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, childhood neighborhood quality shapes adulthood economic opportunities. However, most children raised in bottom-quality neighborhoods still live in low-quality neighborhoods in adulthood. Could childhood neighborhood directly affect adulthood choices? I develop a quantitative spatial model of parental decisions that incorporates a novel mechanism: social learning about the technology of skill formation. Segregation generates information frictions that systematically distort parents' subjective beliefs and behaviors. I calibrate the model using several United States representative datasets. The calibrated model matches targeted and non-targeted parental behaviors and generates an endogenous distribution of subjective beliefs. I find a relatively modest level of delusion that increases inequality by 3% and decreases intergenerational mobility by 12%. 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 subjective beliefs amplify the policy effects. Inequality reduces, and intergenerational mobility improves.

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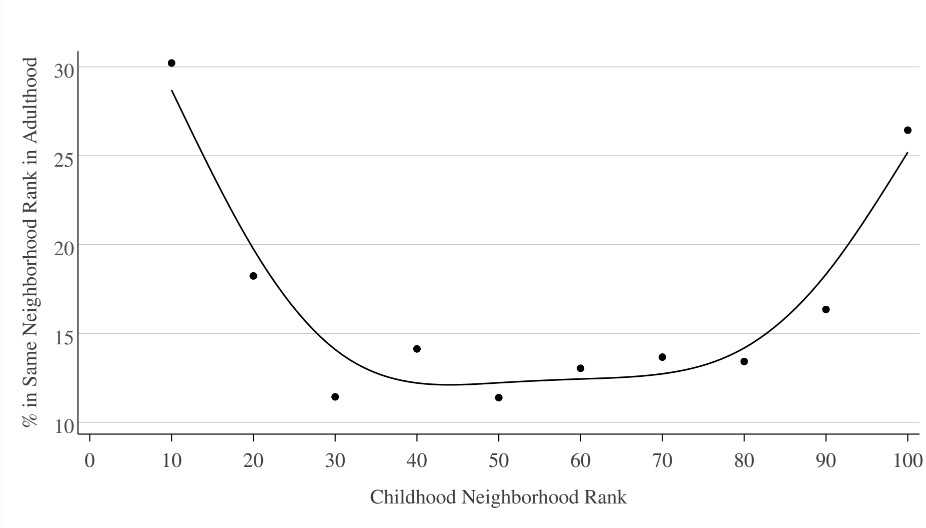
1 Introduction

In the United States, childhood neighborhood quality shapes adulthood economic opportunities.[1] However, most children raised in bottom-quality neighborhoods still live in low-quality neighborhoods in adulthood. Figure 1 shows that while the probability that a child raised in a middle-range quality neighborhood also lives in a middle-range quality neighborhood in adulthood is less than 15%, this number rises to 30% for children raised in the bottom-decile of the neighborhood quality distribution. Given the benefits of escaping low-quality neighborhoods, why do families stay? Could childhood neighborhood quality directly affect adulthood choices?

Figure 1: Intergenerational Residential Mobility in the United States



Notes: This Figure shows the share of children who, in adulthood, choose to live in the same decile of the neighborhood quality distribution as their parents. The dots are data points; the solid line is a smooth interpolation—data source: Add Health; see Appendix for details of data construction.

What if children raised in low-quality neighborhoods choose to stay because they systematically underestimate the returns to neighborhood quality? I depart from perfect information and propose a new mechanism that endogenizes parental subjective beliefs about the child skill technology and generates systematic differences in subjective beliefs by childhood neighborhood. Suppose individuals' human capital depends on past parental inputs—, including neighborhood quality—and a random, idiosyncratic, and unobserved ability shock,

[1] Chetty and Hendren (2018a) show that, in the United States, the neighborhoods in which children grow up shape their earnings, college attendance rates, and fertility and marriage patterns. 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 rates, low crime rates, and high-performing schools.

