Why Don't Poor Families Move? A Spatial Equilibrium Analysis of Parental Decisions with Social Learning*

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Abstract

In the United States, less-educated parents tend to allocate little time to parent-child activities, reside in disadvantaged neighborhoods, and underestimate the relevance of parental inputs for later outcomes. This paper proposes a social learning mechanism that can lead to socioeconomic differences in parental beliefs and decisions. The key elements are young adults learning through the observations of older people within their neighborhood but being prone to erroneous inferences by imperfectly correcting for selection induced by residential segregation. I incorporate the social learning mechanism in a quantitative spatial and overlapping generations model of human capital accumulation and parental decisions. Once calibrated to the United States, the model accurately captures both targeted and non-targeted parental behavior across socioeconomic groups. It displays relatively modest levels of erroneous beliefs, contributing to a 3% increase in income inequality (measured by the income Gini index) and a 14% reduction in social mobility (measured by the income rank-rank coefficient). A housing voucher policy improves the neighborhood quality of eligible families, raising children's future earnings. When the policy is scaled up, long-run and general equilibrium responses in parental beliefs amplify the effects of the policy, reducing inequality and improving social mobility.

Keywords: Neighborhood, Education, Human Capital, Learning, Social Mobility

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1 Introduction

In the United States, parental input decisions differ between more- and less-educated parents. In particular, less-educated parents tend to allocate less time to parent-child activities and reside in worse neighborhoods, two parental inputs that shape children's economic opportunities in adulthood.[1] As less-educated parents tend to work fewer hours than more-educated parents, the primary explanations for these differences are that they have tighter budget constraints, have higher attachments to low-quality neighborhoods, or are less effective at teaching their children (see Guryan et al. (2008) for a discussion). Since Cunha et al. (2013), a growing strand of the empirical literature documents socioeconomic differences in beliefs about the relevance of parental inputs for later outcomes, offering an additional explanation for the socioeconomic gap in parental input decisions.

In this paper, I propose a novel learning mechanism that can lead to socioeconomic differences in parental beliefs. The key elements are young adults learning through the observations of older people *within* their neighborhood but being prone to erroneous inferences by imperfectly correcting for selection induced by residential segregation. Social learning—learning through interactions and observations of others—is a central learning channel (Frick et al., 2022), and selection neglect—the imperfect ability to correct for selection—an experimentally documented cognitive bias (Enke, 2020).[2]

I incorporate the learning mechanism in a quantitative spatial and overlapping generations model of human capital accumulation and parental decisions. The model features heterogeneous and altruistic parents who choose two parental inputs: the quality of their neighborhood and parental time. The technology of skill formation assumes children's future human capital depends on parental inputs and human capital and, importantly, on an idiosyncratic and unobserved ability shock, which can be interpreted—to some extent—as luck. Motivated by Cunha et al. (2013)'s evidence, agents are unaware of the value of the elasticity parameter governing parental inputs' relevance for future human capital. They form beliefs about it through social learning before making parental decisions. Specifically, young agents infer the value of the elasticity parameter by observing current human capital and past parental inputs and human capital among adults in their neighborhoods. However, with a positive selection neglect parameter, young agents cannot fully comprehend selection

[1]The literature shows parental time is a prime factor influencing child skill formation (Heckman and Mosso, 2014) and documents the difference in parental time between more- and less-educated parents in the United States and elsewhere (see Doepke et al. (2023) for a review). Chetty and Hendren (2018a) estimate neighborhoods' causal effect on children's development in the United States.

[2]This cognitive bias is sometimes called "assortativity neglect."

on the unobserved ability shocks and, with selection on those unobservables, are prone to erroneous inferences. As an example, suppose local ability shocks are higher than what young agents perceive. In that case, young agents underestimate local shocks, and will wrongly attribute part of the local human capital that is due to local shocks to parental input decisions, overestimating the elasticity parameter value. Conversely, if local ability shocks are lower than what young agents perceive, young agents will tend to underestimate the relevance of parental inputs. As a result, parents differ in their family history, their human capital, and education status—which influence their budget, labor supply, and time constraints—and potentially, their beliefs. Given the model structure, perfectly competitive land developers, and the social learning process, there are multiple critical equilibrium objects: the distribution of human capital and education, neighborhood choices and local rents, and parental beliefs, which are endogenously determined as fixed points.

With social learning and selection neglect, income residential segregation generates information friction that gives rise to systematic and persistent differences in parental beliefs between socioeconomic groups. In equilibrium, residential decisions partly depend on ability shocks as those shocks affect parents' human capital and, thus, budget constraints. As a result, relatively many low-ability-shock parents reside in low-quality neighborhoods, and relatively many high-ability-shock parents reside in high-quality neighborhoods. With selection neglect, local ability shocks in low-quality neighborhoods are lower than young agents expect, leading to a local underestimation of parental inputs' relevance. The reverse happens in high-quality neighborhoods. In addition, parental beliefs are persistent within families: children of low(high)-belief and low(high)-income parents are likely to live in low(high)-quality neighborhoods, become low(high)-belief and low(high)-income parents next generation.

The model is solved numerically and calibrated to match a set of critical moments from several United States representative datasets. It comprises ten quality-ranked neighborhoods and matches segregation and family earnings dispersion in the average commuting zone in the United States computed from the ACS 2000 and NHGIS 2000 datasets (Ruggles et al., 2023; Manson et al., 2022).[3] In addition, it targets causal neighborhood effects on children's future incomes estimated by Chetty and Hendren (2018b) and social mobility measured by Chetty et al. (2014). Parents' decisions are disciplined by matching active parental time in the ATUS survey (Hofferth et al., 2020) and neighborhood quality choices from Add Health data (Harris et al., 2019). The calibration results in a positive parameter for the selection neglect bias,

[3] I proxy neighborhood "quality" with neighborhoods' median household income that correlates with places' effects measured by Chetty and Hendren (2018b) but also with low poverty, crime, and high-performing schools.

suggesting a need for heterogeneous parental beliefs to match all the moments. Even though it does not feature preference heterogeneity, the calibrated model matches parental behavior across socioeconomic groups well: it provides a rationale for college parents allocating more time to their children's education than non-college parents despite working more hours and correctly matches non-targeted intergenerational residential mobility patterns.

First, I use the calibrated model to explore how parental beliefs affect the economy. Results are two-fold: (i) heterogeneous parental beliefs have sizable effects on the economy and explain a large share of the socioeconomic gap in parental input choices, and (ii) a perfect information version of the model can only replicate the data by imposing sizable heterogeneous preferences across childhood neighborhoods and education status. To understand how heterogeneous parental beliefs affect the economy, I set the selection neglect parameter to zero, ensuring perfect information among parents, and solve for the new steady state. It improves low-income parents' beliefs by 19% and decreases those of high-income parents by 7%.[4] Children born in bottom-quality neighborhoods are half as likely to remain in those neighborhood types in adulthood, and low-income parents allocate 30% more time to their child's education. The intergenerational rank-rank coefficient, a negative measure of social mobility, decreases by 14%, and the Gini index of income, a measure of inequality, by 3%, improving aggregate welfare by 1.8%.

Unsurprisingly, a re-calibrated version of the model with the selection neglect parameter set to zero poorly fit all the now non-targeted parental behavior moments. To provide a fair comparison with the baseline model, I introduce quadratic moving costs and education-specific parental time disutility parameters and define the same set of targeted moments as in the baseline case. Still, this alternative version of the model misses the untargeted intergenerational residential mobility moments. Only with considerable heterogeneity on the preference parameter for the childhood neighborhood type can the model fit all the moments. While the last fit is comparable to the baseline, large heterogeneous preference parameter values are challenging to micro-found. There is no empirical evidence of socioeconomic differences in parental time disutility parameters or for stronger preferences for deprived neighborhoods. On the contrary, when comparing randomly allocated low-income families in deprived and higher-quality neighborhoods, Bergman et al. (2019) find higher satisfaction rates and willingness to stay among families living in higher-quality neighborhoods.

[4] Those numbers are of a reasonable order of magnitude compared to empirical estimates. Cunha et al. (2013) elicit maternal expectations about the technology of skill formation from a sample of socioeconomically disadvantaged African American women. The author's favorite estimates of the percentage difference between the actual and the believed returns to investment range between 4 and 39%.

Second, and motivated by the evidence that housing vouchers improve the neighborhood quality of eligible families (Chetty et al., 2016), I use the calibrated model to study housing vouchers effects on the United States economy. Two key model frictions call for policy interventions: parents cannot borrow against their children's future earnings, and due to social learning and selection neglect, income residential segregation generates information frictions that distort parental decisions. I consider two types of housing vouchers. The first one resembles the one empirically evaluated by Chetty et al. (2016). The policy features a unique rent limit with a voucher covering the difference between 30% of income and the rent up to a limit set at the commuting zone level. Motivated by Collinson and Ganong (2018)'s findings, the second policy features multiple rent limits with a voucher covering the difference between 20% of income and 70% of the rent in each neighborhood. Under both policies, eligible parents are parents from the bottom decile of the income distribution. In the first step, I study the partial equilibrium effects of the two policies.[5] Results are consistent with the empirical findings of Chetty et al. (2016). Compared to the control group—eligible parents who do not receive housing vouchers,—eligible parents who receive the vouchers live in higher-quality neighborhoods, positively affecting their children's earnings at age 26 by \$756 and \$995 a year.[6]

When scaling up the housing voucher policies, general equilibrium responses in local prices and in parental beliefs amplify the partial equilibrium effects. The voucher allows housing voucher holders to move to better neighborhoods, increasing the density in middle-range quality neighborhoods—especially at the rent limit when unique—and forcing non-eligible households to move out. The housing market reaction creates winners and losers, with adverse effects in the aggregates; however, in the long run, information and parental beliefs improve, particularly among low-income households, amplifying partial equilibrium effects on eligible families and generating positive effects on social mobility and equality measures. The effect on aggregate earnings depends on the design of the policy. The housing voucher policy with multiple-rent limits is a better tool to simultaneously address redistribution and efficiency concerns than a single-rent limit housing voucher program. In the long run, the multiple-rent limit housing voucher program increases social mobility by 11%, equality by 2%, earnings by 0.5% and aggregate welfare by 0.9%.

This paper contributes to the macroeconomics literature that studies household hetero-

[5] It can be thought of as simulating a randomized control trial within the model, as in practice, in a randomized control trial, too few people receive a housing voucher to change general equilibrium forces.

[6] The effects on children's earnings enter the confidence interval of the empirical estimates from Chetty et al. (2016).

geneity and its consequences for aggregate outcomes.[7] It builds upon the literature pioneered by Aiyagari et al. (2002); Becker and Tomes (1986); Loury (1981) that models human capital accumulation and parental input decisions. Many subsequent analyses use this framework in quantitative models to study the consequences of parental input decisions for macroeconomic outcomes.[8] This paper not only analyzes the consequences of parental decisions for macroeconomic outcomes but also introduces the environment as a possible driver of parental decisions' heterogeneity. In that sense, it closely relates to Agostinelli et al. (2024), who study parental behavior responses to changes in peer quality in the United States, and to Kim et al. (2024), who rationalize very high education spending in South Korea through a status externality in which parents value their children's education relative to the education of other children. While the concern for status seems less relevant in the United States than in East Asia, the model includes direct peer quality effects and its key novel ingredient, social learning within neighborhoods.[9]

This paper connects residential segregation and social mobility by introducing social learning in a spatial model, contributing to the quantitative spatial economics literature.[10] Several recent quantitative studies underline the relationship between residential segregation and inequality through direct peer effects or local school funding (see, for instance, Chyn and Daruich (2022); Eckert et al. (2019); Fogli and Guerrieri (2019); Gregory et al. (2022)).[11] While the idea that a neighborhood's demographic composition can also affect educational outcomes through social learning has been around for some time (see, for instance, Durlauf (2011)), this paper is the first to develop and calibrate a quantitative model of human capital accumulation with a social learning process that leads to systematic bias in beliefs.[12]

[7]See Quadrini and Ríos-Rull (2015); Krusell and Smith (2006); Guvenen (2016); Heathcote et al. (2009) for surveys.

[8]See, for instance, Daruich (2018); Fuchs-Schündeln et al. (2022); Jang and Yum (2023); Kim et al. (2024); Lee and Seshadri (2019); Restuccia and Urrutia (2004); Yum (2023). The consequences of heterogeneity in parental time for social mobility has been studied by Yum (2023) who builds a heterogeneous-agent overlapping-generations model calibrated to the United States.

[9]Quantitative macroeconomic papers that include parental beliefs in human capital accumulation models are rare. Two major exceptions are Fogli and Veldkamp (2011) and Fernández (2013), which rationalize the change in female labor supply over time through a convergence of beliefs toward the truth. In other sub-areas of macroeconomics, such as finance, individuals' beliefs are considered critical elements in explaining agents' investment behavior (see, for instance, Adam et al. (2017)).

[10]For a review, see Redding and Rossi-Hansberg (2017).

[11]For instance, after documenting a simultaneous increase in income inequality and residential segregation by income in the United States, Fogli and Guerrieri (2019) develop a quantitative model with peer effects and neighborhood choices, with which they find that following a skill premium shock in the 1980s, segregation contributes to 28% of the increase in inequality. Gregory et al. (2022) incorporate a homophily bias in a neighborhood choice model with local school funding and can explain 80% of the Black-White college gap in the St. Louis metro area.

[12]Although not quantitative, Roemer and Wets (1994); Streufert (2000) provide different theoretical

The social learning process primarily builds on Fogli and Veldkamp (2011) who explain geographical and historical changes in female labor supply by a change in local beliefs while abstracting from residential decisions. It results in heterogeneous valuations of neighborhood amenities—through parental beliefs—, adding to the growing literature that considers endogenous neighborhood amenities.[13]

Finally, since Cunha et al. (2013), a large empirical literature documents heterogeneous parental beliefs about the technology of skill formation. There is a relative consensus on the fact that beliefs influence parental decisions and differ by socioeconomic groups, while the technology of skill formation does not.[14] Social learning is a central channel through which people learn about technologies when outcomes are not immediately observable—by observing the history and outcomes among their older peers (Frick et al., 2022). The empirical literature provides examples of social learning in various contexts. It describes situations in which heterogeneous beliefs arise due to the variation of who is observed.[15] In particular, several papers argue that the lack of successful role models among low-income children's older peers partly explains low levels of motivation and effort.[16] The behavioral and psychological literature empirically documents this bias, called selection neglect (Enke, 2020): we are prone to erroneous inferences because we cannot always correct for selection on unobservables.

The remainder of the paper proceeds as follows. Section 2 presents the spatial overlapping generations model. Section 3 explains the model calibration and presents some quantitative results. Section 4 uses the model for policy analysis, and Section 5 concludes.

2 The Model

Consider one commuting zone with a finite number of heterogeneous neighborhood types. The economy is populated by a continuum of heterogeneous families composed of one parent and one child. Time is discrete, and each agent lives for two periods: childhood and

frameworks in which residential sorting could lead to systematic bias in beliefs.

[13]See for instance Ahlfeldt et al. (2015); Bilal (2023); Diamond (2016).

[14]See for instance Attanasio and Kaufmann (2014); Boneva and Rauh (2016, 2018); Belfield et al. (2019); Caucutt et al. (2017); Dizon-Ross (2019); Jensen (2010); Kaufmann (2014); Wiswall and Zafar (2021)). One exception is Attanasio et al. (2019) in the UK who does not find a socioeconomic gradient in beliefs.

[15]In rural Ghana for instance, Conley and Udry (2010) find that the use of fertilizer by small farmers is boosted by the observation of surprisingly successful peer farmers.

[16]See for instance Alan et al. (2019); Algan et al. (2020); Breda et al. (2023); Guyon and Huillery (2020); Nguyen (2008). Recently, Chetty et al. (2022) find that the share of high socioeconomic status friends in a ZIP code best predicts upward income mobility in the United States and propose social learning as one likely explanation.

parenthood. Parents choose two parental inputs that affect their child's adulthood human capital: in which type of neighborhoods to raise their child and how much time to spend on their child's education—parental time. One of the key and novel model mechanisms resides in parents' imperfect information about the technology of skill formation and the social learning process.

The following sections describe the technology of skill formation and social learning within neighborhoods, the economic environment, the parents' optimization problem, and the housing market. Then, I give the equilibrium definition. Primed letters correspond to children's next period variable, lowercase letters to parents' variables, and uppercase letters to grandparents' variables.

2.1 Social Learning and Technology of Skill Formation

Technology of Skill Formation: Children's next period human capital h' mainly depends on their parent as it is a function of their childhood neighborhood quality m, parental time τ, parental human capital h, and unobserved idiosyncratic ability shock a'. The functional form is as follows:

$$\begin{aligned} h' &= (i(m,\ \tau)\ +\ \underline{i})^{\alpha}\ h^{\ \beta}\ \exp(a') \\ i(m,\ \tau) &= \left(\gamma\ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}}, \end{aligned} \tag{1}$$

where $\alpha,\ \beta,\ \gamma \in (0,1)$ and the child's ability shock a' is uncorrelated with parental characteristics and drawn from a normal distribution $\mathcal{N}(0, \sigma_a)$.[17]

By assumption, parental human capital h enhances the productivity of the two parental inputs. This feature seeks to capture that high-human capital parents are better at building child skills and that environmental factors, such as in-utero experiences correlated with parental human capital, influence children's skills (Cunha and Heckman (2007, 2009); Cunha et al. (2010); Heckman and Mosso (2014)). Following the literature, I assume a nested CES function for the skill formation technology, with one of the elasticities set to unity, which imposes a parsimonious Cobb-Douglas outer form.[18] Following Kim et al. (2024),

[17]By assuming uncorrelated ability shocks across generations, I abstract from modeling genetics. If one added it, investment incentives would be distorted as high human capital parents already expect their child to have high ability shocks. However, the main results of the paper would go through. In particular, the relative importance of h in the technology of skill formation captures part of a genetic effect.

