Residential and Social Mobility: A Quantitative Analysis of Parental Decisions with Social Learning *

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Abstract

In the U.S., parental beliefs and decisions differ across socioeconomic groups. Using an overlapping generations framework, this paper introduces a social learning mechanism where young adults learn from observing older neighbors but may make misinferences due to imperfect corrections for selection. Calibrated to the U.S., the model implies that residential segregation creates information frictions, causing low-income parents to under-invest and high-income parents to over-invest in their children, increasing income inequality by 3% and reducing social mobility by 15%. Housing voucher policies that greatly reduce segregation enhance welfare and mobility, whereas policies with mild reductions may harm welfare despite improving mobility.

Keywords: Macroeconomics, Family, Human Capital, Learning, Neighborhood

JEL classification: E24, E7, D13, D83, J13, R2

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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 lower-quality 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.[2] 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, and selection neglect—the imperfect ability to correct for selection—an experimentally documented cognitive bias.[3]

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 fu-

[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] See Guryan et al. (2008) for a discussion.

[3] Frick et al. (2022) theoretically show that selection neglect combined with strategic interactions can lead to stable equilibria with polarization, and Enke (2020) experimentally documents selection neglect bias. This cognitive bias is sometimes called "assortativity neglect."

ture 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 on the unobserved ability shocks and, with selection on those unobservables, are prone to erroneous inferences. For example, suppose local ability shocks are higher than young agents perceive. In that case, young agents underestimate local shocks. They will wrongly attribute part of the local human capital due to local shocks to parental input decisions, overestimating the elasticity parameter value. Conversely, if local ability shocks are lower than 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.

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.[4] In addition, it targets causal estimates of neighborhood effects on children's future income and social

[4]Ruggles et al. (2023); Manson et al. (2022). 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.

mobility from the literature.[5] A key challenge is the lack of data on parental beliefs across neighborhoods, precluding their use as targeted moments. To overcome this difficulty and discipline the model's parental beliefs, I employ parental time and neighborhood quality choices across socioeconomic groups in the ATUS and Add Health data.[6]

The calibration results indicate a positive parameter for selection neglect bias, suggesting that residential segregation creates information frictions that drive heterogeneous parental beliefs and distorted parental decisions. In equilibrium, these endogenous parental beliefs vary across socioeconomic groups and persist within families, leading to a self-fulfilling equilibrium with a stable distribution of beliefs. The underlying mechanism is as follows: equilibrium residential choices are partly influenced by unobserved ability shocks, which affect parents' human capital and, consequently, their budget constraints. This creates a positive correlation between these shocks and neighborhood quality, which young adults fail to fully perceive. Consequently, young adults tend to underestimate the relevance of parental input in low-quality neighborhoods and overestimate it in high-quality ones. In low-quality neighborhoods, young adults, therefore, receive low levels of parental input, dampening their future income, and low signals regarding the relevance of parental input, dampening their beliefs. As adults, they are likely to choose similarly low-quality neighborhoods, perpetuating this cycle for their children. The opposite occurs in high-quality neighborhoods. As a result, in equilibrium, low-income parents tend to under-invest in their children, while high-income parents tend to over-invest in them. Without assuming preference heterogeneity, the calibrated model explains why many parents who grew up in disadvantaged neighborhoods choose similar environments for their children and why college-educated parents, despite longer working hours, allocate more time to their children's education than non-college-educated parents.

First, I use the calibrated model to explore the channel of parental beliefs quantitatively. Results are two-fold: (i) heterogeneous parental beliefs have sizable effects on the economy

[5]Estimates are taken from estimated by Chetty and Hendren (2018b) and Chetty et al. (2014)
[6]Hofferth et al. (2020) and Harris et al. (2019).

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' input by 12.3% and decreases those of high-income parents by 1.4%.[7] The intergenerational rank-rank coefficient, a negative measure of social mobility, decreases by 15.4%, and the Gini index of income, a measure of inequality, by 3%, improving aggregate welfare by 4.9%.

Unsurprisingly, re-calibrating the model while setting the selection neglect parameter to zero results in a poor fit of all the now non-targeted parental behavior moments. To maintain the same set of targeted moments as in the baseline, I modify the model by replacing endogenous parental beliefs with preference heterogeneity, incorporating quadratic moving costs and education-specific parental time disutility parameters. Despite these adjustments, this alternative model still fails to capture untargeted intergenerational residential mobility moments. Only by introducing substantial heterogeneity in preferences for childhood neighborhood types does the alternative model with perfect information fit all moments. However, such large preference heterogeneity is difficult to empirically support. 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 low-income families randomly incentivized to move to higher-quality neighborhoods, the moving to opportunity literature tends to find higher satisfaction rates and willingness to stay among families living in higher-quality neighborhoods.[8]

Second, I use the calibrated model to study the effects of housing vouchers on the United

[7]These figures are consistent with the estimates from Cunha et al. (2013), who elicit the beliefs of disadvantaged African American mothers regarding the elasticity of child development with respect to parental investments. Their findings suggest that shifting median expectations to the lowest estimated elasticity would boost parental investments by 3.6% to 24.3%, with an average increase of 11.6%.

[8]See for instance Bergman et al. (2024).

States economy. Two key model frictions call for policy interventions: first, a friction common to overlapping generation models, parents cannot borrow against their children's future earnings, and second, model-specific frictions, information frictions arising from residential segregation. In the first step, I conduct three field experiments within the model and compare the partial equilibrium effects with empirical estimates from Jacob et al. (2015); Chetty et al. (2016); Bergman et al. (2024). The housing voucher in the model covers the difference between 16% of family income and 60% of median rents.[9] The first experiment targets young adults with income below the tenth percentile, the second adds information about neighborhood quality's impact on children's future human capital, and the third focuses on young adults with income below the third percentile. Although the model predicts higher mobility than observed in empirical studies, likely due to the younger age of the recipients, the partial equilibrium effects of correcting beliefs and improving neighborhood quality align with the empirical literature's estimates.

When scaling up the housing voucher policies to all families below the tenth percentile of the income distribution, general equilibrium effects depend on the policy's effectiveness in reducing residential segregation. I evaluate ten types of vouchers that cover the difference between a fraction Γ_y of income and a fraction Γ_r of the rent in each neighborhood.[10] The more effectively the policy reduces segregation, the greater the resulting improvements in welfare, income, and social mobility, although this would come with a longer transition to the new steady state. Conversely, a policy that only slightly reduces segregation could negatively impact both income and welfare—while potentially enhancing social mobility. Importantly, replacing endogenous parental beliefs with large preference heterogeneity would lead to the opposite conclusion.

[9] To align with historical data, I ensure that the model's housing voucher policy matches the total cost of the historical housing voucher program, achieving similar mobility rates for eligible households in partial equilibrium.

[10] To fix the policy features, specifically the fractions Γ_r and Γ_y, I impose two constraints: (i) the local rent limit must lie between 60% and 90% of the median rent, i.e., $\Gamma_r \in [0.6, 0.9]$, and (ii) in partial equilibrium, the rent in the lowest-quality neighborhood faced by an average eligible household should match the rent level under the historical housing voucher program.

This paper contributes to the macroeconomics literature that studies household heterogeneity and its consequences for aggregate outcomes.[11] 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.[12] 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.[13]

This paper connects residential segregation and social mobility by introducing social learning in a spatial model, contributing to the quantitative spatial economics literature.[14] 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)).[15]

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

[12] 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 have been studied by Yum (2023), who built a heterogeneous-agent overlapping-generations model calibrated to the United States.

[13] 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)).

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

[15] 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

Adding to this literature, this paper endogenizes residential sorting and social learning, resulting in heterogeneous valuations of neighborhood amenities—through parental beliefs—, contributing to the growing literature that considers endogenous neighborhood amenities.[16]

The notion that a neighborhood's demographic composition can influence educational outcomes through social learning has long been discussed (see, for instance, Durlauf (2011)). This paper's contribution lies in developing and calibrating a quantitative model of human capital accumulation that incorporates a social learning process, resulting in a self-fulfilling equilibrium with systematic bias in beliefs.[17] The social learning process primarily builds on Fogli and Veldkamp (2011), who explain geographical and historical variation in the increase of female labor supply by a change in local beliefs while abstracting. Nonetheless, the authors abstract from residential decisions and, hence, systematic and persistent bias in beliefs that this model generates. In a different context, abstracting from residential segregation, Piketty (1995) develops a self-fulfilling equilibrium of effort and social mobility. The author posits that individuals' past experiences shape their beliefs about the relevance of effort for upward mobility, which in turn affects their effort levels. Heterogeneous biased beliefs are stable if they lead individuals to exert effort levels that result in the believed probabilities of upward mobility. Similarly, my model generates a self-fulfilling equilibrium across generations, as parents' residential decisions, on average, provide confirming signals to their children.

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.[18] Social learning is a central channel through

neighborhood choice model with local school funding and can explain 80% of the Black-White college gap in the St. Louis metro area.

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

[17] Roemer and Wets (1994) and Streufert (2000) are two studies that theoretically link beliefs and segregation, although in static settings. While Streufert (2000)'s model suggests the lack of high-income role models could depress schooling years in low-quality neighborhoods, Roemer and Wets (1994) assumes perfect segregation and generate biased beliefs assuming agents linearly extrapolate the actually convex relationship between schooling and the labor market outcomes.

[18] See for instance Attanasio and Kaufmann (2014); Attanasio et al. (2019b); Boneva and Rauh (2016, 2018); Belfield et al. (2019); Caucutt et al. (2017); Dizon-Ross (2019); Jensen (2010); Kaufmann (2014);

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.[19] 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.[20] 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 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.

Wiswall and Zafar (2021)). One exception is Attanasio et al. (2019a) in the UK who does not find a socioeconomic gradient in beliefs.

[19] 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.

[20] 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.

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:

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

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 $\mathcal{N}(0, \sigma_a)$.[21]

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,

[21] 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.

which imposes a parsimonious Cobb-Douglas outer form.[22] Following Kim et al. (2024), the parameter $\underline{i} > 0$ guarantees that every child has a minimal level of baseline human capital.[23] 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 α that governs the relevance of parental inputs. 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:

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

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

[23] This additional parameter also serves a computational purpose. The learning process requires that the logarithm of human capital remains positive. Since there are ex-ante no restrictions on m and τ, which can be very small, the parameter $\underline{i}$ ensures the positivity of the logarithm of human capital.

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 sets are restricted to their neighborhoods. 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. The reasoning behind this assumption is that ability shocks, which, despite being independent of effort, influence future income, reflect innate ability or luck—factors that contribute to intelligence. While diplomas and socioeconomic backgrounds are observable, innate ability is not easily discernible.[24]

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:

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

where $\bar{\bar{a}}_m$ 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.[25] The following equation

[24] Even IQ tests, although often considered more reliable, less subjective, and more valid than personal judgments in measuring intelligence, are subject to criticism (Eysenck, 2018).

[25] 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). Alternatively, the bias could be modeled through learning costs. In this case, π would be an equilibrium parameter where learning is costly, leading agents to optimally weight their guesses toward the population average. Note that this approach requires additional assumptions to justify why the optimal guess is the population average, unless it implicitly assumes

describes the observations and perceptions of every young agent in a given neighborhood m:

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

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:[26]

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

Notice that young agents' inference of the relevance of parental inputs ($\hat{\alpha}_m$) is downward biased if young agents overestimate local ability shocks ($\overline{\tilde{a}}_m \geq \overline{a}_m$). It is upward biased if young agents underestimate local ability shocks ($\overline{\tilde{a}}_m \leq \overline{a}_m$).[27] 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 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.

a form of selection neglect.

[26]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.

[27]If young agents could observe everyone in the economy, or if there were no residential sorting, then $\overline{a} = \overline{a}_m$, making the selection neglect bias irrelevant. In this scenario, or if $\pi = 0$, beliefs would converge toward the truth, as in Fogli and Veldkamp (2011).

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' Income: 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), parents' income, which is pre-tax labor earnings minus taxes plus transfers, is 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: Rents are assumed to be used to pay housing costs such as capital depreciation and maintenance.

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:

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

subject to:

$$c + r_m = \lambda_y \left(w\ h\ (1 + \omega s)\ \overline{\ell_s}\right)^{1-\tau_y}$$

$$\tau \in [0, 1 - \overline{\ell_s}]$$

$$h' = f(\tau,\ m,\ h,\ a'|\tilde{\alpha}), \quad a' \sim \mathcal{N}(0, \sigma_a)$$

$$p(s' = 1) = g(h', h, s),$$

where r_m is the equilibrium rent of neighborhood m, $\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right]$ 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 $\tilde{\alpha}$. 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 $V\left(h, s, m_0, \tilde{\alpha}, m|r_m\right) = \log\left(c_m^*\right) + \frac{\left(1-\overline{\ell_s}-\kappa\,\tau_m^*\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} + \delta\ rank_m + \iota\ \mathbb{1}_{m_0=m} + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right]$ 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

First, I let the discrete distribution for ability shocks to approximate a normal distribution $a \sim \mathcal{N}(0, \sigma_a)$ which I discretize using Tauchen (1986), with a fifteen-point grid. Then, 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 (Ruggles et al., 2023). 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 (Harris et al., 2019).[28] Finally, parents' time use information is taken from the American Time Use Survey (ATUS) 2003 (Hofferth et al., 2020).[29]

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 set the number of neighborhoods N 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

[28] See Appendix Section C.4 for more details on those statistics.