which can be interpreted—to some extent—as luck. Assume people don't know the returns to parental inputs and must learn about them before making decisions. Young adults learn by observing their older neighbors' human capital and past parental inputs; through social learning. However, they only get an informative but discrete and bounded perception of their neighbors' abilities and cannot perfectly infer the returns. Crucially, I assume that people suffer from a selection neglect bias. They think of their neighbors as representative of the population.[2] This assumption is incorrect with income residential segregation—a form of spatial sorting partly based on ability shocks. Indeed, low-ability adults tend to be poor and live in low-rent and low-quality neighborhoods. Since young adults' perception of their neighbors' ability is bounded, in low-quality neighborhoods, where relatively many low-ability parents live, young adults overestimate the average local ability. They then implicitly attribute too much of the local average human capital to ability and underestimate the returns to parental inputs. The reverse happens in high-quality neighborhoods, where relatively many high-ability adults surround young adults. Combined with residential segregation, this mechanism leads to persistent delusion about the returns to parental inputs.

I incorporate this new mechanism into a quantitative spatial overlapping generations model with residential and parental time decisions. The model features heterogeneous agents, where parents choose the quality of their neighborhood and how much time to spend on their child's education. Residential segregation results from parents' location decisions and local rents, which are equilibrium objects. The child's next period human capital is a function of childhood neighborhood quality and parental time, parental human capital, and idiosyncratic ability shocks. Crucially, I depart from perfect information and introduce social learning with selection neglect. Agents are unaware of the returns to parental inputs: neighborhood quality and parental time. Children inherit subjective beliefs from their parents and update them by observing older neighbors' outcomes and history. By assumption, children only imperfectly see ability shocks and suffer from a selection neglect bias. In equilibrium, endogenous segregation generates systematic biases across socioeconomic groups and persistence in subjective beliefs within families. Children of low-subjective beliefs and poor parents are likely to live in low-quality neighborhoods—composed of relatively low-ability parents—, underestimate the returns, and become poor parents next period. The reverse happens to children of high-subjective beliefs and high-income parents. Agents differ in their human capital—

[2]This cognitive bias called "selection neglect" or "assortativity neglect." Enke (2020) provides empirical evidence of it. Jehiel (2018) develops a theoretical model of over-optimism among entrepreneurs driven by selection neglect.

primarily determined by their parents—and in their subjective beliefs—determined mainly by their parent and childhood neighborhood. Given the social learning mechanism, there are multiple critical equilibrium objects: the distribution of human capital, subjective beliefs, neighborhood choices, and local rents, which are endogenously determined as fixed points.

The model is solved numerically and calibrated to match a set of critical moments from several United States representative datasets. The model matches segregation and family earnings dispersion in the average commuting zone in the United States computed from the ACS 2000 and NHGIS 2000 datasets. In addition, it targets causal neighborhoods' 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 parental time in the ATUS survey and neighborhood quality choices from AddHealth. Even though the model does not feature preference heterogeneity, the calibrated model matches parental behaviors across socioeconomic groups well. It provides a rationale for college parents spending more time with their children than non-college parents despite working more hours and matches non-targeted intergenerational residential mobility patterns well.[3]

Conversely, a perfect information version of the model cannot replicate the data without imposing sizable heterogeneous preferences across places of birth and education. To see this, I first re-calibrate the model shutting down the subjective beliefs channel. The calibrated model misses all the non-targeted residential mobility moments. I then introduce heterogeneous preferences across places of birth and add residential mobility moments as targets. I find that with this alternative model, agents born in bottom-quality neighborhoods must like their place of birth thirty times more than the others. This necessary feature is at odds with the empirical findings of Bergman et al. (2019) who compare low-income families who live in deprived neighborhoods and are randomly allocated between treatment and control groups. They find that parents in the treatment group, induced to move to higher-quality neighborhoods, are more satisfied and willing to stay in their neighborhood than those in the control group. Moreover, even if the alternative model matches residential mobility by construction, it fails to generate an education parental time gap that is large enough.