[18]For similar modeling assumptions, see for instance Fuchs-Schündeln et al. (2022); Jang and Yum (2023); Lee and Seshadri (2019); Yum (2023).

the parameter $\underline{i} > 0$ guarantees that every child has a minimal level of baseline human capital. This term captures, for instance, a uniform minimum level of public education across neighborhoods. Finally, parental time τ is normalized by its baseline unconditional mean ($\overline{\tau}$) to achieve unit independence and computational stability following Jang and Yum (2023).

Crucially, the elasticity of adulthood human capital with respect to the combination of parental inputs α is unknown, and ability shocks a' are unobservable.

Social Learning: Let's now turn to one of the key and novel features of the model: the social learning process about the technology parameter that governs the relevance of parental inputs α. Following Fogli and Veldkamp (2011), learning happens in the first period of life, before making parental decisions, using two sources of information: inherited parent's beliefs ($\tilde{\alpha}$) and own inference ($\hat{\alpha}_m$) using the information available at the neighborhood level: through the observation of outcomes and history in neighborhood type m.

The inference process of $\hat{\alpha}_m$ requires several assumptions regarding (i) agents' knowledge of the economy, (ii) the set of information agents have access to, (iii) the cognitive bias they suffer from, and (iv) the way they infer the unknown parameter α.

First, young agents know everything about the model but α, the elasticity of adulthood human capital with respect to the combination of parental inputs. They know the functional form of the technology of skill formation—but α,—the randomness of the ability shock and the parent's problem. The mental model in log form young agents use for an adult j in a given neighborhood m is then:

$$\log h_j = \alpha \ \log\left(i(M_j,\ \mathrm{T_j}) \ + \ \underline{i}\right) \ + \beta \ \log H_j \ + \ a_j, \quad j \in m,$$

where T_j and M_j represent past parental choices, and H_j represents past parental human capital in family j.

Second, young agents' information set is restricted to their neighborhood. They only observe their neighbors and, more specifically, local aggregates. Assuming agents would know all their neighbors' outcomes would be unrealistic, but by talking to neighbors and reading local news, I assume they have a good sense of local averages. Crucially, however, young agents do not observe ability shocks, which prevent them from immediately inferring the value of α.

Third, I depart from rational expectations and introduce a cognitive bias: selection neglect. Even though agents know the parents' problem, they might not fully understand the spatial sorting process in the economy and may not be able to infer local ability shocks perfectly. In a given neighborhood type m, young agents' perceived average local ability shock is given by:

$$\bar{\tilde{a}}_m = \bar{a}_m + \pi(\bar{a} - \bar{a}_m),$$

where $\bar{\tilde{a}}_m$ represents perceived average ability shock in neighborhood m, $\bar{a}_m$ the actual average ability shock in neighborhood m and $\bar{a}$ the average ability shock in the economy. Following Bénabou and Tirole (2005)'s modeling, the strength of the cognitive bias is governed by $\pi \in [0, 1]$. With $\pi = 0$ implying young agents can perfectly infer local ability shocks, i.e., no selection neglect, and $\pi = 1$, young agents mistakenly think of their neighbors as a representative sample of the population, i.e., full selection neglect.[19] The following equation describes the observations and perceptions of every young agent in a given neighborhood m:

$$\overline{\log h}_m = \alpha \, \overline{\log \left(i(M,\ \mathrm{T})\ +\ \underline{i}\right)}_m \ + \beta \, \overline{\log H}_m \ + \ \bar{\tilde{a}}_m,$$

where $\overline{\log \left(i(M,\ \mathrm{T})\ +\ \underline{i}\right)}_m$ stands for the local average in the combination of past parental inputs, and $\overline{\log h}_m, \overline{\log H}_m$ current and past average human capital in neighborhood m.

Finally, every young agent uses their observation of local averages to infer the relevance of parental inputs governed by α:[20]

$$\hat{\alpha}_m = \frac{\overline{\log(h)}_m \ - \ \beta \, \overline{\log H}_m - \bar{\tilde{a}}_m}{\overline{\log \left(i(\mathrm{T}, M) + \underline{i}\right)}_m}.$$

Notice that young agents' inference of the relevance of parental inputs ($\hat{\alpha}_m$) is downward biased if young agents overestimate local ability shocks ($\bar{\tilde{a}}_m \geq \bar{a}_m$). It is upward biased if young agents underestimate local ability shocks ($\bar{\tilde{a}}_m \leq \bar{a}_m$). Intuitively, when young agents over-perceive local ability shocks, they implicitly and wrongly attribute too much of the local human capital to ability shocks and too little to past parental inputs, underestimating the elasticity of human capital with respect to the combination of parental inputs.

Once they have inferred the value of α with local observations, young agents then update

[19] One way to micro-found the bias strength π is through unbiased but bounded signals about ability shocks, as in Jehiel (2018). See Appendix E for more details. Notice that if young agents were to observe everyone in the economy or without residential sorting, then $\bar{a} = \bar{a}_m$, which makes the selection neglect bias irrelevant. In that case, or if $\pi = 0$, there would be convergence in beliefs toward the truth as in Fogli and Veldkamp (2011).

[20] An alternative would be that agents observe individual outcomes of a given number of neighbors and run an OLS regression. To make this assumption realistic, one would have to draw, randomly or not, the number of neighbors each agent observes. This deviation would make the model richer but not change the paper's main intuitions.

their inherited beliefs using a weighted average of both:

$$\tilde{\alpha}' = \mu\hat{\alpha}_m + (1-\mu)\tilde{\alpha}, \tag{2}$$

with $\mu \in (0,1)$ capturing the weight young agents put on their own experience versus parental beliefs and telling.

2.2 Economic Environment

Education Status: I introduce education status to connect the model outputs to the data. Each child has a positive probability of entering and graduating from college. The college graduation probability $g(h', h, s)$ depends on the parent's education status s, the parent's human capital h, and the child's accumulated human capital h'. The agent's education status s' equals one if the agent graduated from college; it is zero otherwise.

Parents' Earnings: Parents' earnings are a function of accumulated human capital h, education status s, and exogenous working time $\overline{\ell_s} > 0$. Exogenous working time depends on the education status s and embeds differences in working hours resulting from non-modeled labor market frictions. Parents' pre-tax labor earnings are:

$$y = w\ h\ (1+\omega s)\ \overline{\ell_s},$$

with w the rental rate of human capital, which is exogenous and common across households and neighborhoods in the commuting zone. The college premium is captured by ω.

Following Heathcote et al. (2017), after-tax labor earnings, which are pre-tax income minus taxes plus transfers, are given by:

$$\hat{y} = \lambda_y y^{1-\tau_y},$$

where $1-\tau_y$ measures the elasticity of post-tax to pre-tax earnings and determines the progressivity of the marginal tax rate.

Geography and Amenities: Consider one commuting zone with a finite number of heterogeneous neighborhood types. Neighborhoods differ in quality m. Thus, a neighborhood type is characterized by its quality m rather than its name. Neighborhood quality is composed of an exogenous and an endogenous component:

$$m = \bar{m} + \xi\bar{y}_m, \tag{3}$$

where $\bar{y}_m$ represents the average pre-tax labor earnings in neighborhood m and $\xi\bar{y}_m$ captures the effect of the demographic composition on the neighborhood quality—or peer effects. The exogenous component is given by $\bar{m}$. As wages do not vary across neighborhoods, sorting across neighborhoods within the labor market is only driven by families seeking better neighborhood environments and better opportunities for their children.

Parents' Preferences: Parents consume and enjoy leisure. In addition, they are altruistic as their child's value enters their utility function. Preferences of a parent raised in childhood neighborhood quality m_0, and with parental beliefs $\tilde{\alpha}$ can be summarized by the following utility function:

$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa\,\tau\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} + \delta\, rank_m + \iota\, \mathbb{1}_{m_0=m} + \nu\varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right],$$

where b is a strength of altruism. Parents derive utility from consumption c and enjoy leisure, defined as one unit of time minus working time and parental time: $1-\overline{\ell_s}-\kappa\,\tau$. Parental time τ is weighted by κ, showing that parents might value time spent at work differently than with their child. The curvature of the utility function with respect to leisure is $-\frac{1}{\psi}$. Parents enjoy living in pleasant and high-quality environments through δ and have a preference for their childhood neighborhood type that is captured by ι. In addition, parents have an idiosyncratic taste shock over neighborhoods ε_m. This shock captures moving motives that are uncorrelated with the neighborhood quality. I assume this shock is i.i.d. across neighborhood qualities and over time and distributed according to a Type-I Extreme Value with parameters $(-\bar{\gamma}, 1)$, where $\bar{\gamma}$ is the Euler-Mascheroni constant which ensures that the distribution has mean zero. The dispersion of the idiosyncratic neighborhood taste shock is measured by ν. Finally, $\tilde{\alpha}$ stands for the parent's beliefs regarding the value of parameter α in the technology of skill formation and $\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right]$ is the expected child lifetime utility with respect to the child's ability shock and neighborhood taste shock conditional on the parent's beliefs $\tilde{\alpha}$.

Housing Supply: There are perfectly competitive land developers who produce housing on a unit endowment of land in each neighborhood with an isoelastic production function: $\mathcal{H}_m = \zeta_m r_m^{\eta}$, where ζ_m and η are parameters, with η the price elasticity of housing supply. Equilibrium rents per housing unit $\{r_m\}$ are determined by rental market clearing, such that housing demand equals housing supply in each neighborhood.

Aggregate Rent Rebates: Rents are redistributed to all families with a non-distortionary flat earnings subsidy. Every household receives a rebate from aggregate rent payments equal to R, where R is the economy's average rent payments.

2.3 Parents' Problem

Parents are the only decision-makers in the economy. They make three decisions, two affecting their child's next period human capital: in which type of neighborhood m to reside and parental time τ. The timing is as follows: parents observe their idiosyncratic taste shocks for neighborhoods, take rents as given, and make decisions by maximizing their utility conditional on their beliefs about the relevance to parental inputs ($\tilde{\alpha}$). The maximization problem is the following:

$$\begin{aligned}\mathcal{V}(h, s, m_0, \tilde{\alpha}) = \max_{c,\tau,m}\{ \log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa\,\tau\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} \\ + \ \delta\ rank_m + \ \iota\ \mathbb{1}_{m_0=m} + \ \nu\varepsilon_m + \ b\mathrm{E}\left[\mathcal{V}(h', s', m, \tilde{\alpha})\,|\tilde{\alpha}\right]\}\end{aligned} \tag{4}$$

subject to:

$$\begin{aligned}& c + r_m = \lambda_y \left(w\ h\ (1+\omega s)\ \overline{\ell_s}\right)^{1-\tau_y} + R \\ & \tau \in [0, 1-\overline{\ell_s}] \\ & h' = f(\tau,\ m,\ h,\ a'|\tilde{\alpha}), \quad a' \sim \mathcal{N}(0, \sigma_a) \\ & p(s'=1) = g(h', h, s),\end{aligned}$$

where r_m is the equilibrium rent of neighborhood m, $\mathrm{E}\left[\mathcal{V}(h', s', m, \tilde{\alpha})\,|\tilde{\alpha}\right]$ is the expected child's utility conditional on the ability and the neighborhood taste shocks, and $f(.)$ is the technology of skill formation defined by (1) conditional on parental beliefs . Parents decide how to allocate their income into consumption c and housing costs r_m, and one unit of time into leisure, exogenous working hours, and parental time.

2.4 Housing Market

Let $U = E(\mathcal{V})$ denote the expected lifetime utility of a representative parent with respect to the vector of idiosyncratic neighborhood taste shocks ε_m. Let $V(h, s, m_0, \tilde{\alpha}, m|r_m) = \log(c_m^*) + \frac{\left(1-\overline{\ell_s}-\kappa\,\tau_m^*\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} + \ \delta\ rank_m + \ \iota\ \mathbb{1}_{m_0=m} + \ b\mathrm{E}\left[\mathcal{V}(h', s', m, \tilde{\alpha})\,|\tilde{\alpha}\right]$ the utility derived from living in neighborhood m abstracting from the neighborhood taste shock, with c_m^* and

τ_m^* the optimal parent's choices given the neighborhood m and the rent price r_m.

Under the Type-I Extreme Value assumption, the expected lifetime utility of a parent is:

$$U\left(h, s, m_0, \tilde{\alpha}\right) = \nu \log \sum_m \exp\{\frac{1}{\nu}\, V\left(h, s, m_0, \tilde{\alpha}, m | r_m\right)\}.$$

The share of parents who choose to locate in neighborhood quality m among parents with human capital h, graduation status s, raised in neighborhood quality m_0 and with parental beliefs $\tilde{\alpha}$ is :

$$\lambda_m(h, s, m_0, \tilde{\alpha} | r_m) = \frac{\exp\{\frac{1}{\nu}\, V\left(h, s, m_0, \tilde{\alpha}, m | r_m\right)\}}{\sum_n \exp\{\frac{1}{\nu}\, V\left(h, s, m_0, \tilde{\alpha}, n | r_n\right)\}}.$$

In equilibrium, rent prices are such that housing demand equals housing supply in each neighborhood m:

$$\sum_{m_0} \sum_s \int \int \lambda_m(h, s, m_0, \tilde{\alpha} | r_m) F(h, s, m_0, \tilde{\alpha})\; dh\; d\tilde{\alpha} = \zeta_m {r_m}^{\eta}, \tag{5}$$

with $F(h, s, m_0, \tilde{\alpha})$ the joint distribution of human capital, graduation status, childhood neighborhood, and parental beliefs.

2.5 Equilibrium

The key objects of the equilibrium in the steady state are the endogenous distribution of human capital, education status, childhood neighborhood, parental beliefs, and rent prices. For a given initial human capital, graduation status, neighborhood of birth, and parental belief distribution $F_0(h, s, m_0, \tilde{\alpha})$, an equilibrium is characterized by a sequence of residential and parental time choices, $\{m\}$ and $\{\tau\}$, a sequence of rents $\{r_m\}$ for each neighborhood, and a sequence of distributions $\{F(h, s, m_0, \tilde{\alpha})\}$, such that the following four conditions are satisfied:

1. agents solve (4).

2. housing market clearing: each neighborhood's quality consistently depends on its demographic composition according to (3), and rent prices $\{r_m\}$ ensure housing demand equals supply in every neighborhood according to (5).

3. beliefs update: young agents update their inherited beliefs according to (2).

4. earnings, graduation status, place of birth, and parental beliefs consistency: those are consistent with the parent's income, education status, parental beliefs, and decisions.

Details on how I compute the steady state equilibrium are provided in Appendix A.1.

3 Calibration

I numerically solve the model as detailed in Appendix A.1 and calibrate it to the average United States commuting zone in the 2000s. The calibration proceeds in multiple steps. First, some parameter values are directly estimated from the data. Second, others are chosen externally based on direct data analogs, the literature, or simple normalization, and finally, the remaining parameters are selected to match relevant data moments. To validate the model, I then compare the model's predictions to non-targeted moments.

3.1 Preliminaries

I let the discrete distribution for a to approximate a normal distribution $a \sim \mathcal{N}(0, \sigma_a)$ which I discretize using Tauchen (1986), with a ten-point grid. Finally, I assume the technology of skill formation has constant returns to scale, $\beta = 1 - \alpha$.

I use multiple data sources to compute the relevant moments to calibrate the model. Earnings distribution moments come from the American Community Surveys (ACS) from 2000. I use the information at the census tract level from the National Historical Geographic Information System (NHGIS) dataset in 2000 (Manson et al., 2022) to construct neighborhood sociodemographic characteristics. I aggregate census tract information at the commuting zone level using a county-to-commuting zone crosswalk. Neighborhood choices and college graduation probabilities are estimated using data from the AddHealth survey described in Appendix Section C.1.2.[21] Finally, parents' time use information is taken from the American Time Use Survey (ATUS) 2003.[22]

3.1.1 Geography

The model is calibrated to the average commuting zone in the United States, matching neighborhoods' impact estimated by Chetty and Hendren (2018a) in the 100 biggest commuting zones. To be consistent, I only use the top 100 commuting zones in NHGIS 2000. I

[21] See Appendix Section C.4.1 for more details on those statistics.

[22] Appendix Section C.1.1 provides detailed information on how I compute parental time using ATUS.

set the number of neighborhoods in the model to ten, representing a synthetic decile census tract in the data. Specifically, in each of the 100 commuting zones of the NHGIS 2000, I sort census tracts by median household income and form ten synthetic neighborhoods from the deciles of this distribution.[23] I then create one average commuting zone by computing the population-weighted average characteristics of each of the ten neighborhoods.[24]

3.2 Empirically Estimated Parameters

Housing Markets: Rental prices are determined in equilibrium given the supply function: $\mathcal{H}_m = \zeta_m r_m^\eta$, where r_m is the equilibrium rent price in the neighborhood m, and η is the price elasticity of housing supply. Saiz (2010) estimates population-weighted average price elasticity in the average metropolitan area of the U.S. to be 1.75, so I set $\eta = 1.75$. The remaining parameters ζ_m can be estimated directly from the synthetic neighborhood density and rents.[25]

College graduation probability: The college graduation probability depends on the parent's education and earnings and the child's accumulated human capital. Following Blandin and Herrington (2022) and using AddHealth, I estimate the following weighted logit regression of college completion:

$$g(h', y, s) = \frac{1}{1 + \exp(-\left(\gamma_1 + \gamma_2 rank_{h'} + \gamma_3 rank_y + \gamma_4 s\right))},$$

where $g(h', y, s)$ is the binary outcome of either graduating college or not in Wave V, $s = 1$ if the highest level of education of the mother is above or equal to a bachelor's degree, $rank_{h'} \in \{1, 2, ..., 10\}$ is the human capital rank proxied by the grade rank in Wave II of the interviewed adolescent in 1996, and $rank_y \in \{1, 2, ..., 10\}$ is the household income rank in 1994-1995.[26]

[23] I use median household income as a proxy for neighborhood quality because it is one of the variables that correlates the most with place-based effects within commuting zones of Chetty and Hendren (2018a). Using their estimates, I find that growing up in one standard deviation higher median income county within a commuting zone increases a given child's income by 1.9%.

