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

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Abstract

In the United States, less-educated parents tend to underestimate the relevance of parental inputs, allocate little time to parent-child activities, and reside in bad neighborhoods. To rationalize these patterns, I introduce social learning about the relevance of parental inputs in a spatial model of human capital accumulation with parental time and neighborhood quality choices. By observing their neighbors, the young infer the relevance of parental inputs. However, crucially, they are prone to misinferences as they may not fully correct for selection induced by residential segregation. The United States calibrated model matches targeted and non-targeted parental behavior moments across socioeconomic groups. I find a relatively modest level of parental delusion that increases income inequality by 3% (income Gini index) and decreases social mobility by 14% (intergenerational rank-rank). A housing voucher policy improves the neighborhood quality of eligible families, raising children's future earnings. When scaling up the policy, long-run and general equilibrium responses in parental beliefs amplify the policy effects. Inequality reduces, and intergenerational mobility improves.

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

In the United States, parental input decisions differ between more- and less-educated parents. In particular, less-educated parents tend to allocate less time to parent-child activities and reside in worse neighborhoods, two parental inputs that shape children's adulthood economic opportunities.[1] As less-educated parents tend to work fewer hours than more-educated parents, under perfect information and rational expectations, the primary explanations for these differences are less-educated parents having tighter budget constraints, higher attachment to low-quality neighborhoods, or being less effective at teaching their children.[2] However, are these explanations complete enough? Recently, Bergman et al. (2019) showed that loosening low-income parents' budget constraints through housing voucher programs alone does not lead to large increases in neighborhood quality, suggesting other mechanisms at play. In parallel, 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.

This paper develops a quantitative spatial model of human capital accumulation and parental decisions in which I introduce imperfect information and social learning about the relevance of parental inputs. Specifically, the model's agents are unaware of the relevance of parental inputs for adulthood human capital and learn about it by observing other agents around them, their neighbors. Crucially, however, agents may suffer selection neglect; they are prone to misinferences as they may not fully correct for selection. Social learning—learning through interactions and observations of others—is a central learning channel (Frick et al., 2022), and selection neglect an experimentally documented cognitive bias (Enke, 2020).[3] The proposed learning mechanism works as follows: suppose adulthood human capital depends on past parental inputs and a random, idiosyncratic, and unobserved ability shock, which can be interpreted—to some extent—as luck. Assume imperfect information about the parameter governing parental inputs' relevance for adulthood human capital. Agents form beliefs about it before they make their parental decisions. Young adults have two sources of information to do so: their parent's beliefs and the inference they make by observing their neighbors' current human capital and past parental inputs. Notice, however,

[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. (2022) for a review). Neighborhoods' causal effect on children's development is studied by Chetty and Hendren (2018a) in the United States.

[2] See Guryan et al. (2008) for a discussion about socioeconomic differences in parental time.

[3] This cognitive bias is called "assortativity neglect."

that they do not observe their neighbors' ability shocks and, with selection neglect, cannot fully correct for selection on unobservables. As a result, if relatively many low-ability-shock neighbors surround young adults, the young overestimate local ability shocks, leading to an underestimation of the relevance of parental inputs. Implicitly, they attribute too much of the local average human capital to local ability shocks and too little to parental inputs. The reverse happens if relatively many high-ability-shock neighbors surround young adults.

The spatial quantitative model features parental input decisions of heterogeneous agents in an overlapping generation framework. The altruistic parents, who have a preference for their childhood neighborhood type and endogenously formed beliefs, choose two parental inputs under time and budget constraints: in which type of neighborhood to reside and how much time to allocate to their child's education. Their budget and time constraints depend on their current earnings and labor supply, which are a function of accumulated human capital during childhood and an exogenously determined education status. In addition, perfectly competitive land developers provide housing in each neighborhood type, and local rents are equilibrium objects. Given the model structure and the social learning process, there are multiple critical equilibrium objects: the distribution of human capital and education status, parental beliefs, neighborhood choices, and local rents, which are endogenously determined as fixed points.

In this model, income residential segregation generates information friction that can give rise, in equilibrium, to systematic and persistent differences in parental beliefs between socioeconomic groups. Indeed, equilibrium residential decisions depend on unobserved ability shocks that affect parents' earnings and budget constraints. As a result, relatively many low-ability-shock parents surround young adults in low-quality neighborhoods, and relatively many high-ability-shock parents surround young adults in high-quality neighborhoods. With selection neglect, young adults in low-quality neighborhoods tend to overestimate local ability shocks and underestimate parental inputs' relevance, and conversely, for young adults in high-quality neighborhoods. Notice that parental beliefs are persistent within families: children of low-(high-)belief and low-(high-)income parents are likely to live in low-(high-)quality neighborhoods, become low-(high-)belief and low-(high-)income parents next generation. Notably, this model embeds the primary explanations for the socioeconomic differences in parental input choices: parents differ in their education status and earnings, which determine their labor supply and budget constraints; their preference for their childhood neighborhood captures attachment for a given type of neighborhood—which can be viewed as a moving cost;—and the child skill technology implies differences in returns to parental inputs by parental human capital capturing socioeconomic differences in teaching effectiveness. Crucially, the model adds a role for endogenous parents' beliefs about the relevance of parental inputs.

The model is solved numerically and calibrated to match a set of critical moments from several United States representative datasets. It comprises ten quality-ranked neighborhoods and matches segregation and family earnings dispersion in the average commuting zone in the United States computed from the ACS 2000 and NHGIS 2000 datasets (Ruggles et al., 2023; Manson et al., 2022).[4] In addition, it targets causal neighborhood effects on children's future incomes estimated by Chetty and Hendren (2018b) and social mobility measured by Chetty et al. (2014). Parents' decisions are disciplined by matching active parental time in the ATUS survey (Hofferth et al., 2020) and neighborhood quality choices from Add Health data (Harris et al., 2019). The calibrated parameter for selection neglect is positive, which suggests that heterogeneous parental beliefs contribute to explaining parental input decisions. Even though the model does not feature preference heterogeneity, the calibrated model matches parental behavior across socioeconomic groups well: it provides a rationale for college parents allocating more time to their children's education than non-college parents despite working more hours and correctly matches non-targeted intergenerational residential mobility patterns.

Parental beliefs explain a large share of the socioeconomic gap in parental input choices. In particular, using the calibrated baseline model and providing complete information about the relevance of parental inputs improves low-income parents' beliefs by 19% and decreases those of high-income parents by 7%.[5] Importantly, parental beliefs have sizable effects on the economy. Children born in bottom-quality neighborhoods would be half as likely to remain in those neighborhood types in adulthood, and low-income parents would allocate 30% more time to their children's education. Perfect information about the relevance of parental inputs would decrease the rank-rank slope, a measure of social immobility, by 14%, and the Gini index of income, a measure of inequality, by 3%, improving welfare by 0.2%.

In contrast, a perfect information version of the model cannot replicate the data without imposing sizable heterogeneous preferences across childhood neighborhoods and education

[4]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.

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

status. To see this, I first re-calibrate the model with a selection neglect parameter set to zero, consequently shutting down the parental beliefs channel. Unsurprisingly, the alternative calibrated model misses all the non-targeted parental behavior moments. I then introduce quadratic moving costs and education-specific parental time disutility parameters and define the same targeted moments as in the baseline model. This extended alternative version of the model misses the untargeted intergenerational residential mobility moments. To improve the alternative model fit, the preference parameter for the childhood neighborhood type must be more than twenty times higher for agents born in the bottom-quality neighborhood than the others. While the obtained extended alternative model fit is comparable to the baseline one, fully justifying the required heterogeneous preference assumptions is challenging. There is no empirical evidence of socioeconomic differences in parental time disutility parameters or for stronger preferences for low-quality neighborhoods. On the contrary, when comparing randomly allocated low-income families in deprived and higher-quality neighborhoods, Bergman et al. (2019) find higher satisfaction rates and willingness to stay among families living in higher-quality neighborhoods.

Motivated by the evidence that housing vouchers improve the neighborhood quality of eligible families (Chetty et al., 2016), I use the calibrated model to study their effects on the United States economy. Two key model frictions call for policy interventions: parents cannot borrow against their children's future earnings, and due to social learning and selection neglect, income residential segregation generates information frictions that distort parental decisions. I consider two types of housing vouchers: one with a unique rent limit that covers the difference between 30% of income and the rent up to a limit set at the commuting zone level, and a second with multiple rent limits that covers the difference between 20% of income and 70% of the rent in each neighborhood. Eligible households are parents from the bottom decile of the income distribution. In the first step, I study the partial equilibrium effects of the two policies by simulating a randomized control trial within the model. Compared to the control group—eligible parents who do not receive housing vouchers,—eligible parents who receive the vouchers live in higher-quality neighborhoods, positively affecting their children's earnings at age 26 by $756 and $1,101 a year.[6]

The second main finding is that, when scaling up the housing voucher policy, general equilibrium responses in local prices and, in particular, in beliefs amplify the partial equilibrium effects. The voucher allows housing voucher holders to move to better neighborhoods, increasing the density in middle-range quality neighborhoods—especially at the rent

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

limit—and forcing non-eligible households to move out. The housing market reaction creates winners and losers, with adverse effects in the aggregates; however, in the long run, information and parental beliefs improve, particularly among low-income households, amplifying partial equilibrium effects on eligible families and generating positive effects on measures of intergenerational mobility, and equality. The effect on aggregate earnings depends on the design of the policy. The housing voucher policy with multiple-rent limits is a better tool to address redistribution and efficiency concerns simultaneously than a single-rent limit housing voucher program. In the long run, the multiple-rent limit housing voucher program increases social mobility by 12%, equality by 2%, and earnings by 0.4%.

Related Literature

This paper links several strands of the literature: the education literature and the beliefs literature, the quantitative family-macroeconomics literature, and the quantitative spatial economics literature.

