Transition Matrices

		Adult Neighborhood		
		Cluster A	Cluster B	Cluster C
	Black			
Child Neighborhood	Cluster A	0.580	0.334	0.086
	Cluster B	0.384	0.508	0.108
	Cluster C	0.364	0.423	0.214
	White			
Child Neighborhood	Cluster A	0.125	0.596	0.278
	Cluster B	0.070	0.623	0.306
	Cluster C	0.052	0.452	0.496

high degree of precision we lose sample size. For this reason, we restrict the sample to people who can be mapped to a given cluster with probability greater than 50 percent at both ages. We then calculate the probability that each individual moved clusters between age 17 and 35, finding that 46 percent of people moved across clusters.

We also use these imputed probabilities to create transition matrices from the parents' neighborhood type to the child's neighborhood type. Like above, we restrict the sample to people for whom we have at least 50 percent certainty of their cluster of residence at each age. We do this for both Black and White children. The results are reported in Table 13.

To obtain our target for m^B, we compare the probability that a Black child who grows up in cluster A lives in cluster B or C as an adult, which is 42 percent, with the same probability for that of a White child, which is 87.5 percent. The table shows that this difference is 45.5 percentage points.

This 45.5 percentage point gap remains stable even after accounting for child and parental characteristics. Table 14 presents regressions analyzing the probability that a child remains in the same cluster type as an adult, controlling for childhood cluster-by-race fixed effects. In Column 1, without additional controls, the results from Table 13 are replicated: Black children who grow up in Cluster A are 45.5 percentage points less likely than their White peers to move out of Cluster A as adults. Column 2 adds controls for household characteristics at age 17, including family income and mother's education. The 45 percentage point gap remains stable. While children from higher-income households or those whose mothers hold college degrees are more likely to move to a different cluster type as adults, these factors do not significantly affect the racial disparity in moving out of Cluster A. Column 3 adds controls for characteristics

Table 14: Probability of Staying in Same Cluster Type

	Same Cluster Age 17 and 35		
	(1)	(2)	(3)
Cluster A at 17 & White	-0.455^{***}	-0.452^{***}	-0.442^{***}
	(0.0201)	(0.0369)	(0.0233)
Cluster B at 17 & Black	-0.0722^{***}	-0.0904^{**}	-0.0691^{***}
	(0.0196)	(0.0366)	(0.0223)
Cluster B at 17 & White	0.0434^{***}	0.0634^{**}	0.0585^{***}
	(0.0138)	(0.0259)	(0.0169)
Cluster C at 17 & White	-0.366^{***}	-0.396^{***}	-0.347^{***}
	(0.0315)	(0.0627)	(0.0353)
Cluster C at 17 & Black	-0.0839^{***}	-0.0963^{***}	-0.0551^{***}
	(0.0146)	(0.0281)	(0.0182)
Controls:			
Household characteristics at age 17		X	
Individual characteristics at age 35			X
Observations	2,133	625	1,753
R-squared	0.065	0.078	0.064

Notes: Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Household characteristics: household income at 17, education category of the mother (less than high school, high school, some college, college or above). Individual characteristics: income at age 35, college attainment, log(ASVAB).*

of the child, such as whether they attained a college degree, income at age 35, and ASVAB score. Again, children with a college degree are more likely to live in a different neighborhood type as an adult, but the racial gap between Black and White children remains stable.

A.3 Black-White Wage Gap

To calibrate the Black-White wage gap we estimate the following equation in the NLSY-97 data:

$$\log(\text{wage}_i) = \beta_0 + \beta_1\ \text{race}_i + \beta_2\ \text{college}_i + \beta_3\ \log(\text{ASVAB}_i) + \beta_4\ \mathbf{X}_i + \varepsilon_i.$$

Table 15 shows the result. Black households earn 8.2 percent lower wages than an otherwise similar White household. Similarly, there is a college premium of 53.8 percent. These two coefficients pin down the calibration of the four wages in Table 1.