[24] Appendix Table S2 summarizes the ten neighborhoods' characteristics.

[25] Appendix Section C.4.2 describes the log-relationship between density (Column (5) Table S2) and rents across the ten synthetic neighborhoods. Without loss of generality, the numeraire is the average household earnings in the economy.

[26] Appendix Section C.4.1 provides details on the variable construction, and Appendix Table S6 shows the weighted logit regression estimates.

3.3 Externally Calibrated Parameters

The term $1/\psi$ governs the curvature of the utility function with respect to leisure. I set the intertemporal elasticity of substitution ψ to 0.5, as is standard in the literature. The parameter that governs the progressivity of the marginal tax rate is set to $\tau_y = 0.18$ (Heathcote et al., 2017). I assume agents have an endowment of one unit of time corresponding to sixteen hours per day in the data.[27] The fraction of time allocated to market work by education comes from ATUS 2003, as described in Appendix Section C.1.1. The wage rate w, the parental investment constant $\underline{i}$, and the average exogenous neighborhood quality component $\mu_{\bar{m}}$ are normalized to 1. I assume the number of neighborhoods N is equal to ten, and the exogenous neighborhood quality component is distributed according to $\bar{m} \sim \mathcal{N}(\mu_{\bar{m}}, \sigma_{\bar{m}})$. Table 1 summarizes the externally calibrated parameters.

3.4 Internally Calibrated Parameters

Table 2 lists the fifteen parameters I calibrate by minimizing the sum of squared percentage differences between data and model moments. The data moments include two measures of household earnings dispersion within commuting zones computed from the ACS 2000: the Gini coefficient of household earnings and the income ratio of non-college and college households. Both are weighted population averages across the 100 biggest commuting zones.[28] The tax rate parameter matches the average marginal income tax rate of 35.1 percent.[29] I further include the rank-rank coefficient from Chetty et al. (2014), a coefficient that captures the income correlation between parents and children. It is an inverse measure of social mobility. To discipline the neighborhood quality distribution ($\{m\}$) that directly enters the child skill production function, I use the causal effect of a one standard deviation improvement in neighborhood quality for a child born in the 25th and 75th percentile of the household income distribution estimated by and the share of the variance of causal placed based effects explained by observable characteristics (24%) Chetty and Hendren (2018b).[30] I add a Gini

[27] I remove eight hours of sleep needs, a standard assumption in the literature.

[28] The Gini coefficient is lower than typically reported because it is a Gini over twenty years of household income. I compute a yearly Gini coefficient from the data and transform it into a twenty-year Gini coefficient using Shorrocks mobility index estimated by Kopczuk et al. (2010) for 2002.

[29] As estimated by the Urban & Brookings Tax Policy Center. See `https://www.taxpolicycenter.org/model-estimates/baseline-effective-marginal-tax-rates-july-2016/t16-0114-effective-marginal-tax`.

[30] Chetty and Hendren (2018a)'s estimates concern causal place effects of counties within commuting zones, arguably larger than neighborhoods. Nevertheless, the authors find nearly as much variation of causal place effects on children's outcomes across counties within commuting zones (6.2 and 4.6 percentage change in income) as across commuting zones (8.3 and 4.4 percentage change in income). One assumption is that the

Table 1: Externally Calibrated Parameters

Parameter	Description	Value	Source
N	Number of neighborhoods	10	Deciles NHGIS
β	Returns on parental human capital	$1-\alpha$	Constant returns
ψ	Intertemporal elasticity of substitution	0.5	Standard
w	Wage rate	1	Normalization
$\underline{\mathrm{i}}$	Parental investment constant	1	Normalization
$\mu_{\bar{m}}$	Average neighborhood quality	1	Normalization
τ_y	Tax progressivity	0.18	Heathcote et al. (2017)
η	Price elasticity of housing supply	1.75	Saiz (2010)
ζ_1	Housing supply coefficient D1	1.859	NHGIS
ζ_2	Housing supply coefficient D2	1.794	NHGIS
ζ_3	Housing supply coefficient D3	1.722	NHGIS
ζ_4	Housing supply coefficient D4	1.661	NHGIS
ζ_5	Housing supply coefficient D5	1.606	NHGIS
ζ_6	Housing supply coefficient D6	1.566	NHGIS
ζ_7	Housing supply coefficient D7	1.479	NHGIS
ζ_8	Housing supply coefficient D8	1.399	NHGIS
ζ_9	Housing supply coefficient D9	1.239	NHGIS
ζ_{10}	Housing supply coefficient D10	0.937	NHGIS
$\overline{\ell_0}$	Non-college labor supply	0.275	ATUS 2003
$\overline{\ell_1}$	College labor supply	0.294	ATUS 2003
γ_1	College graduation coeff. - intercept	-3.83	Add Health
γ_2	College graduation coeff. - human capital	0.35	Add Health
γ_3	College graduation coeff. - income	0.15	Add Health
γ_4	College graduation coeff. - education	1.11	Add Health

Notes: The table shows all the externally calibrated parameters.

coefficient across the ten neighborhoods computed from the NHGIS 2000 dataset to match residential segregation and the slope in monthly rent prices. The place of birth preference parameter is calibrated by matching a moment labeled "residential mobility (D1)". It is defined as the fraction of children born in the first synthetic neighborhood who choose to live in the same synthetic neighborhood in adulthood. The altruism parameters ensure that the average rent price over the average household income corresponds to the observation in the NHGIS 2000 dataset. To capture parental behaviors, I include parental time by education (displayed in Appendix Table S3) and household income. In addition to disciplining parental beliefs, I add the correlation between parents' and children's neighborhood choices.[31]

Table 2: Internally Calibrated Parameters

Parameter	Description	Moment	Data	Model
Preferences and Labor Market				
$b = 0.5$	Altruism	Average rent over income	0.117	0.117
$\kappa = 0.52$	Parental time disutility	Parental time non-college parents	0.075	0.073
$\iota = 0.0001$	Place of birth preference	Residential immobility (D1)	0.302	0.285
$\omega = 0.005$	College wage premium	Earnings ratio non-college - college	0.554	0.555
$\lambda_y = 0.71$	Tax function scalar	Avg. marginal income tax rate	0.351	0.352
Neighborhoods				
$\sigma_m = 0.24$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.058
$\nu = 0.01$	Taste shock variance	Census tract Gini	0.231	0.239
$\xi = 0.175$	Demographics effects	Explained share place-based effects	0.24	0.235
$\delta = 0.007$	Amenities	Rent price gradient	54.2	53.8
Skill Formation: $h' = \left(\left(\gamma\ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}}\ +\ \underline{i} \right)^{\alpha}\ h^{1-\alpha}\ \exp(a')$ with $a' \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0.765$	Parental inputs elasticity	Rank-rank coefficient (IGE)	0.341	0.341
$\gamma = 0.53$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.047
$\varphi = 0.4$	Substitutability	Income gradient in parental time	0.14	0.152
$\sigma_a = 0.553$	Ability shock variance	Income Gini	0.336	0.334
Social Learning Process				
$\mu = 0.55$	Update weight	Ratio parental time by education	0.75	0.823
$\pi = 0.5$	Cognitive bias strength	Neighborhood quality correlation	0.417	0.438

Notes: This table reports the internally calibrated parameters and the observed and simulated moments associated with the parameter estimates.

Table 2 reports calibrated parameters, corresponding moments in the data, and their model analogs. Even though every moment results from combining all parameters, certain

variation of neighborhood effects within commuting zones is similar to counties' effects within commuting zones.

[31] Moments construction and data sources are detailed in Appendix Section C.4.3.

moments are more sensitive to specific parameters. Understanding these intuitive links is informative about the underlying model mechanisms.

The first four parameters are preference parameters and govern parents' choices. In particular, altruism parameter b affects the share of income spent on rents as neighborhood quality is a parental input. The childcare disutility weight κ is pinned down by the fraction of time allocated to childcare by non-college parents, and the preference for place of birth ι is pinned down by residential mobility in the first decile neighborhood. The college wage premium ω directly affects the earnings gap between college and non-college parents. Additionally, the tax function scalar λ_y is tightly linked to the average marginal tax rate.

Neighborhood parameters govern the model geography. In particular, the standard deviation of neighborhood quality σ_m affects how much a child's earnings are affected by neighborhood choices. The relevant moment is the causal effect of neighborhoods measured by Chetty and Hendren (2018b). It determines how much children's future income rank would increase if they had been growing up in one standard deviation better neighborhood. For a child born with a parent at the 25th percentile of the income distribution, the authors find a value of 6.2% of income at the county level within commuting zones. The taste shock variance ν controls residential moves orthogonal to neighborhood quality and affects residential segregation measured by the Gini coefficient across neighborhoods. How much the neighborhood quality changes with a change in the demographic composition depends on ξ, calibrated by matching the estimated explained share of the variance in placed-based effects in Chetty and Hendren (2018b). Finally, additional neighborhood amenities drive parental moves through δ, disciplined by the slope in rent prices across neighborhood types.

The child's skill formation parameters are most relevant for this paper. In particular, the substitutability parameter φ is calibrated by matching the childcare time difference across income groups; here, I use the regression coefficient of parental time on household income quartiles.[32] With social learning and selection neglect, I find that neighborhood quality and parental time are substitute inputs in the child skill production function $\varphi > 0$ (in line with Agostinelli (2018) and Agostinelli et al. (2022)). Parental human capital share $1-\alpha$ mechanically increases the income correlation between parents and children. Thus, the relevant moment is the rank-rank coefficient between parental and child earnings estimated by Chetty et al. (2014). As ability shock variance captures any income variation not explained by parental choices and human capital, it is calibrated by matching household earnings inequality measured by the income Gini coefficient.

[32] In the data, I control for the gender of the respondent and the age of the child.

Lastly, the correlation between parents' and children's beliefs is governed by μ and affects the persistence of beliefs and, hence, parental behavior within families. I discipline this parameter by matching the ratio of parental time choices by parents' education levels. This ratio is below one, meaning college parents spend more time with their children than non-college parents. The parental time ratio results from two opposing forces in the model. Delusion about the technology of skill formation, if correlated with earnings, decreases the ratio. However, the substitutability between parental time, neighborhood quality ($\varphi > 0$), and the differential in working hours increase it. Finally, I calibrate the strength of the selection neglect bias (π) using the correlation between parents' and children's neighborhood-type choices. Parents' neighborhood choices affect children's future neighborhood decisions through two channels: human capital formation and, hence, earnings and beliefs. Parents' influence on children's earnings is calibrated by matching the rank-rank coefficient and place-based effects. Matching the intergenerational neighborhood correlation ensures a correct discipline of the belief channel. Notice that π is above zero, suggesting agents face a selection neglect bias and the model's need of heterogeneous parental beliefs to match parental behavior across socioeconomic groups.

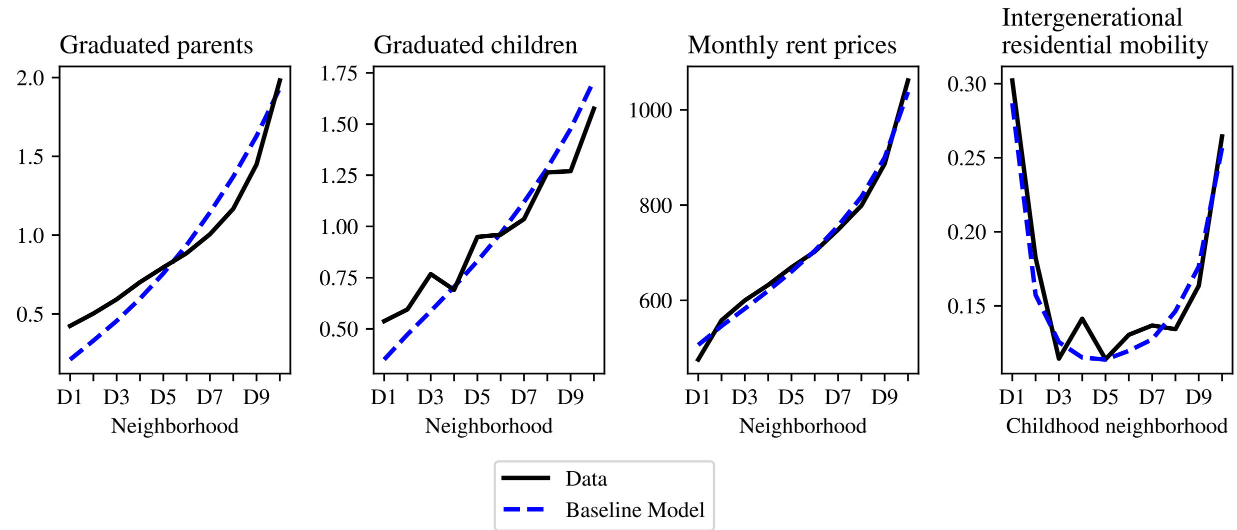
3.5 Non-Targeted Moments

Figure 1 shows that the model, in addition to matching targeted moments well, fits non-targeted moments across neighborhoods and, importantly, intergenerational residential mobility moments.

The first two panels of Figure 1 represent the share of graduated parents and children by neighborhood type, and the third one shows monthly rent prices per neighborhood. Although none of these moments were directly targeted, income segregation, social mobility, place-based causal effects, and the slope in rent prices are. Moreover, the housing supply function is empirically estimated. While a good fit of those moments is not entirely surprising, it comforts the model's internal consistency.

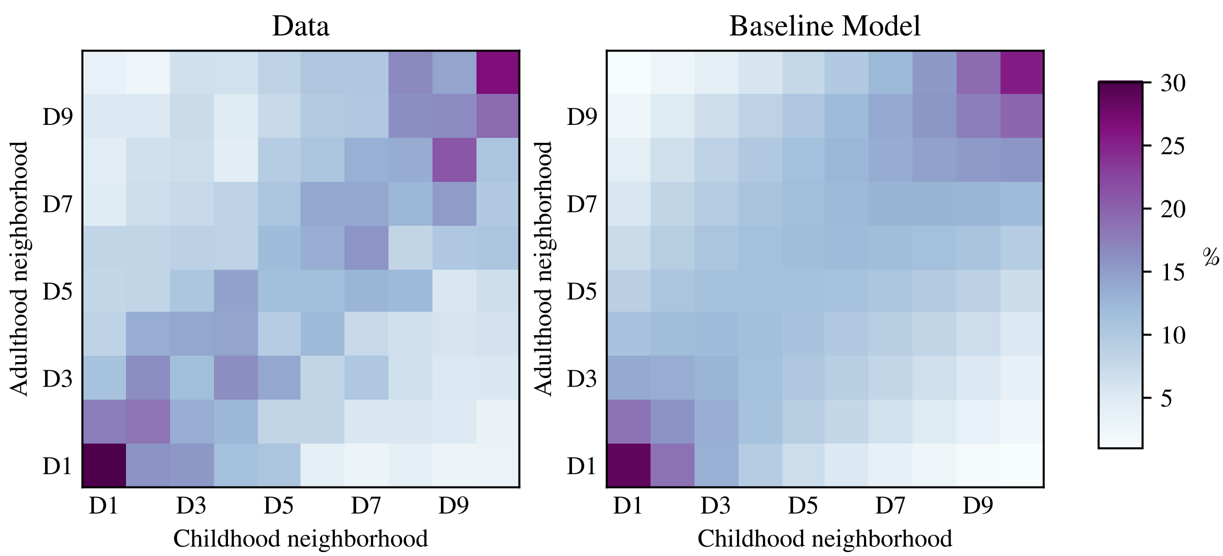
The last panel of Figure 1 presents the share of children living in the same neighborhood type as their parents in adulthood. Only the first synthetic neighborhood statistic is a targeted moment on this graph. The model generates a U-shape that is very close to the data. To go further, Figure 2 illustrates a frequency matrix of all possible intergenerational moves, each represented by a colored square. The darker a square is, the more likely a given move. For instance, a child born in Neighborhood D1 is likely to live in Neighborhood D1 or D2 when she becomes an adult, but she is unlikely to live in Neighborhood D6 or

Figure 1: Non-Targeted Moments by Neighborhood



Notes: This Figure shows four non-targeted moments across the ten neighborhood types: the share of graduated parents and children, rent prices, and intergenerational residential mobility, which represents the share of children who, in adulthood, choose to live in the type of neighborhood as their parents. The solid line shows the data moments, and the dashed line shows the model-simulated analogs. Data Source: NHGIS & Add Health; see Appendix for details of data construction.

Figure 2: Non-targeted Moments: Detailed Intergenerational Residential Mobility



Notes: This Figure shows residential mobility between childhood and adulthood in the data (left panel), and their model simulates analogs (right panel). The x-axis contains the ten synthetic childhood neighborhoods, and the y-axis is the ten synthetic adulthood neighborhoods. The frequency of moves is represented by cell colors, with larger values in darker squares—data source: Add Health, see Appendix C.4.3 for details of data construction.

above. The calibrated model (right panel) matches the data patterns (left panel) remarkably well. These patterns result from different model mechanisms: social mobility and budget constraints, equilibrium rent prices and neighborhood amenities, and parental beliefs about the relevance of parental inputs. The calibrated model successfully replicates non-targeted parental behavior across socioeconomic groups, suggesting that the model's mechanisms are well-quantified.