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

deciles of this distribution.[30] I then create one average commuting zone by computing the population-weighted average characteristics of each of the ten neighborhoods.[31]

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 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 median rents.[32]

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 Waves I, II, and V of AddHealth, I estimate 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 the data, $s = 1$ 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 decile in

[30] 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%.

[31] Appendix Table A2 summarizes the ten neighborhoods' characteristics. Notably, the distribution of all households is close to that of households with children. Including childless households in the model would introduce additional complexity by requiring the consideration of floor space, yet it is unlikely to significantly impact housing market dynamics.

[32] Appendix Section C.5 describes the log-relationship between density (Column (5) Table A2) and rents across the ten synthetic neighborhoods. Without loss of generality, the numeraire is the average household earnings in the economy.

1994-1995.[33]

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.[34] 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 exogenous neighborhood quality component is distributed according to $\bar{m} \sim \mathcal{N}(\mu_{\bar{m}}, \sigma_{\bar{m}})$. Appendix Table A6 summarizes the externally calibrated parameters.

3.4 Internally Calibrated Parameters

Table 1 lists the fifteen parameters I calibrate by minimizing the sum of squared percentage differences between data and model-generated moments. The targeted moments include measures of earnings dispersion, social mobility, parental behavior, segregation, and place-based effects.[35] A key challenge is the lack of data on parental beliefs across neighborhoods, precluding their use as targeted moments. To overcome this difficulty, I employ parental behavior across socioeconomic groups to inform and discipline the model's parental beliefs.

Table 1 outlines a correspondence between the calibrated parameters and the data moments. While all parameters influence each moment, certain moments exhibit greater sensitivity to specific parameters.[36] Understanding these intuitive links is informative about the

[33] Appendix Section C.4 provides details on the variable construction, and Appendix Table A4 shows the weighted logit regression estimates.

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

[35] Moments construction and data sources are detailed in Appendix Section C.6.

[36] Appendix Figure A2 illustrates the percentage change in each moment resulting from a 0.1 level increase

Table 1: Internally Calibrated Parameters

Parameter	Description	Moment	Data	Model
Skill Formation: $h' = \left(\left(\gamma \, \left(\frac{\tau}{\overline{T}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi} \right)^{\frac{1}{\varphi}} \, + \, \underline{i} \right)^{\alpha} \; h^{1-\alpha} \; \exp(a') \text{ with } a' \sim \mathcal{N}(0, \sigma_a)$				
$\alpha \;=\; 0.761$	Parental inputs elasticity	Rank-rank coefficient (IGE)	0.341	0.338
$\gamma \;=\; 0.5$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.047
$\varphi \;=\; 0.476$	Substitutability	Income gradient in parental time	0.14	0.13
$\sigma_a \;=\; 0.713$	Ability shock variance	Income Gini	0.333	0.336
Labor Market and Preferences				
$\omega \;=\; 0.044$	College wage premium	Income ratio non-college - college	0.554	0.547
$\lambda_y \;=\; 0.709$	Tax function scalar	Avg. marginal income tax rate	0.351	0.350
$b \;=\; 0.425$	Altruism	Average rent over income	0.117	0.118
$\kappa \;=\; 0.456$	Parental time disutility	Parental time non-college parents	0.075	0.072
$\iota \;=\; 0.0001$	Place of birth preference	Residential immobility (D1)	0.302	0.306
Neighborhoods				
$\sigma_m = \; 0.3$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.06
$\nu \;=\; 0.018$	Taste shock variance	Census tract Gini	0.231	0.219
$\xi \;=\; 0.133$	Demographics effects	Explained share place-based effects	0.24	0.241
$\delta \;=\; 0.007$	Amenities	Rent price gradient	54.2	55.7
Social Learning Process				
$\mu \;=\; 0.506$	Update weight	Neighborhood quality correlation	0.417	0.452
$\pi \;=\; 0.833$	Cognitive bias strength	Ratio parental time by education	0.75	0.792

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

underlying model mechanisms.

The technology of skill formation parameters φ, γ, α, and σ_a influence human capital accumulation, earning dispersion, and parental choices, affecting most targeted moments. Because φ governs the substitutability between a monetary (neighborhood type) and a non-monetary (time) parental input, I associate it with the parental time difference across income groups. Here, I use the regression coefficient of parental time on household income quartiles.[37] With heterogeneous parental beliefs, 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)). The parental timeshare parameter γ captures the respective parental inputs' influence on human capital. I map this parameter with the causal effect of neighborhood quality for a child born in the 75th percentile of the household income distribution estimated by Chetty and Hendren (2018b).[38] It determines how much children's future income rank would increase if they had been growing up in one standard deviation better neighborhood. Finally, the parental human capital share parameter $1-\alpha$ mechanically increases the income correlation between parents and children. Thus, I use the rank-rank coefficient between parental and child earnings estimated by Chetty et al. (2014), an inverse measure of social mobility that captures the income correlation between parents and children, as the relevant moment. Finally, the ability shock standard deviation σ_a captures any earnings variation not explained by parental choices and human capital. 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

in each parameter.

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

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

the 100 biggest commuting zones.[39] I map the income Gini with the ability shock standard deviation σ_a and the earnings gap between college and non-college parents with the college wage premium ω. More straightforward is the tax function scalar λ_y that is tightly linked to the average marginal tax rate.[40]

The preference parameters b, κ, and ι, together with the neighborhood parameters σ_m, ν, and ξ, govern parents' input choices and the model geography—which are also affected by the skill formation technology parameters. The parental time disutility parameter κ directly affects parental time choice. It is pinned down by the fraction of time allocated to parental time by non-college parents computed from ATUS.[41] The altruism parameter b affects all parental choices, including the share of income spent on rent, so I include the slope in monthly rent prices across neighborhood types as a moment.The preference for place of birth ι influences the share of adults who live in the neighborhood type they grew up in. It is pinned down by a moment labeled "residential immobility (D1)". It is defined as the fraction of children born in the worst synthetic neighborhood who choose to live in the same synthetic neighborhood in adulthood.

Regarding the model geography, the standard deviation σ_m affects the exogenous part of the neighborhood quality distribution ($\{m\}$) that directly enters the child skill production function. Consequently, it influences how much a child's earnings are affected by neighborhood choices. I use a similar moment for calibrating γ, namely the causal effect of neighborhood quality for a child born in the 25th percentile of the household income distribution measured by Chetty and Hendren (2018b). The taste shock variance ν controls residential moves orthogonal to neighborhood quality and directly affects residential segregation that I measure by the Gini coefficient across the ten neighborhoods in the NHGIS

[39] 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.

[40] I use a 35.1 percent average marginal income tax rate estimated by the Urban & Brookings Tax Policy Center. See `https://www.taxpolicycenter.org/model-estimates/baseline-effective-marginal-tax-rates-allocatedjuly-2016/t16-0114-effective-marginal-tax`.

[41] Appendix Table A3 displays parental time by education.

2000 dataset. Finally, how much the neighborhood quality changes with a change in the demographic composition depends on ξ, calibrated by matching the share of the variance in causal placed-based effects explained by observable characteristics estimated by Chetty and Hendren (2018b) (24%).[42]

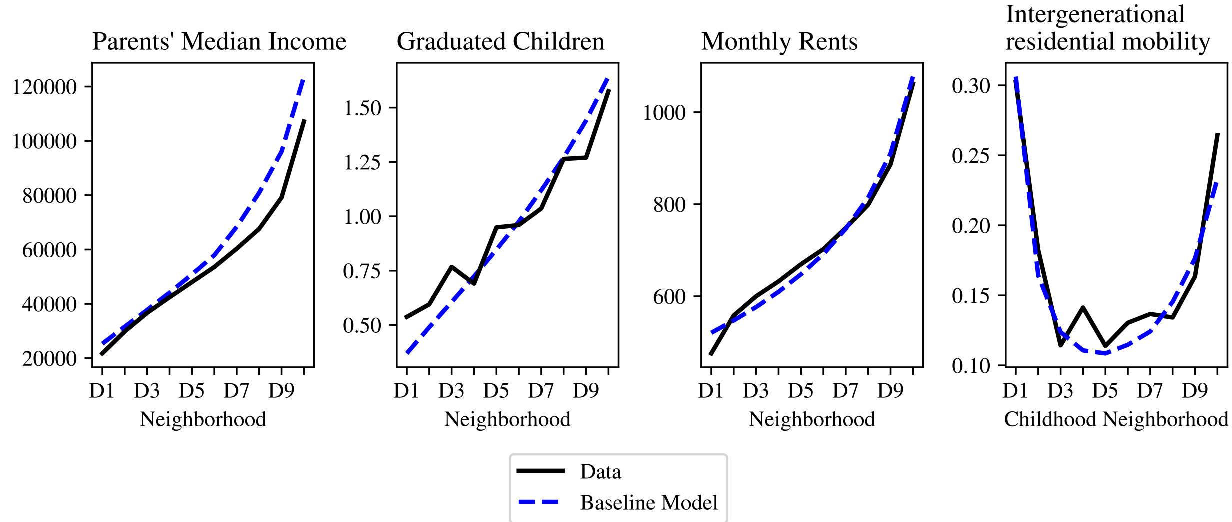
Lastly, I discipline the belief parameters μ and π using additional parental behavior moments. The parameter μ governs the correlation between parents' and children's beliefs. A higher μ generates lower persistence in beliefs and parental behavior within families but a higher influence of neighborhoods on future choices through beliefs. I associate this parameter with the intergenerational correlation in neighborhood types. Parents' neighborhood choices affect children's future neighborhood decisions through earnings and beliefs. Parents' influence on children's earnings is calibrated by matching the rank-rank coefficient and place-based effects, among others. Matching the intergenerational neighborhood correlation ensures a correct discipline of the belief channel. Finally, to discipline the strength of the selection neglect bias (π), I include 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. Notice that π is above zero, suggesting agents face a selection neglect bias and the model's need for 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 mo-

[42]This empirical estimate implies that only a small part of the variance in causal placed-based effects can be attributed to observable characteristics. In the model, this variance is then largely driven by the fixed component, which ensures a unique ordering of neighborhoods.

Figure 1: Non-Targeted Moments by Neighborhood



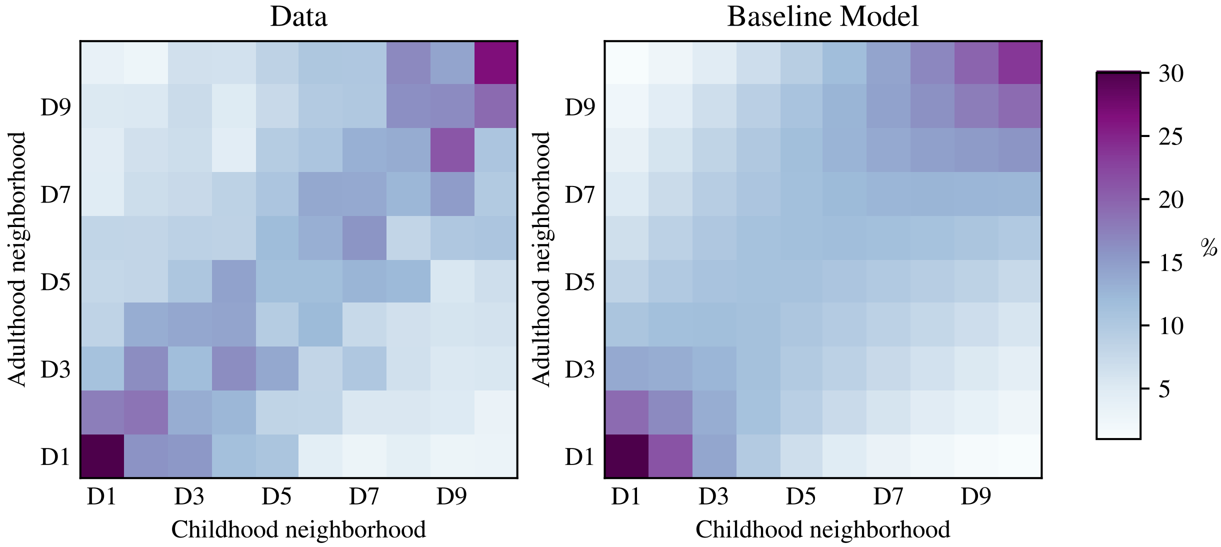
Notes: This Figure shows four non-targeted moments across the ten neighborhood types: median income, the share of graduated children, monthly rents, and intergenerational residential mobility, which represents the share of children who, in adulthood, choose to live in the type of neighborhood as their 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.

bility moments.

