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

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Abstract

We incorporate race into an overlapping-generations spatial-equilibrium model with neighborhood spillovers. The model incorporates race in three ways: (i) a Black-White wage gap, (ii) an amenity externality—households care about the racial composition of their neighbors—and (iii) an additional barrier to moving for Black households. These forces quantitatively account for all of the racial segregation and 80% of the Black-White gap in college attainment in the data for the St. Louis metro area. Counterfactual exercises show that all three forces are quantitatively important. The presence of spillovers and externalities generates multiple equilibria. Although St. Louis is in the segregated equilibrium, there also exists an integrated equilibrium with a lower college gap, and we analyze a transition path between the two.

JEL Classification: J15, J24, O18

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

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1 Introduction

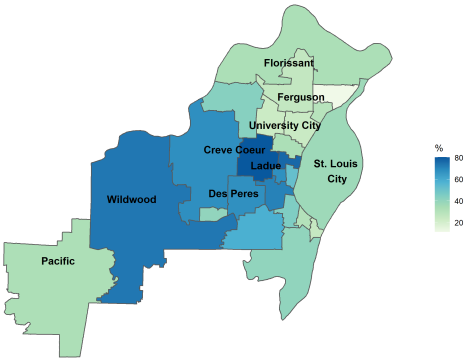
A growing body of research shows that the neighborhood a child grows up in profoundly impacts adult outcomes, such as college attainment, employment, and intergenerational mobility (e.g., Chetty et al., 2018; Chetty and Hendren, 2018; Chyn, 2018). However, segregation by race is a predominant feature of American cities, and as a result, there is substantial racial inequality in exposure to advantageous neighborhoods (e.g., Bayer et al., 2021). This paper explores whether racial differences in neighborhood sorting can account for the Black-White gap in college attainment.

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% of them will earn a college degree, while only 19% of the Black children will (Chetty et al., 2018). At the same time, there is substantial neighborhood segregation by race. To see this, Figure 1 presents two maps of the school districts in St. Louis. The left panel shows the proportion of the district's students who enroll in a four-year college degree program, while the right panel shows the share of the district's students who are Black. The figures 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.

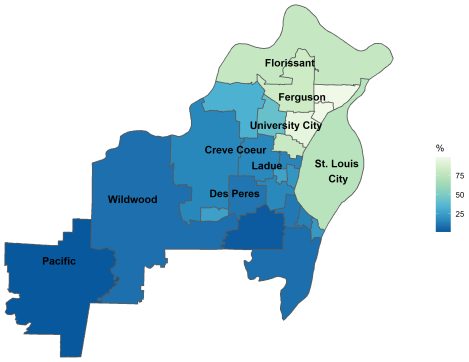
This paper builds an overlapping-generations spatial-equilibrium model to study the mechanisms behind racial segregation and the racial gap in college attainment. The framework incorporates three channels through which race impacts household outcomes and neighborhood choices. Race matters due to: (i) the Black-White wage gap, (ii) *amenity externalities*—households care about the racial composition of neighbors, and (iii) additional barriers to moving faced by Black households. Our first result is that these three channels account for all of the racial segregation and 80% of the college gap in the data. Importantly, neither the level of segregation or the college gap are targeted in the calibration. Our second result is that all three racial differences are crucial

Figure 1: Neighborhood Segregation in St. Louis County

College Enrollment



Black Share



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.

for generating the level of racial segregation and the college gap observed in the data. Counterfactual exercises show that if we remove any of the three racial differences, the college gap and racial segregation reduce substantially, but they are not completely eliminated due to the presence of the other channels. The only way in the model to have a college gap equal to zero and no racial segregation is to remove all three channels at the same time. Finally, 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, but there also exists a more integrated equilibrium with a lower college gap. We conclude that incorporating the three features is essential for understanding segregation and its impact on opportunity and intergenerational mobility.

Section 2 extends a standard overlapping-generations spatial-equilibrium model of a city to include race. Families choose the neighborhood where they live, taking into consideration local spillovers, which, in addition to innate ability and parental private investment, affect their child's future education and income. Local spillovers are a function of the share of adults with a college education in the neighborhood. The model incorporates race in three 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 an *amenity externality*. This captures a number of forces, including the fear of discrimination in all-White neighborhoods, White flight, or homophily.[1] Third, Black households face an additional moving cost. This reduced-form cost captures discrimination in housing markets, which disproportionately impacts the neighborhood choices of Black families.[2] We incorporate only these three aspects because together they capture a broad range of mechanisms with a substantial body of empirical evidence supporting them. We find that these three differences account for a large share of the college gap and all of the racial segregation in the data.

Section 3 takes the model to the data. First, we calibrate the model using a rich set of data moments. We include information on the causal effects of neighborhood racial composition on neighborhood choice, the Black-White wage gap, and differences in the propensity to move across neighborhoods by race, among other moments. We use a k-means clustering algorithm to group the St. Louis MSA Census tracts into three parsimonious neighborhoods: 1) a predominantly Black and low-income neighborhood, 2) a predominantly White and middle-income neighborhood, and 3) a predominantly White and high-income neighborhood. We then carry out two validation tests of the key mechanisms in the model. We compare the model with estimates from the literature on (1) the causal effect of neighborhoods on college attainment estimated by Chetty et al. (2016), and (2) the causal effect of segregation on educational attainment estimated by Ananat (2011). In each case, we find that the model is consistent with the estimates from the literature.

Section 4 uses the model to quantify the importance of each of the three racial differences in generating segregation and the college gap. Despite the fact that the calibration only targets the aggregate college share, we find that the model generates a racial gap in college attendance of 22 percentage points, explaining about 80% of the college gap in the data. The other 20% that the model does not capture is likely coming from other forces that are not present in the model. Similarly, the calibration does not target the racial composition of each neighborhood. Instead, we target the causal effect of a neighborhood's Black share on neighborhood choice, as estimated

[1] 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); Galiani et al. (2015).

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

by Caetano and Maheshri (2021). Yet, we find that the model generates a very similar level of segregation as in the data.

Having established that the model captures the level of segregation and the college gap in the data, we decompose the contribution of each of the three racial differences. Removing the wage gap increases the education of Black children for two reasons. First, Black households now have more resources and use them to invest in their children's education. Second, 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 externality and the barriers to moving, neighborhoods remain substantially segregated, with White households segregating by income across two neighborhoods and Black households clustering in one neighborhood. As a result, there is still a racial gap in educational attainment because the neighborhood spillovers remain smaller in the Black neighborhood than in the high-income White neighborhood.

Next, removing the amenity externality increases neighborhood integration even when the other racial differences remain in place. Some racial segregation remains due to the barriers to moving faced by Black households and because households sort by income, and, due to the Black-White wage gap, Black households earn less than otherwise similar White households. The racial education gap decreases because Black households move to neighborhoods with higher spillovers, but a gap in parental investment remains due to wage differences. Finally, equalizing the mobility costs has qualitatively similar results to removing the amenity externality, but the quantitative effects are smaller. For both the no-wage gap and the equal-mobility cost counterfactuals, we find that the general equilibrium responses of spillovers, segregation, and rents amplify the partial equilibrium effects. However, when removing the amenity externality, we find that most of the effects are similar in the partial and general equilibrium analysis.