3.6 Discussion of the Social Learning Channel

Natural following questions are: How do parental beliefs affect the economy? Furthermore, could a model without heterogeneous beliefs explain parental behavior across socioeconomic groups?

3.6.1 The Role of Parental Beliefs

To understand how parental beliefs' affect the economy, I shut down the selection neglect bias channel ($\pi = 0$). By doing so, I now assume young adults correctly infer the relevance of parental inputs from their neighbors, and in equilibrium, all the parents' beliefs are correct.[33] Table 3 presents the differences in steady-state outcomes between the baseline economy and one with perfect information ($\pi = 0$).

Providing complete information would lead parents in the bottom quartile of the income distribution to upward update their beliefs by 19% and parents in the top quartile of the income distribution to downward update them by 7%.[34] As a result, low-income parents allocate too little time to their children's education and reside in lower-quality neighborhoods, while high-income parents allocate too much time and reside in greater-quality neighborhoods. Providing information to parents would increase low-income households' parental time and neighborhood rank by 30% and 6%, respectively, and decrease high-income households' by 8% and 0.4%. In the aggregate, parents' distorted beliefs decrease social mobility and earnings by 13% and 2% respectively and increase inequality and poverty by 3% and 16%.[35] With perfect information, aggregate welfare, defined by the consumption equivalence under the veil of ignorance in the baseline economy relative to the counterfactual economy,

[33]Notice, with $\pi = 0$, in general equilibrium, the update parameter μ is irrelevant.

[34]These numbers are of a reasonable order of magnitude. Cunha et al. (2013), who elicits disadvantaged African American mothers' beliefs about the elasticity of child development with respect to parental investments, finds greater differences between the truth and their beliefs.

[35]Social mobility is measured by the negative income rank-rank coefficient. Inequality by the income Gini coefficient and poverty by the absolute level of poverty. The poverty threshold is defined at baseline by the tenth percentile of the household income distribution.

would increase by 1.8%, with a more substantial effect for the lowest-income households.[36] In sum, the relatively modest level of parental delusion that the calibrated model implies greatly affects the economy.

Table 3: Providing Information - Parental Beliefs' Role in the Economy

		Household income quartile			
	All	1st	2nd	3rd	4th
Parental beliefs	+3.0%	+19.1%	+7.1%	-1.1%	-7.4%
Parental time	+5.8%	+30.2%	+11.3%	+1.0%	-8.0%
Neighborhood rank	+0.8%	+5.6%	+4.7%	+0.6%	-0.4%
Earnings	+2.0%	+10.1%	+6.4%	+1.6%	-0.3%
Social mobility	+13.5%				
Segregation	-2.0%				
Inequality	-2.6%				
Absolute poverty	-16.3%				
Welfare	+1.8%	+9.9%	+5.1%	+0.0%	-3.5%

Notes: This table displays percentage differences in model-generated moments between the baseline calibrated model with parental beliefs and with perfect information. *Social mobility* is measured by minus the income rank-rank coefficient, *Segregation* by the neighborhood Gini coefficient, and *Inequality* by the income Gini coefficient.

3.6.2 Alternative Modeling under Perfect Information

To match the data moments, the calibrated model requires a positive selection neglect bias parameter ($\pi > 0$), suggesting imperfect information is needed to replicate data patterns. Unsurprisingly, re-calibrating a perfect information version of the model ($\pi = 0$) results in a relatively bad fit for all untargeted moments despite a good match of social mobility and inequality moments.[37] Notice, however, that fixing π to zero removes one key mechanism. Two parental behavior moments targeted at baseline are not, which renders the comparison of the two calibrated models somewhat unfair.

In the second step, I augment the alternative model with heterogeneous preferences regarding the parental time disutility parameter and quadratic moving costs. This extension provides two extra free parameters and mechanically generates heterogeneity in parental

[36] See Appendix Section B for details on welfare computation.

[37] See Appendix Table S8 and Appendix Figures S2 for the fit of targeted and non-targeted moments

input choices by socioeconomic group. Parents' preferences take the following form:

$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa_s\, \tau\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} + \delta\; rank_m + \iota_0\; \mathbb{1}_{m_0=m} - \iota_1 (m_0 - m)^2 + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right],$$

with k_s, the parental time disutility parameter now depends on the college education status s, capturing a difference for time valuation by education. Even though the empirical literature provides no evidence of such an altruism gap, it could generate a differential in parental time by education status. The quadratic moving costs are governed by ι_1, suggesting a homophily bias for neighborhood quality types. Two parents of similar earnings and taste shocks could have different preferences for living in a neighborhood depending on how close their childhood neighborhood quality type was compared to the current one. This last feature mechanically creates a U-shape in residential mobility and a smooth gradient in the frequency matrix of intergenerational residential moves.

This extended perfect information version of the model matches relatively well all the targeted moments but misses untargeted ones.[38] In particular, the intergenerational residential mobility moments are off, suggesting a need for other forms of preference heterogeneity. In addition to quadratic moving costs and differences in time disutility parameters, the preference for the neighborhood should vary by childhood neighborhood type (ι_{0,m_0}). Specifically, to reproduce the U-shape data patterns in intergenerational residential mobility (see right panel of Figure 1), the preference for childhood neighborhoods must be more than twenty times higher in the worst neighborhood than in the other ones.

While preference heterogeneity can help match the data, its origin is difficult to justify. Does parental time disutility systematically differ by education status? Are quadratic moving costs credible? Why would children born in the worst neighborhood type be so much more attached than others to their neighborhood quality given the negative features it has: high crime rates, high poverty rates, and low opportunity for children?[39] This last feature is at odds with Bergman et al. (2019)'s empirical findings, whose authors compare low-income families randomly allocated between treatment and control groups. Parents in the treatment group are induced to move to higher-quality neighborhoods and express higher satisfaction

[38]See Appendix Table S9 for the fit of targeted moments and Figures S3 and S4 for the fit of untargeted moments.

[39]Commuting costs are not explicitly modeled but captured by the idiosyncratic neighborhood taste shocks. However, they are unlikely to explain residential mobility patterns across neighborhood quality. Indeed Chetty and Hendren (2018a) find no correlation between short commute time and place effects on children's future earnings.

rates and willingness to stay than those in the control group—who remained in deprived neighborhoods.[40]

4 Housing Voucher Policies

The baseline model displays two main frictions that motivate government involvement: parents cannot borrow against their children's future earnings and the information frictions that result from segregation and social learning with selection neglect. Both lead to lower neighborhood quality levels for low-income families compared to a perfect information world in which children could control inputs into their development.

Motivated by the evidence that housing vouchers—a housing subsidy for low-income families—improve the neighborhood quality of eligible families (Chetty et al., 2016), I use the quantitative model to study their effects on the U.S. economy. The model provides a new rationale for housing vouchers: in addition to addressing redistribution concerns, they can reduce information friction driven by segregation.

U.S. housing voucher programs target low-income families and typically cover the difference between the rent—up to a rent limit—and a fraction of the family's income. The rent limit was initially designed as the Housing and Urban Development's fair market rent, generally the 40th percentile rent in the metro area. Since 2019, housing agencies can set the rent limit at local rent levels rather than at the metro area level.[41]. This section evaluates two versions of housing vouchers in the commuting zone: 1) single-rent limit housing vouchers and 2) multiple-rent limit housing vouchers. Under both policies, eligible households are those below the relative poverty threshold, defined as the income level at the tenth percentile of the income distribution in the baseline economy. Eligible parents receive the voucher before they make their residential choice.

In the model, the single-rent limit housing vouchers (SHV) closely mimic the initial Housing Choice Voucher program, covering the difference between 30% of the family's income and the rent up to the rent ceiling, the 40th percentile rent in the commuting zone. Let r_{m40} the 40th percentile rent in the commuting zone, then the rent price in the neighborhood m

[40] Discrimination or a homophily bias could motivate other modeling assumptions. However, the fact that Bergman et al. (2019) find higher satisfaction levels of low-income families who moved to higher-quality neighborhoods suggests that if they face discrimination once installed, it does not make them systematically want to move back to low-quality neighborhoods. In Appendix Table S4, I find that while childhood neighborhood quality is correlated with adulthood neighborhood quality, once controlled for childhood neighborhood quality, race is not the primary driver of intergenerational residential mobility.

[41] `https://www.cbpp.org/research/housing/what-are-housing-mobility-programs-and-why-are-they-needed`

for a parent of income $y(h,s)$ who is eligible for the housing voucher is:

$$r^{SHV}_{m,h,s} = \min(0.3 \times y(h,s),\ r_m) + \max(r_m - r_{m40},\ 0).$$

Since the model does not feature heterogeneity in rents within neighborhoods, to design multiple-rent limit housing vouchers (MHV), rent limits are determined by a fraction of the rent in each neighborhood. The multiple-rent limit housing vouchers cover the difference between a fraction of the median rent in each neighborhood and a of the family's income. Those fractions are defined so that (i) in partial equilibrium, the cost of the policy is the same as the cost of a housing voucher with a single-rent limit, and (ii) the rent in the bottom-quality neighborhood that faces the average eligible household is the same across the two policies.[42] Under this new housing voucher policy, housing vouchers cover the difference between 69.7% of the median rent and 20% of the family income in each neighborhood. Under this multiple-rent limit housing vouchers, the rent price in the neighborhood m for a parent of income $y(h,s)$ who is eligible for the housing voucher is:

$$r^{MHV}_{m,h,s} = \min(0.2 \times y(h,s) + 0.303 * r_m,\ r_m).$$

The left panel of Figure 3 illustrates the rent schedule of these two policies for an average eligible household. While the rent schedule has a kink under a housing voucher policy with a single-rent limit, it is smooth under a housing voucher policy with rent limits set at the neighborhood level.

Both housing voucher policies are financed through property taxes, which adds two terms to the household budget constraint:

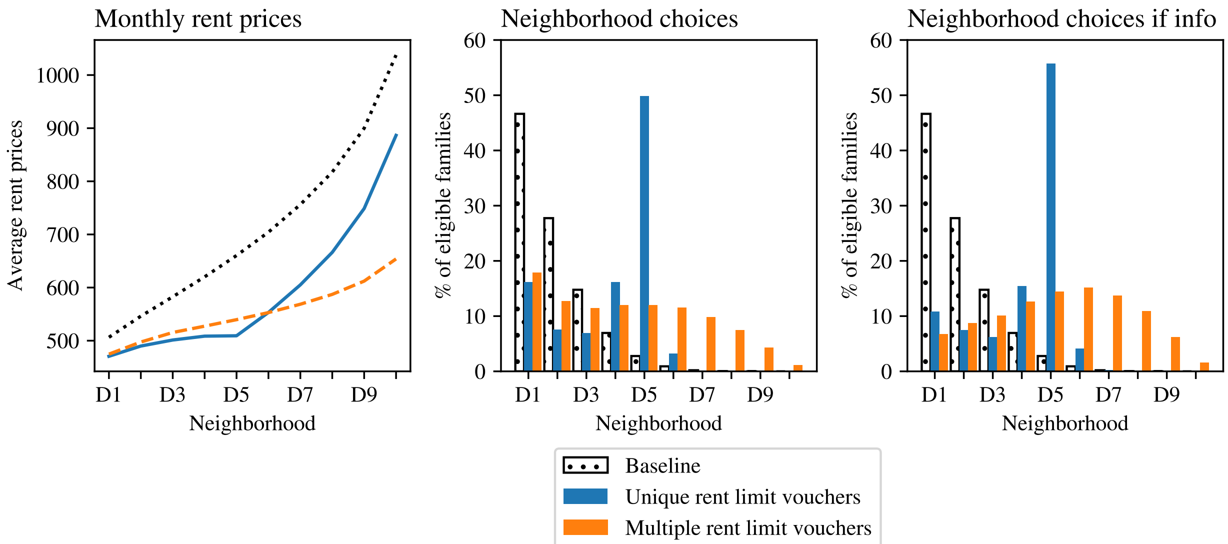
$$c + r^{HV}_{m,h,s}\,(1+\tau_r) = \lambda_y \left(w\ h\ (1+\omega s)\ \overline{\ell_s}\right)^{1-\tau_y} + R,$$

where τ_r is the tax rate and $r^{hv}_{m,h,s}$, is the rent households face once the housing voucher policy is implemented. This policy is fully financed so that:

$$\sum_m \sum_s \int (r_m - r^{HV}_{m,h,s}) F(h,s,m)\, dh = \sum_m \sum_s \int (r^{HV}_{m,h,s}\ \tau_r) F(h,s,m)\, dh.$$

[42] The cost and bottom rent differences between policies in partial equilibrium are less than 1%.

Figure 3: Policy Designs and Partial Equilibrium Effect on Eligible Households



Notes: The left panel shows the rent schedule for the average eligible household under three scenarios: no policy (baseline economy), housing vouchers with a single-rent limit, and housing vouchers with multiple-rent limits. The center and right panels show the residential choices of eligible households under the same three scenarios without and with information on the relevance of neighborhood quality for their child's development.

4.1 Partial Equilibrium Effects of Housing Vouchers

As a first step, I conduct a field experiment within the model to investigate the impact of housing vouchers and compare them to the empirical estimates by Chetty et al. (2016). These are partial equilibrium results, as, in practice, in a randomized control trial, too few people receive a housing voucher to change general equilibrium forces.

The central panel of Figure 3 shows the positive effects of both housing voucher policies on the neighborhood quality of eligible households. With single-rent limit housing vouchers, an extra 65% of eligible families move out of bottom-quality neighborhoods, and their neighborhood rank improves by 1.9 points, improving children's earnings at age 26 by $756 (Panel A Column (4) of Table 4). The predicted effect on children's earnings falls within Chetty et al. (2016)'s estimated confidence interval ($1,452 with a standard error of 736).[43]

[43]Notice that the estimated effect is in the lower bound of Chetty et al. (2016)'s empirical estimate. This is most likely because treated individuals are poorer in the data than in the model. Indeed, while Chetty et al. (2016) evaluate housing vouchers' effects on low-income households who already live in public housing in deprived neighborhoods. In the model, the voucher is offered to young parents with an income below the tenth income percentile, independently of their neighborhood choice. Only 47% of them choose to live in the very bottom decile neighborhood. As a result, in the data, the average family earnings at age 26 of children in the control group is $12,702, while in the model, it is $20,597.

Incorrect parental beliefs partly explain why not all low-income families move out. In the right panel of Figure 3, I conduct the same experiment but provide information about the relevance of neighborhood quality for children's future human capital. Both policies are more effective at improving the neighborhood rank of eligible households when information is provided.[44]

Finally, the partial equilibrium effects of multiple-rent limit housing vouchers are consistent with Collinson and Ganong (2018)'s results. Collinson and Ganong (2018) finds that because most rental units below the payment standard are in low-quality neighborhoods, indexing rent limits to ZIP codes rather than metropolitan areas improves the share of families who move into higher-quality neighborhoods. The center panel of Figure 3 illustrates a bunching effect of eligible households with the single-rent limit housing voucher that disappears with the multiple-rent limit housing voucher. Panel B Column (4) of Table 4 indicates an increase of 2.4 points in the neighborhood rank, improving children's earnings at age 26 by $995.

4.2 General Equilibrium Effects of Housing Vouchers

In the next step, I scale up the policies to all families below the poverty threshold in the economy and compute the new steady states and the transition paths. At every generation of the transition paths, I assume the housing market clears, and neighborhood quality adjusts accordingly.[45] On the other hand, parental beliefs and human capital slowly converge to their new steady state. The steady-state comparisons provide insights into the long-run implications of the policy. Analyzing the transition paths permits us to gauge how long it would take to reach the new steady states and to understand the underlying mechanisms better.

First, general equilibrium responses in parental beliefs largely amplify housing voucher effects on eligible households. Column (6) Panels A and B of Table 4 show the long-run and general equilibrium effects of the single- and multiple-rent limit housing vouchers on eligible households. Eligible children reside in better neighborhoods (+2.4 and +4.3), benefits from

[44] Not displayed here, the single-rent limit housing voucher program combined with information improves the neighborhood rank of treated families by 2.2 points, 0.3 points higher than without information, resulting in a further increase in children's future earnings by $98. The fraction of families who move out of bottom-quality neighborhoods rises to 77%. This is consistent with Bergman et al. (2019) 's empirical findings. The authors randomly provide services and information to reduce barriers to moving to high-upward-mobility areas. The intervention increased the fraction of families who moved to high-upward-mobility areas from 15 to 53%, not reaching 100%.

[45] Details on how I compute the transition paths are provided in Appendix A.2.