The first, second, and third panels of Figure 1 represent median income, the share of graduated children, and monthly rents per neighborhood, respectively. Although none of these moments were directly targeted, income segregation, social mobility, place-based causal effects, and the slope in rents 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

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.6 for details of data construction.

D2 when she becomes an adult, but she is unlikely to live in Neighborhood D7 or above. The calibrated model (right panel) matches the data patterns (left panel) remarkably well. These patterns result from different model mechanisms: intergenerational income mobility and budget constraints, equilibrium rents 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.

It is important to note that the model does not account for wealth accumulation. In the U.S., however, wealth is highly concentrated, and large financial transfers from parents before the age of 45 are uncommon for most of the population. Rodriguez et al. (2002) report that in 1998, 80% of households held almost no wealth, collectively owning less than 20% of the total, while the wealthiest 10% controlled approximately 70% of it. In a recent study, Lee et al. (2020) document that the probability of receiving a parental transfer exceeding

USD 5,000 between the ages of 25 and 44 is about 15% for those in the top quartile of the wealth distribution but falls below 6% for others. These figures suggest that the absence of the wealth channel likely contributes to the model's inability to fully explain the high persistence of neighborhood quality at the top of the distribution—last point of Figure 1 and upper right corner of Figure 2—, though it may have little impact on the rest of the distribution.

3.6 Discussion of the Social Learning Channel

The following sections quantitatively explore the channel of parental beliefs. Specifically, using the calibrated model, I first compare steady states with and without parental beliefs to assess their effects on the U.S. economy. Second, I re-calibrate an alternative model that excludes parental beliefs but introduces preference heterogeneity, examining the extent of heterogeneity required so that this alternative model matches the data.

3.6.1 The Role of Parents' Beliefs

To quantify the effects of parental beliefs on 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.[43] Table 2 presents the percentage differences in outcomes between two economies in steady states: the baseline economy and one imposing perfect information ($\pi = 0$).

Providing full information would lead parents in the bottom quartile of the income distribution to revise their beliefs upward, resulting in a 47.5% increase in parental time and a 12.3% increase in overall parental input. These figures are consistent with the estimates from Cunha et al. (2013), who elicit the beliefs of disadvantaged African American mothers regarding the elasticity of child development with respect to parental investments. Their findings suggest that shifting median expectations to the lowest estimated elasticity would

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

boost parental investments by 3.6% to 24.3%, with an average increase of 11.6%. When considering the higher estimated elasticity, the impact is even more pronounced, with parental investments rising by at least 31.4% and up to 73.3%.

In contrast, parents in the top quartile of the income distribution would adjust their beliefs downward, resulting in reduced levels of parental input. However, this reduction would be less pronounced than the increase observed among parents in the bottom quartile, ultimately leading to higher aggregate parental input (+4.3%) and income (+3.7%).

Due to systematic over- and under-investment behaviors, parents' distorted beliefs reduce social mobility by 15.4% and exacerbate income inequality and absolute poverty by 3% and 21.2%, respectively.[44] With perfect information, aggregate welfare—defined by the consumption equivalence under the veil of ignorance in the baseline economy relative to the counterfactual economy—would increase by 4.9%.[45] In summary, parents' beliefs suggested by the calibrated model have a significant impact on the overall economy, with particularly strong effects on lower-income households.

3.6.2 Alternative Modeling under Perfect Information

The calibrated model implies a positive selection neglect bias parameter ($\pi > 0$), suggesting heterogeneous parental beliefs are needed to replicate data patterns. Unsurprisingly, recalibrating the model imposing perfect information, removing two free parameters ($\pi = 0$ and μ), results in a relatively bad fit for untargeted moments, including parental time by education and neighborhood quality correlation across generations.

I thus introduce preference heterogeneity. First, heterogeneous preferences regarding the parental time disutility parameter and, second, quadratic moving costs. These model-added features provide two extra free parameters that closely relate to parental time by education and neighborhood quality correlation across generations. Parents' preferences

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

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

Table 2: General Equilibrium Effects of Providing Information (% changes)

	All	Income quartile 1st	2nd	3rd	4th
Parental beliefs	+7.6	+45.2	+14.8	+1.3	-11.8
Parental input	+4.3	+12.3	+6.5	+2.7	-1.4
Parental time	+11.6	+47.5	+17.0	+3.6	-9.1
Neighborhood rank	+2.0	+2.3	+5.3	+3.3	+1.5
Income	+3.7	+8.5	+7.0	+5.2	+10.1
Social mobility	+15.4				
Segregation	-0.2				
Income inequality	-3.0				
Absolute poverty	-21.2				
Welfare	+4.9				

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.

take the following form:

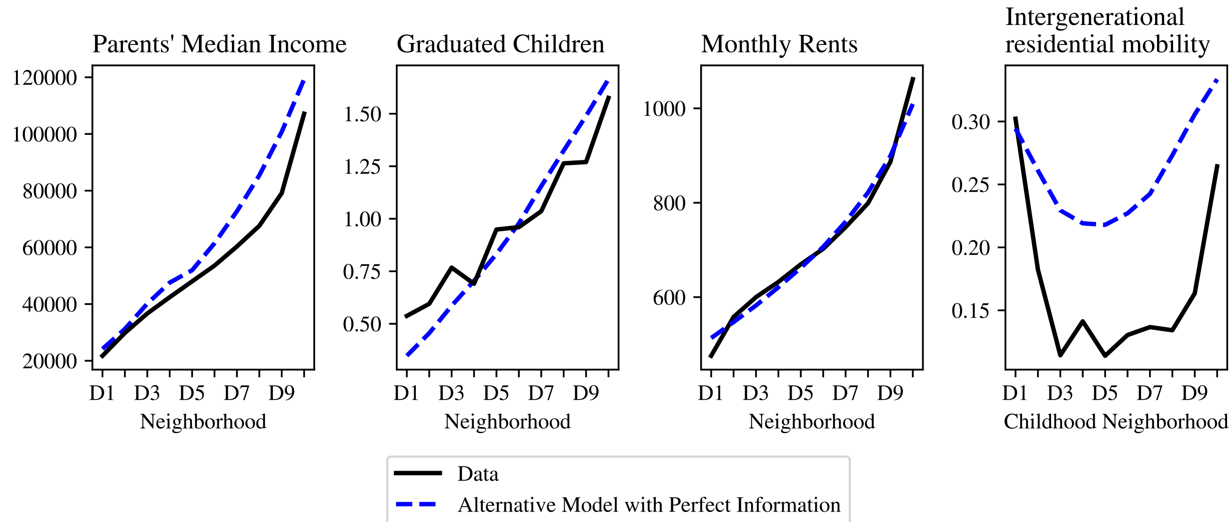
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa_s \, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \delta \; rank_m + \iota \; \mathbb{1}_{m_0 = m} - \tilde{\iota}(m_0 - m)^2 + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right],$$

with k_s, the parental time disutility parameter now depends on the college education status s, capturing a—non-empirically documented—difference in time valuation by education. The quadratic moving costs are governed by $\tilde{\iota}$, 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 alternative version of the model with perfect information matches relatively well all the targeted moments but misses untargeted ones.[46] In particular, as displayed by the

[46] See Appendix Section D.1 for the fit of targeted and additional non-targeted moments.

FIGURE 3: Alternative Model with Perfect Information - Non-Targeted Moments by Neighborhood



Notes: This Figure shows four non-targeted moments across the ten neighborhood types: median income, the share of graduated children, monthly rents, 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 alternative model-simulated analogs. Data Source: NHGIS & Add Health; see Appendix for details of data construction.

last panel of Figure 3, the intergenerational residential mobility moments are off, suggesting other forms of preference heterogeneity are needed.

I then calibrate an extended version of the alternative model with perfect information, achieving a fit comparable to the baseline model. In addition to incorporating quadratic moving costs and variations in time disutility parameters, I introduce a preference for childhood neighborhood that varies by neighborhood type (ι_{m_0}) and include as targeted moments the model-simulated points in the last panel of Figure 1. I find that the preference for childhood neighborhood parameters must be more than forty times higher in the worst neighborhood than in the middle ones to reproduce the U-shaped patterns in intergenerational residential mobility.[47]

While introducing large preference heterogeneity can help match the data, it lacks empirical support. There is no evidence that parental time disutility systematically varies by education level, and the assumption of quadratic moving costs is somewhat ad hoc. Addition-

[47]See Appendix Section D.2 for the fit of targeted and non-targeted moments.

ally, the disproportionately high preference parameter assigned to the worst neighborhoods contradicts empirical evidence, as these areas are often characterized by high crime rates, elevated poverty levels, and limited opportunities for children.[48] Bergman et al. (2024) compare low-income families randomly induced to move to higher-quality neighborhoods or not. Those who move express higher satisfaction rates and willingness to stay than those in the control group—who remain in deprived neighborhoods.[49]

4 Housing Voucher Policies

The baseline model displays two main frictions that motivate government intervention: first, a friction common to overlapping generation models, parents cannot borrow against their children's future earnings, and second, model-specific frictions, information frictions arising from residential segregation. Compared to a scenario with perfect information, the latter frictions lead to lower neighborhood quality for low-income families and higher neighborhood quality for high-income families. This model, therefore, offers a new rationale for housing vouchers—housing subsidies targeted at low-income families—not only as a tool for redistribution but also as a means to mitigate residential segregation and alleviate information frictions.

In this section, I use the quantitative model to study the effects of providing housing vouchers to poor young adults on the U.S. economy. U.S. housing voucher programs typically target extremely low–income families and cover the difference between the rent, up to a limit, and a fraction of the family's income.[50] While public housing agencies used to define the

[48] 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.

[49] Discrimination or a homophily bias could motivate other modeling assumptions. However, the fact that Bergman et al. (2024) 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 A9, 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.

[50] By law, a public housing agencies must provide 75 percent of its voucher to extremely low–income

rent limit by the 40th percentile rent in the metro area, since 2019, those agencies can set the rent limits at local rent levels.

Consistent with U.S. housing voucher programs, I design the housing voucher policy in the model so that it targets low-income families and mimics multiple rent limits at the commuting zone level. Eligible families are those with an income below a relative poverty threshold, defined as the income level at the tenth percentile of the income distribution. Notice that due to the model structure, eligible parents receive the voucher when they reach independence age and must leave their parent's home. In addition, since the model does not feature heterogeneity in rents within neighborhoods, rent limits are determined as a fraction of the neighborhood median rent. In particular, the model's housing vouchers cover the difference between a fraction Γ_r of the neighborhood median rent and a fraction Γ_y of the family's income. The rent that faces an eligible parent of income $y(h,s)$ in neighborhood m is then:

$$r^{HV}_{m,h,s} = r_m - \max(\Gamma_r \, r_m - \Gamma_y \, y(h,s),\ 0).$$

To fix the policy features, specifically the fractions Γ_r and Γ_y, I impose two constraints: (i) the local rent limit must lie between 60% and 90% of the median rent, i.e., $\Gamma_r \in [0.6, 0.9]$, and (ii) in partial equilibrium, the rent in the lowest-quality neighborhood faced by an average eligible household should match the rent level under the historical housing voucher program.[51] Figure 4 displays the rent schedules for an average eligible household across all combinations of fractions meeting these constraints alongside the historical housing voucher program.[52] Notably, while rent schedules are smooth under policies with local rent limits,

applicants. The 2014 Consolidated Appropriations Act (Section 238 on page 128 Stat 635) defines extremely low–income as very low–income families whose incomes do not exceed the higher of the Federal poverty level or 30% of area median income. https://www.huduser.gov/portal/datasets/HOME-Income-limits.html

[51]The historical housing voucher covers the difference between 30% of the family's income and the rent up to the 40th percentile rent in the commuting zone, the rent that faces an eligible parent of income $y(h,s)$ in neighborhood m was:

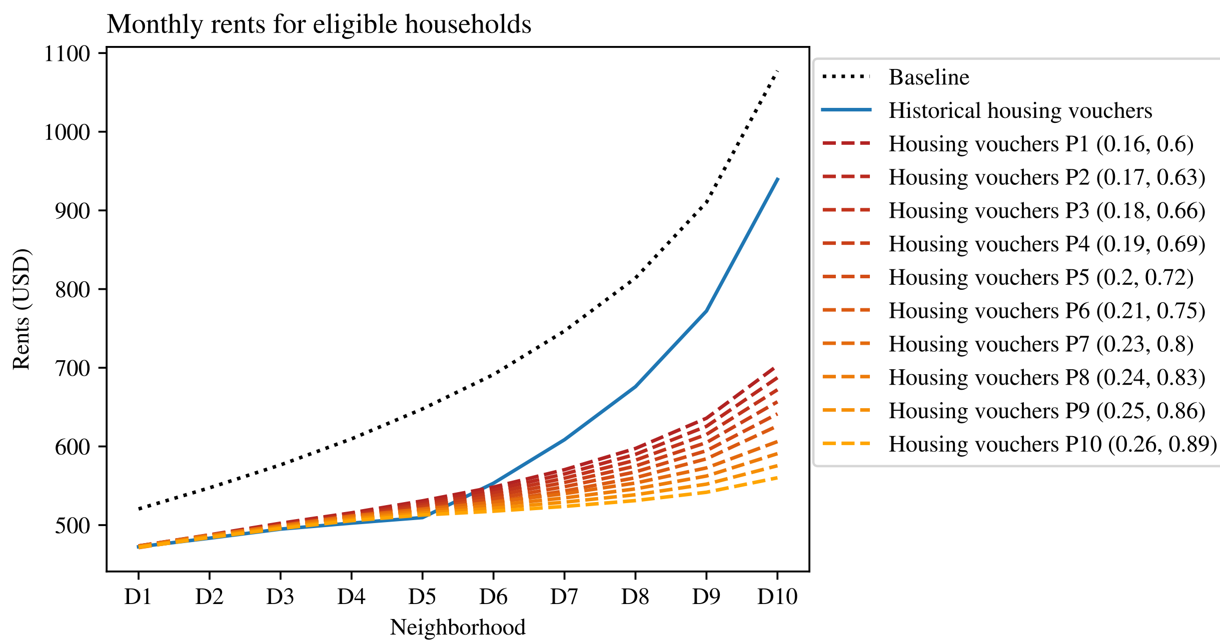
$$r^{HV}_{m,h,s} = r_m - \max(\min(r_m\ , r_{m40}) - 0.3\, y(h,s),\ 0),$$

with r_{m40} the 40th percentile rent in the commuting zone.