Table 15: Mincer Regression

	(1)
log(ASVAB$_i$)	0.1850***
	(0.0243)
College	0.5375***
	(0.0389)
White	0.0821
	(0.0505)
Constant	10.4820***
	(0.0538)
Controls	Gender
R2	0.1898
N	2,372

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A.4 College Attainment and Individual and Neighborhood Characteristics

To create the calibration targets for the skill production function, we regress the log of each individual's ASVAB score on the measure of the parental investments they received and the share of college-educated residents of the county they grew up in from the NLSY data. Table 16 contains the coefficients we target for calibrating θ_i and θ_X. One might wonder if we should allow the skill-production function to differ by race. In Column (2), we show that the coefficients on parental investment and the county college share are not statistically different for Black and White children. Given this, we use the same skill production function for both races.

Next, we regress a dummy for whether the individual obtains at least a bachelor's degree on log skill, where log(ASVAB) is standardized so that both the mean and the standard deviation are 1. Table 5 in the main text shows the regression results. We calibrate the shape parameter σ for the education taste shocks to match the R-squared of 0.157. Intuitively, if the variance of the taste shock is high, then skill should explain little of the variance in college attainment.

Table 16: Skill Formation

	log(ASVAB)	log(ASVAB)
log(parental transfers)	0.151^{***}	0.195^{***}
	(0.0159)	(0.0636)
log(county college share)	0.298^{***}	0.434^{***}
	(0.0381)	(0.1380)
White#log(parental transfers)		-0.0524
		(0.0655)
White#log(county college share)		-0.1785
		(0.1429)
White		1.084
		(0.7350)
Constant	-1.951^{***}	-2.930^{***}
	(0.185)	(0.7126)
Observations	3,898	3,898
R^2	0.050	0.127

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B Model

B.1 Parameter Sensitivity Analysis

In a nonlinear structural general equilibrium model, it is often difficult to see precisely which features of the data drive the results. This appendix follows the approach in Elenev et al. (2021) and Andrews et al. (2017a), to report how the target moments are affected by changes in the model's parameters, in the hope of improving the transparency of the results.

Consider a generic vector of moments $\mathbf{m}$ which depends on a generic parameter vector θ. Let ι_i be a selector vector of the same length as θ taking a value of 1 in the ith position and zero elsewhere. Denote the parameter choices in the benchmark calibration by a superscript b. For each parameter θ_i , we solve the model once for $\theta^b \cdot e^{\iota_i \varepsilon}$ and once for $\theta^b \cdot e^{-\iota_i \varepsilon}$. We then report the symmetric finite difference:

$$\frac{\frac{\mathbf{m}(\theta^b e^{\iota_i \cdot \varepsilon}) - \mathbf{m}(\theta^b e^{-\iota_i \cdot \varepsilon})}{\mathbf{m}(\theta e^{-\iota_i \cdot \varepsilon})}}{2\varepsilon}$$

We set $\varepsilon = 0.01$, or 1 percent of the benchmark parameter value. The results give the elasticities of the moments with respect to the structural parameters.

We report the sensitivity for all the parameters calibrated inside the model (12 parameters

Figure 6: Parameter sensitivity analysis

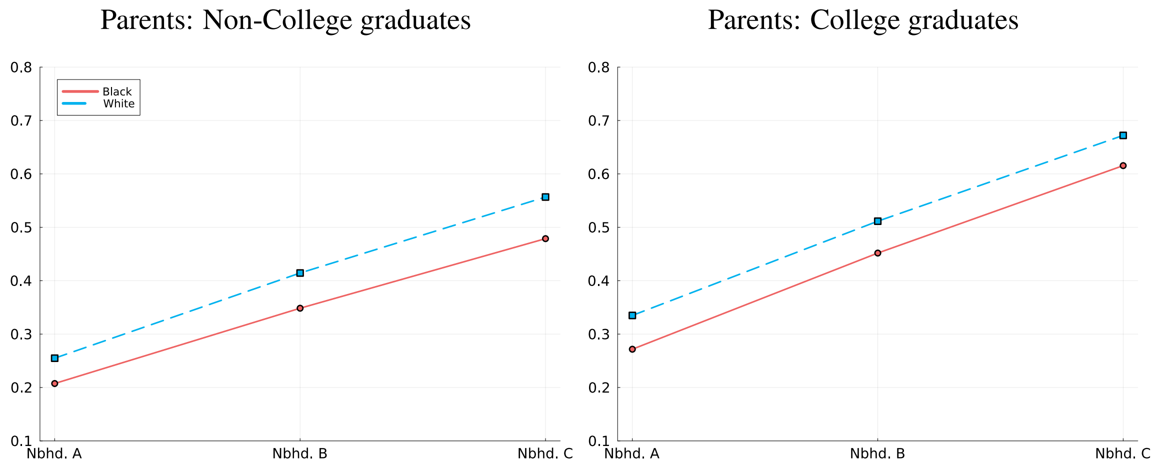
and 15 target moments). Each panel of Figure 6 lists the same 15 moments and shows the elasticity of the moments to one of the 12 parameters.