In Section 5, we show that the presence of spillovers and externalities generates multiple equilibria. The quantitative exploration suggests that although St. Louis is in the 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. Our analysis shows that this segregated equilibrium can be maintained even when these legalized forms of segregation are removed. If

agents could coordinate, it would be possible to transition from the segregated to the integrated equilibrium. The quantitative analysis suggests that such a transition would be fast, with the bulk of the changes occurring within the first few generations.

Related literature. This paper builds on two separate strands of structural literature.[3] First, there is literature examining racial segregation in spatial equilibrium models, first 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.

Second, several papers (e.g. Aliprantis and Carroll, 2018; Chyn and Daruich, 2022; Eckert and Kleineberg, 2019; Fogli and Guerrieri, 2019; 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, 2020; Couture et al., 2019; Hoelzlein, 2020) examine the interaction between endogenous amenities and sorting by income but do not consider race.[4] This second set of papers is built on the literature on discrete choice models with local spillovers (e.g., Benabou, 1994; 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

[3]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 Schonholzer, 2021; Sethi and Somanathan, 2009) and the consequences of segregation (Ananat, 2011; Andrews et al., 2017; Billings et al., 2013; Chyn et al., 2022; Cutler and Glaeser, 1997; Derenoncourt, 2022; Johnson, 2011).

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

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 externality, and removing the barriers to moving. Section 5 analyzes the multiple equilibria feature of the model. Finally, Section 6 concludes.

2 Model

We extend a standard overlapping-generation spatial-equilibrium model to incorporate race. We model a single metro area where families choose a neighborhood to live in, 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.

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.[5] Labor is perfectly mobile across neighborhoods, so wages do not depend on the neighborhood in which a household lives.

[5]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.

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.[6] 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, $e \in \{e^L, e^H\}$, 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 innate ability a 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 and Guerrieri (2019), this local spillover is meant to summarize a variety of neighborhood factors that we do not explicitly model here. 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.

2.2 Adult's Problem

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

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

[6] Following Couture et al. (2019) 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.

subject to

$$
\begin{aligned}
c + i + p_n + m(r)\mathbb{I}_{\{n \neq n_0\}} &= y(r,e,s) \\
\log s' &= F^s(a', i, X_n) \\
P(e' = e^H) &= G^e\left(r, a', s', n\right) \\
a' &\sim \Gamma(a)
\end{aligned}
$$

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, education, 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. They must also pay a moving cost $m(r)$ if they decide to move to a neighborhood different from the one they grow up in. This moving cost depends on the race of the household. This is designed to capture additional barriers to moving faced by Black households, which are not present in the model. These barriers can include discrimination in housing markets, which makes Black households face higher search frictions than White households in finding the same unit of housing.[7]

The function F^s determines the skill of the child, which depends on the child's ability, 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, described in the next subsection. 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.

[7]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.

The child's innate ability a' is drawn from a distribution that depends on the parent's innate ability, $\Gamma(a)$. Thus, innate ability is imperfectly transmitted across generations and does not depend on race or any other factors.

Finally, we model the amenity externality 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 externality incorporates 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.

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

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

Households have preference shocks ε^n that are independently, identical ly distributed, and drawn from an extreme value distribution with shape parameter κ. This distributional assumption allows us to write the probability that a household of type (r,a,s,e,n_0) chooses to live in neighborhood n as

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

and the expected value function is

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

2.3 Child's Problem

A child of race r, innate ability a, skill s, growing up in neighborhood n, with parental investment i chooses their education level $e \in \{e^L, e^H\}$ such that

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

During this stage, children draw preference shocks for education, σ^L and σ^H, that are independently, 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: $C(s) = \bar{c} - s$, where $\bar{c}$ is a parameter that determines the level of the education costs. 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

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

2.4 Equilibrium

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

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

(iii) Spillover consistency:

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

(iv) Location consistency:

$$S_{r,n} = \frac{\int F\left(r, da, ds, de, dn_0, n\right)}{\int F\left(dr, da, ds, de, dn_0, n\right)} \qquad \forall\, n = 1, \ldots, N \text{ and } r = \{b, w\}.$$

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. Second, there are spillovers, summarized by the college share in each neighborhood, X_n. Third, there are amenity externalities, summarized by the racial composition of each neighborhood $S_{r,n}$.

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 that the economy is always in the same equilibrium.

Intergenerational transmission The model captures three channels of intergenerational linkages. First, ability is imperfectly transferred from parent to child; while there is mean reversion in innate ability, a high-ability adult is more likely to have a high-ability child than a low-ability adult. Second, 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 third 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

Table 1: Externally Calibrated Parameters

Parameter	Description	Value	Source
β	Discount factor	0.97^{40}	
γ_B	Bliss points for Black households	0.50	Banzhaf and Walsh (2013)
γ_W	Bliss points for White households	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	1.58	Mincer regressions
$w(W,H)$	Relative wage of White, high education	1.71	Mincer regressions
ψ	Housing supply elasticity	2.36	Saiz (2010)
m	Moving cost, money	0.0033	Bergman et. al. (2019)

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 US, St. Louis has two features that are convenient for our analysis. First, 95% of households are either White or Black. Given the small share of other races, we do not consider them in our analysis, keeping the model tractable. Second, the labor market is well integrated, with low commuting costs across neighborhoods.

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 corresponding moments that are targeted in our internal calibration routine. Although the calibration of all the parameters

Table 2: Internally Calibrated Parameters

Parameter	Description	Value	Moment	Data	Model
Neighborhoods					
A_A	Amenity in A	1.0000	Population neighborhood A	0.1700	0.1743
A_B	Amenity in B	1.1178	Population neighborhood B	0.6200	0.6159
A_C	Amenity in C	1.2207	Population neighborhood C	0.2100	0.2098
η_A	Housing supply in A	25.3023	Rent neighborhood A	0.1200	0.1213
η_B	Housing supply in B	22.6165	Rent neighborhood B	0.2178	0.2172
η_C	Housing supply in C	1.4118	Rent neighborhood C	0.4460	0.4459
κ	Shape parameter for location	0.1492	Neighborhood flows	0.3500	0.4076
m^B	Migration cost for Black HHs	0.0595	Diff in moving prob for Black HHs	-0.0610	-0.0629
Amenities: Importance of bliss point					
φ_W	White	0.6541	Migration response to Black share, Black non-college	0.0241	0.0356
φ_B	Black	1.0420	Migration response to Black share, Black college	0.0345	0.0358
			Migration response to Black share, White non-college	-0.0225	-0.0273
			Migration response to Black share, White college	-0.0283	-0.0270
Skill production					
θ_c	Constant term	0.5552	Mean skills	1.0000	1.2178
θ_a	Ability	0.5471	Regression coefficient of education on skills	0.1910	0.1895
θ_i	Investment	0.4529	Covariance (s,i)	0.1612	0.2199
θ_X	Spillovers	0.1697	Ratio college share neighborhood C to A	3.5333	3.3946
Ability					
ρ_a	Persistence ability	0.3984	Regression coefficient of child on parent ability	0.5100	0.5055
σ_a	Std. dev. ability	1.1881	R^2 child on parent ability	0.2600	0.2555
Education					
$\bar{c}$	Education cost level	2.1125	Educational probability	0.4166	0.4245
σ	Shape parameter education	0.4109	R^2 education choice	0.1570	0.1450

is done jointly, some moments are more informative than others for a given parameter of interest. 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 Externality

Our model includes local amenities that depend on the racial composition of the neighborhood. In the data, there is abundant evidence that households care about the racial composition of a neighborhood when moving.[8] The amenity externality captures many different forces that could lead to this empirical regularity. For example, the externality can be interpreted as homophily, that is, the preference to live with neighbors of your own race. They can also capture the White flight

[8]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); Galiani et al. (2015).