[52]The difference in bottom rents is below 1%.

the historical policy displayed a kink. Up to this kink, all rent schedules exceed the historical one—with a 100% rent limit and a 30% income share. Furthermore, the steepness of the rent schedule increases as the local rent limit Γ_r decreases. While policy P1 has the steepest rent schedule, with relatively low income share and rent limits, $\Gamma_y = 0.16$ and $\Gamma_r = 0.6$, policy P10 has the flattest one, with relatively high income share and rent limits, with $\Gamma_y = 0.26$ and $\Gamma_r = 0.89$.

FIGURE 4: Housing Voucher Policy Rent Schedule



Notes: This figure displays the rent schedules in partial equilibrium for an average eligible household to housing vouchers, comparing all combinations of fractions (Γ_y, Γ_r) (dashed line) with the historical housing voucher program (solid line) and the baseline monthly rents (dotted line).

Finally, in general equilibrium, I assume the housing voucher policy is 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:

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

4.1 Partial Equilibrium Effects of Housing Vouchers

As a first step, I conduct three field experiments within the model and compare the results to the empirical estimates by Jacob et al. (2015); Chetty et al. (2016); Bergman et al. (2024). In field experiments, the intervention typically benefits too few participants to affect prices and distributions. Therefore, within the model, I calculate the partial equilibrium effects of the interventions. This involves holding constant all characteristics of parents and neighborhoods, including beliefs and rents. To closely align with the field experiments, I also ensure that the housing voucher policy in the model has, in partial equilibrium, the same total cost as the historical housing voucher program, resulting in comparable mobility rates of eligible households.[53] As a result, the evaluated housing voucher policy is P1, characterized by the steepest rent schedule, covering the difference between 16% of family income and 60% of the median rents. The first experiment targets families with incomes below the tenth percentile of the distribution. The second experiment replicates this approach but adds information about the relevance of neighborhood quality for children's future human capital. The third experiment focuses on families with incomes below the third percentile of the distribution.

Panel A of Table 3 contains the partial equilibrium effects of the first experiment and highlights higher mobility rates of eligible families in the model than in the empirical study. While the model predicts that families eligible for housing vouchers experience an increase in neighborhood quality, with an average improvement of +2.1 neighborhood ranks, Jacob et al. (2015) find no effect of housing vouchers on the neighborhood quality of beneficia-

[53] In partial equilibrium, the total policy costs difference across the historical and the current policies is below 1%.

Table 3: Partial Equilibrium Effects of Three Housing Voucher Interventions

	Data		Model	
	Control Mean	Treatment Effect	Baseline	Treatment Effect
Panel A: Housing vouchers for families with income below the 10th pct				
Jacob et al. (2015) - Housing vouchers for low-income families in private housing				
Neighborhood rank$^{(a)}$	1	0	2.0	+2.1
Child's future earnings (percentile)$^{(b)}$	na	0	33	+1.6
% in top 3 neighborhoods	na	na	0	+7.9
Panel B: Information to families receiving a housing voucher (income below the 10th pct)				
Bergman et al. (2024) - Information to low-income families receiving a housing voucher				
Neighborhood rank$^{(a)}$	3	0	4.0	+0.9
Child's future earnings (percentile)	na	na	35	+0.6
% in top 3 neighborhoods$^{(c)}$	13	+8.9	8	+4.2
Panel C: Housing vouchers for families with income below the 3rd pct				
Chetty et al. (2016) - Experimental vouchers for low-income families in public housing				
Neighborhood rank$^{(a)}$	≤1	+1.0	1.5	+1.0
Child's future earnings (percentile)$^{(d)}$	29	+3.2	30	+3.8
% in top 3 neighborhoods	na	na	0	+0.4

Notes: This table displays the partial equilibrium effects of three interventions related to housing vouchers. The first two columns summarize the results of the empirical literature. The last two columns present the model results with $\Gamma_y = 0.16$ and $\Gamma_r = 0.6$. Panel A describes the effect of providing housing vouchers to low-income families. The data source is Jacob et al. (2015), who investigate the effects of housing vouchers in Chicago in 1997. In the model, families below the 10th income percentile receive a housing voucher. Panel B describes the effect of providing incentivized information to housing voucher recipients. The data source is Bergman et al. (2024), who investigate the effects of housing vouchers in the Seattle and King County area. In the model, families below the 10th income percentile with a housing voucher receive information about the relevance of neighborhood quality for children's future human capital. Panel C describes the effect of providing housing vouchers to extremely low-income households. The data source is Chetty et al. (2016), who investigate the effects of experimental housing vouchers on extremely low-income households living in public housing at baseline. In the model, families below the 3rd income percentile receive a housing voucher. *(a):* Neighborhood rank in the literature is determined by census tract poverty rates, and *(d):* income rank by "Crosswalk Between Income/Wage Percentiles and 2015 Dollars". *(b):* Jacob et al. (2015) do not provide effects on children's future income but find no effect on measurable child outcomes such as achievement test scores or high school graduation. *(c):* Bergman et al. (2024) define high-opportunity areas as the top-third census tracts with the highest historical rates of upward income mobility.

ries.[54] Consistently, the authors who study the housing voucher lottery in Chicago report no significant impact on measurable child outcomes such as achievement test scores or high school graduation.[55] In contrast, the model predicts a positive impact of housing vouchers on children's future earnings, with an improvement of 1.6 percentiles.

A key distinction between the housing voucher programs evaluated in the empirical literature and the one analyzed in this model lies in the age of the recipients. In the model, recipients are young adults moving out of their parent's homes, whereas Jacob et al. (2015) report an average recipient age of 32, with three children per household. The model's neighborhood taste shocks are calibrated using neighborhood choices when leaving the parents' place. Intuitively, younger adults with fewer attachments to a specific neighborhood due to work or childcare needs may be more inclined to relocate than their older counterparts. This intuition aligns with the findings of Jacob and Ludwig (2012) and Bergman et al. (2024). Jacob and Ludwig (2012), comparing compliers and non-compliers of the housing voucher lottery in Chicago, observe that older or employed applicants are less likely to move when offered a voucher. Similarly, Bergman et al. (2024) find that when incentivizing housing voucher recipients to move to high-opportunity areas, the treatment effect is twice as large for families not using childcare compared to those who do and a third higher for non-employed than for employed parents.

Panel B of Table 3 examines the effects of an information treatment for housing voucher holders and displays similar effects in the model and in the empirical study. Bergman et al. (2024) randomly provide information about the benefits of moving to high-opportunity areas to low-income families with a child below age 15 and a housing voucher in the Seattle and King County area. The authors define high-opportunity areas as the top-third census tracts with the highest historical rates of upward income mobility. In the model, I provide information about the relevance of neighborhood quality for children's future human capital

[54] Census tract poverty rates are similar between treatment and control families. About 30%, which is the average in the first synthetic neighborhood, see Appendix Table A2.

[55] I translate this null effect into a zero effect on future earnings in Table 3.

to families with a housing voucher. The top 3 neighborhoods represent the high-opportunity areas. The model's predictions align with the empirical findings. In Bergman et al. (2024), the information treatment increases the share of families who moved to high-opportunity areas by 8.9 pp relative to the control group (though not statistically significant). In the model, the information treatment leads to a 4.2 pp increase. These relatively small effects of information in both the model and the empirical study indicate that factors beyond beliefs hinder housing voucher holders from moving to the highest opportunity areas.

Finally, Panel C contains the empirical estimates of Chetty et al. (2016). The authors evaluate experimental housing vouchers' effects on extremely low-income households living in public housing at baseline. The eligible families in this study are poorer, with household heads less likely to be employed and residing in more disadvantaged areas than in previous studies.[56] The average household earnings of children in the control group between 2008-2012 is $12,702, placing them at the 29th percentile of the household earnings distribution at age 26 in 2015 dollars.[57] In the model, I focus on extremely poor parents with incomes below the 3rd percentile to align children's future earnings with the 30th percentile at baseline.[58] As treated families are incentivized to move to low-poverty areas, Chetty et al. (2016) find an effect of a 10 pp reduction in census tract poverty rates or an improvement of about one neighborhood rank, which generates an increase of about $2,230 (with a $771 standard error) or 3.2 percentiles (with a 1.05 standard error) in children's future earnings.[59] The model's predictions are close to those estimates and fall within their confidence intervals. Young families with a housing voucher move to a +1 higher neighborhood rank, which translates into a +3.8 income percentiles for children.

[56]Employment rates in Chetty et al. (2016) are 23.8% versus 46.2% in Jacob et al. (2015) and 56.6% in Bergman et al. (2024) and the census tract poverty rates are 41% versus 30% in Jacob et al. (2015) and 17% in Bergman et al. (2024).

[57]The "Crosswalk Between Income/Wage Percentiles and 2015 Dollars" is from the data files of the project The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility published by Opportunity Insights, `https://opportunityinsights.org/data/`.

[58]While Chetty et al. (2016) restrict vouchers to households in deprived areas, there is no such restriction in the model, resulting in eligible families living in relatively better neighborhoods at baseline.

[59]I translate the 10 pp reduction in census tract poverty rates into a +1 neighborhood rank improvement as is close to the difference between synthetic neighborhoods one and two (see Appendix Table A2 displays).

To conclude this section, although the model predicts higher mobility than observed in empirical studies, likely due to the younger age of the recipients, the partial equilibrium effects of correcting beliefs and improving neighborhood quality align with the empirical literature's estimates.

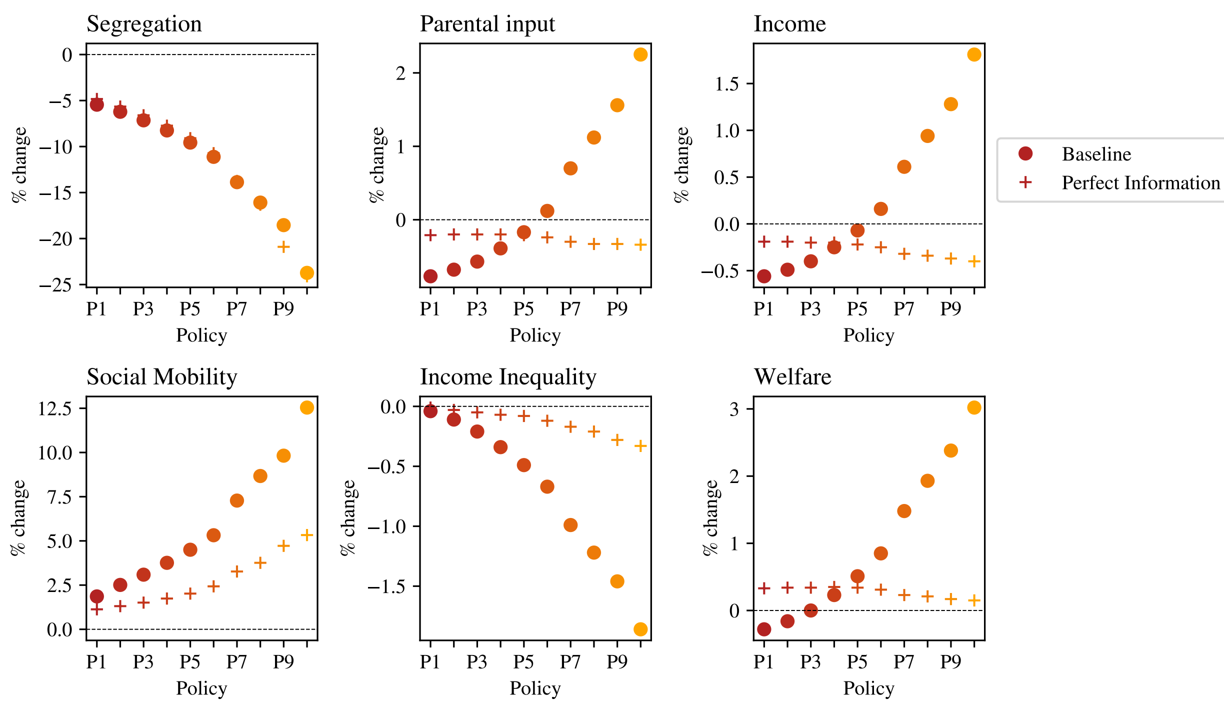
4.2 General Equilibrium Effects of Housing Vouchers

In the next step, I scale up the housing voucher policies to all families below the tenth percentile of the income distribution and compute the new steady states. The steady-state comparisons provide insights into the long-run implications of the policy, integrating general equilibrium responses of the housing market and parental beliefs.