I then use the calibrated model with social learning to understand parents' residential-quality choices and to conduct policy experiments. The first finding is that social learning and subjective beliefs explain a large share of the socioeconomic gap in parental decisions. Segregation generates information frictions that systematically distort parents' subjective beliefs concerning the technology of skill formation. Providing information would improve

[3]Parental time gap by education is a well-known puzzle described in Guryan et al. (2008). See Doepke et al. (2022) for a review.

low-income parents' subjective beliefs on the returns by 17% and decrease high-income parents' by 7%. Those numbers are of a reasonable order of magnitude compared to empirical estimates.[4] Importantly, I find that subjective beliefs have sizable effects on the economy. Children born in bottom-quality neighborhoods would be half as likely to remain in those neighborhoods in adulthood, and low-income parents would spend 31% more time with their children. Social mobility would improve by 12% and inequality decrease by 3%.

The model features two key frictions that motivate a policy intervention. Parents cannot borrow against their children's future earnings, and due to the novel mechanism, segregation generates information frictions that distort parental decisions. 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. One could expect housing vouchers to decrease segregation, improve information, and dampen subjective beliefs' distorting effects. I consider a housing voucher that covers the difference between 30% of income and the rent up to a limit. Eligible households are parents from the bottom decile of the income distribution. In the first step, I study the partial equilibrium effects of the policy 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. The effects on children's earnings are of a similar order of magnitude to the empirical estimates from Chetty et al. (2016). Subjective beliefs play a substantial role. If parents had perfect information about the returns to neighborhood quality, they would move to even higher quality neighborhoods, increasing their children's earnings at age 26 by an additional $132 per year.

The second finding is that, when scaling up the housing voucher policy, general equilibrium responses in local prices and, in particular, in subjective beliefs amplify the effects of the housing voucher policy. The voucher allows housing voucher holders to move to better neighborhoods, increasing the density in middle-range quality neighborhoods—especially at the rent limit—and forcing non-eligible households to move out. The housing market reaction creates winners and losers, with adverse effects in the aggregate; however, in the long run, information and subjective beliefs improve, particularly among low-income households, amplifying partial equilibrium effects on eligible households and generating aggregate positive effects. Social mobility improves by 3.8%, and inequality decreases by 0.8%.

[4] 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%.

Despite positive long-run effects, a housing voucher policy with a unique rent limit at the commuting zone has unintended consequences. It generates a bunching behavior of eligible households in middle-range quality neighborhoods, segregating the housing market and increasing the already overestimated subjective beliefs of rich households. I find that designing a housing voucher policy with rent limits set at a more granular level is a better tool for mitigating the distorting effects of parents' subjective beliefs.

Related Literature

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

First, this paper builds on empirical evidence from the parental subjective beliefs literature to carefully model endogenous parental subjective beliefs about the technology of skill formation. 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' subjective 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)).[5] The idea that technology diffuses through social learning—by observing how older community members do—is consensual, and there is also evidence of it in education.[6] However, in education, because people sort based on the outcome—their human capital,—social learning effects often relate to selection. For instance, the fact that low-income people lack successful role models around them could explain low level of motivation and effort (Nguyen, 2008; Alan et al., 2019; Breda et al., 2019; Algan et al., 2020; Guyon and Huillery, 2020). Social learning is one likely explanation for Chetty et al. (2022)'s recent findings; upward income mobility in the United States is best predicted by the share of high socioeconomic status friends in a ZIP code.

Second, this paper quantifies the macroeconomic effects of endogenous subjective 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 litera-

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

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

ture. 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, subjective expectations are considered critical elements in explaining agents' investment behavior (see, for instance, Adam et al. (2017)), in family macroeconomics, heterogeneous subjective beliefs are usually ignored. 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 subjective 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 Jehiel (2018), generates a bias, rationalizing the fact that low-income children living in poor-neighborhoods lack motivation due to a lack of successful role models. In equilibrium, the learning process generates a stable distribution of heterogeneous parental subjective beliefs that affects 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 subjective 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 subjective beliefs. However, this paper is the first to develop and calibrate a quantitative model with social learning.