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.

To calibrate the amenity externality, 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 neighborhood characteristics that 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 externality, which 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% White and 50% Black, while White households prefer a mix that is about 90% White and 10% Black. 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 com-

position on neighborhood choice from other local characteristics. They build a dynamic discrete choice model for neighborhoods 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 externality for Black and White households, respectively. Specifically, we calculate the change in the probability 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 Black share in both the model and the data.[9]

Table 2 shows that the model is consistent with the causal effects of the Black share on neighborhood choice. Both in 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%. For Black households, the response is between 2% and 3.5%. Importantly, note that 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 that the model can match these non-targeted moments.

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. This exercises shows that it is reasonable to assume three neighborhoods for the model in this paper. We use data on Census tracts from the 2000 Census, and Chetty et al. (2018) to group tracts according to their socioeconomic characteristics. Specifically, we cluster Census tracts into groups using a k-means clustering

[9]For the data target, in Caetano and Maheshri (2021), the marginal effect of the Black share is given by the equation $\frac{\partial P_{gj}}{\partial s_j} = \beta_g P_{gj}(1 - P_{gj})$. 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 the 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 models' 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 for St. Louis MSA. Data from 2000 Census and Chetty et al. (2018)

algorithm. We focus on four different characteristics: 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.[10] Each of these characteristics has a counterpart in our model.

Table 3 shows our results for the St. Louis MSA. In the entire MSA, the share of Black households is 20%. The clustering algorithm creates two predominantly White neighborhoods, B and C, which have 9% and 7% Black households, respectively. Neighborhood C has the highest income, house prices, and share of college graduates. In neighborhood A 78% 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.

In Appendix A.1, we perform robustness exercises by extending the analysis to four 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 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.

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

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 and the ratio of the share of college graduates in neighborhood C relative to neighborhood A—which we explain in Section 3.5. 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.[11]

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 elasticities, 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% of the housing price.

3.3 Moving Across Neighborhoods

We parameterize the moving cost for White households as m and the moving cost for Black households as $m + m^B$. We externally set m to be equivalent to \$2,660 from the experimental evidence in Bergman et al. (2019) about movers in Seattle.[12]

The additional moving cost for Black households, m^B, is a reduced-form way of capturing a range of barriers to moving faced by Black households. To discipline this parameter, we quantify the racial difference in the probability of moving across neighborhood types. 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 make the regression in the data comparable by assigning types to neighborhoods on a national level, as we did in our clustering exercise.[13] We estimate a regression of an indicator for moving across neighborhoods on neighborhood fixed effects, a race dummy, and we control for household income, parental education, and childhood neighborhood type. Table 13 in Appendix A.4 shows that Black households are 6.1 percentage points less likely to move across neighborhood types after controlling for household income and parental education.

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

[12] In the model, we normalize $w(W,L) = 1$, so 1 dollar is equivalent to $\$34443.96\frac{1-\beta^{40}}{1-\beta}$, the average life-time earnings of a White low-educated worker.

[13] See Appendix A.4 for details.

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 for 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 35% of people who live in a different neighborhood type than where they were born (see Appendix A.4 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. We use data from the 1997 National Longitudinal Survey of Youth (NLSY97), which contains wage and salary income, race, gender, age, usual hours and weeks worked, labor force participation, and skill measures. We use individuals' total wage and salary income at age 34 or 35.[14] 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. This notion of skill is distinct from innate ability, which we model as being passed imperfectly from parent to child and as an input to skill production, but it is unobservable in the data.

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; and 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 11 in Appendix A.2 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

[14] Respondents in the NLSY97 are interviewed every two years, which is why we cannot focus on a single age.

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: $w(W,e_L) = 1$. 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. The wages for White households are 1.00 and 1.71 for low and high education, respectively, while for Black households they are 0.92 and 1.58 for low and high education, respectively. Note that, by assumption, the skill premium for both Black and White households is equal to 71%. 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, Educational Attainment, and Ability

To inform the calibration of the skill production function, F^s, college choice, and the ability process, we study various relationships between college attainment, skill, and parental investment in the NLSY97. We first need to map various objects in the model to the data. As described above, skill is distinct from innate ability, which is unobserved in the data. We measure skill using the ASVAB score. To measure parental investments, we use data on parent-to-child transfers from Abbott et al. (2019). Their methodology constructs these transfers from questions on income transfers and allowances from parents from the NLSY97.

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

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

There are three inputs into skill: two at the individual level and one at the neighborhood level. First, skill is increasing in individual innate ability a and parental investment i with elasticities θ_a and θ_i, respectively. Second, skill is increasing with neighborhood spillovers X_n, with elasticity θ_X.

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. To estimate the return on the individual-level variables of ability and investment, we calculate cross-sectional moments on individuals in both the model and the data. For θ_a, we target the estimate of a regression coefficient of education on skill. Table 12 in Appendix A.3 shows the results of a regression of a dummy for whether the individual obtains at least a bachelor's degree on log skill, where skill is measured as log(ASVAB) and standardized so that both the mean and the standard deviation are 1. For θ_i, we target the covariance between skill and parental investment. This moment provides information about the importance of parental investments. For θ_X, the return on neighborhood externalities, we look at a moment at the neighborhood level. We target the ratio of the share of college graduates in neighborhood C relative to neighborhood A. This moment provides information on the relative spillovers in the richest neighborhood relative to the poorest one, which is valuable information regarding the role of externalities and the incentives for high-education adults to cluster in a given neighborhood.[15] 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. Aside from skill, this also depends on the level of the cost, $\bar{c}$, as well as the realization of taste shocks with shape parameter σ. We calibrate $\bar{c}$ to target the aggregate education level of 42%—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% 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.[16] 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

[15] Ideally we would use information on the college attainment of children growing up in each neighborhood instead of the share of adults with a college degree. Unfortunately, this information is not available at the granularity needed for mapping into the three neighborhood clusters. Similarly, we also consider using the relationship between the share of adults with a college degree and skills in the NLSY. However, the finest location provided in the restricted-access NLSYGeocode Data is the county, which is too broad to map to our notion of a neighborhood.

[16] 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% and 80% for Black and White children, respectively. At the 75th percentile, these probabilities are 73% and 75%.

the aggregate level of college attainment is equal to 42%; 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%, respectively. To calibrate σ, we use the R-squared from the regression of education on skill from Table 12. 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.

Finally, we use these data to discipline the stochastic process by which ability is transmitted from parent to child. Because innate ability, a, is unobserved, we instead measure the intergenerational persistence of observed skill, s. We estimate an AR(1) process for skill using our measure of the mother's and child's skills from the NLSY79 (see Appendix A.5). We assume that innate ability in the model follows an AR(1) process and internally choose the persistence parameter, ρ_a, and the standard deviation of the shocks, σ_a, to match the persistence and the R-squared of the regression between the parent's and child's skills.

3.6 Validation: Causal Estimates in the Data and Model

Given the calibration, we validate our model using credible estimates of the causal effect of segregation and childhood neighborhood on adult outcomes from the literature. The model is consistent with these non-targeted moments that form the basis for the key mechanisms of the model.