To illustrate the role of parental beliefs, Figure 5 uses both the baseline model and the extended alternative model with perfect information to evaluate the general equilibrium effects of the housing voucher programs. The models' predictions diverge across all outcomes except for residential segregation. Both models predict a stronger impact of housing voucher policies on segregation as the rent schedule flattens. Policy P1 has the smallest effect, reducing segregation by approximately 5%, while policy P10 has the largest impact, lowering segregation by about 25%. However, while the effects on welfare increase as the rent schedule flattens under the baseline model, they tend to decrease when assuming perfect information. Additionally, the policy effects on social mobility and income inequality are always stronger within the baseline model.

Understanding these differences in predictions across model specifications requires a closer examination of parental beliefs and input responses that Table 4 presents. By assumption, parental beliefs do not change within the perfect information model—last five columns of Table 4. In this case, the negative effect of housing voucher policies on parental input is driven by the complementarity between neighborhood quality and parental time. As eligible parents move to better neighborhoods, local rents increase, which forces non-eligible parents to relocate to lower-ranked neighborhoods. In general equilibrium, this results in a decline in neighborhood rank for most of the population, decreasing parental time and aggregate parental investment. Consequently, human capital and income decrease. This effect strengthens as the policy rent schedule flattens for eligible households, decreasing the welfare effects.

FIGURE 5: General Equilibrium Effects of Housing Vouchers



Notes: This figure displays the general equilibrium effects of the ten housing voucher policies in percentage change. Plain dots represent the predicted effects according to the baseline model. Crosses represent the predicted effects according to the extended alternative model with perfect information. *Social mobility* is measured by minus the income rank-rank coefficient, *Segregation* by the neighborhood Gini coefficient, and *Income inequality* by the income Gini coefficient.

In contrast, when considering the baseline model with endogenous beliefs (first five columns of Table 4), where neighborhood quality and parental time are substitutes, the mechanism operates in the opposite direction. In addition, as eligible parents move to better neighborhoods and segregation decreases, parental beliefs converge to the truth. This improves beliefs and parental input among the lowest-income parents while reducing them for others. Only when segregation decreases sufficiently does the improvement in beliefs among low-income parents outweigh the decrease among higher-income parents, ultimately improving aggregate parental input and income. The flatter the policy rent schedule, the greater the reduction in residential segregation and the more pronounced the improvement in aggregate outcomes.

Table 4: General Equilibrium Effects of Housing Vouchers (% changes)

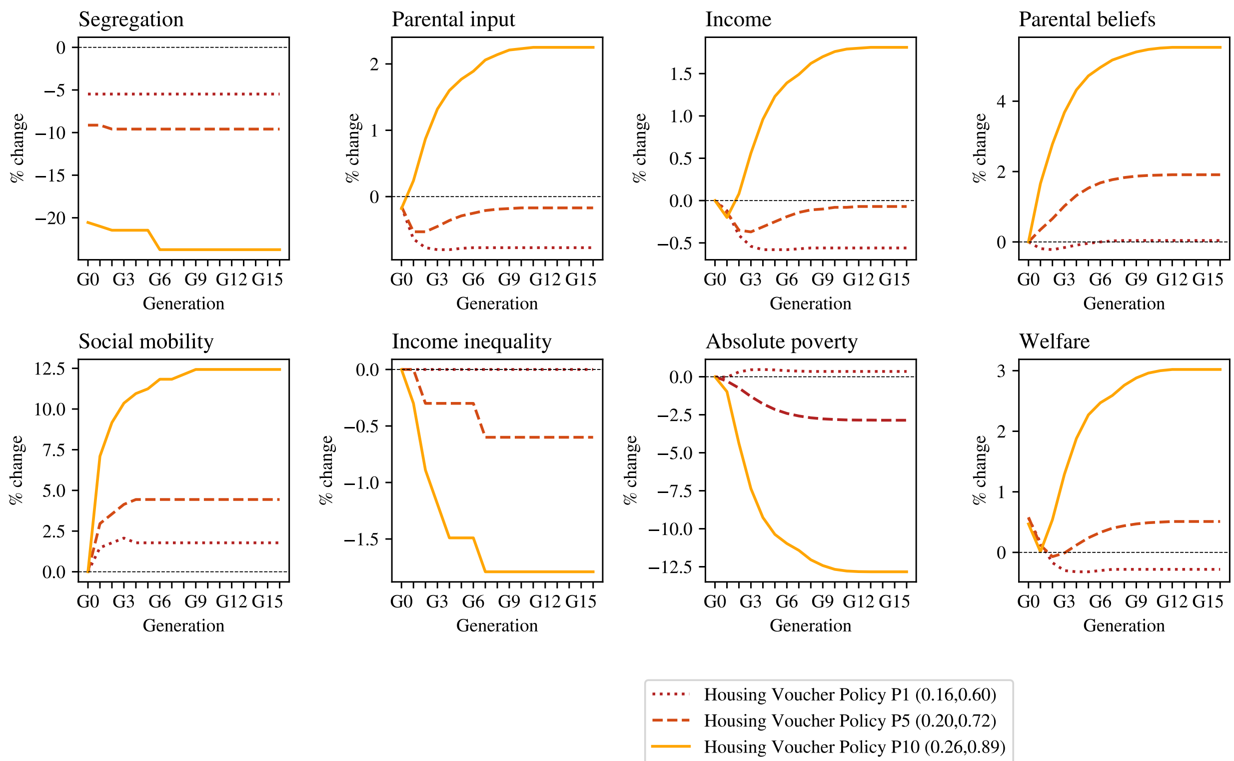
	Baseline Model					Perfect Information				
		Income quartile					Income quartile			
	All	1st	2nd	3rd	4th	All	1st	2nd	3rd	4th
Panel A: Policy P1 (0.16, 0.60)										
Parental beliefs	+0.0	+5.6	+0.6	-1.1	-2.1					
Parental input	-0.8	+0.8	-1.3	-1.1	-1.0	-0.2	+1.2	-1.1	-0.5	-0.1
Parental time	-3.5	-2.9	-3.5	-3.8	-3.3	-0.6	+1.5	-2.2	-1.1	-0.2
Neighborhood rank	+0.5	+14.8	-3.6	-0.8	-0.2	+0.3	+15.4	-4.3	-0.9	-0.1
Panel B: Policy P5 (0.20, 0.72)										
Parental beliefs	+1.9	+12.6	+3.2	-0.4	-3.0					
Parental input	-0.2	+2.9	-0.9	-1.0	-1.1	-0.2	+2.0	-1.4	-0.8	-0.3
Parental time	-2.0	+2.1	-1.7	-3.3	-3.9	-0.7	+2.8	-2.8	-1.4	-0.4
Neighborhood rank	+1.1	+24.0	-5.9	-1.6	-0.4	+0.5	+27.2	-6.9	-2.0	-0.5
Panel C: Policy P10 (0.26, 0.89)										
Parental beliefs	+5.5	+27.8	+9.2	+1.2	-6.0					
Parental input	+2.3	+10.6	+1.1	-0.0	-1.3	-0.3	+4.5	-2.0	-1.7	-1.2
Parental time	+5.0	+20.6	+6.9	+1.2	-3.6	-1.1	+6.2	-3.8	-3.0	-1.7
Neighborhood rank	+2.7	+54.7	-11.1	-5.2	-2.4	+1.0	+63.1	-12.3	-6.2	-2.9

Notes: This table shows the general equilibrium effects of three housing voucher policies using the calibrated models. The first five columns contain the predictions of the baseline model. The last five columns contain the predictions of the extended perfect information model with heterogeneous preferences.

Similarly, while the positive effects of the policies on social mobility and income inequality are driven by the complementarity between neighborhood quality and parental time in the perfect information model, they are amplified by the convergence of beliefs in the baseline model.

Finally, Figure 6 uses the baseline model and illustrates the transition path of three policies, P1, P5, and P10. At every generation of the transition paths, I assume the housing market clears, and neighborhood quality adjusts accordingly.[60] In contrast, parental beliefs and human capital slowly converge to their new steady state. Analyzing the transition paths helps gauge how long it would take to reach the new steady states.

Figure 6: Transition Dynamics of the Economy with Housing Voucher Policies (% deviation from initial steady state)



Notes: The figure shows the transition path of eight aggregate outcomes under three housing voucher policies with fractions (Γ_y, Γ_r). *Social mobility* is measured by minus the income rank-rank coefficient, *Segregation* by the neighborhood Gini coefficient, and *Income inequality* by the income Gini coefficient.

In all policies, eligible parents receive vouchers in the first generation (G0), but their beliefs remain unchanged initially. This leads to an increase in neighborhood rank and a decrease in parental time, resulting in lower aggregate parental input and income for the next generation of parents (G1). Only with the substantial improvement in beliefs associated with policy P10 do parental input and income increase in the following generation. It then

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

takes up to ten generations for all aggregate outcomes to reach their new steady states. Nevertheless, the impact on social mobility and income equality is positive for the first generation of affected children.

In summary, the model, which predicts high mobility rates likely influenced by the recipients' age, suggests that the overall effects of housing vouchers in general equilibrium will hinge on the policy's effectiveness in reducing residential segregation. The more the policy mitigates segregation, the greater the improvements in welfare, income, and social mobility, though this comes with a longer transition to a new steady state. Conversely, a policy that only mildly reduces segregation—despite enhancing social mobility—could actually harm both income and welfare. Notably, omitting endogenous parental beliefs from the model would lead to the opposite conclusion.

5 Conclusion

In this paper, I develop an overlapping generations model that incorporates social learning within neighborhoods to explore residential and parental time decisions across socioeconomic groups. Calibrating the model to the average commuting zone in the United States requires having a cognitive bias—selection neglect—that prevents parents from perfectly learning about the skill formation technology. This bias implies that residential segregation generates information friction, leading to heterogeneous parental beliefs and distorted parental decisions. In equilibrium, low-income parents tend to under-invest in their children, while high-income parents tend to over-invest in them. The calibrated model accounts for why relatively many parents who grew up in disadvantaged neighborhoods choose similar environments for their children and why college-educated parents, despite working longer hours, allocate more time to their children's education than non-college-educated parents.

Heterogeneous parental beliefs have substantial macroeconomic effects, exacerbating income inequality, reducing social mobility, and decreasing aggregate income, thereby diminishing consumption equivalence welfare. Although one could replicate the data patterns by substituting the unconventional mechanisms of social learning and parental beliefs with large preference heterogeneity across socioeconomic groups, this approach would lack empirical support.

The model's frictions motivate government intervention. I evaluate housing voucher policies in both partial and general equilibrium, considering short- and long-term implications. The model suggests that the effectiveness of housing vouchers in general equilibrium depends on their ability to reduce residential segregation. Greater reductions in segregation lead to higher welfare, income, and social mobility, though with a longer transition period. Conversely, a policy that only slightly reduces segregation could harm income and welfare, despite improving social mobility. Importantly, substituting endogenous parental beliefs with large preference heterogeneity would lead to the opposite conclusion.

References

Adam, K., Marcet, A., and Beutel, J. (2017). Stock price booms and expected capital gains. *American Economic Review*, 107(8):2352–2408.

Agostinelli, F. (2018). Investing in children's skills: An equilibrium analysis of social interactions and parental investments. *Unpublished Manuscript, University of Pennsylvania.*

Agostinelli, F., Doepke, M., Sorrenti, G., and Zilibotti, F. (2022). When the great equalizer shuts down: Schools, peers, and parents in pandemic times. *Journal of public economics*, 206:104574.