First, this paper builds on empirical evidence from the parental beliefs literature. Since Cunha et al. (2013), a large body of research documents that actual technology of skill formation does not systematically differ by socioeconomic groups but that parents' beliefs about the technology of skill formation differ, correlate with income and influence their decisions (see for instance Jensen (2010); Attanasio and Kaufmann (2014); Kaufmann (2014); Caucutt et al. (2017); Boneva and Rauh (2016, 2018); Belfield et al. (2019); Dizon-Ross (2019); Wiswall and Zafar (2021)).[7] A central channel through which people learn about their societies is through social learning—by observing the history and outcomes among their peers (Frick et al., 2022),—and the behavioral and psychological literature documents selection neglect (Enke, 2020).[8] Relatedly, the empirical education literature highlights the importance of role models, and, in some cases, to the selection in the observation of those role models. For instance, low-income children lacking successful role models among their peers could explain the low levels of motivation and effort (Nguyen, 2008; Alan et al., 2019; Breda et al., 2019; Algan et al., 2020; Guyon and Huillery, 2020). 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

[7] One exception is Attanasio et al. (2019) in the UK who does not find a socioeconomic gradient in beliefs.

[8] The literature provides evidence of social learning with selection neglect in different settings. An empirical example of the role of social learning and selection neglect for technology adoption is given by Conley and Udry (2010). In rural Ghana, the authors find that the use of fertilizer by small farmers is boosted by the observation of surprisingly successful peer farmers.

for it. In the model, I develop a social learning process with selection neglect and extend it to learning about the child's skill technology.

Second, this paper quantifies the macroeconomic effects of endogenous beliefs by incorporating social learning into a quantitative spatial model of overlapping generations in which parents affect their child's human capital by choosing their neighborhood and parental time. By doing so, I contribute to the quantitative family macroeconomics literature. Human capital accumulation is modeled following recent macroeconomic papers such as Daruich (2018); Jang and Yum (2020); Kim et al. (2021); Yum (2022); Chyn and Daruich (2022). While 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)), heterogeneous beliefs are usually ignored in family macroeconomics. Two major exceptions are Fogli and Veldkamp (2011) and Fernández (2013) who rationalize the change in female labor supply over time by a change in beliefs. In this paper, the learning process builds on Fogli and Veldkamp (2011). A key difference is the introduction of residential choices, which, combined with a selection neglect modeled as in Bénabou and Tirole (2005), generates a bias. In equilibrium, the learning process generates a stable distribution of heterogeneous parental beliefs that affect parental input choices. While the idea of neighborhood effects through social learning has been largely developed (see, for instance, Durlauf (2011)), very few papers have linked heterogeneous beliefs with residential choices. Roemer and Wets (1994); Streufert (2000) are two exceptions. They provide different theoretical frameworks in which the selection induced by residential sorting could lead to systematic bias in beliefs. However, this paper is the first to develop and calibrate a quantitative model with social learning and residential choices.

Finally, the paper contributes to the neighborhood literature by linking segregation and inequality. I use methods from the quantitative spatial economics literature reviewed in Redding and Rossi-Hansberg (2017). Motivated by recent evidence of a causal relationship between exogenous neighborhoods and child's skills (Chyn, 2018; Chetty and Hendren, 2018a,b; Hwang, 2022; Nakamura et al., 2022), the model displays exogenous amenities. As in Fogli and Guerrieri (2019); Eckert et al. (2019); Chyn and Daruich (2022); Gregory et al. (2022), neighborhoods' environment quality directly affects children's future human capital. By having endogenous valuations of neighborhood quality through beliefs, I contribute to the growing literature that considers endogenous neighborhood amenities (Ahlfeldt et al., 2015; Diamond, 2016; Bilal, 2021). A few papers have quantitatively linked segregation and inequality. Fogli and Guerrieri (2019) and Gregory et al. (2022) incorporate peer effects in spatial equilibrium, and Eckert et al. (2019); Chyn and Daruich (2022) model the effect of local taxes on neighborhood environment quality. This model provides and quantifies a new mechanism for the relationship between segregation and inequality. Segregation creates informational frictions: the more the economy is segregated, the steeper the socioeconomic gradient in parental beliefs and, consequently, parental input choices.

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.

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

2.1 Social Learning and Technology of Skill Formation

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

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

where $\alpha,\ \beta,\ \gamma \in (0,1)$ and the child's ability shock a' is uncorrelated with parental characteristics and drawn from a normal distribution $\mathcal{N}(0, \sigma_a)$.[9]

By assumption, parental human capital h enhances the productivity of the two parental inputs. This feature seeks to capture that high-human capital parents are better at building child skills and that environmental factors, such as in-utero experiences correlated with parental human capital, influence children's skills (Cunha and Heckman (2007, 2009); Cunha et al. (2010); Heckman and Mosso (2014)). Following the literature, I assume a nested CES function for the skill formation technology, with one of the elasticities set to unity, which imposes a parsimonious Cobb-Douglas outer form.[10] Following Kim et al. (2021), the parameter $\underline{i} > 0$ guarantees that every child has a minimal level of baseline human capital. This term captures, for instance, a uniform minimum level of public education across neighborhoods. Finally, parental τ is normalized by its baseline unconditional mean ($\overline{\tau}$) to achieve unit independence and computational stability following Jang and Yum (2020).

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

Social Learning: Let's now turn to one of the key and novel features of the model: the social learning process about the technology parameter that governs the relevance of parental inputs α. Following Fogli and Veldkamp (2011), learning happens in the first period of life, before 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

[9] 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.

[10] For similar modeling assumptions, see for instance Fuchs-Schündeln et al. (2022); Jang and Yum (2020); Lee and Seshadri (2019); Yum (2022).

given neighborhood m is then:

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

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

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

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

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

where $\bar{\tilde{a}}_m$ represents perceived average ability shock in neighborhood m, $\overline{a}_m$ the actual average ability shock in neighborhood m and $\overline{a}$ 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.[11] The following equation describes the observations and perceptions of every young agent in a given neighborhood m:

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

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

Finally, every young agent uses their observation of local averages to infer the relevance

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

of parental inputs governed by α:[12]

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

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 ($\overline{\tilde{a}}_m \leq \overline{a}_m$). Intuitively, when young agents overestimate ability shocks, they implicitly 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.

2.2 Economic Environment

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

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

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

[12] 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.

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

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

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

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

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

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

where $\bar{y}_m$ represents the average pre-tax labor earnings in neighborhood m and $\xi \bar{y}_m$ captures the effect of the demographic composition on the neighborhood quality. 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 zero mean. The dispersion of the idiosyncratic neighborhood taste shock is measured by ν. Finally, $\tilde{\alpha}$ stands for the parent's beliefs regarding the value of parameter α in the technology of skill formation and $\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right]$ is the expected child lifetime utility with respect to the child's ability shock and neighborhood taste shock conditional on the parent's beliefs $\tilde{\alpha}$.

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

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

2.3 Parents' Problem

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

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

subject to:

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

where r_m is the equilibrium rent of neighborhood m, $\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right]$ 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). 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, neighborhood of birth, and parental beliefs

2.5 Equilibrium

The key objects of the equilibrium in the steady state are the endogenous distribution of human capital, 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, graduation status, parental beliefs, and decisions.

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

3 Calibration

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

3.1 Preliminaries

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

I use multiple data sources to compute the relevant moments to calibrate the model. Earnings distribution moments come from the American Community Surveys (ACS) from 2000. I use the information at the census tract level from the National Historical Geographic Information System (NHGIS) dataset in 2000 (Manson et al., 2022) to construct neighborhood sociodemographic characteristics. I aggregate census tract information at the commuting zone level using a county-to-commuting zone crosswalk. Neighborhood choices and college graduation probabilities are estimated using data from the AddHealth survey described in Appendix Section A.1.[13] Finally, parents' time use information is taken from the American Time Use Survey (ATUS) 2003.[14]

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 in the model to ten, representing a synthetic decile census tract in the data. Specifically, in each of the 100 commuting zones of the NHGIS 2000, I sort census tracts by median household income and form ten synthetic neighborhoods from the deciles of this distribution.[15] I then create one average commuting zone by computing the population-weighted average characteristics of each of the ten neighborhoods.[16]

3.2 Empirically Estimated Parameters

Housing Markets: Rental prices are determined in equilibrium given the supply function: $\mathcal{H}_m = \zeta_m r_m^{\eta}$, where r_m is the equilibrium rent price in the neighborhood m, and η is the price elasticity of housing supply. Saiz (2010) estimates population-weighted average price elasticity in the average metropolitan area of the U.S. to be 1.75, so I set $\eta = 1.75$. The remaining parameters ζ_m can be estimated directly from the synthetic neighborhood density and rents.[17]

[13]See Appendix Section E.3 for more details on those statistics.

[14]Appendix Section A.3 provides detailed information on how I compute parental time using ATUS.

[15]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%.

[16]Appendix Table S3 summarizes the ten neighborhoods' characteristics.

[17]Appendix Figure S2 summarizes the log-relationship between density (Column (5) Table S3) and rents across the ten synthetic neighborhoods. Without loss of generality, the numeraire is the average household

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

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

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.[18]

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.[19] The fraction of time allocated to market work by education comes from ATUS 2003, as described in Appendix Section A.3. The wage rate w, the parental investment constant $\underline{i}$, and the average exogenous neighborhood quality component $\mu_{\bar{m}}$ are normalized to 1. I assume the number of neighborhoods N is equal to ten, and the exogenous neighborhood quality component is distributed according to $\bar{m} \sim \mathcal{N}(\mu_{\bar{m}}, \sigma_{\bar{m}})$. Table 1 summarizes the externally calibrated parameters.

3.4 Internally Calibrated Parameters

Table 2 lists the fifteen parameters I calibrate by minimizing the sum of squared percentage differences between data and model moments. The data moments include two measures of household earnings dispersion within commuting zones computed from the ACS 2000: the Gini coefficient of household earnings and the income ratio of non-college and college house-

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earnings in the economy.