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 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.

Table 4: Validation: Replicating Empirical Causal Effects

	Data	Model
I. Moving to Opportunity		
Takeup rate (%)	[46.0 , 49.3]	31.0
Δ College attainment, treatment-on-the-treated (%)	[2.9 , 7.6]	5.0
Δ College attainment, intent-to-treat (%)	[1.4 , 3.7]	1.6
II. Segregation		
Δ College attainment, White	[-0.292 , 0.012]	0.079
Δ College attainment, Black	[-0.516 , -0.078]	-0.211

Notes: Data estimates from Ananat (2011); Chetty et al. (2016). Data shows one standard deviation confidence intervals.

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. The subsidy in our simulation covers 50 percent of the rent differential between the previous and the new neighborhood. 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 two critical choices in our model. First, they must decide whether to take up the voucher and relocate to the more advantageous neighborhood. Panel I of Table 4 shows that 31% of households opt for the voucher in our simulation, while in the data, it is a bit higher, between 46 and 49%. Second, households also change their investment and education choice. We find that for college graduation, treatment-on-the-treated (TOT) estimate is 5.0 percentage points, while the intent-to-treat (ITT) estimate is 1.6 percentage points, meaning that college attainment increases by 1.6 percentage points for families offered the voucher regardless of whether they used it. Note that the TOT and the ITT are within the one standard deviation confidence interval of the data estimates. Reassuringly, we see that the simulation generates very close results to the MTO results from Chetty et al. (2016).

Segregation: Second, the model is consistent 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 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, to test the impact of segregation, we set the parameters governing the amenity externalities to zero, $\varphi_B = \varphi_W = 0$, and solve the general equilibrium. Then, we calculate the change in educational attainment per change in the dissimilarity index, as in the data.

Panel II of Table 4 shows that the model is consistent with the reduced-form causal estimates: more segregation implies lower educational attainment for Black children and higher attainment for White children, with more substantial effects for Black than for White children.[17]

4 Sources of Segregation and College Attainment Gap

What are the sources of segregation and the college attainment gap? 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 22 percentage points, explaining 78.6% of the college gap in the data (see Table 5). In the model, college attainment is 47% and 25% for White and Black households, respectively. In the data, college attainment is 47% and 19% for White and Black households, respectively. The 21.4% 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

[17] In robustness exercises, we verify that the model predictions are similar if we reduce φ_B and φ_W by 50% instead of 100%.

Monge-Naranjo, 2011).[18]

Importantly, 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 almost the same racial distribution as in the data. Using the dissimilarity index as our baseline measure of segregation, the model is able to generate levels of segregation that are very similar to the data. The dissimilarity index in the model is 0.65 versus 0.61 in the data.

We conclude that the combination of (i) racial disparities in the labor market, (ii) racial differences in barriers to moving across neighborhoods, and (iii) preferences over the racial composition of the neighborhood jointly do 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.

Table 5: College Attainment and Segregation

	Data	Model
College attainment:		
All	0.42	0.42
White	0.47	0.47
Black	0.19	0.25
Racial gap	0.28	0.22
Black Share:		
Neighborhood A	0.78	0.79
Neighborhood B	0.09	0.09
Neighborhood C	0.07	0.04
Dissimilarity Index	0.61	0.65

4.1 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 assess the importance of each form of heterogeneity across neighborhoods for the racial college gap and segregation. The first row of Table 6 shows the benchmark economy, i.e., we include all three sources of neighborhood

[18] Appendix B.1 explains how different households choose education and neighborhood in the benchmark model, which generates the college gap and racial segregation in equilibrium.

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. In this counterfactual the college gap reduces 14 percentage points from 0.22 to 0.08. However, the dissimilarity index has a relatively smaller reduction of 12%. This result shows that the heterogeneity in spillovers across neighborhoods are not an important factor behind the racial segregation, but they are important for the college gap.

The third and fourth rows of Table 6 consider counterfactuals that remove neighborhood heterogeneity in the amenity externality or rents. The third row sets the racial composition for amenities to the city-wide Black share of 20% instead of the neighborhood Black share. Row 4 sets rents to the city-wide average instead of the neighborhood market-clearing rental rate. In both cases, there is a large reduction in segregation, but due to different forces. With equal racial shares households agree on the relative amenities provided by each neighborhood. Therefore, neighborhood choices are more similar, leading to more integration. In the case of equal rents, we also see a reduction in segregation. This is because the low rents in neighborhood A are one of the driving forces behind segregation: Black households choose to live in neighborhood A due to the low rents, while for White households, the low rents do not compensate for the low amenities due to the externality. When rents are equalized across neighborhoods, Black households are less likely to live in A. In turn, this equalizes the racial shares across neighborhoods, reducing the role of the amenity externality and leading to more integration. In both counterfactuals, because of the reduction in segregation, White and Black children are exposed to more similar neighborhood spillovers, generating a reduction in the college gap.

We conclude that local spillovers are important for the college gap but not for segregation, while the racial composition and rent heterogeneity matter for segregation, and as a consequence, for the college gap.

Table 6: Neighborhood Heterogeneity Matters

	Heterogeneity in				
	Spillovers, X_n	Race, $S_{r,n}$	Rents, p_n	College gap	Dissimilarity Index
Benchmark	$\surd$	$\surd$	$\surd$	0.22	0.65
Equal spillovers	$\times$	$\surd$	$\surd$	0.08	0.57
Equal racial shares	$\surd$	$\times$	$\surd$	0.05	0.07
Equal rents	$\surd$	$\surd$	$\times$	0.04	0.36
All equal	$\times$	$\times$	$\times$	0.03	0.05

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.

4.2 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. In the model, 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 average skill differs. Equalizing wages entails increasing wages, $w(B,l)$, for Black non-college workers from 0.90 to 1.00 and increasing wages, $w(B,h)$, from 1.58 to 1.71 for Black college workers. We compare the new equilibrium with the baseline in panel A of Table 7.

We start by evaluating the changes between the baseline steady state and the new counterfactual general equilibrium. The college gap reduces by 16 percentage points (from 22pp to 6pp) when we remove the wage gap. The education probability of White households is almost unchanged—it reduces from 47% to 45% (see Table 8). Instead, for Black households, college attainment increased from 25% to 38%. However, there is also a small reduction in segregation. The dissimilarity index declines from 0.65 to 0.46. Hence, many racial disparities across neighborhoods remain, and, as a result, the college gap is not fully closed.

The second row of panel A Table 7 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 exer-

cise reveals that there are strong general equilibrium effects. The college gap reduces 5 percentage points in partial equilibrium while the general equilibrium effect is 15 percentage points. The next rows examine why the general equilibrium effect is so much larger than the partial equilibrium effect. Each of the next three rows considers each of the three GE forces in isolation. We find that the general equilibrium change in spillovers has a strong effect on the college gap. This is because as college attainment for Black households increases, so does the neighborhood spillover in neighborhood A. As the spillover increases, the skill and college attainment of children growing up in neighborhood A further increases, amplifying the partial equilibrium effect of closing the wage gap. However, while the general equilibrium effect of neighborhood spillovers is the most important for closing the college attainment gap, the general equilibrium effects of the racial composition and rents have the strongest impact on segregation. This is because they are the most important in determining the differences in neighborhood choice between White and Black households.