Agostinelli, F., Doepke, M., Sorrenti, G., and Zilibotti, F. (2024). It takes a village: The economics of parenting with neighborhood and peer effects. Technical report, Journal of public economics, Forthcoming.

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The economics of density: Evidence from the berlin wall. *Econometrica*, 83(6):2127–2189.

Aiyagari, S. R., Greenwood, J., and Seshadri, A. (2002). Efficient investment in children. *Journal of economic theory*, 102(2):290–321.

Alan, S., Boneva, T., and Ertac, S. (2019). Ever failed, try again, succeed better: Results from a randomized educational intervention on grit. *The Quarterly Journal of Economics*, 134(3):1121–1162.

Algan, Y., Bouguen, A., Chevallier, C., and Charpentier, A. (2020). The impact of a large-scale mindset intervention on school outcomes: Experimental evidence fromfrance. *Working paper*.

Attanasio, O., Boneva, T., and Rauh, C. (2019a). Parental beliefs about returns to different types of investments in school children. Working Paper 25513, National Bureau of Economic Research.

Attanasio, O., Cunha, F., and Jervis, P. (2019b). Subjective parental beliefs. their measurement and role. Working Paper 26516, National Bureau of Economic Research.

Attanasio, O. P. and Kaufmann, K. M. (2014). Education choices and returns to schooling: Mothers' and youths' subjective expectations and their role by gender. *Journal of Development Economics*, 109:203–216.

Becker, G. S. and Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of labor economics*, 4(3, Part 2):S1–S39.

Belfield, C., Boneva, T., Rauh, C., and Shaw, J. (2019). What drives enrolment gaps in further education? the role of beliefs in sequential schooling decisions. *Economica*.

Bénabou, R. and Tirole, J. (2005). Self-confidence and personal motivation. *Psychology, Rationality and Economic Behaviour: Challenging Standard Assumptions*, pages 19–57.

Bergman, P., Chetty, R., DeLuca, S., Hendren, N., Katz, L. F., and Palmer, C. (2024). Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice. *American Economic Review*, 114(5):1281–1337.

Bilal, A. (2023). The geography of unemployment. *The Quarterly Journal of Economics*, 138(3):1507–1576.

Blandin, A. and Herrington, C. (2022). Family heterogeneity, human capital investment, and college attainment. *American Economic Journal: Macroeconomics*, 14(4):438–78.

Boneva, T. and Rauh, C. (2016). Human capital production and parental beliefs. *Unpublished Manuscript, University College London*.

Boneva, T. and Rauh, C. (2018). Parental beliefs about returns to educational investments—the later the better? *Journal of the European Economic Association*, 16(6):1669–1711.

Breda, T., Grenet, J., Monnet, M., and Van Effenterre, C. (2023). How effective are female role models in steering girls towards stem? evidence from french high schools. *The Economic Journal*, 133(653):1773–1809.

Caucutt, E. M., Lochner, L., and Park, Y. (2017). Correlation, consumption, confusion, or constraints: Why do poor children perform so poorly? *The Scandinavian Journal of Economics*, 119(1):102–147.

Chetty, R. and Hendren, N. (2018a). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3):1107–1162.

Chetty, R. and Hendren, N. (2018b). The impacts of neighborhoods on intergenerational mobility ii: County-level estimates. *The Quarterly Journal of Economics*, 133(3):1163–1228.

Chetty, R., Hendren, N., and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4):855–902.

Chetty, R., Hendren, N., Kline, P., Saez, E., and Turner, N. (2014). Is the united states still a land of opportunity? recent trends in intergenerational mobility. *American Economic Review*, 104(5):141–47.

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., Johnston, D., Koenen, M., Laguna-Muggenburg, E., Mudekereza, F., Rutter, T., Thor, N., Townsend, W., Zhang, R., Bailey, M., Barberá, P., Bhole, M., and Wernerfelt, N. (2022). Social capital i: measurement and associations with economic mobility. *Nature*.

Chyn, E. and Daruich, D. (2022). An equilibrium analysis of the effects of neighborhood-based interventions on children. Working Paper 29927, National Bureau of Economic Research.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in ghana. *American economic review*, 100(1):35–69.

Cunha, F., Elo, I., and Culhane, J. (2013). Eliciting maternal expectations about the technology of cognitive skill formation. Working Paper 19144, National Bureau of Economic Research.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 97(2):31–47.

Cunha, F. and Heckman, J. J. (2009). The economics and psychology of inequality and human development. *Journal of the European Economic Association*, 7(2-3):320–364.

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931.

Daruich, D. (2018). The macroeconomic consequences of early childhood development policies. *FRB St. Louis Working Paper*, (2018-29).

Das, J., Dercon, S., Habyarimana, J., Krishnan, P., Muralidharan, K., and Sundararaman, V. (2013). School inputs, household substitution, and test scores. *American Economic Journal: Applied Economics*, 5(2):29–57.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980-2000. *American Economic Review*, 106(3):479–524.

Dizon-Ross, R. (2019). Parents' beliefs about their children's academic ability: Implications for educational investments. *American Economic Review*, 109(8):2728–65.

Doepke, M., Hannusch, A., Kindermann, F., and Tertilt, M. (2023). The economics of fertility: A new era. *Handbook of the Economics of the Family*, 1(1):151–254.

Durlauf, S. N. (2011). *Chapter 6. Groups, Social Influences, and Inequality*, pages 141–175. Princeton University Press.

Eckert, F., Kleineberg, T., et al. (2019). Can we save the american dream? a dynamic general equilibrium analysis of the effects of school financing on local opportunities. In *2019 Meeting Papers*, number 1197. Society for Economic Dynamics.

Enke, B. (2020). What you see is all there is. *The Quarterly Journal of Economics*, 135(3):1363–1398.

Eysenck, H. (2018). *Intelligence: A new look*. Routledge.

Fernández, R. (2013). Cultural change as learning: The evolution of female labor force participation over a century. *American Economic Review*, 103(1):472–500.

Fogli, A. and Guerrieri, V. (2019). The end of the american dream? inequality and segregation in us cities. Working Paper 26143, National Bureau of Economic Research.

Fogli, A. and Veldkamp, L. (2011). Nature or nurture? learning and the geography of female labor force participation. *Econometrica*, 79(4):1103–1138.

Frick, M., Iijima, R., and Ishii, Y. (2022). Dispersed behavior and perceptions in assortative societies. *American Economic Review*, 112(9):3063–3105.

Fuchs-Schündeln, N., Krueger, D., Ludwig, A., and Popova, I. (2022). The long-term distributional and welfare effects of covid-19 school closures. *The Economic Journal*, 132(645):1647–1683.

Gregory, V., Kozlowski, J., and Rubinton, H. (2022). The impact of racial segregation on college attainment in spatial equilibrium. Working Paper 2022-36, FRB St. Louis Working Paper.

Guryan, J., Hurst, E., and Kearney, M. (2008). Parental education and parental time with children. *Journal of Economic Perspectives*, 22(3):23–46.

Guvenen, F. (2016). Quantitative economics with heterogeneity: An a-to-z guidebook. *Princeton University Press*, 26(51):155.

Guyon, N. and Huillery, E. (2020). Biased Aspirations and Social Inequality at School: Evidence from French Teenagers. *The Economic Journal*.

Harris, K., Halpern, C., Whitsel, E., Hussey, J., Killeya-Jones, L., Tabor, J., and Dean, S. (2019). Cohort profile: The national longitudinal study of adolescent to adult health (add health). *International Journal of Epidemiology*, 48(5):1415–1425.

Heathcote, J., Storesletten, K., and Violante, G. L. (2009). Quantitative macroeconomics with heterogeneous households. *Annu. Rev. Econ.*, 1(1):319–354.

Heathcote, J., Storesletten, K., and Violante, G. L. (2017). Optimal tax progressivity: An analytical framework. *The Quarterly Journal of Economics*, 132(4):1693–1754.

Heckman, J. J. and Mosso, S. (2014). The economics of human development and social mobility. *Annual Review of Economics*, 6(1):689–733.

Hofferth, S. L., Flood, S. M., Sobek, M., and Backman, D. (2020). American time use survey data extract builder: Version 2.8 [dataset]. *College Park, MD: University of Maryland and Minneapolis, MN: IPUMS*.

Jacob, B. A., Kapustin, M., and Ludwig, J. (2015). The impact of housing assistance on child outcomes: Evidence from a randomized housing lottery. *The Quarterly Journal of Economics*, 130(1):465–506.

Jacob, B. A. and Ludwig, J. (2012). The effects of housing assistance on labor supply: Evidence from a voucher lottery. *American Economic Review*, 102(1):272–304.

Jang, Y. and Yum, M. (2023). Aggregate and Intergenerational Implications of School Closures: A Quantitative Assessment. *American Economic Journal: Macroeconomics*.

Jehiel, P. (2018). Investment strategy and selection bias: An equilibrium perspective on overoptimism. *American Economic Review*, 108(6):1582–97.

Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics*, 125(2):515–548.

Kaufmann, K. M. (2014). Understanding the income gradient in college attendance in mexico: The role of heterogeneity in expected returns. *Quantitative Economics*, 5(3):583–630.

Kiessling, L. (2021). How do parents perceive the returns to parenting styles and neighborhoods? *European Economic Review*, 139:103906.

Kim, S., Tertilt, M., and Yum, M. (2024). Status externalities in education and low birth rates in korea. *American Economic Review, Forthcoming*.

Kling, J. R., Liebman, J. B., and Katz, L. F. (2001). Bullets don't got no name: Consequences of fear in the ghetto. Working paper, JCPR.

Kopczuk, W., Saez, E., and Song, J. (2010). Earnings inequality and mobility in the united states: evidence from social security data since 1937. *The Quarterly Journal of Economics*, 125(1):91–128.

Krusell, P. and Smith, A. A. (2006). Quantitative macroeconomic models with heterogeneous agents. *Econometric Society Monographs*, 41:298.

Lee, H., Myers, D., Painter, G., Thunell, J., and Zissimopoulos, J. (2020). The role of parental financial assistance in the transition to homeownership by young adults. *Journal of Housing Economics*, 47:101597.

Lee, S. Y. and Seshadri, A. (2019). On the intergenerational transmission of economic status. *Journal of Political Economy*, 127(2):855–921.

Loury, G. C. (1981). Intergenerational transfers and the distribution of earnings. *Econometrica: Journal of the Econometric Society*, pages 843–867.

Manson, S., Schroeder, J., Van Riper, D., Kugler, T., and Ruggles, S. (2022). Ipums national historical geographic information system: Version 17.0 [dataset]. *Minneapolis, MN: IPUMS.*

Nguyen, T. (2008). Information, role models and perceived returns to education: Experimental evidence from madagascar. *Unpublished manuscript*, 6.

Piketty, T. (1995). Social mobility and redistributive politics. *The Quarterly journal of economics*, 110(3):551–584.

Pop-Eleches, C. and Urquiola, M. (2013). Going to a better school: Effects and behavioral responses. *American Economic Review*, 103(4):1289–1324.

Quadrini, V. and Ríos-Rull, J.-V. (2015). Inequality in macroeconomics. 2:1229–1302.

Redding, S. J. and Rossi-Hansberg, E. (2017). Quantitative spatial economics. *Annual Review of Economics*, 9:21–58.

Restuccia, D. and Urrutia, C. (2004). Intergenerational persistence of earnings: The role of early and college education. *American Economic Review*, 94(5):1354–1378.

Rodriguez, S. B., Díaz-Giménez, J., Quadrini, V., Ríos-Rull, J.-V., et al. (2002). Updated facts on the us distributions of earnings, income, and wealth. *Federal Reserve Bank of Minneapolis Quarterly Review*, 26(3).

Roemer, J.-E. and Wets, R.-J.-B. (1994). Neighborhood Effects on Belief Formation and the Distribution of Education and Income. Papers 94-02, California Davis - Institute of Governmental Affairs.

Ruggles, S., Flood, S., Sobek, M., Brockman, D., Cooper, G., Richards, S., and Schouweiler, M. (2023). Ipums usa: Version 13.0 [dataset]. *Minneapolis, MN: IPUMS.*

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics*, 125(3):1253–1296.

Streufert, P. (2000). The effect of underclass social isolation on schooling choice. *Journal of Public Economic Theory*, 2(4):461–482.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics letters*, 20(2):177–181.

Wiswall, M. and Zafar, B. (2021). Human capital investments and expectations about career and family. *Journal of Political Economy*, 129(5):1361–1424.

Yum, M. (2023). Parental time investment and intergenerational mobility. *International Economic Review.*

Appendix

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 $t = 0, \ldots, T-1$, 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 $t = 0, \ldots, T-1$,

   (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 $t = 0, \ldots, T-1$, 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 $t = 0, \ldots, T-1$, 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 $t = 0, \ldots, T-2$, 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 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 :

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

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.

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 and Additional Information on the Calibration

C.1 Data Description

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 childcare 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.[61] 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.[62] Table A1 describes how married couples with a child below 18 in the household in the United States allocate their time in 2003.