Some parameters are identified mainly by their target moment. For example, changes in the exogenous amenity parameter A_b and A_c generate large changes in the population in neighborhoods A, B, and C.

B.2 Segregation and Education Attainment

In this appendix we examine education and neighborhood choices in the model. Figure 7 shows the probability of becoming a college graduate for a child with median skills as a function of the other state variables: parental education, race, and neighborhood. First, the

Figure 7: College Attainment



Notes: College attainment for a child with median skills, as a function of parental education, race, and neighborhood.

left panel shows the education probability of a child with non-college parents as a function of the neighborhood in which they grow up, for both Black and White families. There is a striking difference in college attainment across races, although we are comparing children with the same level of skills. It is clear that in any neighborhood, Black children have between 5 and 7 percentage point lower probability of going to college.

The right panel shows the college attainment probability for Black and White children of college-graduate parents. Again, White children have a higher probability of going to college than Black ones. However, compared with the left panel, having college-educated parents increases the probability of college attainment for both Black and White children in all neighborhoods.

Table 17 presents a breakdown of the race and education composition of each neighborhood's residents. Most neighborhood A residents are Black, and the vast majority are non-college graduates. Residents of neighborhoods B and C are primarily White households with a higher share of college households, particularly for neighborhood C. Overall, the basic features of our three neighborhoods match up well with the three clusters we identify in the data for St. Louis. Importantly, neighborhood C has the highest college share, meaning it also has the highest spillover effect for children who grow up there.

Neighborhood choices are also very different for Black and White households. Figure 8 shows the probability of going to each neighborhood for an agent with median skill as a function

Table 17: Neighborhood Demographics

	Neighborhood A	Neighborhood B	Neighborhood C
Black non-college	0.64	0.09	0.01
Black college	0.15	0.05	0.05
White non-college	0.15	0.52	0.22
White college	0.05	0.34	0.72
Total	1.00	1.00	1.00

Notes: The table shows the composition of each neighborhood by race and education level.

of the initial neighborhood, race, and parental education. Examining the figures reveals two patterns. First, Black households have a much higher probability than White households of living in neighborhood A, and this probability is more significant for children of non-college parents than for children of college-graduate parents. Second, the probability of going to either B or C is larger for White than for Black households. The probability of going to C is almost zero for Black non-college households, although neighborhood C has the highest spillover and school quality.