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 Black share of neighborhood A. It also affects the college share of neighborhoods, primarily by increasing the college share of neighborhood A. According to the right panel, there was a 29 percentage points gap in the share of college graduate workers between neighborhoods A and C, which closes to 14 percentage points 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 externality. 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.2 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 8 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 chil-

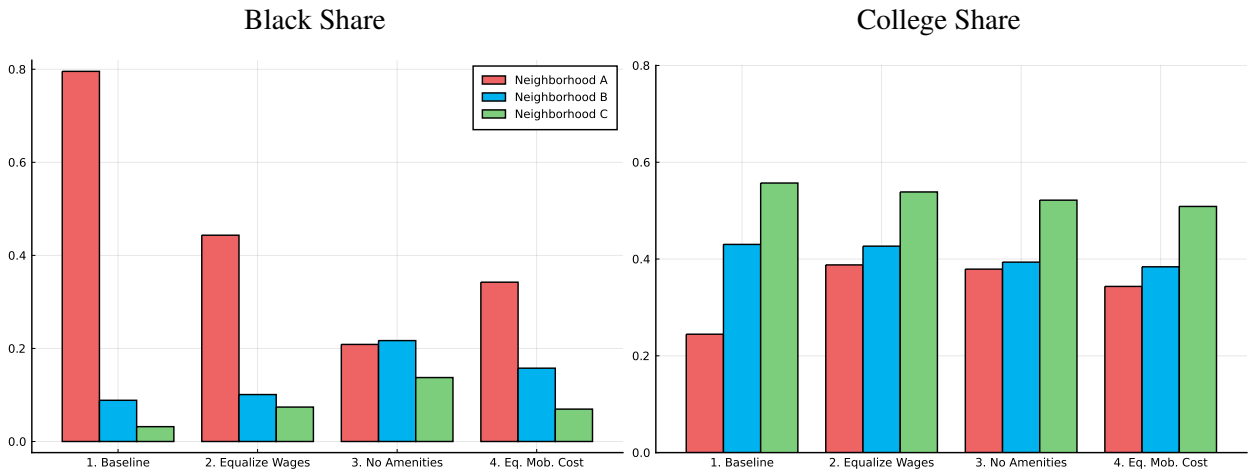
Table 7: Sources of Segregation and College Attainment Gap

	GE change in X_n	GE change in $S_{r,n}$	GE change in p_n	College gap	Dissimilarity index
Benchmark				0.22	0.65
A. No Wage Gap Counterfactual					
General equilibrium	$\surd$	$\surd$	$\surd$	0.06	0.46
Partial equilibrium	$\times$	$\times$	$\times$	0.17	0.60
No Δ *spillovers*	$\times$	$\surd$	$\surd$	0.16	0.61
No Δ *race amenities*	$\surd$	$\times$	$\surd$	0.13	0.59
No Δ *rental price*	$\surd$	$\surd$	$\times$	0.10	0.47
B. Race-blind Counterfactual					
General equilibrium	$\surd$	$\surd$	$\surd$	0.05	0.07
Partial equilibrium	$\times$	$\times$	$\times$	0.06	0.07
No Δ *spillovers*	$\times$	$\surd$	$\surd$	0.05	0.07
No Δ *race amenities*	$\surd$	$\times$	$\surd$	0.05	0.07
No Δ *rental price*	$\surd$	$\surd$	$\times$	0.06	0.07
C. Equal Mobility Cost Counterfactual					
General equilibrium	$\surd$	$\surd$	$\surd$	0.12	0.28
Partial equilibrium	$\times$	$\times$	$\times$	0.22	0.59
No Δ *spillovers*	$\times$	$\surd$	$\surd$	0.16	0.40
No Δ *race amenities*	$\surd$	$\times$	$\surd$	0.22	0.60
No Δ *rental price*	$\surd$	$\surd$	$\times$	0.15	0.37

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* $m^B = 0$*.* $\times$ *indicates that we keep that variable at the benchmark value, while* $\surd$ *indicates that we let it adjust to its new general equilibrium value. For each case, we compute the college gap and dissimilarity index.*

dren of college-graduate parents, the racial gap in college attainment decreases from 17 percentage points to 4 percentage points. Similarly, for children of non-college parents, the racial gap in college attainment decreases from 14 percentage points to 4 percentage points. Hence, we see an equalization of intergenerational mobility across races for children of both non-college and college graduates.

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



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

4.3 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 17 percentage points when both White and Black households are race-blind (panel B of Table 7, first row). This reduction results from two forces: (a) White households reduce their education—from 47% to 42%, and (b) Black households increase their education—from 25% to 37% percent. Interestingly, in the race-blind counterfactual most of the gains are in partial equilibrium (panel B of Table 7, second to fifth rows). By making households race-blind, even in partial equilibrium, households adjust their neighborhood choice. In fact, all the change in the segregation index (from 0.65 to 0.07) occurs in partial equilibrium. As a consequence, the college gap reduces to almost the same level as in general equilibrium (0.06 in partial equilibrium relative to 0.05 in general equilibrium).

Table 8: Intergenerational Mobility

	Education probability			
	Benchmark	No wage gap	Race blind	Equal mobility cost
All	0.42	0.44	0.41	0.39
White	0.47	0.45	0.42	0.42
Black	0.25	0.38	0.37	0.30
Gap	0.22	0.06	0.05	0.12
College parent	0.62	0.62	0.60	0.59
Non-college parent	0.28	0.29	0.28	0.26
Gap	0.34	0.32	0.32	0.33
Non-college parent, White	0.32	0.30	0.29	0.28
Non-college parent, Black	0.17	0.26	0.25	0.20
Gap	0.14	0.04	0.04	0.08
College parent, White	0.64	0.63	0.61	0.61
College parent, Black	0.48	0.58	0.58	0.52
Gap	0.17	0.04	0.03	0.09

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* $m^B = 0$.

Figure 2 shows that without the amenity externality, 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 0.07. This is due to households segregating themselves by income, which, in turn, differs by race. 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 externality also affects educational attainment for Black children through an increase in investment of Black parents, as in the wage-gap counterfactual. 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 17 percentage points to 3 percentage points for college households. For non-college households, the gap goes from 14 percentage points to 4 percentage points.

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.

4.4 Equal Mobility Cost

Finally, we remove the differential mobility cost by setting $m^B = 0$. Black families will still be subject to a migration cost when they move, but it will now be the same as the migration cost paid by White families. Panel C of Table 7 shows that in this counterfactual the college gap closes by 10 percentage points and the segregation index falls by 57%. In this counterfactual it becomes cheaper to move for Black households. As a consequence, there are more Black households in the neighborhoods with the larger spillovers (i.e., B and C). As a result, the college attainment of Black households increases from 0.25 to 0.30. On the other hand, the spillover of neighborhoods B and C fall and, as a consequence, the college attainment of White households falls from 0.47 to 0.42.

The general equilibrium effects are important in this counterfactual, similar to the case of equal wages. The general equilibrium change in spillovers matters for the college gap. As college attainment for Black households increases, the neighborhood spillovers equalize; this can be seen in Figure 2, which shows a much more equal college share across neighborhoods under the equal mobility costs counterfactual. This amplifies the partial equilibrium effect of equalizing the mobility

cost; Black children benefit from higher spillovers, further increasing their college attainment.