[18] Appendix Section E.3 provides details on the variable construction, and Appendix Table S4 shows the weighted logit regression estimates.

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

Table 1: Externally Calibrated Parameters

Parameter	Description	Value	Source
N	Number of neighborhoods	10	Deciles NHGIS
β	Returns on parental human capital	$1-\alpha$	Constant returns
ψ	Intertemporal elasticity of substitution	0.5	Standard
w	Wage rate	1	Normalization
$\underline{\mathrm{i}}$	Parental investment constant	1	Normalization
$\mu_{\bar{m}}$	Average neighborhood quality	1	Normalization
τ_y	Tax progressivity	0.18	Heathcote et al. (2017)
η	Price elasticity of housing supply	1.75	Saiz (2010)
ζ_1	Housing supply coefficient D1	1,859	NHGIS
ζ_2	Housing supply coefficient D2	1,794	NHGIS
ζ_3	Housing supply coefficient D3	1,722	NHGIS
ζ_4	Housing supply coefficient D4	1,661	NHGIS
ζ_5	Housing supply coefficient D5	1,606	NHGIS
ζ_6	Housing supply coefficient D6	1,566	NHGIS
ζ_7	Housing supply coefficient D7	1,479	NHGIS
ζ_8	Housing supply coefficient D8	1,399	NHGIS
ζ_9	Housing supply coefficient D9	1,239	NHGIS
ζ_{10}	Housing supply coefficient D10	0,937	NHGIS
$\overline{\ell_0}$	Non-college labor supply	0.275	ATUS 2003
$\overline{\ell_1}$	College labor supply	0.294	ATUS 2003
γ_1	College graduation coeff. - intercept	-3.83	Add Health
γ_2	College graduation coeff. - human capital	0.35	Add Health
γ_3	College graduation coeff. - income	0.15	Add Health
γ_4	College graduation coeff. - education	1.11	Add Health

Notes: The table shows all the externally calibrated parameters.

holds. Both are weighted population averages across the 100 biggest commuting zones.[20] The tax rate parameter matches the average marginal income tax rate of 35.1 percent.[21] I further include the rank-rank coefficient from Chetty et al. (2014), a coefficient that captures the income correlation between parents and children. It is an inverse measure of social mobility. To discipline the neighborhood quality distribution ($\{m\}$) that directly enters the child skill production function, I use the causal effect of a one standard deviation improvement in neighborhood quality for a child born in the 25th and 75th percentile of the household income distribution estimated by and the share of the variance of causal placed based effects explained by observable (24%) Chetty and Hendren (2018b). I add a Gini coefficient across the ten neighborhoods computed from the NHGIS 2000 dataset to match residential segregation and the slope in monthly rent prices. The place of birth preference parameter is calibrated by matching a moment labeled "residential mobility (D1)". It is defined as the fraction of children born in the first synthetic neighborhood who choose to live in the same synthetic neighborhood in adulthood. The altruism parameters ensure that the average rent price over the average household income corresponds to the observation in the NHGIS 2000 dataset. To capture parental behaviors, I include parental time by education (displayed in Appendix Table S2) and household income. In addition to disciplining parental beliefs, I add the correlation between parents' and children's neighborhood choices.[22]

Table 2 reports calibrated parameters, corresponding moments in the data, and their model analogs. Even though every moment results from combining all parameters, certain moments are more sensitive to specific parameters. Understanding these intuitive links is informative about the underlying model mechanisms.

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

[20] 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.

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

[22] Moments construction and data sources are detailed in Appendix Section E.4.

Table 2: Internally Calibrated Parameters

Parameter	Description	Moment	Data	Model
Preferences and Labor Market				
$b = 0{,}5$	Altruism	Average rent over income	0,117	0,117
$\kappa = 0{,}52$	Parental time disutility	Parental time non-college parents	0,075	0,073
$\iota = 0{,}0001$	Place of birth preference	Residential immobility (D1)	0,302	0,285
$\omega = 0{,}005$	College wage premium	Earnings ratio non-college - college	0,554	0,555
$\lambda_y = 0{,}71$	Tax function scalar	Avg. marginal income tax rate	0,351	0,352
Neighborhoods				
$\sigma_m = 0{,}24$	Neighborhood quality	Neighborhood effect (25th pct.)	0,062	0,058
$\nu = 0{,}01$	Taste shock variance	Census tract Gini	0,231	0,239
$\xi = 0{,}175$	Demographics effects	Explained share place-based effects	0,24	0,235
$\delta = 0{,}007$	Amenities	Rent price gradient	54,2	53,8
Skill Formation: $h' = \left(\left(\gamma \ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}} \ + \ \underline{i} \right)^{\alpha} \ h^{1-\alpha} \ \exp(a') \text{ with } a' \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0{,}765$	Parental inputs elasticity	Rank-rank coefficient (IGE)	0,341	0,341
$\gamma = 0{,}53$	Parental time share	Neighborhood effect (75th pct.)	0,046	0,047
$\varphi = 0{,}4$	Substitutability	Income gradient in parental time	0,14	0,152
$\sigma_a = 0{,}553$	Ability shock variance	Income Gini	0,336	0,334
Social Learning Process				
$\mu = 0{,}55$	Update weight	Ratio parental time by education	0,75	0,823
$\pi = 0{,}5$	Cognitive bias strength	Neighborhood quality correlation	0,417	0,438

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

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

The child's skill formation parameters are most relevant for this paper. In particular, the substitutability parameter φ is calibrated by matching the childcare time difference across income groups; here, I use the regression coefficient of parental time on household income quartiles.[23] With social learning and selection neglect, I find that neighborhood quality and parental time are substitute inputs in the child skill production function $\varphi > 0$ (in line with Agostinelli (2018) and Agostinelli et al. (2022)). Parental human capital share $1-\alpha$ mechanically increases the income correlation between parents and children. Thus, the relevant moment is the rank-rank coefficient between parental and child earnings estimated by Chetty et al. (2014). As ability shock variance captures any income variation not explained by parental choices and human capital, it is calibrated by matching household earnings inequality measured by the income Gini coefficient.

Lastly, the correlation between parents' and children's beliefs is governed by μ and affects the persistence of beliefs and, hence, parental behavior within families. I discipline this parameter by matching the ratio of parental time choices by parents' education levels. This ratio is below one, meaning college parents spend more time with their children than non-college parents. The parental time ratio results from two opposing forces in the model. Delusion about the technology of skill formation, if correlated with earnings, decreases the ratio. However, the substitutability between parental time, neighborhood quality ($\varphi > 0$), and the differential in working hours increase it. Finally, I calibrate the strength of the selection neglect bias (π) using the correlation between parents' and children's neighborhood-

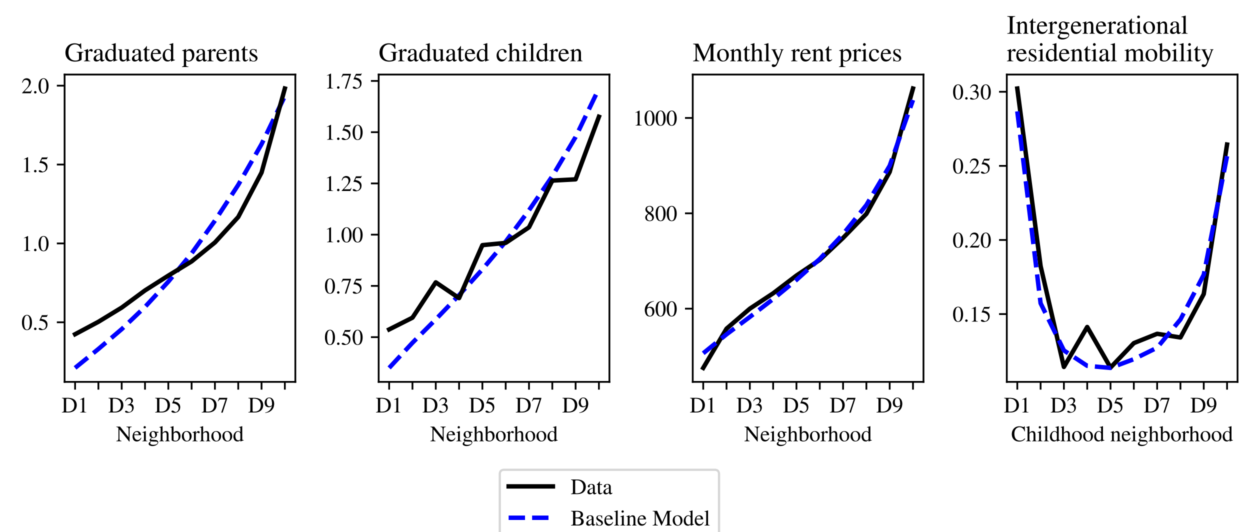
[23] In the data, I control for the gender of the respondent and the age of the child.

type choices. Parents' neighborhood choices affect children's future neighborhood decisions through two channels: human capital formation and, hence, earnings and beliefs. Parents' influence on children's earnings is calibrated by matching the rank-rank coefficient and place-based effects. Matching the intergenerational neighborhood correlation ensures a correct discipline of the belief channel. Notice that π is above zero, suggesting that agents face a selection neglect bias and that the resulting distribution of parental beliefs is needed to match parental behavior across socioeconomic groups.