Finally, the paper contributes to the quantitative spatial economics literature as it links 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 subjective beliefs, I also 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 investment.

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. Section 5 empirically tests two of the social learning implications, and Section 6 concludes.

2 The Model

Consider one labor market composed of a finite number of neighborhoods populated by families of one parent and one child. Children's future earnings depend on childhood neighborhood quality, parental time, parental human capital, and imperfectly observed idiosyncratic ability shocks. Parents decide on two parental inputs of the child skill technology: in which neighborhood to raise their child and how much time to spend on their child's education. Sorting within the labor market and across neighborhoods is only driven by families seeking better opportunities for their children. However, the model's novel and critical feature is imperfect information and social learning about the returns to parental inputs. Before making decisions, young agents learn about the returns using the information available at the neighborhood level.

The following sections describe the economic environment, the novel mechanism—social learning within neighborhoods—the parents' optimization problem, and the housing market. Then I give the equilibrium definition.

2.1 Economic Environment

Geography and Amenities: Consider one commuting zone with a finite number of ex-ante heterogeneous neighborhoods. Neighborhoods differ in quality m. Thus, a neighborhood is characterized by its quality m rather than its particular name. As wages do not vary across neighborhoods, the neighborhood quality is the only exogenous amenity.

Families: The economy is populated by a continuum of families composed of one parent and one child. Time is discrete and each agent lives for two periods: childhood and parenthood. Parents choose in which neighborhood to raise their child and on how much time to spend on their child's education—parental time. Families are heterogeneous concerning four parental characteristics: accumulated human capital, college graduation status, naighborhood of birth, and subjective beliefs about the technology of skill formation.

In the following, primed letters correspond to children's next period variable, and lowercase letters to parents' variables.

Technology of Skill Formation: Children's next period human capital h' mainly depends on their parents as it is a function of their childhood neighborhood quality m, parental time τ, parental human capital h, and 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 $\mathcal{N}(0, \sigma_a)$.[7] Crucially, ability shocks are imperfectly observed.

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.[8] 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).

College Graduation Probability: To connect the model outputs to the data, I introduce college graduation status. 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 schooling status, earnings, and the child's accumulated human capital. Agent's schooling status s is equal to one if the agent graduated from college, zero otherwise.

[7]By assuming uncorrelated ability shocks across generations, I abstract from modeling genetics. If one added it, incentives to invest would be distorted as high human capital parents would 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.

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

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

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

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

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 subjective beliefs $\tilde{\alpha}$ can be summarized by the following utility function:

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

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 have a preference for their childhood neighborhood quality that is captured by ι. In addition, parents have idiosyncratic taste shocks over neighborhoods ε_m. It 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 shocks is measured by ν. Finally, $\tilde{\alpha}$ stands for the parent's subjective beliefs regarding the value of elasticity 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 subjective 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: $\mathcal{H}_m = \zeta r_m^\eta$, where η is the price elasticity of housing supply that can take any real value. 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.

2.2 Social Learning

One key feature of the model is the social learning process. I depart from rational expectations and perfect information. I assume agents know everything about the model but the returns to parental inputs; specifically, they do not know the value of α, and they cannot perfectly infer it because, by assumption, they only imperfectly see abilities (a).

Young agents must form expectations about the returns to parental inputs ($\tilde{\alpha}'$) before making parental decisions. Following Fogli and Veldkamp (2011), they have two sources of information: they inherit their parent's subjective beliefs ($\tilde{\alpha}$) and make their own inference by observing outcomes and history in their neighborhood m ($\hat{\alpha}_m$).