[61] 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.

[62] 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 numbers in Table A3. 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 A1: 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 restricted-use data sets include detailed information on family background and 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 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). 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.

C.2 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 A2 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.

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).[63] The

[63] In Appendix Section F.3, I also proxy neighborhood quality by the share of residents above 25 with a

Table A2: Characteristics of Synthetic Neighborhoods

Neigh.	Fraction of households (1)	Median household income (USD) (2)	Fraction of people aged 25+ with college degree (3)	Fraction below poverty level (4)	Median rent over median household income (5)	Fraction of households with child below 18 (6)	Median income households with child below 18 (USD) (7)
D1	0.071	20,638	0.113	0.358	0.286	0.081	21,756
D2	0.088	28,883	0.134	0.233	0.234	0.095	29,819
D3	0.093	34,259	0.158	0.167	0.211	0.096	36,683
D4	0.096	38,652	0.187	0.133	0.197	0.095	42,420
D5	0.100	42,957	0.212	0.105	0.187	0.097	48,006
D6	0.105	47,552	0.236	0.085	0.177	0.100	53,568
D7	0.107	52,547	0.268	0.069	0.170	0.102	60,314
D8	0.111	58,810	0.311	0.054	0.163	0.107	67,597
D9	0.114	67,780	0.386	0.042	0.156	0.110	79,120
D10	0.115	91,273	0.528	0.030	0.141	0.117	107,147

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.

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 lived during adulthood, in 2016-2018.

C.3 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

college degree as a robustness check (Diamond, 2016).

work.[64] 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.[65]

Table A3 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.[66] 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.[67]

In addition, Add Health survey contains information about ten parent-child activities in 1994-1995.[68] To proxy for time allocated in childcare, I construct a variable that counts the number of activities that happened over the past four weeks with the mother and the

[64] 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".

[65] 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 A1 provides detailed information on each activity.

[66] 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.

[67] Appendix Table A1 describes how parents allocate their time in each ATUS activity.

[68] 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 A3: 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 A1.

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".[69] 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.4 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 A4 contains the estimates of the following

[69] As a robustness check in Appendix Section F.3, I construct an alternative proxy of parental time removing the activity "went to a movie, play, museum, concert, or sports event".

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 A4: Estimated Parameters of the College Graduation Probability

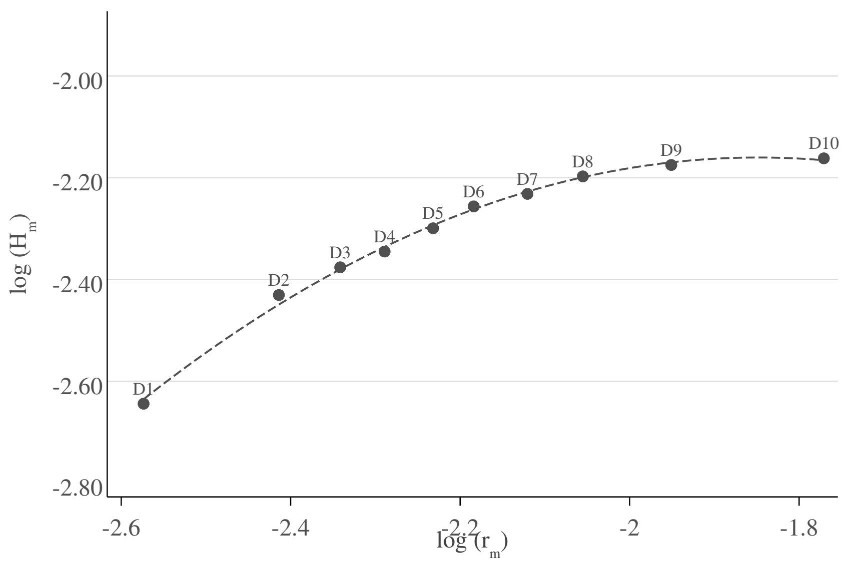
	College graduation probability	
γ_1	-3.83	(0.35)
γ_2	0.35	(0.02)
γ_3	0.15	(0.02)
γ_4	1.11	(0.11)
Pseudo R^2	0.28	

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.5 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 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 A1 summarizes the log-relationship between density (Column (5) Table A2) and rents across the ten synthetic neighborhoods. Without loss of generality, the numeraire is the average household earnings in the economy.

FIGURE A1: 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.

C.6 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 neighborhoods, I compute the share of children in each of the ten adulthood synthetic neighborhoods (wave V).

Targeted moments:

Table A5: Moments Description

Moment	Description	Data restriction	Source
Income			
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 A2.	100 biggest commuting zones - families with a own child below 18	ACS 2000, NHGIS 2000
Income 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 gradient	Regression coefficient of rent on neighborhood rank.	100 biggest commuting zones	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

C.7 Externally Calibrated Parameters

Table A6: Externally Calibrated Parameters

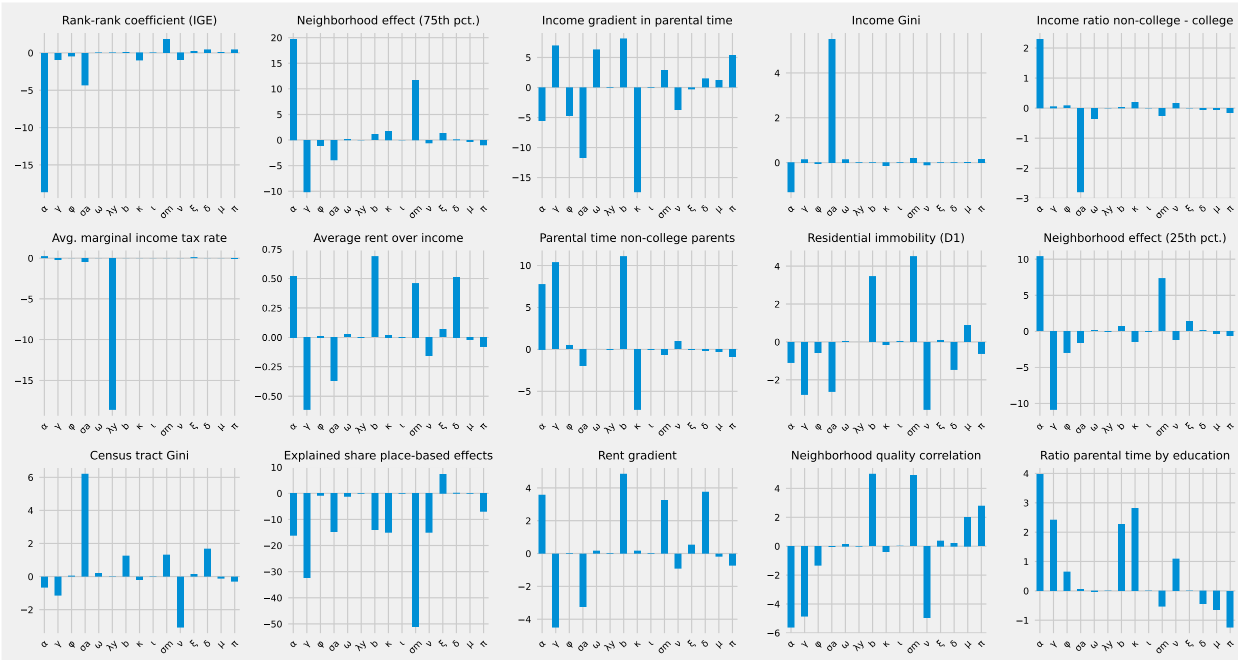
Parameter	Description	Value	Source
N	Number of neighborhoods	10	Deciles NHGIS
β	Returns on parental human capital	$1-\alpha$	Constant returns
ψ	Intertemporal elasticity of substitution	0.5	Standard
w	Wage rate	1	Normalization
$\underline{\mathrm{i}}$	Parental investment constant	1	Normalization
$\mu_{\bar{m}}$	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.

C.8 Model Sensitivity

Figure A2 shows the percentage change in each moment with respect to a 0.1 level increase in each parameter. The results are computed by comparing steady states.

Figure A2: Model Sensitivity



Notes: This Figure shows the percentage change in each moment with respect to a 0.1 level increase in each parameter.

D Alternative Modeling

D.1 Alternative Model with Perfect Information

This section describes the calibration of an alternative version of the model with perfect information and 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:

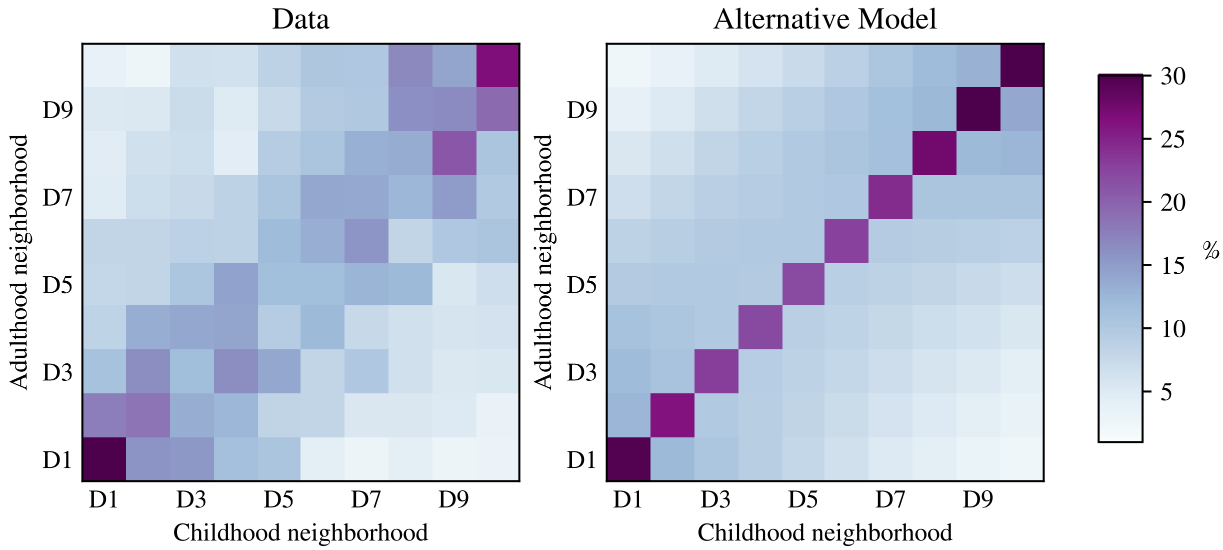
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa_s\, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \delta\, rank_m + \iota\, \mathbb{1}_{m_0 = m} - \tilde{\iota}(m_0 - m)^2 + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right].$$

Table A7: Internally Calibrated Parameters - Alternative Model with Perfect Information

Parameter	Description	Moment	Data	Model
Skill Formation: $\boldsymbol{h' = \left(\left(\gamma\ (\frac{\tau}{\overline{\tau}})^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}}\ +\ \underline{i}\right)^{\alpha}\ h^{1-\alpha}\ \exp(a)}$ **with** $\boldsymbol{a \sim \mathcal{N}(0, \sigma_a)}$				
$\alpha = 0.71$	Parental inputs elasticity	Rank-rank coefficient (IGE)	0.341	0.339
$\gamma = 0.585$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.05
$\varphi = -1.8$	Substitutability	Income gradient in parental time	0.14	0.136
$\sigma_a = 0.713$	Ability shock variance	Income Gini	0.333	0.331
Labor Market and Preferences				
$\omega = 0.033$	College wage premium	Income ratio non-college - college	0.554	0.55
$\lambda_y = 0.709$	Tax function scalar	Avg. marginal income tax rate	0.351	0.354
$b = 0.575$	Altruism	Average rent over income	0.117	0.117
$\kappa_0 = 0.87$	Parental time disutility	Parental time non-college parents	0.075	0.078
$\iota = 0.012$	Place of birth preference	Residential immobility (D1)	0.302	0.294
Neighborhoods				
$\sigma_m = 0.18$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.062
$\nu = 0.014$	Taste shock variance	Census tract Gini	0.231	0.231
$\xi = 0.29$	Demographics effects	Explained share place-based effects	0.24	0.23
$\delta = 0.007$	Amenities	Rent price gradient	54.2	52
Belief Updating Process				
$\tilde{\iota} = 0.0003$	Quadratic costs	Neighborhood quality correlation	0.417	0.413
$\kappa_1 = 0.645$	Parental time disutility	Ratio parental time by education	0.75	0.754

Notes: This table reports the internally calibrated parameters of the alternative model with perfect information and the observed and simulated moments associated with the parameter estimates.