Similarly, the general equilibrium change in the racial composition matters for segregation and, as a consequence, for the college gap. If one were to hold the racial composition fixed in the amenity externality, Black and White households would continue to make very different neighborhood choices. As a result, realized segregation would remain high and the neighborhood spillovers would not equalize, maintaining the Black-White gap in college attainment.

Finally, the general equilibrium change in rents has only a relatively minor effect on segregation and the college gap. If rents remain as in the initial steady state, the college gap still closes to 15 percentage points (versus 12 percentage points in the full counterfactual), and the dissimilarity index still falls by 43% (versus 57% in the full counterfactual). Thus, we conclude that the general equilibrium response of rents has only a minor impact on the equal mobility cost counterfactual.

5 Segregation Traps

The presence of spillovers and amenity externalities imply that the model has multiple equilibria. We search for all possible equilibria of the model and find three candidates, described in Table 9.[19] The first equilibrium is the one that matches the data, with a sum of squared errors (SSE) of 0.03. This equilibrium has a relatively large segregation index, so we label it as the *segregated equilibrium*. All of the analysis in the previous sections refer to this particular equilibrium.

We also find two other equilibria. Equilibrium 2 has a lower dissimilarity index, so we label it as the *integrated equilibrium*. This second equilibrium has a similar aggregate level of education but a much lower college gap of 10 percentage points, instead of 22 percentage points as in the segregated equilibrium. Note that this equilibrium is much further away from the data, with an SSE of 1.27.

Finally, we also find a third equilibrium, Equilibrium 3, in which almost everyone (96% of the households) live in neighborhood C and almost no one is educated. Because neighborhood C is too

[19] Specifically, we consider 10,000 quasi-random initial guesses for the 9 general equilibrium values $(X_n, S_{r,n}, S_n)$. For each of these values we solve the general equilibrium model. We find that, depending on the initial guess, the model converges to one of the three equilibria discussed here.

expensive, households do not invest in their children and the spillover is low, meaning the utility cost of college will be high. The education probability is only 1% due to the extreme value shocks. We do not believe that the third equilibrium is a realistic one, so we exclude it from our analysis, focusing instead on the segregated and the integrated equilibrium.[20]

Table 9: Multiple Equilibrium

	Equilibrium 1 Segregated	Equilibrium 2 Integrated	Equilibrium 3 All in C
Dissimilarity index	0.65	0.42	0.04
Population neighborhood A	0.17	0.31	0.01
Population neighborhood B	0.62	0.51	0.02
Population neighborhood C	0.21	0.18	0.96
Black share, neighborhood A	0.80	0.08	0.01
Black share, neighborhood B	0.09	0.33	0.01
Black share, neighborhood C	0.03	0.04	0.21
Education, neighborhood A	0.21	0.32	0.16
Education, neighborhood B	0.38	0.35	0.17
Education, neighborhood C	0.72	0.68	0.00
Neighborhood flows	0.41	0.55	0.05
Education	0.42	0.40	0.01
College gap	0.22	0.10	0.00
Education, White	0.47	0.42	0.01
Education, Black	0.25	0.32	0.01
SSE	0.03	1.27	2800.42

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

5.1 Escaping the Segregation Trap

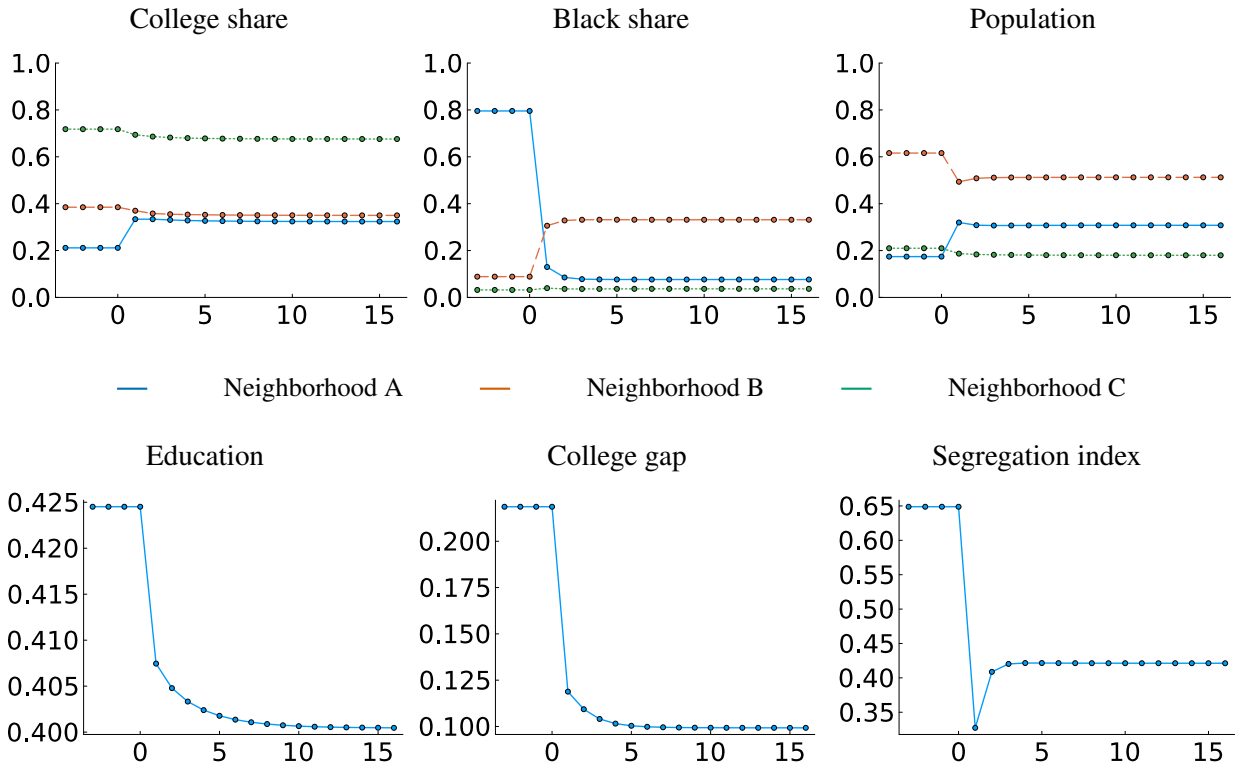
The presence of multiple equilibria might allow the economy to coordinate and improve outcomes. We study what would happen if households could coordinate to move the economy from the segregated to the integrated equilibrium. We start the economy in the steady-state of the segregated

[20]It might be puzzling that this is maintained as an equilibrium. The main reason is the neighborhood racial compositions. Since everyone lives in C, the racial composition of neighborhood C is close to that of the population (79% White, 21% Black), while the racial composition of neighborhoods A and B are mostly White (the Black share is 3% and 4% in A and B, respectively). As a consequence, the value of the amenities in both A and B are very low for both White and Black households because of the difference in the exogenous amenity and a racial composition that differs from their bliss point. The low rents in neighborhoods B and C are not enough to compensate for the differences in amenities. In other words, the housing supply elasticity, which pins down rents, is not enough to make everyone living in C unattractive.

equilibrium. In period $t = 0$, agents learn that in period $t = \tau$ they will coordinate to be in the integrated equilibrium. We then solve a shooting algorithm to study the transition path from the segregated to the integrated equilibrium.

Figure 3 shows the transition path when agents in period $t = 0$ learn that in period $\tau = 15$ 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 $t = 0$. We also find very similar results for different values of τ.