Crucially, I depart from rational expectations by assuming agents suffer a cognitive selection neglect bias. Agents know the functional form of the technology of skill formation—but α,—the randomness of ability shock and the parents' problem. Still, they do not fully understand the spatial sorting process in the economy. In particular, young agents draw conclusions from the observation of their neighbors without correcting for the fact that their adult neighbors are not representative of the population with respect to abilities.[9] The mental model young agents use for an adult j in a given neighborhood m is:

$$h_j = (i(\mathrm{T}_j, M_j) + \underline{i})^{\alpha} \ H_j^{\beta} \ \exp(a_j), \quad a_j \sim \mathcal{N}(0, \sigma_a), \quad j \in m,$$

where T and M represent past parental choices, and H represents past parental human capital. While with spatial sorting, in a given neighborhood m, the true model is $h_j = (i(\mathrm{T}_j, M_j) + \underline{i})^{\alpha} \ H_j^{\beta} \ \exp(a_j), \quad a_j \not\sim \mathcal{N}(0, \sigma_a), \quad j \in m.$

Young agents see average local human capital and know about average past parental choices in their neighborhood. 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. In addition, they have information about average local abilities. Following Jehiel (2018) who develops a theoretical framework of selection neglect with bounded signals, I assume young agents receive informative but noisy and bounded

[9] Enke (2020) provide empirical evidence of the selection neglect cognitive bias. People tend to draw general conclusions from what they observe, ignoring that what they observe is selected. Frick et al. (2022) develop a theoretical framework in which the selection neglect persists.

signals about their adult neighbors' abilities.[10] Signals are noisy because there is no real way to perfectly gauge ability—which can be interpreted here as intelligence and luck—by simply observing people. Signals are bounded because we tend to classify people's abilities within predefined categories.[11] Every intelligence test has a scale with a minimum and maximum. The IQ test, for instance, classifies people's Intelligence Quotient between "*very superior*" and "*extremely low*" levels. Note that the bounds of the signals are the same across neighborhoods. This common scale assumption is 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 is defined by:

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

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 $[-z, z]$ with z, the bound, a real value. The precision of the signal is governed by the signal variance ${\sigma_s}^2$. The distribution of adults' ability in a given neighborhood m is denoted by $l(\cdot|m)$ and results from residential decisions in equilibrium. Note that, because of the bounds, despite the informativeness of the signal, the expected perceived ability is not always equal to the ability. The signal is upward biased whenever the actual ability is below the average ability in the economy ($\forall\ a \leq 0$ then $\mathrm{E}\left[\tilde{a}|a\right] \geq a$), and downward biased, whenever the actual ability is above the average ability in the economy ($\forall\ a \geq 0$ then $\mathrm{E}\left[\tilde{a}|a\right] \leq a$).[12] 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. Consequently, in neighborhoods in which the average local ability is below the average ability in the economy, young agents overestimate

[10] 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.

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

[12] See Appendix D for a proof.

average local ability among adults (if $\overline{a}_m \leq 0$ then $\overline{a}_m \geq \overline{\tilde{a}}_m$), and conversely if the average local ability is above the average ability in the economy (if $\overline{a}_m \geq 0$ then $\overline{a}_m \leq \overline{\tilde{a}}_m$).[13]

Under the assumption of selection neglect, however, every agent in a given neighborhood m thinks of their perception of the average local ability as the truth ($\overline{\tilde{a}}_m = \overline{a}_m$).[14] She uses her observations of local averages. She makes the following estimation:[15]

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

Young agents' estimate ($\hat{\alpha}_m$) is downward biased if they overestimate the average ability ($\overline{\tilde{a}}_m \geq \overline{a}_m$) and upward biased if they underestimate the average ability ($\overline{\tilde{a}}_m \leq \overline{a}_m$). Intuitively, when young agents overestimate abilities, they implicitly attribute too much of the local human capital to ability and too little to past parental inputs, underestimating the returns to parental inputs. Note that because the signal variance ${\sigma_s}^2$ governs the precision of the perceived local ability, it also regulates the strength of the bias in the estimation.

Young agents then update their inherited subjective beliefs using a weighted average of the local estimate ($\hat{\alpha}_m$) and the inherited subjective beliefs ($\tilde{\alpha}$):

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

with $\mu \in (0, 1)$.