Table 4: Effects of a Housing Voucher Policies on Eligible Households

	Data Chetty et al. (2016)		Model			
	Control	Housing vouchers	Baseline	PE	GE short-run	GE long-run
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Single-rent limit housing vouchers						
% in worse neighborhood	100%	-66% ± 4	47%	-65%	-77%	-78%
Child's future earnings	\$12,702	+\$1,452 ± 1,441	\$20,597	+\$756	+\$678	+\$1,201
Neighborhood rank			1.95	+1.9	+2.4	+2.4
Parental time (min./day)			51	+1.1	-1.9	+3.3
Panel B: Multiple-rent limit housing vouchers						
% in worse neighborhood			47%	-62%	-85%	-78%
Child's future earnings			\$20,597	+\$995	+\$1,529	+\$3,160
Neighborhood rank			1.95	+2.4	+4.4	+4.3
Parental time (min./day)			51	+1.6	-0.0	+14.2

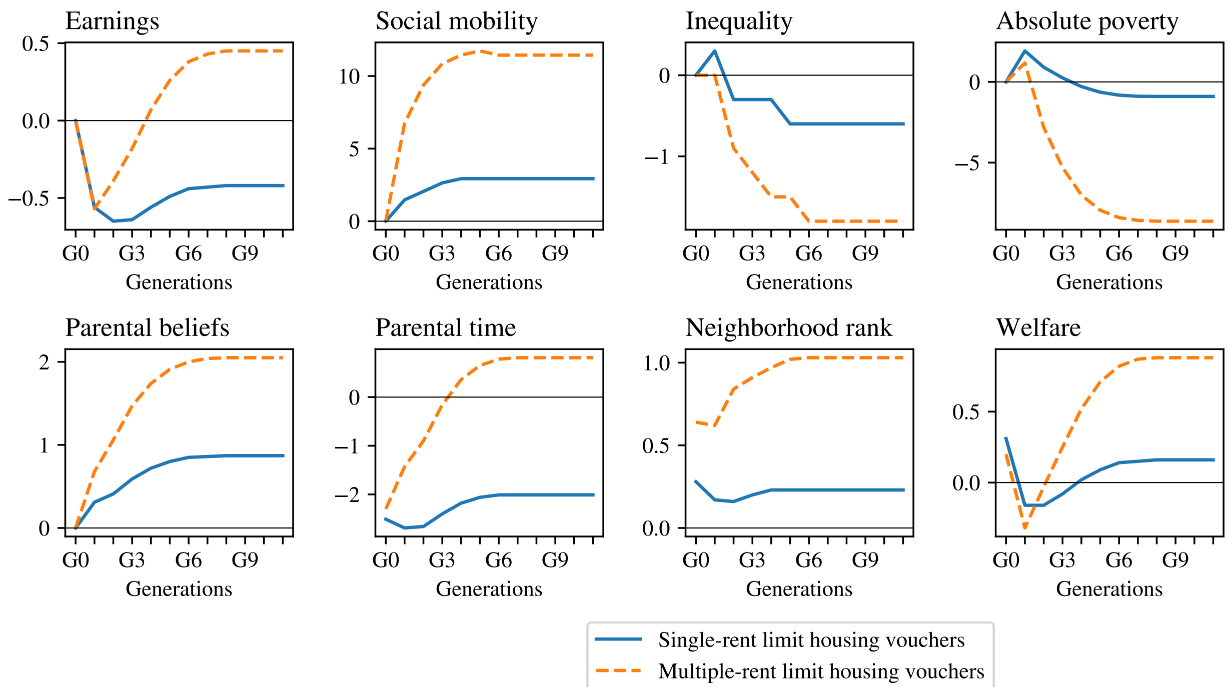
Notes: This table shows the effects of housing vouchers on eligible families, from the data, and simulated by the calibrated baseline model. Column (4) presents partial equilibrium results. Column (5) and (6) the very short-run and long-run effects of housing voucher policies on eligible households in general equilibrium using the calibrated model. Data source: Chetty et al. (2016).

more parental time (+3.3 and +14.2 minutes per day) and have higher expected future earnings (+\$1,201 and +\$3,160 per year, versus \$756 and \$995 in partial equilibrium). Results in Column (5) indicate that a change in parental beliefs primarily drives this amplification effect. This column shows the effects of the policies on the very first generation of families who benefit from them, considering equilibrium responses on the housing market. The first-generation eligible parents hold the same beliefs as in the baseline economy steady state. However, every eligible parent receives a voucher, and any housing voucher holder can move to better neighborhoods, increasing the density in middle-range quality neighborhoods—especially at the rent limit when unique—and its rent prices, but lowering the neighborhood quality. Equilibrium rent price responses lead the first generation of eligible parents to live in higher rank neighborhoods compared to the partial equilibrium case (+2.4 and + 4.4 respectively). Note, however, that eligible parents allocate less time to their child's education (-1.9 and -0.0 minutes per day, respectively), which, combined with a change in neighborhood quality, dampens the neighborhood rank effect on their child's future earnings, even dampening partial equilibrium effects in the case of the single-rent limit housing vouchers.

Second, both policies' aggregate and long-run effects on equality, social mobility, welfare, and absolute poverty are positive. Still, aggregate earnings only increase under the multiple-rent limit housing voucher policy. Figure 4 illustrates the dynamics of the economy under both housing voucher policies. The first generation of eligible parents, G0, receives the vouchers, which results in an increase in aggregate neighborhood rank but a decrease in aggregate parental time. Note that the change in aggregate parental time is similar across policies, suggesting that the multiple-rent limit housing voucher is a better tool to loosen the budget constraint of financially constrained parents. The change in parental input choices leads to lower earnings for the next generation of parents (G1). Aggregate earnings start increasing once aggregate parental beliefs improve, improving parental input choices. Aggregate welfare follows a similar pattern. It is positive for the first generation of parents (G0) and becomes negative for the second one (G1) as earnings drop. It increases again in the third generation and becomes positive in the long run. All aggregate outcomes reach a steady state in the seventh generation, with a substantial difference between the two policies: the multiple-rent limit housing vouchers are much more welfare-improving than the single-rent limit housing vouchers.

Table 5 helps understand the difference in long-run effects across policies. Under both policies, while higher-income households' parental beliefs decrease, lower-income households' parental beliefs increase. Parental behaviors coherently move with the change in parental

Figure 4: Transition Dynamics of the Economy with Housing Voucher Policies
(% deviation from initial steady state)



Notes: The left and right panels show the transition path of aggregate human capital and parental beliefs under the two policy regimes: housing vouchers with a single-rent and multiple-rent limits. *Social mobility* is measured by minus the income rank-rank coefficient, *Segregation* by the neighborhood Gini coefficient, and *Inequality* by the income Gini coefficient.

Table 5: General Equilibrium Effects Housing Voucher Policies by Income Quartile (in %)

	Single-rent limit housing vouchers					Multiple-rent limit housing vouchers				
		Income quartile					Income quartile			
	All	1st	2nd	3rd	4th	All	1st	2nd	3rd	4th
Parental beliefs	+0.9	+4.7	+1.2	-1.2	-0.8	+2.1	+11	+4.2	-0.4	-3.2
Parental time	-2.0	+0.3	-2.6	-3.8	-2.0	+0.8	+14	+2.5	-2.7	-4.3
Neighborhood rank	+0.2	+20	-6.0	-2.6	-0.9	+1.0	+51	-8.3	-5.6	-2.0
Earnings	-0.4	+0.5	-0.1	-2.9	-3.6	+0.5	+8.0	+3.6	-0.0	-0.3
Welfare	+0.1	+2.6	+0.0	-2.1	-3.1	+0.9	+8.3	+2.9	-0.8	-2.0

Notes: This table shows the general equilibrium effects of housing voucher policies by income group using the calibrated model.

beliefs. However, only with the multiple-rent limit housing voucher—that leads to a great decrease in segregation (-20%),—does the increase in parental inputs from low-income households compensate for the decrease in parental inputs from high-income households, increasing aggregate parental time and earnings. In sum, a housing voucher policy with multiple-rent limits is a better tool than a single-rent limit housing voucher program to address redistribution and efficiency concerns simultaneously. In the long run, the multiple-rent limit housing voucher program increases social mobility by 11%, equality by 2%, and earnings by 0.5%.

5 Conclusion

In this paper, I present a quantitative spatial model of residential and parental time decisions with social learning about the technology of skill formation and potential selection neglect. Once calibrated to the average commuting zone in the United States, the model indicates that residential segregation generates information friction that drives heterogeneous parental beliefs and distorts parental input choices across socioeconomic groups. In equilibrium, low-income parents under-invest in their children, while high-income parents over-invest in them. Without heterogeneous preferences by socioeconomic groups, the social learning mechanism rationalizes the high share of parents raised in disadvantaged neighborhoods choosing similar environments for their children and college parents despite working longer hours, allocating more time to their children's education than non-college parents.

Using the baseline calibrated model, I investigate how heterogeneous parental beliefs affect the United States economy. Relatively modest levels of parental misconceptions have substantial macroeconomic effects, exacerbating inequality, reducing social mobility, and decreasing aggregate earnings, thereby diminishing consumption equivalence welfare. The model's frictions motivate government involvement. I evaluate housing voucher policies in both partial and general equilibrium, considering short- and long-term implications. Housing vouchers targeted to low-income households induce them to move to higher-quality neighborhoods. The policy improves aggregate consumption equivalence welfare in general equilibrium and the long run. The magnitude of the effects depends on the policy features: they are larger when residential segregation decreases the most, namely, with multiple-rent limits at the commuting zone level. Indeed, by reducing residential segregation, a housing voucher policy, designed to address redistribution concerns, improves information and parental beliefs. It results in higher social mobility and equality after a couple of generations.

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A Equilibrium and Transition Path Computation

A.1 Equilibrium Computation

The below algorithm uses an iterative method to find the steady state.

1. Make an initial guess for the distribution $F(h, s, m_0, \tilde{\alpha})$, the share of families $(h, s, m_0, \tilde{\alpha})$ in each neighborhood ($\lambda_m(h, s, m_0, \tilde{\alpha})$ for every m) and value function $U(h, s, m_0, \tilde{\alpha})$.
2. Given $U(h, s, m_0, \tilde{\alpha})$, compute the policy function $\tau(h, s, m_0, \tilde{\alpha}, m)$ and the corresponding $V(h, s, m_0, \tilde{\alpha}, m)$
3. Make an initial guess for rent prices $\{r_m\}_{m \in \mathbb{M}}$
4. Given $V(h, s, m_0, \tilde{\alpha}, m)$, $\tau(h, s, m_0, \tilde{\alpha}, m)$ and $\{r_m\}_{m \in \mathbb{M}}$, compute the share of families $(h, s, m_0, \tilde{\alpha})$ in each neighborhood ($\lambda_m(h, s, m_0, \tilde{\alpha})$ for every m).
5. Compute $\{r_m\}_{m \in \mathbb{M}}$ given the share of families in each neighborhood.
6. Iterate 3 to 5 until $\{r_m\}_{m \in \mathbb{M}}$ converges.
7. Given $\{r_m\}_{m \in \mathbb{M}}$, compute the expected value function $U(h, s, m_0, \tilde{\alpha})$ and based on it, obtain the policy function for time investment $\tau(h, s, m_0, \tilde{\alpha})$.
8. Compute the distribution $G(H, \mathrm{T}, m_0, h, m)$ given λ_m, and obtain updated beliefs in each neighborhood $\tilde{\alpha}(\tilde{\alpha}, m)$.
9. Compute the time-invariant distribution $F(h, s, m_0, \tilde{\alpha})$, based on the initial guess, the policy functions for neighborhoods $\lambda_m(h, s, m_0, \tilde{\alpha})$, and $\tau(h, s, m_0, \tilde{\alpha}, m)$, and on beliefs updating $\tilde{\alpha}(\tilde{\alpha}, m)$ obtained above.
10. Iterate from 1 to 9 until $F(h, s, m_0, \tilde{\alpha})$ converges.

A.2 Transition Path Computation

The economy is initially in steady state. In period $t = 0$, the economy is hit by the policy change. At every period of the transition path, I assume the housing market clears, and neighborhood quality adjusts accordingly. Let T denote the time period sufficiently long enough so that the economy converges to the new steady state with the policy.

1. Compute the baseline steady state and the new steady state following the algorithm above. Store the information of the original steady state as $t = 0$ and that of the new steady state as $t = T$.

2. Make an initial guess for the evolution of the distribution $\{F_t(h, s, m_0, \tilde{\alpha})\}_{t=0}^{T-1}$, the share of families $(h, s, m_0, \tilde{\alpha})$ in each neighborhood $(\{\lambda_{m,t}(h, s, m_0, \tilde{\alpha})\}_{t=0}^{T-1}$ for every m), the value function $\{U_t(h, s, m_0, \tilde{\alpha})\}_{t=0}^{T-1}$ and resulting human capital $\{h_t\}_{t=1}^{T-1}$.

3. For each period $t = 0, \dots, T-1$, given $U_t(h, s, m_0, \tilde{\alpha})$, compute the policy function $\tau_t(h, s, m_0, \tilde{\alpha}, m)$ and the corresponding $V_t(h, s, m_0, \tilde{\alpha}, m)$

4. For each period $t = 0, \dots, T-1$,

   (a) Make an initial guess for rent prices $\{\{r_m\}_{m\in\mathbb{M}}\}_t$

   (b) Given $V_t(h, s, m_0, \tilde{\alpha}, m)$, $\tau_t(h, s, m_0, \tilde{\alpha}, m)$ and $\{\{r_m\}_{m\in\mathbb{M}}\}_t$, compute the share of families $(h, s, m_0, \tilde{\alpha})$ in each neighborhood $(\lambda_{m,t}(h, s, m_0, \tilde{\alpha})$ for every m).

   (c) Compute $\{\{r_m\}_{m\in\mathbb{M}}\}_t$ given the share of families in each neighborhood.

   (d) Iterate 3 to 5 until $\{\{r_m\}_{m\in\mathbb{M}}\}_t$ converges.

5. For each period $t = 0, \dots, T-1$, given $\{\{r_m\}_{m\in\mathbb{M}}\}_t$, compute the expected value function $U_t(h, s, m_0, \tilde{\alpha})$ and based on it, obtain the policy function for time investment $\tau_t(h, s, m_0, \tilde{\alpha})$.

6. For each period $t = 0, \dots, T-1$, compute the distribution $G_t(H, \mathrm{T}, m_0, h, m)$ given $\lambda_{m,t}$, and obtain updated beliefs in each neighborhood $\tilde{\alpha}(\tilde{\alpha}, m)_t$.

7. For each period $t = 0, \dots, T-2$, compute the distribution $F_{t+1}(h, s, m_0, \tilde{\alpha})$, based on the initial guess, the policy functions for neighborhoods $\lambda_{m,t}(h, s, m_0, \tilde{\alpha})$, and $\tau_t(h, s, m_0, \tilde{\alpha}, m)$, and on beliefs updating $\tilde{\alpha}(\tilde{\alpha}, m)_t$ obtained above. Compute the resulting human capital h_{t+1}

8. Iterate from 1 to 7 until $\{h_t\}_{t=1}^{T-1}$ converges.

B Welfare Measure

Welfare is defined by the consumption equivalence under the veil of ignorance in the baseline economy relative to the economy with the counterfactual policy in place. Formally, let $P \in \{0, 1, 2, ...\}$ denote the set of policy counterfactuals, with $\mathrm{P} = 0$ being the baseline economy in steady state. The consumption equivalence refers to the percentage change in consumption Δ in the baseline economy that makes individuals indifferent between being born in the baseline economy (P = 0) and the one in which the counterfactual policy $P \neq 0$ is in place. Denote by $V^P(h, s, m_0, \tilde{\alpha}, \Delta)$ the welfare of agents in the initial state of the economy if their consumption (and that of their descendants) were multiplied by $(1 + \Delta)$:

$$V^P(h,s,m_0,\tilde{\alpha},\Delta) = \mathbb{E}^P \ \log\left(c^{*P}(1+\Delta)\right) + \ \frac{\left(1-\overline{\ell_s}-\kappa\ \tau^{*P}\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} \ + \ \delta\ rank_m$$
$$+ \ \iota\ \mathbb{1}_{m_0=m^{*P}} + \ \nu\varepsilon_{m^{*P}} + \ bV^P\left(h', s', m^{*P}, \tilde{\alpha}, \Delta\right).$$

Note that the policy functions are assumed to be unchanged when Δ is introduced. The welfare of agents can then be written as :

$$V^P(h,s,m_0,\tilde{\alpha},\Delta) = (1+\ b)\ \log\left(1+\Delta\right)\ +\ \mathcal{V}^P(h,s,m_0,\tilde{\alpha}).$$

The average welfare is:

$$\bar{V}^P(\Delta) = \sum_{s,m_0}\int_{h,\tilde{\alpha}} V^P(h,s,m_0,\tilde{\alpha},\Delta)\Lambda^P(h,s,m_0,\tilde{\alpha}),$$

where Λ^P is the distribution of initial states $\{h, s, m_0, \tilde{\alpha}\}$ in the economy P or in a subgroup of the economy P.

The consumption equivalence Δ^P makes the average individual indifferent between being born in the baseline economy $P = 0$ and one in which policy $P \neq 0$ is in place, such that:

$$\bar{V}^0(\Delta^P) = \bar{V}^P(0).$$

Which can be written as:

$$\Delta^P = \exp\left(\frac{\bar{V}^P(0)-\bar{V}^0(0)}{1+b}\right) - 1.$$

C Data Appendix

C.1 Preliminaries

I use several representative datasets of the United States to describe parental behavior across socioeconomic groups and calibrate the model.

C.1.1 The American Time Use Survey (ATUS)

The American Time Use Survey (ATUS) is a nationally representative survey of Americans aged 15 or over that provides extensive information on how and where Americans spend their time. From 2003 to 2020, almost 219,000 interviews were conducted, all of which can be linked to data files from the Current Population Survey (CPS). I use already linked datasets provided by Hofferth et al. (2020) and available on the IPUMS website.

The ATUS asked interviewees about their activities the day before the interview–the "diary day." For each activity, respondents are asked how long the activity lasted and, for most activities, where they were and who was with them. After completing the time diary, there are additional questions to identify work, volunteering, eldercare, and secondary child-care activities. Several activity categories are then defined by the United States Bureau of Labor Statistics (BLS), among which one is of particular interest for this research project: "primary childcare activities." This activity category includes time spent providing physical care, playing with children, reading with children, assisting with homework, attending children's events, taking care of children's health needs, and dropping off, picking up, and waiting for children. Passive childcare was included as a primary activity (such as "keeping an eye on my son while he swam in the pool"). However, a child's presence during the training is insufficient to classify it as childcare; "watching television with my child" is coded as a leisure activity, not as childcare.