FIGURE A3: Non-targeted Moments: Detailed Residential Mobility - Alternative Model with Perfect Information



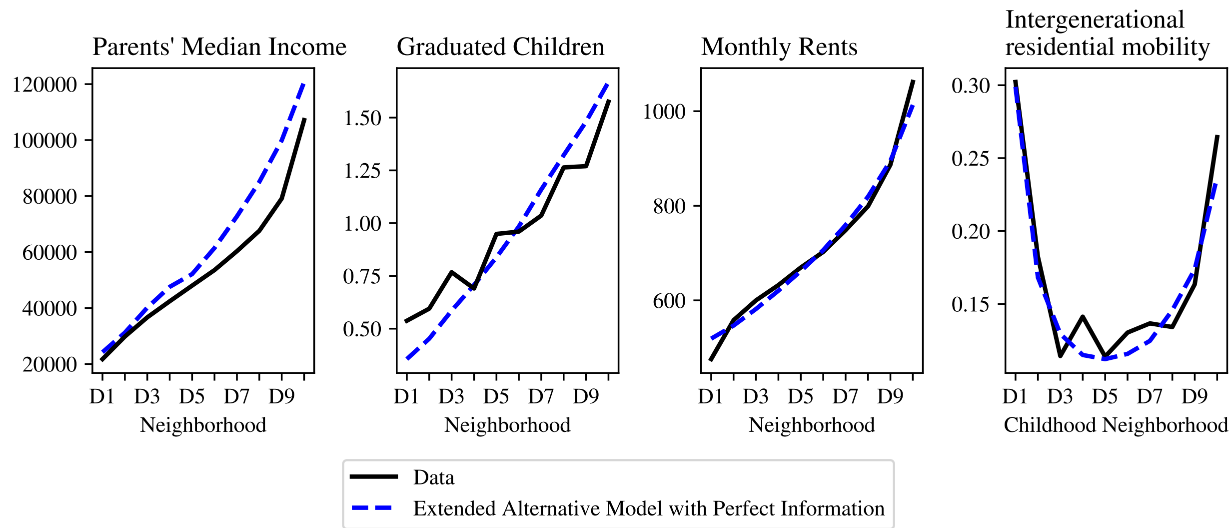
Notes: This Figure shows residential mobility between childhood and adulthood in the data (left panel), and their model simulates analogs (right panel). The x-axis contains the ten synthetic childhood neighborhoods, and the y-axis is the ten synthetic adulthood neighborhoods. The frequency of moves is represented by cell colors, with larger values in darker squares—data source: Add Health, see Appendix C.6 for details of data construction.

D.2 Extended Alternative Model with Perfect Information

This section describes the calibration of an extended alternative version of the model with perfect information and heterogeneous preferences. Parents' preferences feature a heterogeneous time disutility parameter by education, I assume a quadratic moving cost function, and the preference for the neighborhood parameter varies by childhood neighborhood type. Parents' preferences take the following forms:

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

Figure A4: Non-Targeted Moments by Neighborhood - Extended Alternative Model with Perfect Information



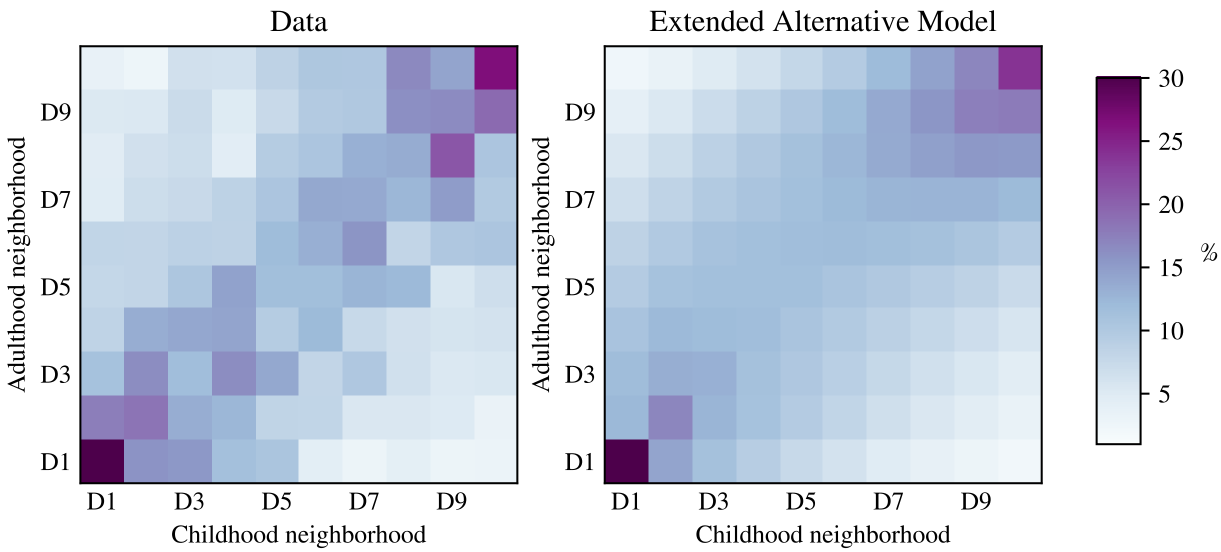
Notes: This Figure shows four non-targeted moments across the ten neighborhood types: median income, the share of graduated children, monthly rents, and intergenerational residential mobility, which represents the share of children who, in adulthood, choose to live in the type of neighborhood as their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

Table A8: Internally Calibrated Parameters - Extended Alternative Model, Perfect Information

Parameter	Description	Moment	Data	Model
Skill Formation: $\boldsymbol{h' = \left(\left(\gamma\ \left(\frac{\tau}{\bar{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}}\ +\ \underline{i}\right)^{\alpha}\ h^{1-\alpha}\ \exp(a)}$ **with** $\boldsymbol{a \sim \mathcal{N}(0, \sigma_a)}$				
$\alpha\ =\ 0.71$	Parental inputs elasticity	Rank-rank coefficient (IGE)	0.341	0.339
$\gamma\ =\ 0.585$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.05
$\varphi\ =\ $-1.8	Substitutability	Income gradient in parental time	0.14	0.136
$\sigma_a\ =\ 0.713$	Ability shock variance	Income Gini	0.333	0.331
Labor Market and Preferences				
$\omega\ =\ 0.033$	College wage premium	Income ratio non-college - college	0.554	0.55
$\lambda_y\ =\ 0.709$	Tax function scalar	Avg. marginal income tax rate	0.351	0.353
$b\ =\ 0.575$	Altruism	Average rent over income	0.117	0.117
$\kappa_0\ =\ 0.87$	Parental time disutility	Parental time non-college parents	0.075	0.078
$\iota_1\ =$ 1.4E-2	Place of birth pref. 1	Residential immobility (D1)*	0.306	0.299
$\iota_2\ =$ 2.0E-3	Place of birth pref. 2	Residential immobility (D2)*	0.164	0.168
$\iota_3\ =$ 9.8E-4	Place of birth pref. 3	Residential immobility (D3)*	0.124	0.129
$\iota_4\ =$ 3.3E-4	Place of birth pref. 4	Residential immobility (D4)*	0.111	0.115
$\iota_5\ =$ 2.9E-4	Place of birth pref. 5	Residential immobility (D5)*	0.109	0.112
$\iota_6\ =$ 9.8E-5	Place of birth pref. 6	Residential immobility (D6)*	0.115	0.116
$\iota_7\ =$ 6.5E-5	Place of birth pref. 7	Residential immobility (D7)*	0.124	0.125
$\iota_8\ =$ 6.5E-5	Place of birth pref. 8	Residential immobility (D8)*	0.145	0.146
$\iota_9\ =$ 2.0E-4	Place of birth pref. 9	Residential immobility (D9)*	0.176	0.174
$\iota_{10}\ =$ 3.6E-3	Place of birth pref. 10	Residential immobility (D10)*	0.233	0.237
Neighborhoods				
$\sigma_m =\ 0.18$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.062
$\nu\ =\ 0.014$	Taste shock variance	Census tract Gini	0.231	0.231
$\xi\ =\ 0.29$	Demographics effects	Explained share place-based effects	0.24	0.247
$\delta\ =\ 0.007$	Amenities	Rent price gradient	54.2	51.7
Belief Updating Process				
$\tilde{\iota}\ =\ 0.0003$	Quadratic costs	Neighborhood quality correlation	0.417	0.378
$\kappa_1\ =\ 0.645$	Parental time disutility	Ratio parental time by education	0.75	0.755

Notes: This table reports the internally calibrated parameters of the extended alternative model with perfect information and the observed and simulated moments associated with the parameter estimates. * To improve smoothness and similarity between calibrated models, residential immobility moments are not taken from data but from the baseline model simulation.

FIGURE A5: Non-targeted Moments: Detailed Residential Mobility - Extended Alternative Model with Perfect Information



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.6 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.[70] The signal noisiness could capture the fact that there is no real way to perfectly gauge ability—which

[70] 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.

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 predefined categories.[71] 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:

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

while the actual average local ability is:

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

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

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

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.[72] Consequently, in neighborhoods in which the average local ability is below the average ability in the economy, young agents overestimate average local ability (if $\overline{a}_m \leq 0$ then $\overline{a}_m \geq \overline{\tilde{a}}_m$), and conversely if the average local ability is above the average ability in the economy (if $\overline{a}_m \geq 0$ then $\overline{a}_m \leq \overline{\tilde{a}}_m$).

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 $\overline{\tilde{a}}_m = \overline{a}_m$. Note that at any given level of bounds below infinity, the signal variance ${\sigma_s}^2$ 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 A6 illustrates a conditional signal distribution of y given $d > \overline{\mu} > 0$.

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

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

[72] See Appendix Figure A6 for an illustration.

(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),

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

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

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

(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,

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

□

(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 $lim_{\sigma_s\to+\infty} \Phi\left(\frac{d-\overline{\mu}}{\sigma_s}\right) = 0.5$.

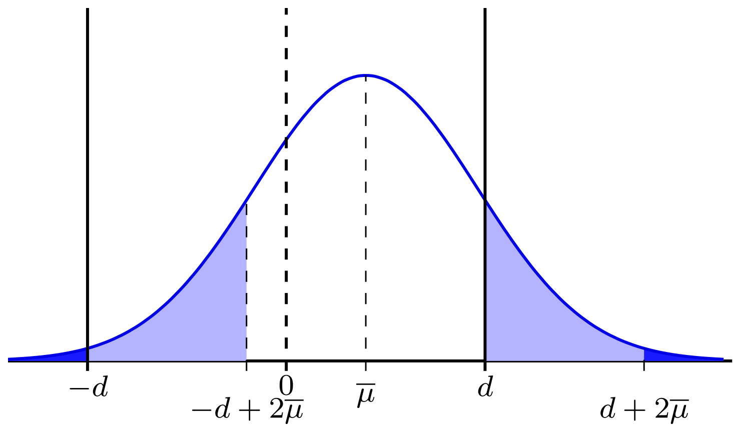
By (a)

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

.

□

Figure A6: Signal Illustration



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

F 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.

F.1 Correlation between Time and Neighborhood

The baseline model implies a positive correlation between parental inputs—neighborhood quality and time—due to individual parental beliefs. Indeed, all else equal, parents with low (high) beliefs will tend to live in worse (better) quality neighborhoods and spend less (more) time with their children. The model predicts a positive correlation between time and neighborhood quality in the data due to the omitted parental beliefs variable. I find this positive correlation in the data.

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.[73] Columns (1) and (2) of Table A9 show that parental time and neighborhood quality positively correlate with later child skills.[74] 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, I consider the parental time and neighborhood quality variables to be good proxies for parental inputs of the technology of skill formation.[75]

Columns (3) and (4) of Table A9 display a positive and significant correlation between the two parental inputs.[76] Note that in both regressions of Column (3) and (4) of Table A9, 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 A9, I control for three variables measuring households' socioeconomic status: parents' highest level of education, family income, and parent's marital status.[77] 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 the neighborhood composition effect does not drive all the correlation between the two

[73] See Appendix section for variable construction.

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

[75] Appendix Table A10 presents the OLS regression coefficients with a different definition of neighborhood quality and parental time variables. Results are robust to definition changes.

[76] The results are robust to the use of alternative proxies for parental inputs. See Appendix Table A10.

[77] 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.

parental inputs.

Table A9: 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.

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 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, 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).

F.2 Childhood Neighborhood and Adulthood Choices

The second testable implication of the model is that childhood neighborhood quality and later parental decisions, including neighborhood quality, are positively correlated due to social learning. In low-quality (high-quality) neighborhoods, children tend to underestimate (overestimate) the relevance of parental input and later on under-(over-)invest in their own child's human capital. This implies that in the data, keeping income constant, childhood neighborhood quality should be positively correlated with later neighborhood quality.

Column (5) of Table A9 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 zones 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 A9, 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.[78] 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.[79]

Neither of the two testable implications of the model is rejected.

F.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

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

[79] The results are robust to the use of the fraction of adults with a college degree for neighborhood quality. See Appendix Table A10.

parent-child activities excluding "went to a movie, play, museum, concert, or sports event".[80] Results are unchanged.

Table A10: 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.

[80] 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".