In equilibrium, this social learning process generates persistent delusion about the value of α across socioeconomic groups and within families. Children of poor and low-subjective beliefs parents are raised in low-quality neighborhoods, observe on average low-ability neighbors, overestimate local abilities, and are comforted in their inherited low subjective beliefs about the returns to parental inputs. Those children will likely become poor and low-subjective beliefs parents next period. The opposite happens for children of high-income

[13] In the limit, if the signal variance (σ_s) tends to zero, or if the bounds (z) tend to infinity, agents' perception about their neighbors' ability shocks would always be equal to the truth and $\overline{\tilde{a}}_m = \overline{a}_m$. See Appendix D for proof.

[14] This assumption would be correct if young agents were to observe everyone in the economy or without residential sorting ($l(\cdot|m) = \mathcal{N}(0, \sigma_a)$). Similar to Fogli and Veldkamp (2011), there would be convergence in subjective beliefs. Suppose young agents did not suffer from selection neglect and understood the spatial sorting process. Only if young agents knew the joint distribution between subjective beliefs, human capital, college graduation status, and place of birth could they compute the distribution of adults' ability in their neighborhood $l(\cdot|m)$ and then back out the actual average ability in their neighborhood.

[15] 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 wouldn't change the paper's main results.

and high-subjective beliefs parents.

2.3 Parents' Problem

Parents are the only decision-makers in the economy. They make three decisions of which two that affect their child's next period human capital: neighborhood quality m 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 subjective belief about the returns to parental inputs ($\tilde{\alpha}$). The maximization problem is the following:

$$\begin{aligned}\mathcal{V}(h, s, m_0, \tilde{\alpha}) = \max_{c,\tau,m}\Big\{ \log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa\,\tau\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} \\ + \ \iota\, \mathbb{1}_{m_0=m} + \ \nu\varepsilon_m + \ b\mathrm{E}\left[\mathcal{V}(h', s', m, \tilde{\alpha})\,|\tilde{\alpha}\right]\Big\}\end{aligned} \tag{3}$$

subject to:

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

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

2.4 Housing Market

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

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

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

The share of parents who choose to locate in neighborhood quality m among parents with human capital h, graduation status s, raised in neighborhood quality m_0 and with subjective 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:

$$\sum_{m_0} \sum_{s} \int \int \lambda_m(h, s, m_0, \tilde{\alpha}|r_m) F(h, s, m_0, \tilde{\alpha})\ dh\ d\tilde{\alpha} = \zeta {r_m}^{\eta}, \tag{4}$$

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

2.5 Equilibrium

The key objects of the equilibrium in the steady state are the endogenous distribution of human capital, subjective beliefs, and rent prices. For a given initial human capital, graduation status, neighborhood of birth, and subjective 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 (3).

2. housing market clearing: rent prices $\{r_m\}$ ensure housing demand equals supply in every neighborhood according to (4).

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

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

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

3 Calibration

I numerically solve the model as detailed in Appendix C 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. As standard in the literature, I set the grid bound to 2.5 times the standard deviation ($z = 2.5\ \sigma_a$). 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 Section 5.1.[16] Finally, parents' time use information is taken from the American Time Use Survey (ATUS) from 2003.[17]

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. In the model, I set the number of neighborhoods to ten, representing a synthetic decile census tract in the data. Specifically, in each of the 100 commuting zones of the NHGIS 2000, I

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

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

sort census tracts by median household income and form ten synthetic neighborhoods from the deciles of this distribution.[18] I then create one average commuting zone by computing the population-weighted average characteristics of each of the ten neighborhoods.[19]

3.2 Empirically Estimated Parameters

Housing Markets: Rental prices are determined in equilibrium given the supply function: $\mathcal{H}_m = \zeta r_m^{\eta}$, where r_m is the equilibrium rent price in the neighborhood m, and η is the price elasticity of housing supply. η and ζ can be estimated directly from the synthetic neighborhood density and rents.[20,21]

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.[22]

3.3 Externally Calibrated Parameters

The parameter ψ can be interpreted –to some extent– as a Frisch labor supply elasticity. Since the model's labor supply is exogenous, this interpretation is irrelevant. Still, it allows me

[18] I use median household income as 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%.