I restrict the sample to individuals in a two-parent household, defined as married individuals whose youngest child is under age 18.[46] As all the other datasets are from 2000, I use the earliest ATUS survey year, 2003. In 2003, 5,597 married parents were interviewed, 2,168 of whom had a college degree.[47,48]. Table S1 describes how married couples with a child below 18 in the household in the United States allocate their time in 2003.

[46] I only keep two-parent households for consistency with the model that does not consider marital status. 78% of parents in the sample are married.

[47] Parent's education is defined as the highest level of education of the respondent. Using the highest education level of both parents or the mother doesn't change the results in Table S3.

[48] I removed 255 observations that have less than 23 hours of activity a day reported. 92% of the remaining observations have precisely 24 hours of activity a day reported.

Table S1: ATUS Activity Coding Structure, 2003

Label	Description	Non-college parents	College parents
		Hours per day	
Childcare		**1.17**	**1.58**
Caring for and helping household children	Time spent in caring for or helping household children	1.17	1.58
Work and Education		**4.36**	**4.66**
Working and Work-related Activities	Time spent in work activities such as working, doing activities as part of one's job, engaging in income-generating activities (not as part of one's job), and looking for jobs and interviewing.	4.27	4.56
Educational activities	Time spent in non-work education activities, such as taking classes, conducting research and homework, administrative tasks, and extracurricular activities except sports.	0.10	0.10
Personal leisure		**14.39**	**13.64**
Personal care	Time spent in personal care activities such as sleeping, grooming, and health-related self care.	9.05	8.66
Eat and drinking	Time spent in activities such as eating and drinking not done as work or a volunteer activity, whether the respondent was alone, with others, at home, at a place of purchase, in transit, or somewhere else.	1.02	1.19
Socializing, relaxing, and leisure	Time spent in personal interest or leisure activities such as communicating with others and attending parties and meetings; and leisure activities such as relaxing, playing (passive) games (unless playing with children only), watching television, playing or listening to music, reading, writing, and all hobbies.	3.69	2.88
Sports, exercise, and recreation	Time spent in sports, exercise and recreational activities such as pleasure boating, throwing a Frisbee, kite flying, or ballooning, and active, participatory outdoor games or activities, such as horseshoes, croquet, and paintball.	0.25	0.33

Religious and spiritual activities	Time spent in work activities such as working, doing activities as part of one's job, engaging in income-generating activities (not as part of one's job), and looking for jobs and interviewing.	0.14	0.17
Volunteer activities	Time spent in volunteer (unpaid) activities done by the respondent for individuals or institutions through formal organizations, such as unpaid performance arts activities, socializing related to volunteering and attending church service as a volunteer activity.	0.13	0.25
Telephone calls	Time spent in telephone communication activities such as talking on phone, waiting for a phone call or Skyping (2011+).	0.05	0.07
Professional and personal care services	Time spent in activities such as obtaining, receiving, and/or purchasing professional and personal care services provided by someone else. Professional services include child care, financial, legal, medical, and other adult care, real estate, and veterinary. Personal care service activities include massages, haircuts, manicures, and tanning at salons.	0.07	0.09
Other		**4.04**	**4.07**
Household activities	Time spent in household activities such as maintaining their household, household management and organizational activities.	2.13	1.94
Caring for and helping household members (except household children)	Time spent in caring for or helping any adult in the respondent's household, regardless of relationship, age, or physical or mental health status.	0.04	0.03
Caring for and helping non-household members	Time spent in caring for or helping any child or adult who is not part of the respondent's household, regardless of relationship, age, or physical or mental health status.	0.10	0.08

Household services	Time spent in activities such as obtaining and purchasing household services provided by someone else. Household services include yard and house cleaning, cooking, pet care, tailoring and laundering services, vehicle and home repairs, maintenance, and construction. Watching someone else perform paid household activities (cooking, cleaning, repairing, etc.) should be coded here, provided "watching" was the respondent's primary activity.	0.01	0.02
Government services and civic obligations	Time spent in activities such as using government services (police, fire, social services), purchasing government-required licenses or paying fines or fees, fulfilling government-required duties (jury duty, parole meetings, court appearances), and participating in activities that assist or impact government processes (voting, town hall meetings).	0.00	0.00
Consumer purchases	Time spent in activities such as purchases and rentals of consumer goods, regardless of mode or place of purchase or rental (in person, via telephone, over the internet, at home, or in a store).	0.43	0.49
Travel	Time spent in travel or transportation activities such as commuting, walking someplace or waiting for the bus or train.	1.33	1.51
Total		**24.0**	**24.0**

Notes: This table provides information on time allocation by married couples with a child below 18 in the household in the United States. Data source: ATUS 2003.

C.1.2 National Longitudinal Study of Adolescent to Adult Health (Add Health)

The National Longitudinal Study of Adolescent to Adult Health (Add Health) survey is a nationally representative longitudinal survey of adolescents in the United States. In the academic year 1994-1995, about 20,000 students in grades 7-12 were sampled to complete an in-home interview. They come from 132 schools; in 1994-1995, most were aged between 12 and 17. In 2016-2018, about 12,300 of them answered the Wave V survey. At the date of the last survey wave, most of the interviewees were aged between 35 and 40 years old. The analysis focuses on the baseline survey in 1994 (Wave I), when interviewees were between 12 and 17, and the last follow-up survey in 2018 (Wave V), when interviewees were aged between 35 and 40.

The data set includes detailed information on family background and a rich information on neighborhood characteristics. In 1994, we observe the parents' highest education level of about 17,000 interviewed adolescents, and we have information on residential neighborhood characteristics for about 18,100 adolescents. Information on neighborhoods is available at the census tract level. In addition, Add Health contains questions on the frequency of ten parent-child activities. Add-Health structure allows me to correlate the number of parent-child activities with neighborhood characteristics, which can't be done using the more detailed American Time Use Survey (ATUS) (see Appendix Section C.1.1).

C.1.3 National Historical Geographic Information System (NHGIS)

The National Historical Geographic Information System (NHGIS) provides access to summary tables and time series of population, housing, agriculture, and economic data, along with GIS-compatible boundary files, for years from 1790 through the present and for all levels of U.S. census geography, including states, counties, tracts, and blocks. Data is easily accessible on the IPUMS Website (Manson et al., 2022).

C.1.4 National Historical Geographic Information System (NHGIS)

The ACS is a project of the U.S. Census Bureau that has replaced the decennial census as the key source of information about the American population and housing characteristics. The IPUMS database contains samples from the 2000-present ACS.

C.1.5 American Community Surveys (ACS) 2000

The 2000 ACS is census data nationally representative of the United States. It includes information on a broad range of population characteristics, including income, fertility, labor-force participation, occupational structure, education, and household composition. Data is easily accessible on the IPUMS Website (Ruggles et al., 2023).

C.2 Parental Time and Neighborhoods Construction

C.2.1 Ten Synthetic Neighborhoods

Using the NHGIS 2000 dataset, I proxy neighborhood quality by the household median income of the census tract. I create ten synthetic neighborhoods by ranking all census tracts by neighborhood quality and grouping them into ten groups of equal size within commuting zones. Following Chetty and Hendren (2018a), I restrict the sample to the 100 biggest commuting zones. One synthetic neighborhood represents a decile of the census tract distribution in the average biggest commuting zone in the United States.

Table S2 summarizes the characteristics of these neighborhoods. By construction, median household income increases with neighborhood quality. As expected, so does the fraction of individuals above 25 with a college degree (Column (2)). Note that housing expenditure shares decrease with neighborhood quality (Column (4)), which suggests and motivates non-homothetic preferences.

Table S2: Characteristics of Synthetic Neighborhoods

	Median household income (USD)	Fraction of people aged 25+ with college degree	Fraction below poverty level	Median rent over median household income	Fraction of households
	(1)	(2)	(3)	(4)	(5)
Neighborhood D1	20,638	0.113	0.358	0.286	0.071
Neighborhood D2	28,883	0.134	0.233	0.234	0.088
Neighborhood D3	34,259	0.158	0.167	0.211	0.093
Neighborhood D4	38,652	0.187	0.133	0.197	0.096
Neighborhood D5	42,957	0.212	0.105	0.187	0.100
Neighborhood D6	47,552	0.236	0.085	0.177	0.105
Neighborhood D7	52,547	0.268	0.069	0.170	0.107
Neighborhood D8	58,810	0.311	0.054	0.163	0.111
Neighborhood D9	67,780	0.386	0.042	0.156	0.114
Neighborhood D10	91,273	0.528	0.030	0.141	0.115

Notes: This table provides average sociodemographic characteristics in the ten synthetic neighborhoods. The data source is the NHGIS data from 2000 at the census tract level for the 100 biggest commuting zones. The associated distributions serve as targeted and untargeted moments for the model calibration.

I use Add Health data and repeat the same exercise to construct the ten synthetic neighborhoods in which the interviewee resided in waves I (1994-1995) and V (2016-2018).[49] The sample is restricted to interviewees who do not live in their parent's houses in adulthood in Wave V. All observations are weighted by the sampling weights of the corresponding wave provided by Add Health. I only use the information at the census tract level available in the Add Health dataset, and due to the sample size, I do it at the U.S. level instead of within commuting zones. Thanks to the panel form of the dataset, I can observe in which synthetic neighborhood an adolescent lived in 1994-1995 and in which synthetic neighborhood she

[49] In Appendix Section C.3.3, I also proxy neighborhood quality by the share of residents above 25 with a college degree as a robustness check (Diamond, 2016).

lived during adulthood, in 2016-2018.

C.2.2 Parental Time

To measure parental time, I use the BLS definition of childcare as "primary childcare activities" and respect the activity coding structure of ATUS to describe how parents from different socioeconomic groups allocate their time between childcare, leisure, and market work.[50] Market work hours include all hours spent in work-related and education-related activities. The rest of the time is considered leisure time. For informational purposes, I divide this last group into two sub-groups: all personal leisure activities and other activities.[51]

Table S3 summarizes parents' time use in the United States by education. Note that the sample only contains two-parent households, defined as married individuals whose youngest child is under age 18. As standard in the literature, I assume 16 hours of disposable hours and eight hours of sleep are needed per day. I consider an endowment of 16 disposable hours per day in the model and normalize it to one. Parental time patterns are moments to match.

Both parental time and market work time increase in education. Parents with a college degree spend about 1.6 hours per day in childcare activities and 4.7 hours in market work activities, while parents without a college degree spend 1.2 hours in childcare and 4.4 hours in market work.[52] Leisure time mechanically decreases in education. It is interesting to note, however, that this decrease is entirely driven by college parents spending less time on personal leisure activities compared to non-college parents. Time spent in other types of activities is relatively constant across educational groups.[53]

In addition, Add Health survey contains information about ten parent-child activities in 1994-1995.[54] To proxy for time allocated in childcare, I construct a variable that counts

[50] The definition of "primary childcare activities" that is provided by the United States Bureau of Labor Statistics (BLS) includes time spent providing physical care; playing with children; reading with children; assisting with homework; attending children's events; taking care of children's health needs; and dropping off, picking up, and waiting for children. It does not include activities with children without active childcare, such as "watching television with my child".

[51] Personal leisure is composed of eight activities: "eat and drink", "personal care", "telephone calls", "professional and personal care services", "religious and spiritual activities", "socializing, relaxing, and leisure", "sports, exercise, and recreation", "volunteer activities". I remove eight hours of sleep needs from "personal care" that includes sleep time, a standard assumption in the literature. Others are "household activities," "household services," "government services and civic obligations," "consumer purchases," "travel,"' and "caring for and helping non-household and [other] household members." Appendix Table S1 provides detailed information on each activity.

[52] The number of children is close to two for both groups. Time per child in a two-parent household is similar to childcare time: 1.1 hours for non-college and 1.6 hours for college-graduated households.

[53] Appendix Table S1 describes how parents allocate their time in each ATUS activity.

[54] The question of interest is: "Which of the things listed on this card have you done with [resident mother/father] in the past four weeks (check all that apply)".

Table S3: Parents' Time Allocation by Education, ATUS 2003

	Non-college graduated parents		College graduated parents	
	Hours per day	% of total	Hours per day	% of total
Market work	4.4	27.5%	4.7	29.4%
Childcare	1.2	7.5%	1.6	10.0%
Leisure				
Personal leisure	6.4	40.0%	5.6	35.0%
Other	4.0	25.0%	4.1	25.6%
Total	16.0	100%	16.0	100%

Notes: This table provides information on time allocation by married parents in the United States. The data source is ATUS 2003. Childcare activity follows the BLS definition of "primary childcare activities." Market work contains all work-related and educational activities. Leisure includes all the other activities. For more details on activity grouping, see Appendix Table S1.

the number of activities that happened over the past four weeks with the mother and the father of the child. I follow the United States Bureau of Labor Statistics (BLS) definition of "primary childcare activities" constructed and exclude two out of the ten events: "shopping" and "went to a religious service or church-related event".[55] The remaining eight activities are: "played a sport", "talked about someone you're dating, or a party you went to", "talked about a personal problem you were having", "had a serious argument about your behavior", "talked about your school work or grades", "worked on a project for school", "talked about other things you're doing in school", "went to a movie, play, museum, concert, or sports event".

C.3 Neighborhood Quality and Parental Time in the United States

In addition to the extensive subjective beliefs literature, the model builds on suggestive evidence from the National Longitudinal Study of Adolescent to Adult Health (Add Health). In this section I derive and test for two implications of the model.

C.3.1 Correlation between Time and Neighborhood

Suppose neighborhood quality and parental time are two inputs of the technology of skill formation. Assume parents' decisions are driven by their perceived value of the returns to both inputs – neighborhood quality and parental time. All else equal, parents with low (high) beliefs will tend to live in worse (better) quality neighborhoods and spend less (more) time

[55] As a robustness check in Appendix Section C.3.3, I construct an alternative proxy of parental time removing the activity "went to a movie, play, museum, concert, or sports event".

with their children. I expect to see a positive correlation between time and neighborhood quality in the data due to the omitted subjective beliefs variable. The data support this assumption.

As a first step, using the Add Health datasets, I verify the two parental inputs—parental time measured by the number of parent-child activities done over four weeks and standardized neighborhood quality proxied by household median income—matter for later outcomes.[56] Columns (1) and (2) of Table S4 show that parental time and neighborhood quality positively correlate with later child skills.[57] Conditional on other parents' socioeconomic status (SES), the number of parent-child activities and neighborhood quality co-move with the graduation probability measured twenty-two years later. All coefficients are positive and significant at a one percent level. Motivated by this evidence, in the following, I consider the parental time and neighborhood quality variables are good proxies for parental inputs of the technology of skill formation.[58]

Columns (3) and (4) of Table S4 display a positive and significant correlation between the two parental inputs.[59] Note that in both regressions of Column (3) and (4) of Table S4, I control for school ID fixed effects. A systematic difference in school characteristics is not what drives the correlation. Nevertheless, research finds that parental time increases with parents' education in the United States (see Doepke et al. (2023) for a review). This observed correlation could be driven by a neighborhood composition effect. In Column (4) of Table S4, I control for three variables measuring households' socioeconomic status: parents' highest level of education, family income, and parent's marital status.[60] The sample size shrinks to 12,633 observations due to missing values in household characteristics variables, but the relationship remains positive and significant at a one percent level. This suggests that neighborhood composition effect does not drive all the correlation between the two parental inputs.

While this result is consistent with the assumption of parental beliefs being an omitted variable, it is also compatible with a human capital production function in which neighborhood quality and parental time are complementary inputs. There is no consensus in the literature about this relationship. Chyn and Daruich (2022) find a complementarity between

[56]See Appendix section for variable construction.

[57]All observations are weighted. When variables from different waves are used simultaneously, I use weights from the latest wave.

[58]Appendix Table S5 presents the OLS regression coefficients with a different definition of neighborhood quality and parental time variables. Results are robust to definition changes.

[59]The results are robust to the use of alternative proxies for parental inputs. See Appendix Table S5.

[60]Not displayed in the table, the coefficient of parents' education is positive and significant, which is consistent with the educational gradient in childcare time observed in ATUS.

Table S4: Parental Time and Neighborhood Quality, Add-Health 1994-1995 and 2016-2018

	College Graduation 2016-2018		Parental Time 1994-1995		Neighborhood (std) 2016-2018	
	(1)	(2)	(3)	(4)	(5)	(6)
Neighborhood (std)	0.56***		0.212***	0.078***	0.146***	0.111**
1994-1995	(0.012)		(0.03)	(0.028)	(0.038)	(0.043)
Parental Time		0.031***				
1994-1995		(0.006)				
Race						0.08
						(0.051)
Controls:						
Childhood SES	yes	yes	no	yes	yes	yes
Adulthood SES	no	no	no	no	no	yes
Same decile census tract	no	no	no	no	yes	yes
School ID FE	yes	yes	yes	yes	no	no
Commuting zone FE	no	no	no	no	yes	yes
No. of obs.	8,518	8,543	17,102	12,633	7,982	6,064
Clusters	101	101	120	105	97	90

Notes: This table provides between parental investment choices and college graduation (Columns (1) and (2)) correlations between parental investment choices (Columns (2) and (3)) and between childhood and adulthood neighborhood quality (Columns (5) and (6)). Socioeconomic status variables are family income, highest education level, and marital status. See Appendix Section C.1.2 for details on variable construction. The dependent variables are indicated in the column title. All regressions control for age fixed effects. All observations are weighted by Wave specific sample weights provided by AddHealth. Standard errors displayed in brackets are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

time and neighborhoods, but Agostinelli (2018) and Agostinelli et al. (2022)'s calibrated models imply that parental time and environment quality are substitute inputs in producing children's skills. To the best of my knowledge, all empirical estimates of the relationship between parental time and environment quality suggest that they are substitutes (Kling et al., 2001; Pop-Eleches and Urquiola, 2013; Das et al., 2013; Kiessling, 2021).