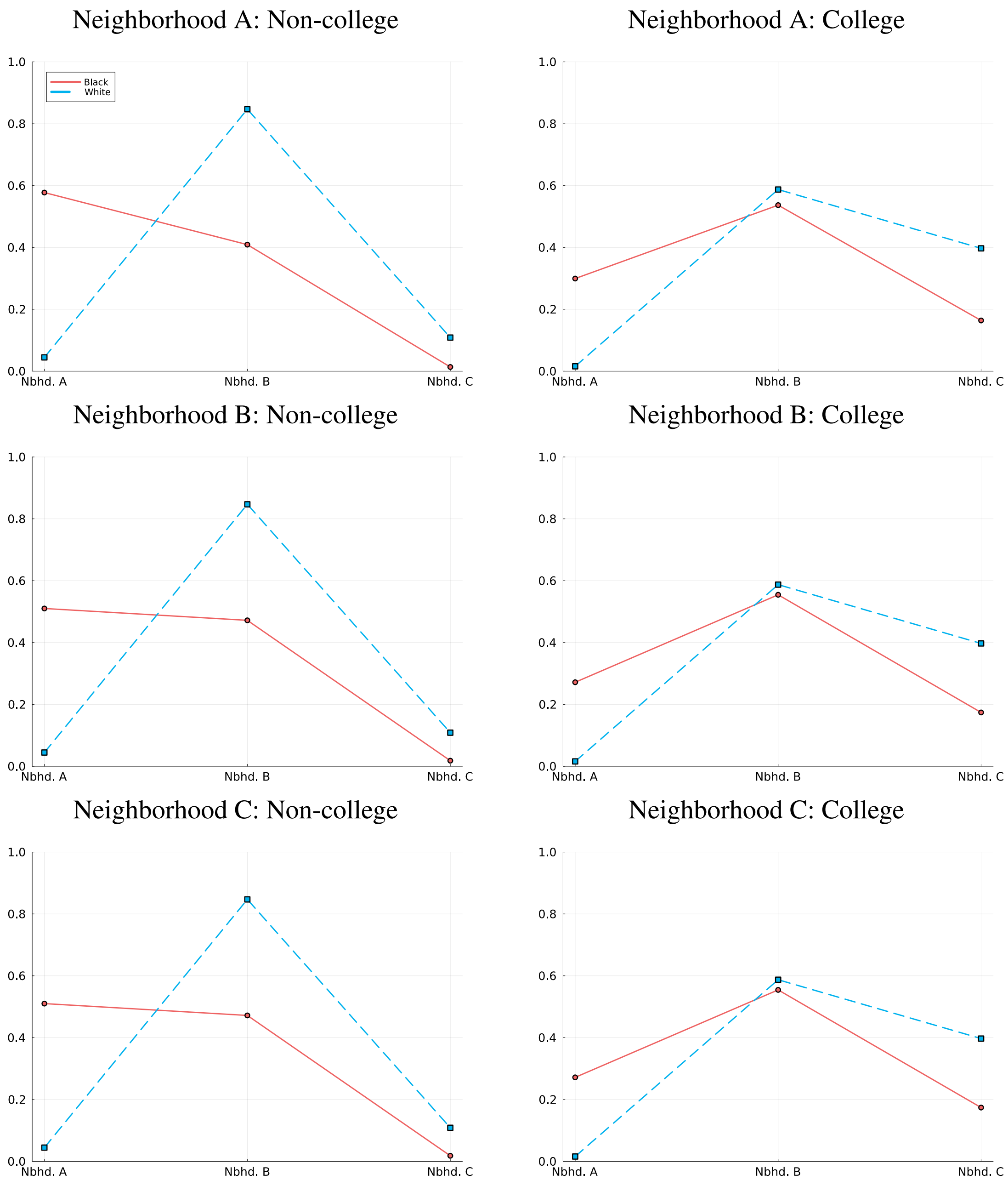
B.3 Parental Investment: Comparison Among Counterfactuals

In Figure 9, we plot the average investment in the model conditional on race and parental skill. Moving from the baseline in the solid red line to the equalized wages counterfactual in the dashed blue line increases Black investment. These households react to the increase in their wages by investing in their children. In contrast, White households do not significantly change their investment because their wages have not changed, and their neighborhoods have barely changed. Moving to the race-blind counterfactual also increases parental investment for Black parents across the skill distribution. This is because of the large increase in college attainment. In this setting, Black households now earn more and choose to spend some of that extra income on investment into their children. Finally, consistent with the discussion in the main part of the paper, eliminating the mobility cost has little impact.