3.5 Non-Targeted Moments

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

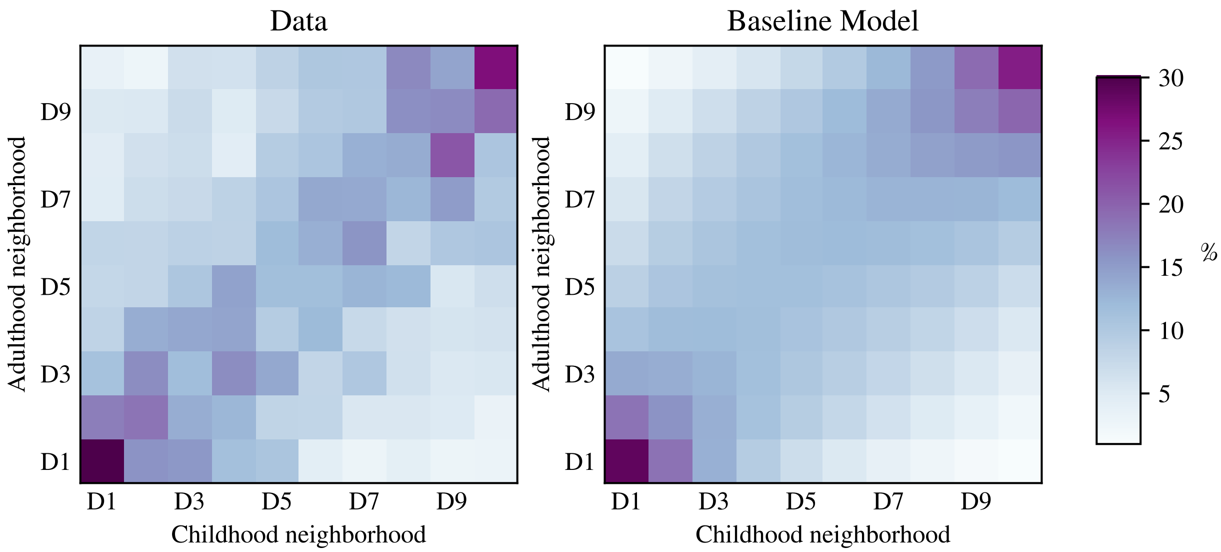
Figure 1: Non-Targeted Moments by Neighborhood



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

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

Figure 2: Non-targeted Moments: Detailed 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 E.4 for details of data construction.

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 One is likely to live in Neighborhood One or Two when she becomes an adult, but she is unlikely to live in Neighborhood Six 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 rent prices and neighborhood amenities, and parental beliefs about the relevance of parental inputs. The excellent match of these non-targeted moments indicates the model's mechanisms are well quantified, resulting in a calibrated model that successfully replicates parental behavior across socioeconomic groups.

3.6 Discussion of the Social Learning Channel

The alert reader might ask the following questions: How do parental beliefs impact the economy? Furthermore, could a model without parental beliefs explain parental behavior across socioeconomic groups?

3.6.1 The Role of Parental Beliefs

To understand parental beliefs' role in 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.[24] Table 3 presents the differences in steady-state outcomes between the baseline economy and one with perfect information ($\pi = 0$).

Providing complete information would lead parents in the bottom quartile of the income distribution to update their beliefs about the relevance of parental inputs upward by 19% and parents in the top quartile of the income distribution to update them downward by 7%. These numbers are of a reasonable order of magnitude. Cunha et al. (2013), who elicits disadvantaged African American mothers' beliefs about the elasticity of child development with respect to parental investments, finds greater differences between the truth and their beliefs. As a result, low-income parents allocate too little time to their children's education and reside in lower-quality neighborhoods, while high-income parents allocate too much time and reside in greater-quality neighborhoods. Providing information to parents would increase low-income households' parental time and neighborhood rank by 30% and 6%, respectively, and decrease high-income households' by 8% and 0.4%. In the aggregate, parents' distorted beliefs decrease social mobility—negative rank-rank coefficient—and earnings by 13% and 2% respectively and increase inequality and poverty by 3% and 16%.[25] 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 0.2%, with a more substantial effect for the lowest-income households.[26] In sum, the relatively modest level of parental delusion that the calibrated model implies greatly affects the economy.

[24]Notice, in general equilibrium, the update parameter μ is irrelevant.

[25]Poverty is measured by the absolute level of poverty. The poverty threshold is defined at baseline by the tenth percentile of the household income distribution.

[26]See Appendix Section C for details on welfare computation.

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

		Household income quartile			
	All	1st	2nd	3rd	4th
Parental beliefs	+3.0%	+19.1%	+7.1%	-1.1%	-7.4%
Parental time	+5.8%	+30.2%	+11.3%	+1.0%	-8.0%
Neighborhood rank	+0.8%	+5.6%	+4.7%	+0.6%	-0.4%
Earnings	+2.0%	+10.1%	+6.4%	+1.6%	-0.3%
Rank-rank coefficient (Social immobility)	-13.5%				
Census tract Gini (Segregation)	-2.0%				
Income Gini (Inequality)	-2.6%				
Absolute poverty	-16.3%				
Welfare	+0.17%	+0.52%	+0.14%	+0.05%	+0.03%

Notes: This table displays percentage differences in model-generated moments between the baseline calibrated model with parental beliefs and with perfect information.

3.6.2 Alternative Modeling under Perfect Information

To match the data moments, the calibrated model requires a positive selection neglect bias parameter ($\pi > 0$), suggesting imperfect information is needed to replicate data patterns. Unsurprisingly, re-calibrating a perfect information version of the model ($\pi = 0$) results in a relatively bad fit for all untargeted moments despite a good match of social mobility and inequality moments.[27] Notice, however, that two parental behavior moments targeted at baseline are not, which renders the comparison of the two calibrated models somewhat unfair.

In the second step, I augment the alternative model with heterogeneous preferences regarding the parental time disutility parameter and quadratic moving costs. This extension provides two extra free parameters and mechanically generates heterogeneity in parental input choices by socioeconomic group. Parents' preferences take the following form:

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

with k_s, the parental time disutility parameter now depends on the college education

[27]See Appendix Table S6 and Appendix Figures S3 for the fit of targeted and non-targeted moments

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

This extended perfect information version of the model matches relatively well all the targeted moments but misses untargeted ones.[28] In particular, the intergenerational residential mobility moments are off, suggesting a need for other forms of preference heterogeneity. In addition to quadratic moving costs and differences in time disutility parameters, the preference for the neighborhood should vary by childhood neighborhood type (ι_{0,m_0}). Specifically, to reproduce the U-shape data patterns in intergenerational residential mobility (see right panel of Figure 1), the preference for childhood neighborhoods must be more than twenty times higher in the worst neighborhood than in the other ones.

While preference heterogeneity can help match the data, its origin is difficult to justify. Does parental time disutility systematically differ by education status? How does it transmit to the next generation? Are quadratic moving costs credible? Why would children born in the worst neighborhood type be so much more attached than others to their neighborhood quality given the negative features it has: high crime rates, high poverty rates, and low opportunity for children?[29] This last feature is at odds with Bergman et al. (2019)'s empirical findings, whose authors compare low-income families randomly allocated between treatment and control groups. Parents in the treatment group are induced to move to higher-quality neighborhoods and express higher satisfaction rates and willingness to stay than those in the control group—who remained in deprived neighborhoods.[30]

[28]See Appendix Table S7 for the fit of targeted moments and Figures S4 and S5 for the fit of untargeted moments.

[29]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.

[30]Discrimination or a homophily bias could motivate other modeling assumptions. However, the fact that Bergman et al. (2019) find higher satisfaction levels of low-income families who moved to higher-quality neighborhoods suggests that if they face discrimination once installed, it does not make them systematically want to move back to low-quality neighborhoods. In Appendix Table S8, 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.

4 Housing Voucher Policies

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

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

U.S. housing voucher programs target low-income families and typically cover the difference between the rent—up to a rent limit—and a fraction of the family's income. The rent limit was initially designed as the Housing and Urban Development's fair market rent, generally the 40th percentile rent in the metro area. Since 2019, housing agencies can set the rent limit at local rent levels rather than at the metro area level.[31]. This section evaluates two versions of housing vouchers in the commuting zone: 1) single-rent limit housing vouchers and 2) multiple-rent limit housing vouchers. Under both policies, eligible households are those below the poverty threshold, defined as the income level at the tenth percentile of the income distribution in the baseline economy. They receive the voucher before they make their residential choice.

The single-rent limit housing vouchers (SHV) closely mimic the initial Housing Choice Voucher program, covering the difference between 30% of the family's income and the rent up to the rent ceiling, the 40th percentile rent in the commuting zone. Let r_{m40} the 40th percentile rent in the commuting zone, then the rent price in the neighborhood m for a parent of income $y(h, s)$ who is eligible for the housing voucher is:

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

Since the model does not feature heterogeneity in neighborhood rents, to design multiple-rent limit housing vouchers, rent limits are determined by the median rent in each neighborhood. The multiple-rent limit housing vouchers cover the difference between a fraction of the median rent in each neighborhood and a of the family's income. Those fractions are