C.3.2 Childhood Neighborhood and Adulthood Choices

The second testable implication of the mechanism is that childhood neighborhood quality and later parental decisions, including neighborhood quality, are positively correlated due to social learning. In poor (wealthy) neighborhoods, I expect children to become pessimistic (over-optimistic) about parenting and later on to under-(over-)invest in their own child's human capital. In the data, childhood neighborhood quality should be positively correlated with later neighborhood choices.

Column (5) of Table S4 displays a positive and significant correlation between childhood (Wave I) and adulthood (Wave V) neighborhood quality. I restrict the sample to interviewees who do not live with their parents and control for commuting zone and age fixed effects. The correlation remains highly significant even after controlling for household income, marital status, and education status. Other factors might affect residential choices. Racial discrimination and wealth are two of them. In Column (6) of Table S4, to proxy for inherited wealth, I control for three variables measuring the parents' socioeconomic status: parents' highest level of education, family income, and parents' marital status. In addition, I control for the race of the interviewee.[61] The coefficient of relationships between neighborhood qualities barely decreases and remains highly significant. Interestingly, the race coefficient is insignificant, suggesting that race is not the main driver of residential quality choices after controlling for neighborhood quality.[62]

Neither of the two testable implications of the model is rejected. Combined with the extensive literature on subjective beliefs and the great fit of the calibrated model, this suggestive evidence supports the plausibility of the social learning mechanism.

[61] The variable is one if the race is white, zero otherwise.

[62] The results are robust to the use of the fraction of adults with a college degree for neighborhood quality. See Appendix Table S5.

C.3.3 Robustness checks

As a robustness check, I proxy neighborhood quality by the share of residents above 25 with a college degree (Diamond, 2016). In addition, the proxy of parental time is a count of parent-child activities excluding "went to a movie, play, museum, concert, or sports event".[63] Results are unchanged.

Table S5: Parental Time and Neighborhood Quality, Add-Health 1994-1995 and 2016-2018

	College Graduation 2016-2018		Parental Time 1994-1995		Neighborhood 2016-2018	
	(1)	(2)	(3)	(4)	(5)	(6)
Neighborhood 1994-1995	0.448***		0.758***	0.451***	0.25***	0.211***
	(0.1)		(0.195)	(0.185)	(0.037)	(0.032)
Parental Time 1994-1995		0.029***				
		(0.007)				
Race						-0.003
						(0.008)
Controls:						
Childhood SES	yes	yes	no	yes	yes	yes
Adulthood SES	no	no	no	no	no	yes
Same decile census tract	no	no	no	no	yes	yes
School ID FE	yes	yes	yes	yes	no	no
Commuting zone FE	no	no	no	no	yes	yes
No. of obs.	8,525	8,543	17,073	12,608	7,952	6,039
Clusters	101	101	120	105	97	90

Notes: This table provides between parental investment choices and college graduation (Columns (1) and (2)) correlations between parental investment choices (Columns (2) and (3)) and between childhood and adulthood neighborhood quality (Columns (5) and (6)). Socioeconomic status variables are family income, highest education level, and marital status. See Appendix Section C.1.2 for details on variable construction. The dependent variables are indicated in the column title. All regressions control for age fixed effects. All observations are weighted by Wave specific sample weights provided by AddHealth. Standard errors displayed in brackets are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01.

[63] The remaining seven activities are: "played a sport", "talked about someone you're dating, or a party you went to", "talked about a personal problem you were having", "had a serious argument about your behavior", "talked about your school work or grades", "worked on a project for school", "talked about other things you're doing in school".

C.4 Additional Information on the Calibration

C.4.1 College Graduation

I use AddHealth to estimate the individual probability of having a college degree conditional on parents and child variables. In the sample, anyone with at least a bachelor's degree in Wave V is considered to have a college degree. To proxy for children's realized human capital, I use an average of Wave II (1996) grades in English, mathematics, social science, and science. Information on parents' highest education level and income comes from the parent survey conducted in 1994-1995. Table S6 contains the estimates of the following weighted logit regression of college completion:

$$g(h', y, s) = \frac{1}{1 + \exp(-(\gamma_1 + \gamma_2 rank_{h'} + \gamma_3 rank_y + \gamma_4 s))},$$

where $g(h', y, s)$ is the binary outcome of either graduating college or not in Wave V, $s = 1$ if the highest level of education of the mother is above or equal to a bachelor's degree, $rank_{h'} \in \{1, 2, ..., 10\}$ is the human capital rank proxied by the grade rank in Wave II of the interviewed adolescent in 1996, and $rank_y \in \{1, 2, ..., 10\}$ is the household income rank in 1994-1995.

Table S6: Estimated Parameters of the College Graduation Probability

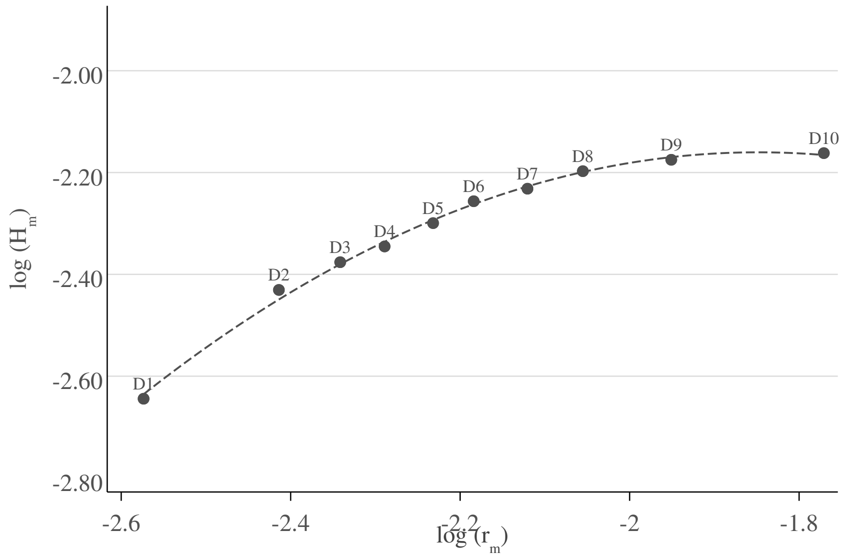
	College graduation probability	
γ_1	-3.83	(0.35)
γ_2	0.35	(0.02)
γ_3	0.15	(0.02)
γ_4	1.11	(0.11)
Pseudo R^2	0.28	

Notes: The table shows the weighted logit regression results. The regression includes county-fixed effects. All observations are weighted. Robust standard errors are in parenthesis. These are all the estimated parameters. Source: Add Health.

C.4.2 Housing Supply

Rental prices are determined in equilibrium given the supply function: $\mathcal{H}_m = \zeta_m r_m^{\eta}$, where r_m is the equilibrium rent price in the neighborhood m, and η is the price elasticity of housing supply. Saiz (2010) estimates population-weighted average price elasticity in the average

Figure S1: Housing Supply



Notes: The dots display log rent prices and log density for each of the ten synthetic neighborhoods. The dash-line is a quadratic fit. Source: NHGIS.

metropolitan area of the U.S. to be 1.75, so I set $\eta = 1.75$. The remaining parameters ζ_m can be estimated directly from the synthetic neighborhood density and rents. Figure S1 summarizes the log-relationship between density (Column (5) Table S2) and rents across the ten synthetic neighborhoods. Without loss of generality, the numeraire is the average household earnings in the economy.

C.4.3 Moments

Intergenerational residential mobility:

Figure 2: To create Figure 2, I use waves I (1994-1995) and V (2016-2018) of the Add Health survey. For each of the ten childhood synthetic neighborhood, I compute the share of children in each of the ten adulthood synthetic neighborhood (wave V).

Targeted moments:

Table S7: Moments Description

Moment	Description	Data restriction	Source
Earnings			
Average rent over income	Ratio of average rent over average household income of families families. The average rent is computed using the density and the rent prices in each of the ten neighborhoods in Table S2.	100 biggest commuting zones - families with a own child below 18	ACS 2000, NHGIS 2000
Earnings ratio non-college - college	Household income of non-college parents over household income of college parents.	100 biggest commuting zones - families with a own child below 18	ACS 2000
Income Gini [inequality]	Families' income Gini, transformed in a 20 years Gini using the 2002 Shorrocks mobiliy index estimated by Kopczuk et al. (2010).	100 biggest commuting zones - families with a own child below 18	ACS 2000

Avg. marginal income tax	Average in the population of the marginal income tax that can be written as $1 - \lambda_y * (1 - \tau_y) * y^{-\tau_y}$.		Urban & Brookings Tax Policy Center.
Residential mobility			
Census tract Gini [segregation]	Gini coefficient across the ten synthetic neighborhoods household median income.	100 biggest commuting zones - families with a own child below 18	NHGIS 2000
Neighborhood effect (25th pct.)	For families with below-median income (p = 25). Simulate moves to every neighborhoods. Regress children's income on fixed effects for each neighborhood controlling for origin-by-destination fixed effects.	Tax records covering the U.S. population, spanning 1996-2012. 100 biggest commuting zones (CZ). Within CZ estimates. The authors use income ranks at age 26 because of outliers. In addition, they control for the fraction of childhood spent in a county.	Chetty and Hendren (2018a)
Neighborhood effect (75th pct.)	For families with above-median income (p = 75). Simulate moves to every neighborhoods. Regress children's income on fixed effects for each neighborhood controlling for origin-by-destination fixed effects.	Tax records covering the U.S. population, spanning 1996-2012. 100 biggest commuting zones (CZ). Within CZ estimates. The authors use income ranks at age 26 because of outliers. In addition, they control for the fraction of childhood spent in a county.	Chetty and Hendren (2018a)

Residential immobility (D1)	Fraction of children born in the first synthetic neighborhood who live in this same neighborhood when they are adults.	1994-2018. Interviewees who do not live in their parent's houses in adulthood (2018).	AddHealth Wave I and Wave V
Explained share place-based effects by demographics	One minus ratio of variance of neighborhood effects (25th pct.) without demographics effects over variance of neighborhood effects (25th pct.) with demographics effects.	Variance explanation of neighborhood effects (25th pct.) of all observed demographics factors. Tax records covering the U.S. population, spanning 1996-2012. 100 biggest commuting zones (CZ). Within CZ estimates. The authors use income ranks at age 26 because of outliers. In addition, they control for the fraction of childhood spent in a county.	Chetty and Hendren (2018a)
Rent price gradient	Regression coefficient of rent on neighborhood rank.	100 biggest commuting zones - families with a own child below 18	NHGIS 2000
Social mobility			
Rank-rank coefficient	Regression coefficient of child household income rank on parental household income rank.	Tax records covering the U.S. population, spanning 1996-2012.	Chetty et al. (2014)
Parental time			
Income gradient in parental time	Regression coefficient of parental time on income quartile of the parents.	Two-parent households with a own child below 18. Weighted. Additional controls on gender, child age, number of children, and date of interview.	ATUS 2003

Ratio parental time by education	Parental time of non-college parents over parental time of college parents	Two-parent households with a own child below 18. Weighted. Additional controls on gender, child age, number of children, and date of interview.	ATUS 2003
Parental time non-college parents	Average parental time of non-college parents.	Two-parent households with a own child below 18. Weighted.	ATUS 2003

D Alternative Modeling

D.1 Perfect Information Model

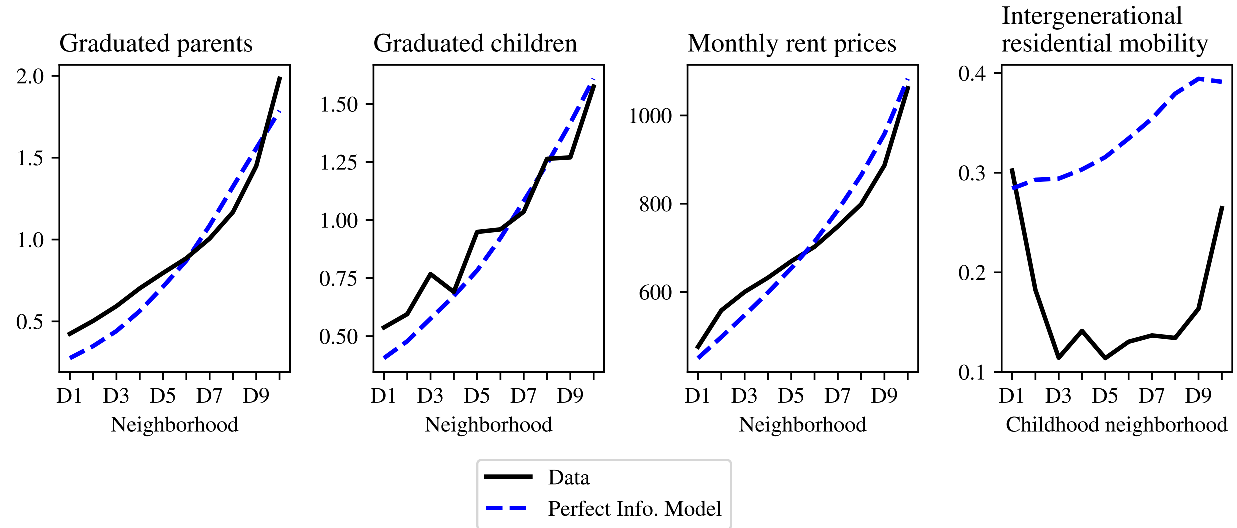
This section describes the calibration of a model with perfect information ($\pi = 0$).

Table S8: Internally Calibrated Parameters Assuming Perfect Information

Parameter	Description	Moment	Data	Model
Preferences and Labor Market				
$b = 0.48$	Altruism	Average rent over income	0.117	0.121
$\kappa = 0.6$	Parental time disutility	Parental time non-college parents	0.075	0.075
$\iota = 0.0001$	Place of birth preference	Residential immobility (D1)	0.302	0.284
$\omega = 0.01$	College wage premium	Earnings ratio non-college - college	0.554	0.563
$\lambda_y = 0.73$	Tax function scalar	Avg. marginal income tax rate	0.351	0.337
Neighborhoods				
$\sigma_m = 0.12$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.051
$\nu = 0.015$	Taste shock variance	Census tract Gini	0.231	0.224
$\xi = 0.19$	Demographics on quality	Chetty estimates	0.24	0.239
$\delta = 0.015$	Amenities	Rent price gradient	54.2	67.4
Skill Formation: $h' = \left(\left(\gamma\ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}}\ +\ \underline{i}\right)^{\alpha} h^{1-\alpha}\ \exp(a')$ with $a' \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0.72$	Parental inputs elasticity	Rank-rank coefficient (IGE)	0.341	0.332
$\gamma = 0.45$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.046
$\varphi = -5$	Substitutability	Income gradient in parental time	0.14	0.084
$\sigma_a = 0.55$	Ability shock variance	Income Gini	0.336	0.326
Heterogeneous Parental Behavior				
		Ratio parental time by education	0.75	0.948
$\pi = 0$	Cognitive bias strength	Neighborhood quality correlation	0.417	0.32

Notes: This table reports the internally calibrated parameters assuming perfect information ($\pi = 0$) and the observed and simulated moments associated with the parameter estimates.

Figure S2: Non-Targeted Moments by Neighborhood - Perfect Information Model ($\pi = 0$)



Notes: This Figure shows four non-targeted moments across neighborhoods: the share of graduated parents and children, rent prices, and intergenerational residential mobility, which represents the share of children who, in adulthood, choose to live in the type of neighborhood as their parents. The solid line shows the data moments, and the dashed line shows the model-simulated analogs. Data Source: NHGIS & Add Health; see Appendix for details of data construction.