B.4 Sensitivity Analysis: Counterfactual Results and Parameter Values

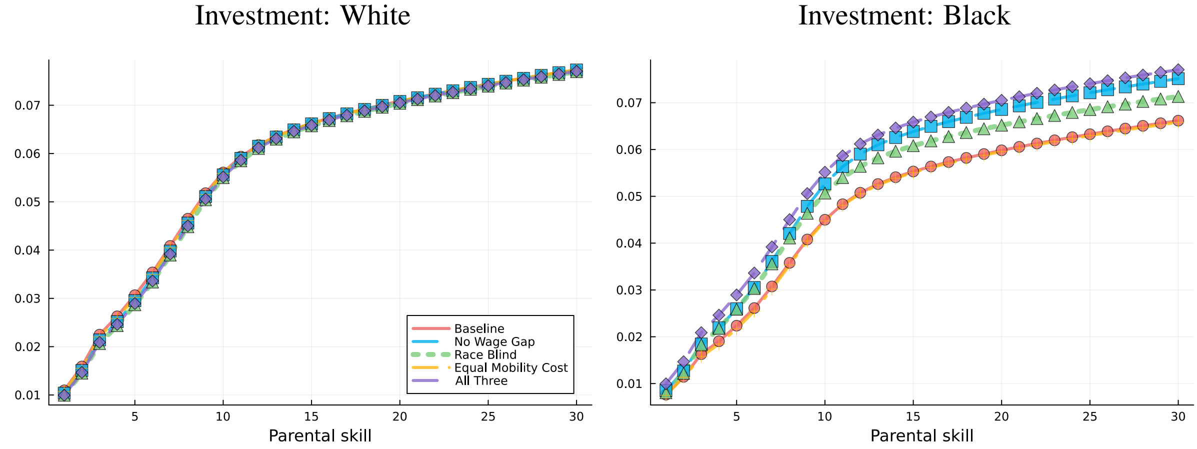
In this appendix, we explore how our main counterfactuals (i.e., no wage gap, race-blind, and equal mobility cost) change under different parameter estimates. We focus on the parameters governing amenity externalities, as we relied on external studies to determine their values. In particular, these are the bliss points, γ_B and γ_W, as well as the weights in utility for the racial

Figure 8: Neighborhood Choice



Notes: Neighborhood choice for a child with median skill as a function of parent's education, race, and neighborhood.

Figure 9: Parental Investment: Comparison Among Counterfactuals



Notes: Parental investment for each race and parental skill level in the baseline and counterfactual economies.