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

defined so that (i) in partial equilibrium, the cost of the policy is the same as the cost of a housing voucher with a unique rent limit, and (ii) the rent in the bottom-quality neighborhood that faces the average eligible household is the same across the two policies. Under this new housing voucher policy, housing vouchers cover the difference between 70.5% of the median rent and 20% of the family income in each neighborhood. Under this multiple-rent limit housing vouchers (MHV), the rent price in the neighborhood m for a parent of income $y(h, s)$ who is eligible for the housing voucher is:

$$r^{MHV}_{m,h,s} = \min(0.2 \times y(h, s) + 0.295 * r_m,\ r_m).$$

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

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

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

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

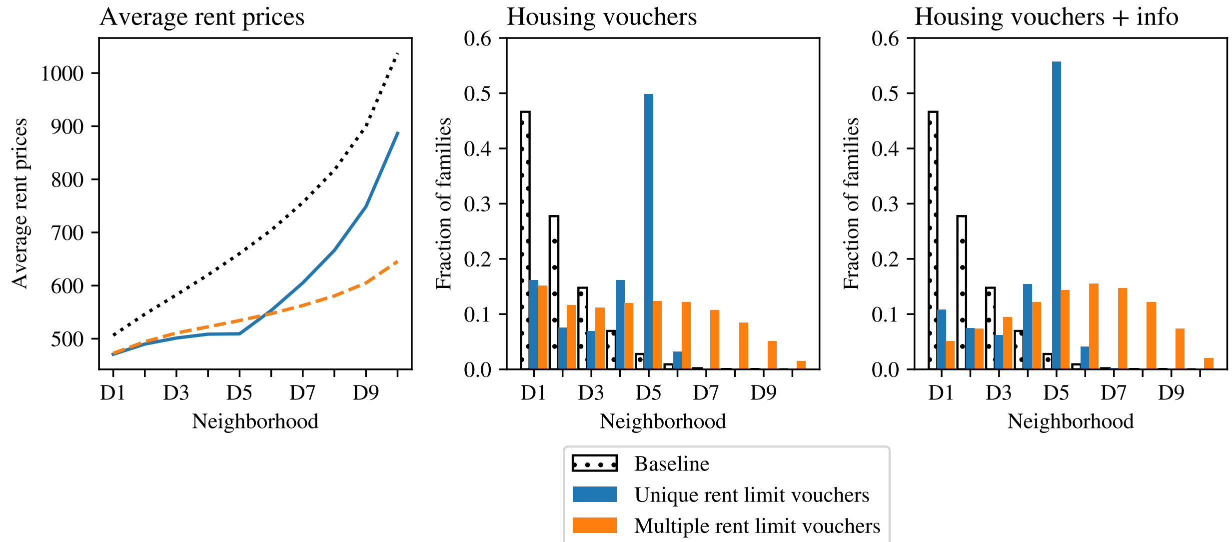
$$\sum_m \sum_s \int (r_m - r^{HV}_{m,h,s}) F(h, s, m)\ dh = \sum_m \sum_s \int (r^{HV}_{m,h,s}\ \tau_r) F(h, s, m)\ dh.$$

4.1 Partial Equilibrium Effects of Housing Vouchers

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

The central panel of Figure 3 shows the positive effects of both housing voucher policies on the neighborhood quality of eligible households. With single-rent housing vouchers, an extra 65% of eligible families move out of bottom-quality neighborhoods, and their neighborhood rank improves by 1.9 points, improving children's earnings at age 26 by \$756 (Column (4) of Table 4). The predicted effect on children's earnings falls within Chetty et al. (2016)'s

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



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

estimated confidence interval ($1,452 with a standard error of 736).[32]

Incorrect parental beliefs partly explain why not all low-income families move out. In the right panel of Figure 3 and in Columns (5) and (7) of Table 4, I conduct the same experiment but provide information about the relevance of neighborhood quality for children's future human capital. The single-rent housing voucher program is more effective when information is provided. The neighborhood rank of treated families improves by 2.2 points, 0.3 points higher than with only housing vouchers (Column (5)). As a result, perfect information further increases eligible children's adulthood earnings by $98. Notice here that the fraction of families who move out of bottom-quality neighborhoods with information rises to 77%. This is consistent with Bergman et al. (2019)'s empirical findings, whose authors randomly provide services and information to reduce barriers to moving to high-upward-mobility areas.

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

Although the intervention increased the fraction of families who moved to high-upward-mobility areas, this number did not reach 100%.

Finally, multiple-rent housing voucher effects are consistent with Collinson and Ganong (2018)'s results. Collinson and Ganong (2018) finds that because most rental units below the payment standard are in low-quality neighborhoods, indexing rent limits to ZIP codes rather than metropolitan areas improves the share of families who move into higher-quality neighborhoods. The center panel of Figure 3 illustrates a bunching effect of eligible households with the single-rent housing voucher that disappears with the multiple-rent limit housing voucher. Column (6) of Table 4 indicates an increase of 2.6 points in the neighborhood quality ranks, improving children's earnings at age 26 by $1,101. Providing information renders the policy intervention even more effective (Column (7) of Table 4).

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

	Data		Model				
				Single rent limit housing vouchers		Multiple rent limit housing vouchers	
	Control	Housing vouchers	Control	SHV	SHV + info	MHV	MHV + info
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% in bottom-quality neighborhood	100%	[-62%; -70%]	47%	-65%	-77%	-68%	-89%
Child's future earnings	$12,702	[+$11; +$2,893]	$20,597	+$756	+$852	+$1,101	+$1,435
Neighborhood rank			1.95	+1.9	+2.2	+2.6	+3.5
Parental time (min./day)			51	+1.1	+1.3	+1.8	+2.6

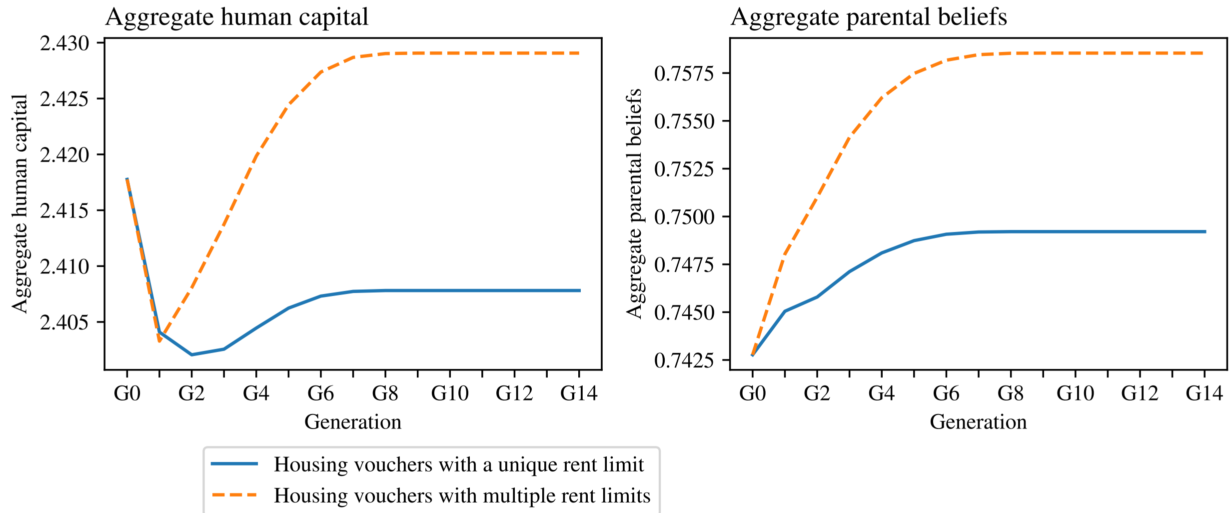
Notes: This table shows the effects of housing vouchers on eligible families, from the data, and simulated by the calibrated baseline model. Data source: Chetty et al. (2016).

4.2 General Equilibrium Effects of Housing Vouchers

In the next step, I scale up the policies to all families below the poverty threshold in the economy and compute the new steady states and the transition paths. The steady-state comparisons provide insights into the long-run implications of the policy.

First, I compute the transition paths to gauge how long it would take to reach the new steady state. Figure 4 illustrates the dynamics of aggregate human capital and parental beliefs. Under both housing voucher policies, aggregate human capital first decreases and

Figure 4: Transition Dynamics of the Economy with Housing Voucher Policies



Notes: The left and right panels show the transition path of aggregate human capital and parental beliefs under the two policy regimes: housing vouchers with a unique rent and multiple-rent limits.

starts to increase for the second generation. Aggregate parental beliefs slowly increase and reach a steady state in the sixth generation.

General equilibrium rent responses and beliefs amplify housing voucher effects on eligible households. Columns (1) and (3) of Table 6 show the long-run and general equilibrium effects of the single- and multiple-rent housing voucher policy on eligible households. Parental time and neighborhood rank of eligible households increase more in general equilibrium than in partial equilibrium (+3.3, +2.4, and +14.5, +4.6, respectively), increasing eligible children's earnings by +\$1,201 and +\$3,281 per year (versus \$756 and \$1,101). This amplification effect is primarily driven by an increase in parental beliefs of low-income households: among the first-income quartile households, it increases by + 4.7% and + 12% with the single- and multiple rent housing vouchers, respectively (Table 7).

The general equilibrium effects of both policies on equality, social mobility, welfare, and absolute poverty are positive, but aggregate earnings only increase under the multiple-rent housing voucher policy. Table 7 helps understand why. In general equilibrium, income segregation changes, and the distribution of parental beliefs evolves. While higher-income households' parental beliefs decrease, lower-income households' parental beliefs increase. Parental behaviors coherently move with the change in parental beliefs. However, only with the multiple-rent housing voucher—that leads to a great decrease in segregation (-21%), does the increase in parental inputs from low-income households compensate for the decrease

Table 6: General Equilibrium Effects Housing Voucher Policies

	Single-rent limit housing vouchers		Multiple-rent limit housing vouchers	
Households	Eligible (1)	All (2)	Eligible (3)	All (4)
% in bottom-quality neighborhood	-78%	-4%	-81%	-8%
Children's future earnings	+$1,201	-$138	+$3,281	+$133
Neighborhood rank	+2.4	+0.0	+4.6	+0.1
Parental time (min./day)	+3.3	-1.5	+14.5	+0.5
Income Gini (Inequality)		-0.5%		-1.8%
Absolute poverty		-0.8%		-8.9%
Census tract Gini (Segregation)		-6.4%		-20.9%
Rank-rank coefficient (Social immobility)		-2.9%		-11.9%

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

Table 7: General Equilibrium Effects Housing Voucher Policies by Income Quartile

	Single-rent limit housing vouchers					Multiple-rent limit housing vouchers				
		Income quartile					Income quartile			
	All	1st	2nd	3rd	4th	All	1st	2nd	3rd	4th
Par. beliefs	+0.9%	+4.7%	+1.2%	-1.2%	-0.8%	+2.1%	+12%	+4.3%	-0.4%	-3.3%
Par. time	-2.0%	+0.3%	-2.6%	-3.8%	-2.0%	+0.7%	+15%	+2.1%	-2.7%	-4.6%
Nbh. rank	+0.2%	+20%	-6.0%	-2.6%	-0.9%	+1.0%	+54%	-8.9%	-6.0%	-2.2%
Earnings	-0.4%	+0.5%	-0.1%	-2.9%	-3.6%	+0.4%	+8.1%	+3.6%	-0.0%	-0.3%
Welfare	+0.3%	+1.8%	+0.0%	-0.1%	-0.1%	+0.3%	+1.9%	0.0%	-0.3%	-0.4%

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

in parental inputs from high-income households, increasing aggregate earnings. In sum, a housing voucher policy with multiple-rent limits is a better tool to address redistribution and efficiency concerns simultaneously than a single-rent limit housing voucher program. In the long run, the multiple-rent limit housing voucher program increases social mobility by 12%, equality by 2%, and earnings by 0.4%.