[19] Appendix Table S4 summarizes the ten neighborhoods' characteristics.

[20] Appendix Figure S2 summarizes the log-relationship between density (Column (5) Table S4) and rents across the ten synthetic neighborhoods.

[21] Note that in the literature, ζ is sometimes neighborhood specific (ζ_m). In this context, there is an almost linear log relationship between density and rent prices (see Appendix Figure S2); I choose to have the same ζ value across neighborhoods. Without loss of generality, the numeraire is the average household earnings in the economy.

[22] Appendix Section E.3 provides details on the variable construction, and Appendix Table S5 shows the weighted logit regression estimates.

to use a direct standard analog in the literature: 0.5. I assume agents have an endowment of one unit of time corresponding to sixteen hours per day in the data.[23] 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 neighborhood quality is normalized to 1. I assume the number of neighborhoods N equal to ten, and neighborhood quality distributed according to $m \sim U(\underline{m}, \overline{m})$. Table 1 summarizes the parameters that are externally calibrated.

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
$\overline{\ell_0}$	Non-college labor supply	0.275	ATUS 2003
$\overline{\ell_1}$	College labor supply	0.294	ATUS 2003
ψ	Frisch elasticity	0.5	Standard
w	Wage rate	1	Normalization
$\underline{\mathrm{i}}$	Parental investment constant	1	Normalization
μ_m	Average neighborhood quality	1	Normalization
ζ	Housing supply coefficient	-1.04	NHGIS
η	Price elasticity of housing supply	0.58	NHGIS
γ_1	College graduation probability coefficient	-3.83	Add Health
γ_2	College graduation probability coefficient	0.35	Add Health
γ_3	College graduation probability coefficient	0.15	Add Health
γ_4	College graduation probability coefficient	1.11	Add Health

Notes: The table shows all the externally calibrated parameters.

3.4 Internally Calibrated Parameters

The remaining twelve parameters to calibrate are listed in Table 2. I calibrate them by minimizing the sum of squared percentage differences between data and model moments. The data moments include two measures of household earnings dispersion within commuting zones computed from the ACS 2000: the Gini coefficient of household earnings and the income ratio of non-college and college households. Both are weighted population averages across the 100 biggest commuting zones.[24] In addition, I ensure income and college gradua-

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

[24] 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 years Gini coefficient using Shorrocks mobility index estimated by Kopczuk et al. (2010) for 2002.

tion status relationship matches the data by incorporating the ratio of college-parents share in the first to the fourth quartile of the income distribution. 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 Chetty and Hendren (2018b). To match residential segregation, I add a Gini coefficient across the ten neighborhoods computed from the NHGIS 2000 dataset. 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. I include parental time by education (displayed in Appendix Table S3) and household income and education gradients to capture parental behaviors. In addition, to discipline subjective beliefs, I add the correlation between parents' and children's neighborhood choices.[25]

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

The first three parameters are preference parameters and govern parents' choices. In particular, 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.

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 would increase children's future income rank if they had been growing up in one standard deviation better neighborhoods. 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.

[25] 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	Ratio share college parents Q1 to Q4	0.102	0.120
$\kappa = 0.6$	Parental time disutility	Parental time non-college parents	0.075	0.079
$\iota = 0.0001$	Place of birth preference	Residential mobility (D1)	0.302	0.274
$\omega = 0.005$	College wage premium	Earnings ratio non-college - college	0.554	0.556
Neighborhoods				
$\sigma_m = 0.26$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.056
$\nu = 0.01$	Taste shock variance	Census tract Gini	0.231	0.212
Skill Formation: $h' = \left(\left(\gamma \ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}} \ + \ \underline{i} \right)^{\alpha} \ h^{1-\alpha} \ \exp(a')$ with $a' \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0.77$	Elasticity of investments	Rank-rank coefficient	0.341	0.339
$\gamma = 0.55$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.047
$\varphi = 0.5$	Substitutability	Income gradient in parental time	0.140	0.144
$\sigma_a = 0.55$	Ability shock variance	Income Gini	0.336	0.334
Belief Updating Process				
$\sigma_s = 2.5$	Cognitive bias strength	Neighborhood quality correlation	0.417	0.460
$\mu = 0.3$	Update weight	Education parental time gap	0.750	0.850

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

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.[26] With subjective beliefs and social learning, 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.