Figure 3: 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 equilibrum.

This exercise reveals that the presence of spillovers and externalities generates multiple equilibria. While the data indicate that St. Louis is currently in the segregated equilibrium, there also exists a more integrated equilibrium with a lower college gap. Thus, if agents were able to coordinate, it would be possible to switch from one equilibrium to the other.[21] The quantitative analysis

[21] A natural question would be to ask if the government could implement a policy incentivizing agents to move, as in

suggests 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.

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 good schools and significant spillovers may systematically differ by race and be partly responsible for the racial gap in adult outcomes.

To examine these issues, we develop an overlapping-generations spatial-equilibrium model that incorporates race in three ways. First, there is a Black-White wage gap. Second, households have preferences over the racial composition of the neighborhood in which they live. Third, Black households face additional barriers to moving. Households in the model choose where to live and how much to invest in their child's education, affecting whether the child goes to college and receives higher wages as an adult.

We calibrate the model to match the neighborhood characteristics of the St. Louis metro area. We find that the presence of the Black-White wage gap, the amenity externalities, and barriers to moving generate a college gap of 22 percentage points—about 80% of the college gap in the data. We also find that removing the racial wage gap helps improve Black workers' educational attainment. However, the amenity externalities and the barriers to moving are also essential for reducing neighborhood segregation and improving access to neighborhoods with the spillovers that are important inputs into skill and college attainment.

the MTO experiment, facilitating a transition to the integrated equilibrium. With this objective in mind, we analyzed perfect foresight transitions, starting in the segregated equilibrium and providing transfers to movers. We find that the key assumption is to which of the terminal equilibria the perfect foresight economy converges. Specifically, if the economy converges to the integrated equilibrium, then for any transfer scheme, including a scenario with no transfers, agents quickly move from the segregated to the integrated equilibirum. This exercise underscores the fact that, in this model, segregation is a coordination failure, and that more integration would be possible even without monetary compensation, provided that agents could coordinate effectively on a transition. Perhaps a policy could provide transfers that would serve as a nudge to facilitate this coordination in the presence of additional forces not present in the model, such as behavioral agents.

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Appendix

A Data **43**

A.1 Neighborhoods 43

A.2 Black-White Wage Gap 44

A.3 College Attainment and Individual and Neighborhood Characteristics 44

A.4 Neighborhood Flows 44

A.5 NLSY: Ability 46

B Model **47**

B.1 Segregation and Education Attainment 47

B.2 Parental Investment: Comparison Among Counterfactuals 48

A Data

A.1 Neighborhoods

Table 10 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 10: 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 Black-White Wage Gap

Table 11 shows the result of the wage regressions used to estimate 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 11: Mincer Regression

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

A.3 College Attainment and Individual and Neighborhood Characteristics

Table 12 shows the regression results that are used to calibrate the return to ability θ_a and the shape parameter σ for the education taste shocks. 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.

A.4 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 probability of Black relative to White households.

Table 12: College Attainment and Skills

	Bachelor's Degree or More
Log(skills)	0.1910
	(0.0059)
Constant	0.4200
	(0.0074)
Observations	4,997
R^2	0.1570

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 high degree of precision we lose sample size. For these reasons, we consider two cases, restricting the sample to people who can be mapped to a given cluster with probability greater than 50% and 75% at both ages, respectively.

For each case we calculate the probability that each individual moved clusters between age 17 and 35. In the first restriction we get that 46% of people moved across clusters, while in the second restriction 25% of people moved across clusters. To calibrate the model, we use the midpoint of these estimates, 35%.

Next, we examine the differences in moving probability between Black and White children. Table 13 displays the results for the regression of a mobility indicator on fixed effects for childhood neighborhood, parent's education, parental income, and race. We add childhood neighborhood

fixed effects to control for the differences in neighborhood size that would impact the probability a child would move to each neighborhood as an adult. The coefficient on race is used to calibrate the additional moving cost for Black households.

Table 13: Mobility Difference for Black Households

	(1)
Childhood neighborhood type	
B	-0.328^{***}
	(0.026)
C	-0.188^{***}
	(0.029)
Log income	0.003
	(0.009)
Race	-0.061^{**}
	(0.028)
Constant	0.681^{***}
	(0.102)
N	3848
R^2	.047
FE for parents' education	✓

A.5 NLSY: Ability

This appendix describes the estimation of the AR(1) process for the intergenerational transmission of skill. We use data from the Children of the NLSY-79 Survey via Abbott et al. (2019), which contains information on the ability of the child matched to the ability of the mother. For the mother, the data include the AFQT score, which is the typical measure of ability used in this literature. For the child, we do not have AFQT score, so, following Abbott et al. (2019), we use the first principal component of their PIAT math, reading recognition, and reading comprehension scores. For comparability, we transform both mother's and child's scores into Z-scores.

We assume the inter-generational transmission of skill follows an AR(1) process and estimate its parameters with a regression of child's ability on mother's ability. The persistence parameter of the AR(1) is equal to the coefficient (0.51) and the R2 is equal to 0.26. We use these numbers as targets in the internal calibration of the AR(1) process for innate ability. We note that the mean of the ability is a normalization and will not affect the results (we set it to 2). Finally, we discretize

the AR(1) process using Tauchen's method, which creates a 3-point grid and transition matrix.

B Model

B.1 Segregation and Education Attainment

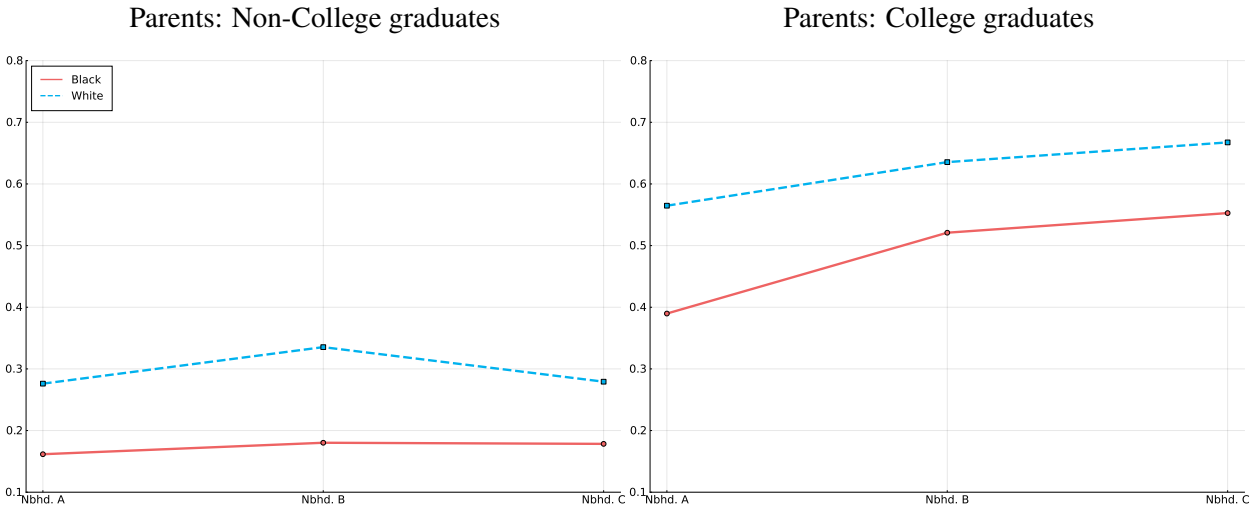
We first examine education and neighborhood choices in the baseline model. Figure 4 shows the probability of becoming a college graduate for a child with median innate ability and skills as a function of the other state variables: parental education, race, and neighborhood. First, the left panel shows 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 innate ability. While White children have a college attainment probability around 30%, it is less than 20% for Black children.