5 Conclusion

In this paper, I present a quantitative spatial model of residential and parental time decisions with social learning about the technology of skill formation and potential selection neglect. Once calibrated to the average commuting zone in the United States, the baseline model has residential segregation generating information frictions that shape parental beliefs and distort parental input choices. In equilibrium, while low-income parents underestimate the relevance of parental inputs for the child's development, high-income parents overestimate it. Introducing endogenous parental beliefs helps rationalize two surprising parental behaviors across socioeconomic groups: parents raised in the worst neighborhood types tend to raise their children in the same type of neighborhoods, and college parents, despite working more hours, tend to allocate more active time to their children's education than non-college parents. While heterogeneous preferences by socioeconomic groups could rationalize those data patterns, they would need to be rather large and are difficult to defend for some of them empirically.

Using the baseline calibrated model, I investigate the effects of parental beliefs on the United States economy. Relatively modest levels of parental delusion have significant macroeconomic effects as they increase inequality and decrease social mobility and aggregate earnings, reducing consumption equivalence welfare. A housing voucher policy that induces low-income households to move to higher-quality neighborhoods improves welfare in the long run. Indeed, the model predicts positive economic impacts, as a housing voucher program can decrease residential segregation, leading to a shift in parental beliefs in the long run, reducing inequality and poverty, and increasing social mobility.

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A Data

A.1 National Longitudinal Study of Adolescent to Adult Health (Add Health)

A.1.1 Description

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, and in 1994-1995, most of them were aged between 12 and 17 years old. 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 aged between 12 and 17, and the last follow-up survey in 2018 (Wave V), when interviewees were aged between 35 and 40.

The data set includes detailed information on family background and a rich set of information on neighborhood characteristics. In 1994, we observe the highest education level of the parents 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 A.3).

A.1.2 Neighborhood and Parental Time

The Add Health data includes detailed information on parents, children, and neighborhood characteristics, which allows me to construct two parental inputs in the child skill production function: parental time and neighborhood quality. I proxy neighborhood quality by the household median income of the census tract in which the interviewee resided in 1994 and 2018.[33] I create ten synthetic neighborhoods by ranking all census tracts by neighborhood quality and grouping them into ten groups of equal size. One synthetic neighborhood represents a decile of the census tracts distribution in the United States. Thanks to the panel

[33] In Appendix Section F.3 I also use the share of residents above 25 with a college degree as a robustness check of the results (Diamond, 2016).

form of the data set, I can observe in which synthetic neighborhood an adolescent lives in 1994-1995 and in which synthetic neighborhood she lives during adulthood, in 2016-2018.

Add Health survey contains information about ten parent-child activities in 1994-1995.[34] 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 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", "went to a religious service or church-related event" and.[35] 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".

A.2 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).

A.3 The American Time Use Survey (ATUS)

A.3.1 Description

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, and all of those can be linked to data files from the Current Population Survey (CPS). I use already linked

[34]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)".

[35]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". As a robustness check, I construct an alternative proxy without the activity"went to a movie, play, museum, concert, or sports event".

datasets provided by Hofferth et al. (2020) and available on the IPUMS website. As all the other datasets are from the year 2000, I use the earliest ATUS survey year, 2003.

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

A.3.2 Parental Time

To measure parental time, I first restrict the sample to individuals in a two-parent household, defined as married individuals whose youngest child is under age 18. In 2003, 5,597 married parents were interviewed, among which 2,168 have a college degree.[36]. I use the BLS definition of childcare as "primary childcare activities" and respect the activity coding structure of ATUS to describe how parents from different socioeconomic groups allocate their time between childcare, leisure, and market work. 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 types of activities.[37]

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

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

Table S1: ATUS Activity Coding Structure, 2003

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

Sports, exercise, and recreation	Time spent in sports, exercise and recreational activities such as pleasure boating, throwing a Frisbee, kite flying, or ballooning, and active, participatory outdoor games or activities, such as horseshoes, croquet, and paintball.	0.25	0.33
Religious and spiritual activities	Time spent in work activities such as working, doing activities as part of one's job, engaging in income-generating activities (not as part of one's job), and looking for jobs and interviewing.	0.14	0.17
Volunteer activities	Time spent in volunteer (unpaid) activities done by the respondent for individuals or institutions through formal organizations, such as unpaid performance arts activities, socializing related to volunteering and attending church service as a volunteer activity.	0.13	0.25
Telephone calls	Time spent in telephone communication activities such as talking on phone, waiting for a phone call or Skyping (2011+).	0.05	0.07
Professional and personal care services	Time spent in activities such as obtaining, receiving, and/or purchasing professional and personal care services provided by someone else. Professional services include child care, financial, legal, medical and other adult care, real estate, and veterinary. Personal care service activities include massages, haircuts, manicures, and tanning at salons.	0.07	0.09
Other		**4.04**	**4.07**
Household activities	Time spent in household activities such as maintaining their household, household management and organizational activities.	2.13	1.94
Caring for and helping household members (except household children)	Time spent in caring for or helping any adult in the respondent's household, regardless of relationship, age, or physical or mental health status.	0.04	0.03

Caring for and helping non-household members	Time spent in caring for or helping any child or adult who is not part of the respondent's household, regardless of relationship, age, or physical or mental health status.	0.10	0.08
Household services	Time spent in activities such as obtaining and purchasing household services provided by someone else. Household services include yard and house cleaning, cooking, pet care, tailoring and laundering services, and 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.

B Equilibrium Computation

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

1. Make an initial guess for the distribution $F(h, s, m_0, \tilde{\alpha})$ 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.

C 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 $\Delta_{h,s,m_0,\tilde{\alpha}}$ in the baseline economy that makes individuals with state variables $(h, s, m_0, \tilde{\alpha})$ 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 $V^P(h, s, m_0, \tilde{\alpha}, \Delta_{h,s,m_0,\tilde{\alpha}})$ the welfare of agents in the initial state of the economy if their consumption (and that of their descendants) were multiplied by $(1 + \Delta_{h,s,m_0,\tilde{\alpha}})$:

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

Note that the policy functions are assumed to be unchanged when $\Delta_{h,s,m_0,\tilde{\alpha}}$ is introduced. The welfare of agents can then be written as :

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

The state-specific consumption equivalence $\Delta^P_{h,s,m_0,\tilde{\alpha}}$ makes the individual indifferent between being born in the baseline economy $P=0$ and one in which policy $P \neq 0$ is in place. It can be computed using the following formula:

$$V^0(h,s,m_0,\tilde{\alpha},\Delta^P_{h,s,m_0,\tilde{\alpha}}) = V^P(h,s,m_0,\tilde{\alpha},0),$$

which results in the following analytical formula:

$$\Delta^P_{h,s,m_0,\tilde{\alpha}} = \exp\left(\frac{\mathcal{V}^P(h,s,m_0,\tilde{\alpha}) - \mathcal{V}^0(h,s,m_0,\tilde{\alpha})}{1+b}\right) - 1.$$

Aggregate consumption equivalence welfare is then the average state-specific welfare:

$$\bar{\Delta}^P = \sum_{s,m_0} \int_{h,\tilde{\alpha}} \Delta^P_{h,s,m_0,\tilde{\alpha}} \Lambda^0(h,s,m_0,\tilde{\alpha}),$$

where Λ^0 is the distribution of initial states $\{h,s,m_0,\tilde{\alpha}\}$ in the baseline economy.

D Theory Appendix

D.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.[38] The signal noisiness could capture the fact that there is no real way to perfectly gauge ability—which can be interpreted as a combination of intelligence and luck—by simply observing people. The signal boundedness would embed the tendency to classify people's abilities within predefined categories.[39] Intelligence tests always have a scale with a predefined minimum and

[38] 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.

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

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

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

while the actual average local ability is:

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

where conditional on the shock realization a, the signal realization $\tilde{a}$ is distributed according to the density $f(\cdot|a) = \mathcal{N}(a, \sigma_s)$ with full support in $[-d, d]$ with z, the bound, a real value. The precision of the signal is governed by the signal variance ${\sigma_s}^2$. The distribution of adults' ability in a given neighborhood m is denoted by $l(\cdot|m)$ and results from residential decisions in equilibrium. Note that, because of the bounds, despite the informativeness of the signal, the expected perceived ability is not always equal to the ability. The signal is upward biased whenever the actual ability is below the average ability in the economy ($\forall\ a \leq 0$ then $\mathrm{E}[\tilde{a}|a] \geq a$), and downward biased whenever the actual ability is above the average ability in the economy ($\forall\ a \geq 0$ then $\mathrm{E}[\tilde{a}|a] \leq a$). Intuitively, because the conditional signal is bounded, if the realization is closer to one of the bounds, many more high signals will be censored by this bound than by the other.[40] Consequently, in neighborhoods in which the average local ability is below the average ability in the economy, young agents overestimate average local ability (if $\bar{a}_m \leq 0$ then $\bar{a}_m \geq \bar{\tilde{a}}_m$), and conversely if the average local ability is above the average ability in the economy (if $\bar{a}_m \geq 0$ then $\bar{a}_m \leq \bar{\tilde{a}}_m$).