D.2 Perfect Information Model with Heterogeneity

This section describes the calibration of a model with perfect information but with heterogeneous preferences. Parents' preferences feature a heterogeneous time disutility parameter by education, and I assume a quadratic moving cost function. Parents' preferences take the following forms:

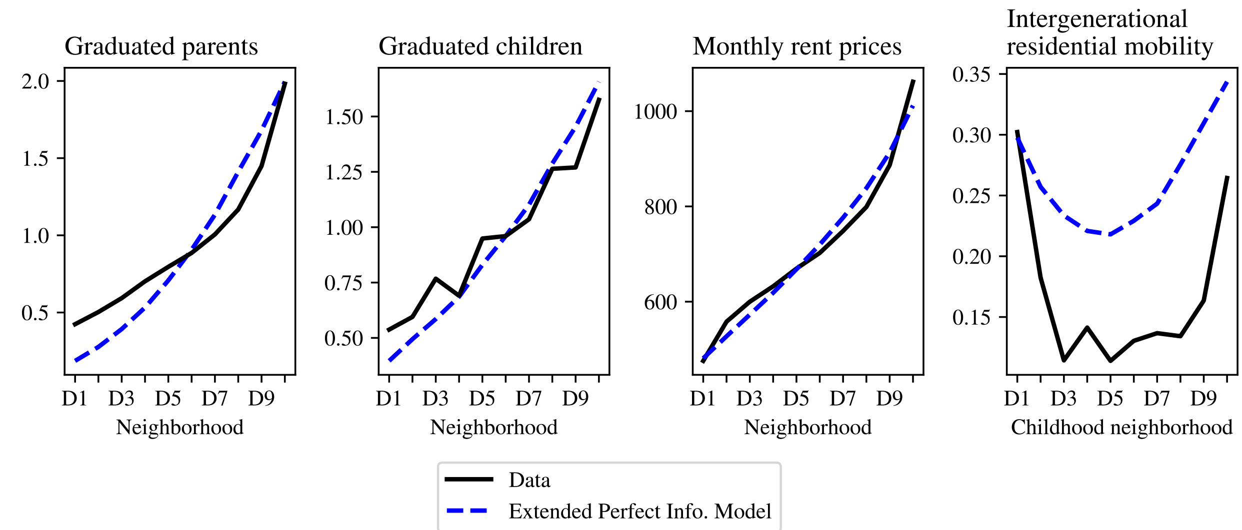
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa_s\, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \delta\, rank_m + \iota_0\, \mathbb{1}_{m_0 = m} - \iota_1 (m_0 - m)^2 + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right],$$

Table S9: Internally Calibrated Parameters - Extended Model with Perfect Information

Parameter	Description	Moment	Data	Model
Preferences and Labor Market				
$b = 0.45$	Altruism	Average rent over income	0.117	0.118
$\kappa_0 = 0.6$	Parental time disutility	Parental time non-college parents	0.075	0.077
$\iota_0 = 0.012$	Place of birth preference	Residential immobility (D1)	0.302	0.298
$\omega = 0.01$	College wage premium	Earnings ratio non-college - college	0.554	0.556
$\lambda_y = 0.73$	Tax function scalar	Avg. marginal income tax rate	0.351	0.337
Neighborhoods				
$\sigma_m = 0.12$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.051
$\nu = 0.015$	Taste shock variance	Census tract Gini	0.231	0.214
$\xi = 0.21$	Demographics on quality	Chetty estimates	0.24	0.259
$\delta = 0.012$	Amenities	Rent price gradient	54.2	56.5
Skill Formation: $h' = \left(\left(\gamma\ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}}\ +\ \underline{i} \right)^{\alpha}\ h^{1-\alpha}\ \exp(a')$ with $a' \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0.72$	Parental inputs elasticity	Rank-rank coefficient (IGE)	0.341	0.344
$\gamma = 0.45$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.048
$\varphi = -5$	Substitutability	Income gradient in parental time	0.14	0.131
$\sigma_a = 0.55$	Ability shock variance	Income Gini	0.336	0.327
Heterogeneous Parental Behavior				
$\kappa_1 = 0.42$		Ratio parental time by education	0.75	0.793
$\iota_1 = 0.0004$	Cognitive bias strength	Neighborhood quality correlation	0.417	0.445

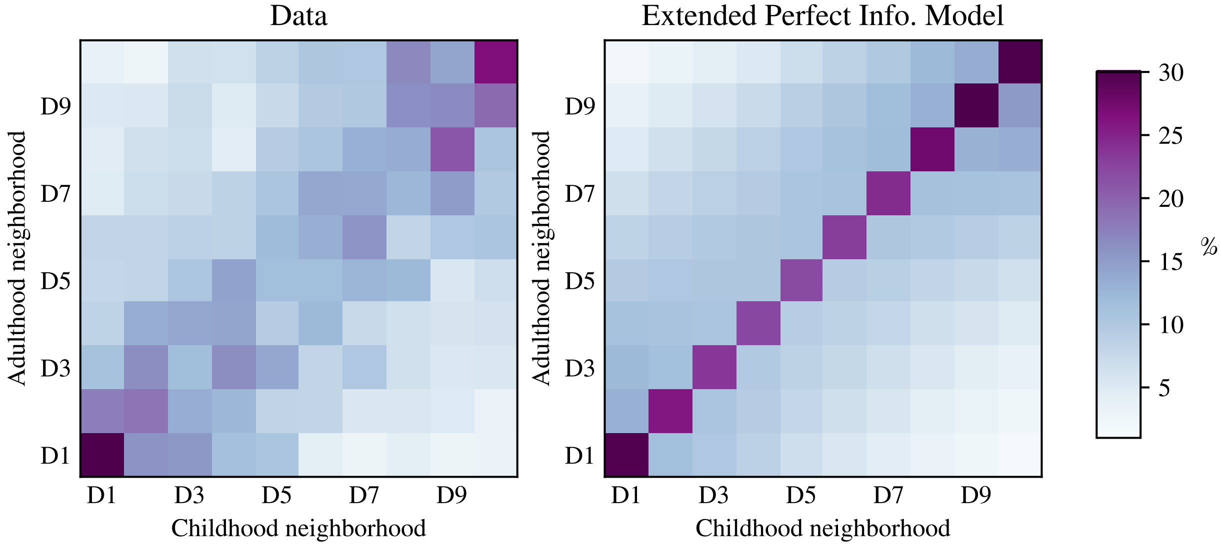
Notes: This table reports the internally calibrated parameters of the extended alternative model with perfect information ($\pi = 0$) and the observed and simulated moments associated with the parameter estimates.

Figure S3: Non-Targeted Moments by Neighborhood - Extended Perfect Information Model ($\pi = 0$)



Notes: This Figure shows four non-targeted moments across neighborhoods: the share of graduated parents and children, rent prices, and intergenerational residential mobility, which represents the share of children who, in adulthood, choose to live in the type of neighborhood as their parents. The solid line shows the data moments, and the dashed line shows the model-simulated analogs. Data Source: NHGIS & Add Health; see Appendix for details of data construction.

Figure S4: Non-targeted Moments: Detailed Residential Mobility - Extended Perfect Information Model ($\pi = 0$)



Notes: This Figure shows residential mobility between childhood and adulthood in the data (left panel), and their model simulates analogs (right panel). The x-axis contains the ten synthetic childhood neighborhoods, and the y-axis is the ten synthetic adulthood neighborhoods. The frequency of moves is represented by cell colors, with larger values in darker squares—data source: Add Health, see Appendix C.4.3 for details of data construction.

E Theory Appendix

E.1 Modeling a micro-foundation of the selection neglect bias

The strength of the bias π can be micro-founded following Jehiel (2018) who develops a theoretical framework of selection neglect with bounded signals. Assume young agents receive informative but noisy and bounded signals about their adult neighbors' abilities.[64] The signal noisiness could capture the fact that there is no real way to perfectly gauge ability—which can be interpreted as a combination of intelligence and luck—by simply observing people. The signal boundedness would embed the tendency to classify people's abilities within pre-

[64] Jehiel (2018) develops a theoretical framework of entrepreneurial decisions with bounded signals about the quality of businesses and selection based on success. He obtains over-optimism among entrepreneurs in equilibrium.

defined categories.[65] Intelligence tests always have a scale with a predefined minimum and maximum level. The IQ test, for instance, classifies people's Intelligence Quotient between "*very superior*" and "*extremely low.*" Note that the bounds of the signals are the same across neighborhoods. This common scale assumption could be motivated by identical reference points regarding abilities. In every neighborhood, young agents interact with other young agents who are representative of the population with respect to abilities. They can all watch national media and gauge the speaker's ability. In a given neighborhood m, young agents' perception of the average local ability among adults would then be defined by:

$$\bar{\tilde{a}}_m = \int_{-\infty}^{+\infty} \int_{-d}^{d} \tilde{a}\ f(\tilde{a}|a)\ l(a|m)\ d\tilde{a}\ da,$$

while the actual average local ability is:

$$\bar{a}_m = \int_{-\infty}^{+\infty} a\ l(a|m)\ da,$$

where conditional on the shock realization a, the signal realization $\tilde{a}$ is distributed according to the density $f(\cdot|a) = \mathcal{N}(a, \sigma_s)$ with full support in $[-d, d]$ with z, the bound, a real value. The precision of the signal is governed by the signal variance ${\sigma_s}^2$. The distribution of adults' ability in a given neighborhood m is denoted by $l(\cdot|m)$ and results from residential decisions in equilibrium. Note that, because of the bounds, despite the informativeness of the signal, the expected perceived ability is not always equal to the ability. The signal is upward biased whenever the actual ability is below the average ability in the economy ($\forall\ a \leq 0$ then $\mathrm{E}\left[\tilde{a}|a\right] \geq a$), and downward biased whenever the actual ability is above the average ability in the economy ($\forall\ a \geq 0$ then $\mathrm{E}\left[\tilde{a}|a\right] \leq a$). Intuitively, because the conditional signal is bounded, if the realization is closer to one of the bounds, many more high signals will be censored by this bound than by the other.[66] Consequently, in neighborhoods in which the average local ability is below the average ability in the economy, young agents overestimate average local ability (if $\bar{a}_m \leq 0$ then $\bar{a}_m \geq \bar{\tilde{a}}_m$), and conversely if the average local ability is above the average ability in the economy (if $\bar{a}_m \geq 0$ then $\bar{a}_m \leq \bar{\tilde{a}}_m$).

In the limit, if the signal variance (σ_s) tends to zero, or if the bounds (d) tend to infinity, agents' perception about their neighbors' ability shocks would always be equal to the truth and $\bar{\tilde{a}}_m = \bar{a}_m$. Note that at any given level of bounds below infinity, the signal variance ${\sigma_s}^2$

[65] The signal can be thought of as continuous or discrete. For computational reasons, in practice, every shock is discretized.

[66] See Appendix Figure S5 for an illustration.

governs the precision of the perceived local ability and regulates the strength of the bias in the estimation, which allows a direct mapping with π.

E.2 Proofs

Assume $x \sim \mathcal{N}(\overline{\mu}, \sigma_s^2)$ and define the function $\text{bound}(x, d) := x\mathbb{1}_{\{-d \leq x \leq d\}} + d\mathbb{1}_{\{x>d\}} - d\mathbb{1}_{\{x<d\}}$.

Let $d > 0$ constant and $y := \text{bound}(x, d)$. Let Φ the CDF of the standard normal distribution and ϕ the PDF of the standard normal distribution.

Then it holds:

1. If $\overline{\mu} \geq 0$ then $\mathbb{E}(y) \geq 0$ and if $\overline{\mu} \leq 0$ then $\mathbb{E}(y) \leq 0$
2. If $\overline{\mu} \geq 0$ then $\mathbb{E}(y) \leq \overline{\mu}$ and if $\overline{\mu} \leq 0$ then $\mathbb{E}(y) \geq \overline{\mu}$
3. $\lim_{\sigma_s \to 0} \mathbb{E}(y) = \overline{\mu}$ and $\lim_{d \to +\infty} \mathbb{E}(y) = \overline{\mu}$
4. $\lim_{\sigma_s \to +\infty} \mathbb{E}(y) = 0$

Figure S5 illustrates a conditional signal distribution of y given $d > \overline{\mu} > 0$.

Preliminary common results for (1)-(4):

Assume $\overline{\mu} \geq 0$

(a) Let

$$\mathbb{E}(y) = \int_{-d}^{d} \frac{u}{\sigma_s} \, \phi\left(\frac{u - \overline{\mu}}{\sigma_s}\right) \, du + d \, \left(1 - \Phi\left(\frac{d - \overline{\mu}}{\sigma_s}\right)\right) - d \, \Phi\left(\frac{-d - \overline{\mu}}{\sigma_s}\right)$$

(b) Let $u = v + \overline{\mu}$. By properties of the Gaussian distribution, $\forall u \geq 0$ $\phi(v) = \phi(-v)$ and $\phi(v) \geq \phi(-v - 2\overline{\mu})$ or $\phi(u - \overline{\mu}) = \phi(-u + \overline{\mu})$ and $\phi(u - \overline{\mu}) \geq \phi(-u - \overline{\mu})$

(c) Let

$$\begin{aligned}
\mathbb{E}(x) &= \int_{-\infty}^{\infty} \frac{u}{\sigma_s} \, \phi\left(\frac{u - \overline{\mu}}{\sigma_s}\right) \, du \\
&= \int_{-d}^{d+2\overline{\mu}} \frac{u}{\sigma_s} \, \phi\left(\frac{u - \overline{\mu}}{\sigma_s}\right) \, du \; + \; (d + 2\overline{\mu}) \, \left(1 - \Phi\left(\frac{d + \overline{\mu}}{\sigma_s}\right)\right) - d \, \Phi\left(\frac{-d - \overline{\mu}}{\sigma_s}\right) \\
&= \overline{\mu}
\end{aligned}$$

Proof. (1) Assume $\overline{\mu} \geq 0$. By (b),

$$\int_0^d \frac{1}{\sigma_s}\, u\, \phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\, du \;\geq\; \left|\int_0^d \frac{1}{\sigma_s}\, (-u)\, \phi\left(\frac{-u-\overline{x}}{\sigma_s}\right)\, du\right| \;=\; \left|\int_{-d}^0 \frac{1}{\sigma_s}\, u\, \phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\, du\right|$$

and

$$\left(1-\Phi\left(\frac{d-\overline{x}}{\sigma_s}\right)\right) \;\geq\; \Phi\left(\frac{-d-\overline{x}}{\sigma_s}\right) \geq 0$$

Hence, by (a), $\mathbb{E}(y) \geq 0$.

By the symmetry of the Gaussian distribution, if $\overline{\mu} \leq 0 \;\Rightarrow\; \mathbb{E}(y) \leq 0$. $\square$

(2) Assume $\overline{\mu} \geq 0$. By (c),

$$\begin{aligned}
\overline{\mu} &= \int_{-d}^{d} \frac{u}{\sigma_s}\, \phi\left(\frac{u-\overline{\mu}}{\sigma_s}\right)\, du \;+\; \int_{d}^{d+2\overline{\mu}} \frac{u}{\sigma_s}\, \phi\left(\frac{u-\overline{\mu}}{\sigma_s}\right)\, du \\
&\quad - \; d\, \Phi\left(\frac{-d-\overline{\mu}}{\sigma_s}\right) \;+\; (d+2\overline{\mu})\, \left(1-\Phi\left(\frac{d+\overline{\mu}}{\sigma_s}\right)\right) \\
&\geq \int_{-d}^{d} \frac{u}{\sigma_s}\, \phi\left(\frac{u-\overline{\mu}}{\sigma_s}\right)\, du \;+\; d\, \left(1-\Phi\left(\frac{d-\overline{\mu}}{\sigma_s}\right) - \left(1-\Phi\left(\frac{d+\overline{\mu}}{\sigma_s}\right)\right)\right) \\
&\quad - \; d\, \Phi\left(\frac{-d-\overline{\mu}}{\sigma_s}\right) \;+\; (d+2\overline{\mu})\, \left(1-\Phi\left(\frac{d+\overline{\mu}}{\sigma_s}\right)\right) \\
&= \int_{-d}^{d} \frac{u}{\sigma_s}\, \phi\left(\frac{u-\overline{\mu}}{\sigma_s}\right)\, du \;+\; d\, \left(1-\Phi\left(\frac{d-\overline{\mu}}{\sigma_s}\right)\right) \\
&\quad - \; d\, \Phi\left(\frac{-d-\overline{\mu}}{\sigma_s}\right) \;+\; 2\overline{\mu}\, \left(1-\Phi\left(\frac{d+\overline{\mu}}{\sigma_s}\right)\right) \\
&= \mathbb{E}(y) + \; 2\overline{\mu}\, \left(1-\Phi\left(\frac{d+\overline{\mu}}{\sigma_s}\right)\right) \qquad \text{(by (a))} \\
&\geq \mathbb{E}(y)
\end{aligned}$$

Hence, $\mathbb{E}(y) \leq \overline{\mu}$.

By the symmetry of the Gaussian distribution, if $\overline{\mu} \leq 0 \;\Rightarrow\; \mathbb{E}(y) \geq \overline{\mu}$. $\square$

(3) Note $\lim_{x\to+\infty} \Phi(x) = 1$ and $\lim_{x\to+\infty} \Phi(-x) = 0$. By (a)

$$\lim_{d\to+\infty} \mathbb{E}(y) = \overline{\mu}$$

Trivially,

$$\lim_{\sigma_s \to 0} \mathbb{E}(y) = \overline{\mu}$$

$\square$

(4) Note $\lim_{\sigma_s \to +\infty} \int_{-d}^{d} \frac{u}{\sigma_s} \phi\left(\frac{u-\overline{\mu}}{\sigma_s}\right) du = 0$ and $lim_{\sigma_s \to +\infty} \Phi\left(\frac{d-\overline{\mu}}{\sigma_s}\right) = 0.5.$

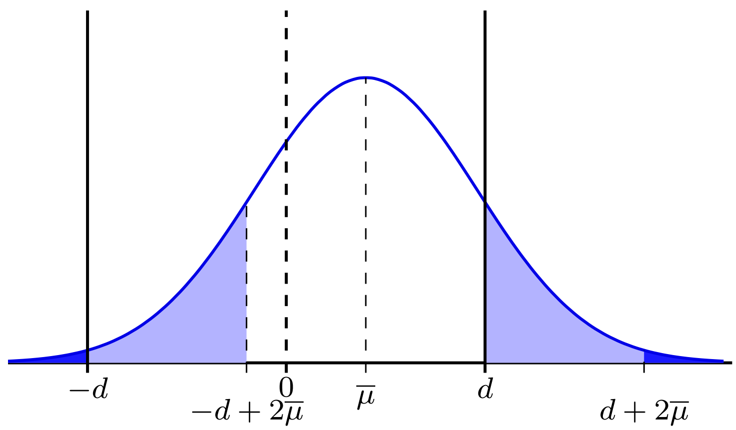
By (a)

$$\lim_{\sigma_s \to +\infty} \mathbb{E}(y) = 0$$

.

$\square$

Figure S5: Signal Illustration



Notes: This Figure illustrates a conditional signal distribution of y given $d > \overline{\mu} > 0$.