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. Having college parents increases the probability of college attainment for Black and White children.

Table 14 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 5 shows the probability of going to each neighborhood for an agent with median innate ability and skills as a function of the initial neighborhood, race, and education. Examining the figures reveals two patterns. First, Black households have a much higher probability than White households of living

Figure 4: College Attainment



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

Table 14: Neighborhood Demographics

	Neighborhood A	Neighborhood B	Neighborhood C
Black non-college	0.64	0.06	0.01
Black college	0.15	0.03	0.03
White non-college	0.14	0.56	0.28
White college	0.06	0.36	0.69
Total	1.00	1.00	1.00

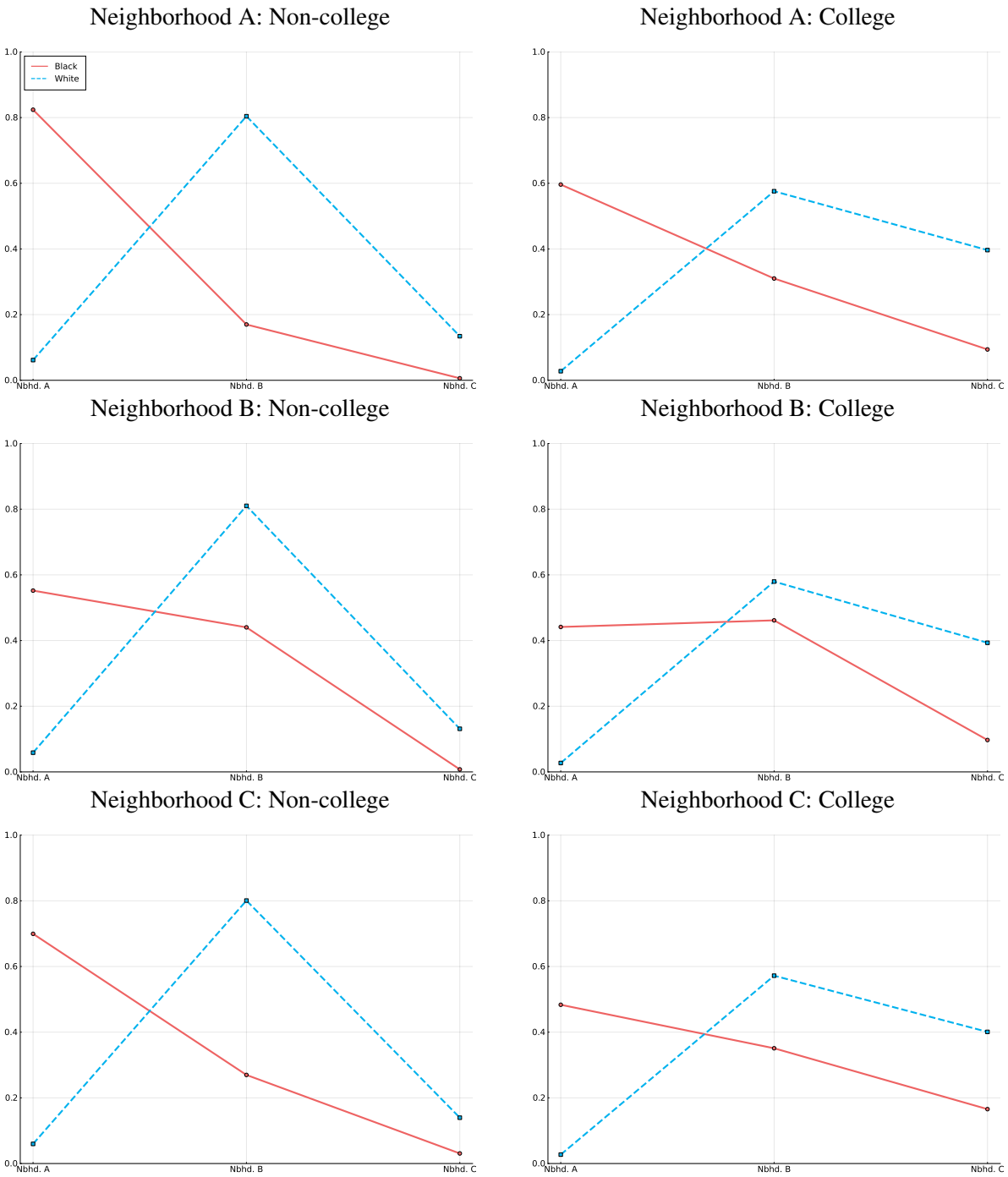
Notes: The table shows the composition of each neighborhood by race and education level.

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.2 Parental Investment: Comparison Among Counterfactuals

In Figure 6, we plot the average investment in the model conditional on race and innate ability for average parental education and skill. Moving from the baseline in the solid red line to the equalized

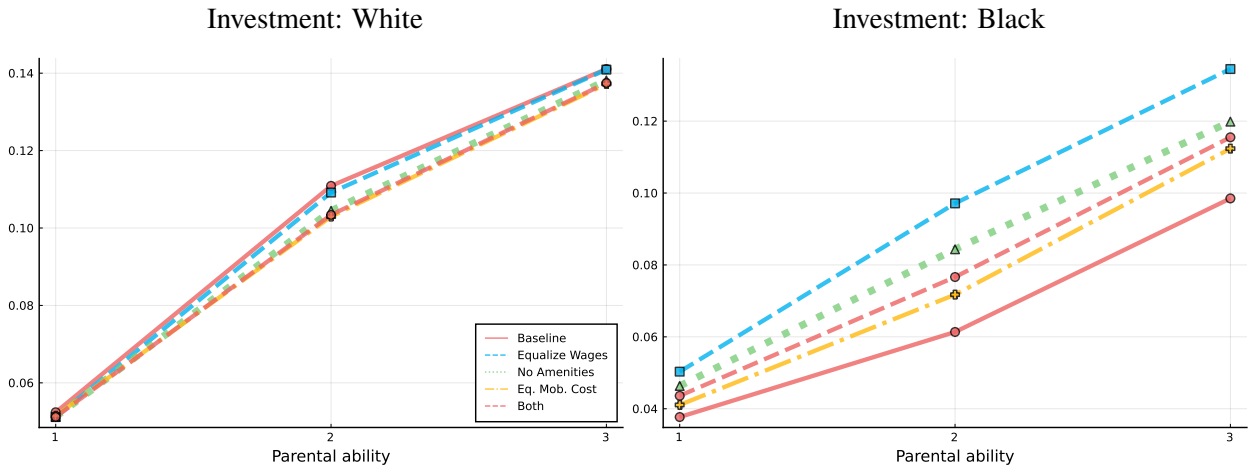
Figure 5: Neighborhood Choice



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

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. If anything, White households reduce a bit their investment.

Figure 6: Parental Investment: Comparison Among Counterfactuals



Notes: Parental investment for each race and innate ability and average parental education and skills, of the baseline and counterfactual economies.