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

[40]See Appendix Figure S1 for an illustration.

D.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 S1 illustrates a conditional signal distribution of y given $d > \overline{\mu} > 0$.

Preliminary common results for (1)-(4):
Assume $\overline{\mu} \geq 0$

(a) Let

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

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

(c) Let

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

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

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

and

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

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

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

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

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

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

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

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

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

Trivially,

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

$\square$

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

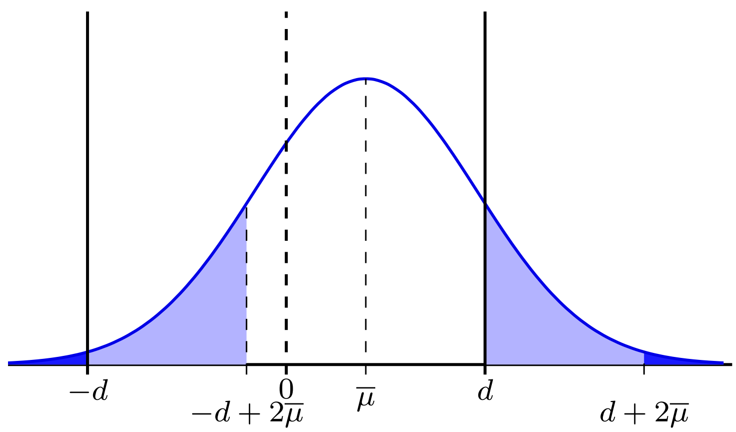
By (a)

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

.

□

Figure S1: Signal Illustration



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

E Additional Information on the Calibration

E.1 Parental Time

Table S2 summarizes parents' time use in the United States by education. I first restrict the sample to individuals in a two-parent household, defined as married individuals whose youngest child is under age 18.[41] In 2003, 5,597 married parents were interviewed, among which 2,168 have a college degree.[42,43] As standard in the literature, I assume 16 hours of disposable hours and eight hours of sleep needs per day.

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

[41] 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.

[42] Parent's education is defined as the highest level of education of the respondent. Using the highest education level of both parents or of the mother doesn't change the results in Table S2.

[43] As, for Table S1, I removed 255 observations that have less than 23 hours of activity a day reported. 92% of the remaining observations have exactly 24 hours of activity a day reported.

activities, while parents without a college degree spend 1.2 hours in childcare and 4.4 hours in market work.[44] 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.[45] In the following, I consider an endowment of 16 disposable hours per day and normalize it to one. Parental time patterns are moments to match.

Table S2: Parents' Time Allocation by Education, ATUS 2003

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

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

E.2 Synthetic Neighborhoods Characteristics

Table S3 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)).[46] Note that housing expenditure shares decrease with neighborhood quality (Column (4)), which suggests and motivates non-homothetic preferences.

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

[45] Appendix Table S1 describes how parents allocate their time spent in each of the ATUS activities.

[46] See Appendix Section A.2 for more detailed information on each of the variables used to calibrate the model.

Table S3: Characteristics of Synthetic Neighborhoods

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

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

E.3 Estimated Parameters: Neighborhood Choices and College Graduation

I use the AddHealth survey, detailed in Appendix Section A.1. First, to compute intergenerational residential mobility. To do so, as in the NHGIS data analysis, I created ten synthetic neighborhoods in 1994-1995, 2008-2009, and 2016-2018 by ranking all census tracts by median household income and grouping them into ten groups of equal size. Thanks to the panel form of the data set, I can observe in which synthetic neighborhood an adolescent lived in 1994-1995 and in which artificial neighborhood she lived during adulthood, in 2008-2009 and 2016-2018. I restricted the sample to people no longer living at their parents' place. Even though, due to attrition, samples are smaller in Wave V than in Wave IV, I use estimates from Wave V.[47] In 2016-2018, interviewees were older, between 35 and 40, and more likely to be married than ten years before.[48] 30.2% of adolescents who lived in a first decile census tract in 1994 lived in the same decile census tract in 2016-2018. In the sixth decile, this percentage falls to 13.0%.

[47] All observations are weighted by the sampling weights of the corresponding wave provided by AddHealth. When variables from different waves are used simultaneously, I use weights from the latest wave.

[48] Intergenerational residential mobility patterns are similar whether I use Wave V or Wave IV.

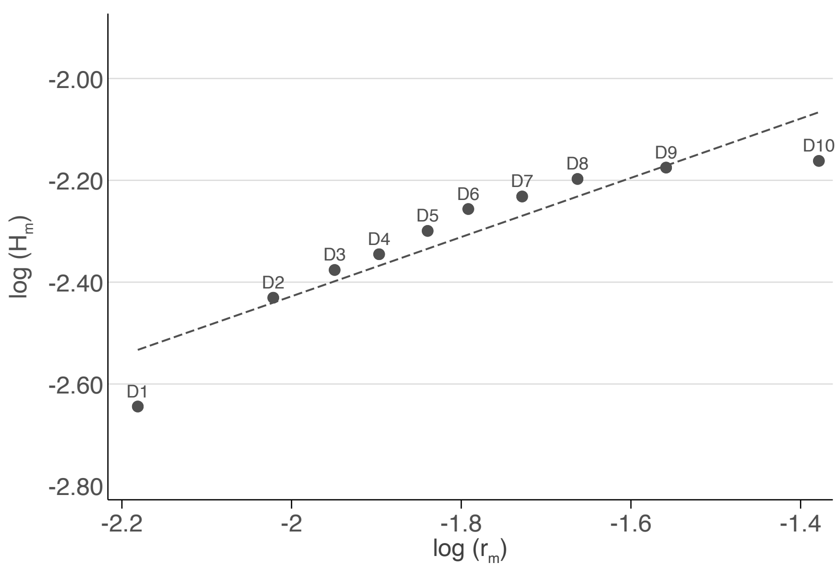
Second, I use AddHealth to estimate the individual probability of having a college degree conditional on parents and child variables. In the sample, anyone with at least a bachelor's degree is considered to have a college degree. Here again, because interviewees are older and more likely to have completed their education in 2016-2018 than in 2008-2009, I use data from Wave V to estimate the highest level of education. 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 S4: Estimated Parameters

	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. Robust standard errors are in parenthesis. These are all the estimated parameters.

Figure S2: Housing Market Estimation



Notes: This Figure displays the estimated housing supply equation, as a function of the relative rent price. Data points show actual rent prices and density for each of the ten synthetic neighborhoods.

E.4 Moments

Intergenerational residential mobility:

Data: I use the Add Health survey that contains census tract-level information. The sample is restricted to interviewees who do not live in their parent's houses in adulthood. Census tracts are ordered by household median income and divided into ten synthetic neighborhoods. For each decile neighborhood, I compute the share of children who, in adulthood, choose to live in the same decile of the neighborhood quality distribution as their parents.

Model: For each neighborhood, I compute the share of children who, in adulthood, choose to live in the same decile of the neighborhood quality distribution as their parents.

Other moments:

Table S5: Moments Description

Moment	Description	Data restriction	Source
Earnings			
Share college parents in Q1 over Q4	Fraction of college parents in the first quartile of the income distribution over the fraction of college parents in the fourth quartile of the income distribution.	100 biggest commuting zones - families with a own child below 18	ACS 2000
Earnings ratio non-college - college	Household income of non-college parents over household income of college parents.	100 biggest commuting zones - families with a own child below 18	ACS 2000
Income Gini [inequality]	Families' income Gini, transformed in a 20 years Gini using the 2002 Shorrocks mobiliy index estimated by Kopczuk et al. (2010).	100 biggest commuting zones - families with a own child below 18	ACS 2000

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
Social mobility			

Rank-rank coefficient	Regression coefficient of child household income rank on parental househod income rank.	Tax records covering the U.S. population, spanning 1996-2012.	Chetty et al. (2014)
Parental time			
Parental time income coeff.	Income regression coefficient of parental time on income quartile and college graduation status 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
Parental time education coeff.	Income regression coefficient of parental time on income quartile and college graduation status 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
Parental time non-college parents	Average parental time of non-college parents.	Two-parent households with a own child below 18. Weighted.	ATUS 2003

E.5 Perfect Information Model

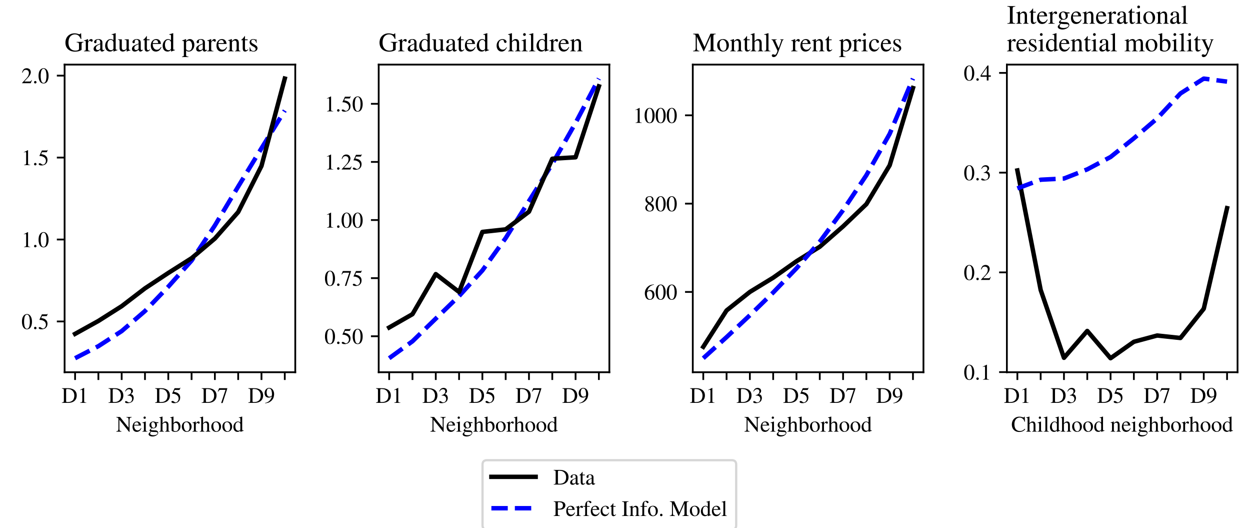
This section describes the calibration of a model with perfect information ($\pi = 0$).