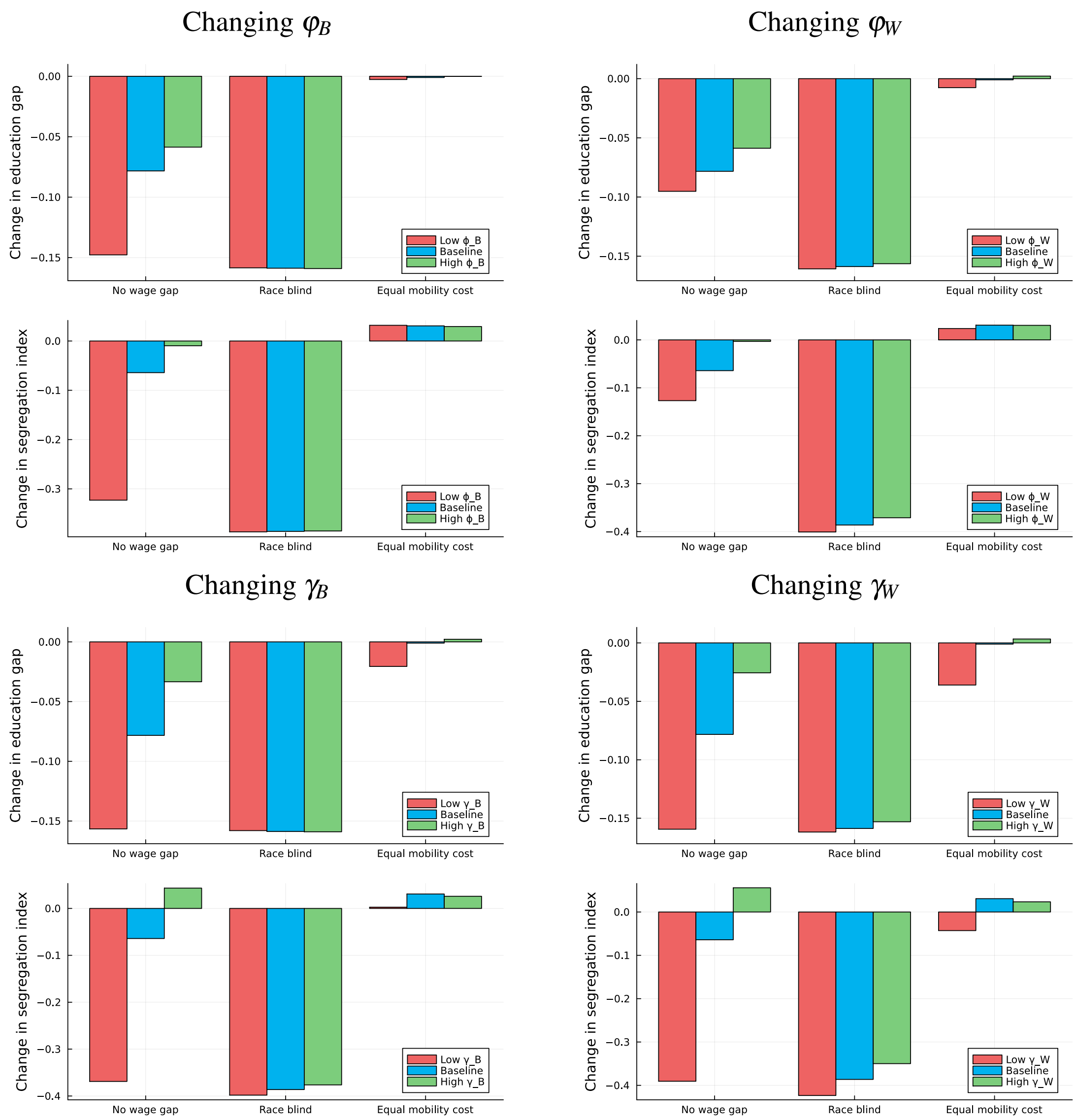
makeup of the neighborhood, φ_B and φ_W.

For each of these four parameters, we increase and decrease them by 1%. Holding all other parameters fixed, we re-solve our model as well as all of the counterfactual versions of the model. Then, under each set of alternative parameter values, we compare the changes in the college attainment gap and the segregation indices to the results from our baseline set of parameter values.

The results are shown in Figure 10. We can see that the results for the race blind and equal mobility cost counterfactuals change little from the baseline parameter set. However, in some cases, the effects of the wage gap on education and segregation change with the parameter values. For example, decreasing the importance of the amenity externalities leads to more equalization of education and neighborhood choices when the wage gap closes (red bars in the "Changing φ_B" and "Changing φ_W" panels). This is because households are more willing to move in response to income changes if they are discouraged less by the racial makeup of neighborhoods. The effect is stronger for Black households because their incomes are the ones that change in this counterfactual. The logic goes in the opposite direction when the importance of amenity externalities is increased (green bars in the "Changing φ_B" and "Changing φ_W" panels).

As for the bliss points, decreasing γ_B makes Black households now prefer to live in majority White neighborhoods, which makes them more willing to move around when the wage gap is closed, which decreases segregation and the education gap further. The opposite is true when their bliss point increases, and it actually increases segregation slightly in the equilibrium without the wage gap. The logic is similar for γ_W. Decreasing it encourages more neighborhood mixing in the preferences of Whites, whereas increasing it leads to more segregation and a smaller closure of the college gap when the wage gap is removed.

Figure 10: Counterfactuals Under Different Parameter Values



Notes: Each set of bars shows the change in the education gap or segregation index going from the baseline to the given counterfactual. The red bar refers to the parameter set where the given parameter is decreased by 1%. The green bar refers to the parameter set where the given parameter is increased by 1%. The blue bar refers to the results from the baseline set of the parameter values (which are the same as in the body of the paper and by construction are the same on every panel of this figure).