Table S6: Internally Calibrated Parameters Assuming Perfect Information

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

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

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



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

E.6 Perfect Information Model with Heterogeneity

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

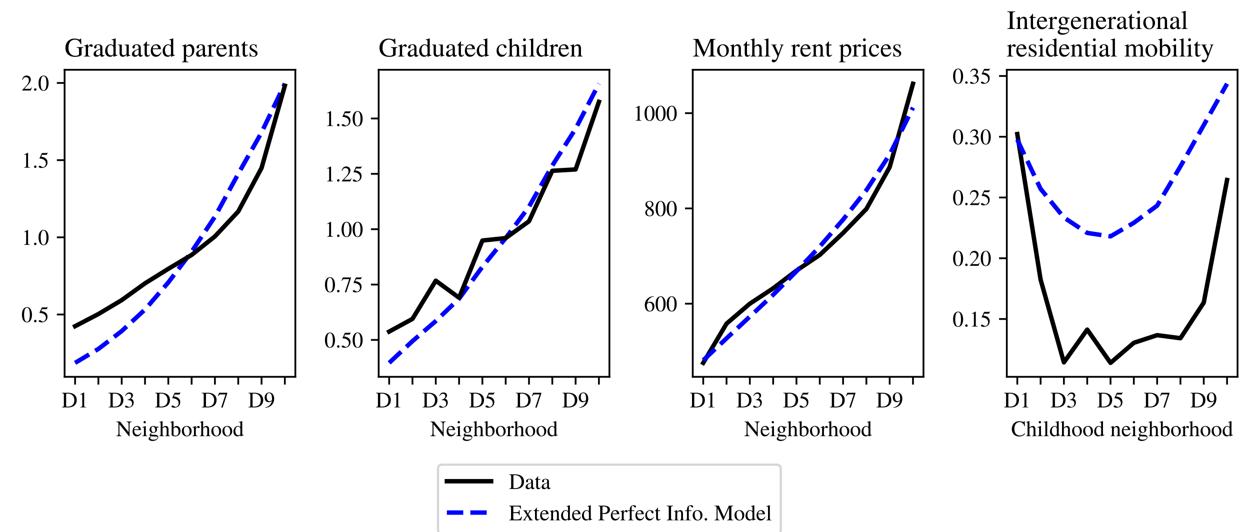
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa_s\, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \delta\, rank_m + \iota_0\, \mathbb{1}_{m_0=m} - \iota_1 (m_0 - m)^2 + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right],$$

Table S7: Internally Calibrated Parameters - Extended Model with Perfect Information

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

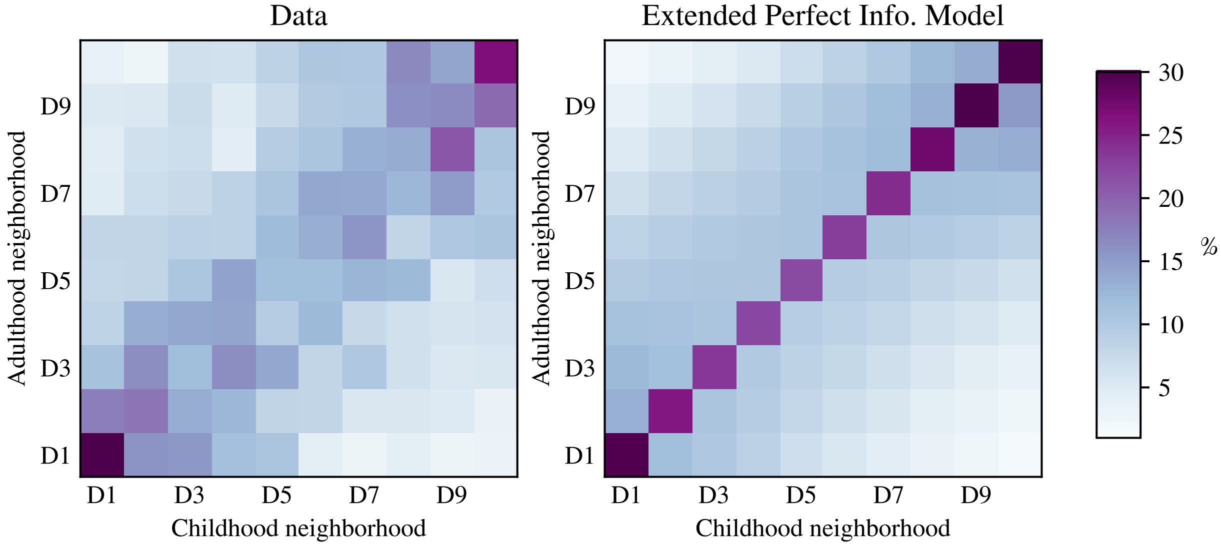
Notes: This table reports the internally calibrated parameters of the extended alternative model with perfect information ($\pi = 0$) and the observed and simulated moments associated with the parameter estimates.

Figure S4: Non-Targeted Moments by Neighborhood - Extended Perfect Information Model ($\pi = 0$)



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

Figure S5: Non-targeted Moments: Detailed Residential Mobility - Extended Perfect Information Model ($\pi = 0$)



Notes: This Figure shows residential mobility between childhood and adulthood in the data (left panel), and their model simulates analogs (right panel). The x-axis contains the ten synthetic childhood neighborhoods, and the y-axis is the ten synthetic adulthood neighborhoods. The frequency of moves is represented by cell colors, with larger values in darker squares—data source: Add Health, see Appendix E.4 for details of data construction.

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. None of the implications are rejected which comforts the plausibility of the social learning mechanism.

F.1 Correlation between Time and Neighborhood

Suppose neighborhood quality and parental time are two inputs of the technology of skill formation. Assume parents' decisions are driven by their perceived value of the returns to both inputs – neighborhood quality and parental time. All else equal, parents with low (high) beliefs will tend to live in worse (better) quality neighborhoods and spend less (more) time with their children. I expect to see a positive correlation between time and neighborhood quality in the data due to the omitted subjective beliefs variable. The data support this assumption.

The Add Health data includes detailed information on parents, children, and neighborhood characteristics, which allows me to construct two parental inputs in the child skill production function: parental time and neighborhood quality. Appendix Section E.3 describes the variable construction. As a first step, I verify the two constructed variables correctly proxy for two parental inputs of the technology of skill formation. Columns (1) and (2) of Table S8 show that parental time and neighborhood quality positively correlate with later child skills. Conditional on other parents' socioeconomic status (SES), the number of parent-child activities and neighborhood quality co-move with the graduation probability measured twenty-two years later. All coefficients are positive and significant at a one percent level. Motivated by this evidence, in the following, I consider the parental time and neighborhood quality variables are good proxies for parental inputs of the technology of skill formation.[49]

Columns (3) and (4) of Table S8 display a positive and significant correlation between parental time measured by the number of parent-child activities done over four weeks and standardized neighborhood quality proxied by household median income.[50] Note that in both regressions of Column (3) and (4) of Table S8, 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. (2022) for a review).[51] This observed correlation could be driven by a neighborhood composition effect. In Column (4) of Table S8, I control for three variables measuring households' socioeconomic status: parents' highest level of education, family income, and parent's marital status.[52] The sample size shrinks to 12,633 observations due to missing values in household characteristics variables, but the relationship remains positive and significant at a one percent level. This suggests that neighborhood composition effect does not drive all the correlation between the two parental inputs.

While this result is consistent with the assumption of parental beliefs being an omitted

[49]Appendix Table S9 presents the OLS regression coefficients with a different definition of neighborhood quality and parental time variables. Results are robust to definition changes.

[50]The results are robust to the use of alternative proxies for parental inputs. See Appendix Table S9.

[51]In Appendix E.1 I analyze the ATUS data set, and consistent with Guryan et al. (2008), I find a positive relationship between parental time and parental education.

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

Table S8: 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) 1994-1995	0.56***		0.212***	0.078***	0.146***	0.111**
	(0.012)		(0.03)	(0.028)	(0.038)	(0.043)
Parental Time 1994-1995		0.031***				
		(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 A.1 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.

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.[53]

F.2 Childhood Neighborhood and Adulthood Choices

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

Column (5) of Table S8 displays a positive and significant correlation between childhood (Wave I) and adulthood (Wave V) neighborhood quality. I restrict the sample to interviewees who do not live with their parents and control for commuting zone and age fixed effects. The correlation remains highly significant even after controlling for household income, marital status, and education status. Other factors might affect residential choices. Racial discrimination and wealth are two of them. In Column (6) of Table S8, 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.[54] 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.[55]

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

[53] 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 my knowledge, all empirical estimates of the relationship between parental time and environment quality suggest that they are substitutes (Kling et al., 2001; Pop-Eleches and Urquiola, 2013; Das et al., 2013; Kiessling, 2021).

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

[55] The results are robust to the use of the fraction of adults with a college degree for neighborhood quality. See Appendix Table S9.

F.3 Robustness checks

Table S9: 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	0.448***		0.758***	0.451***	0.25***	0.211***
1994-1995	(0.1)		(0.195)	(0.185)	(0.037)	(0.032)
Parental Time		0.029***				
1994-1995		(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 A.1 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.