Finally, the correlation between parental and children's subjective beliefs is governed by μ and affects the persistence of beliefs and hence, parental behavior within families. Since there is also persistence in earnings and schooling status within families, I discipline this parameter by matching parental time by schooling status. Specifically, I compute the parental time ratio by the college status of the parents. It is below one, meaning college parents spend more time with their children than non-college parents. This moment is labeled the education parental time gap. In the model, the parental time gradient in education result from two opposing forces. Delusion about the technology of skill formation, if correlated with earnings, increases the gap. However, the substitutability between parental time and neighborhood quality ($\varphi > 0$) and the differential in working hours decrease it. Finally, I calibrate the signal variance (σ_s) using the correlation between parents' and children's neighborhood choices. Parents' neighborhood choices affect children's future decisions through two channels: human capital formation and hence earnings and subjective beliefs. Parents influence on children's earnings is calibrated by matching the rank-rank coefficient and places effects. It is then essential to match this correlation to ensure that the subjective beliefs channel is not too strong.

3.5 Non-Targeted Moments

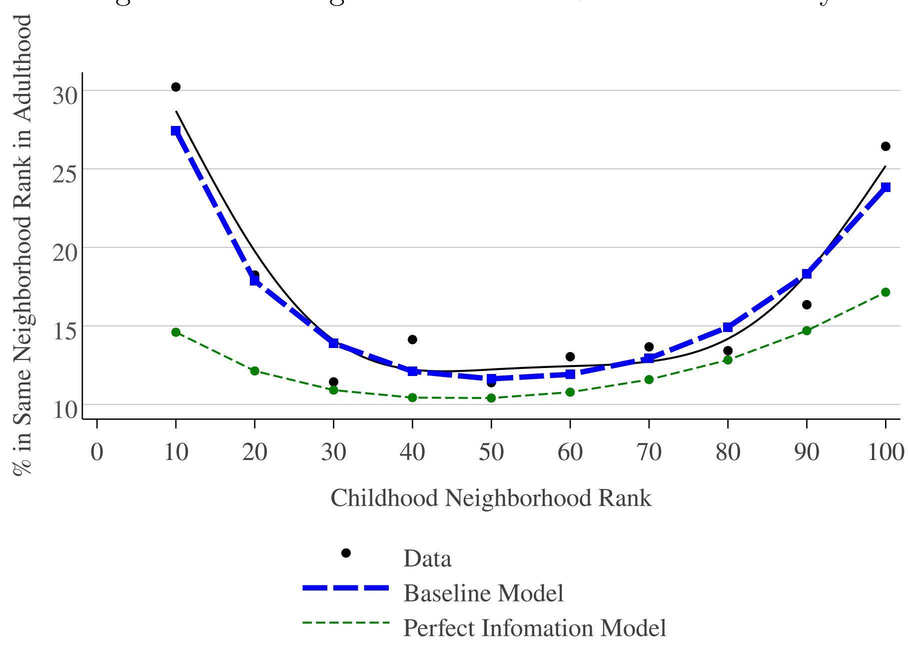
The calibrated model matches the targeted moments well and fits the non-targeted residential mobility patterns.[27] Figure 2 reproduces the motivating Figure 1 and presents the share of children who live in the same neighborhood in adulthood. The solid line is a smooth

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

[27] Appendix Section E.5 shows non-targeted moments at the neighborhood level and income quintile matrix.

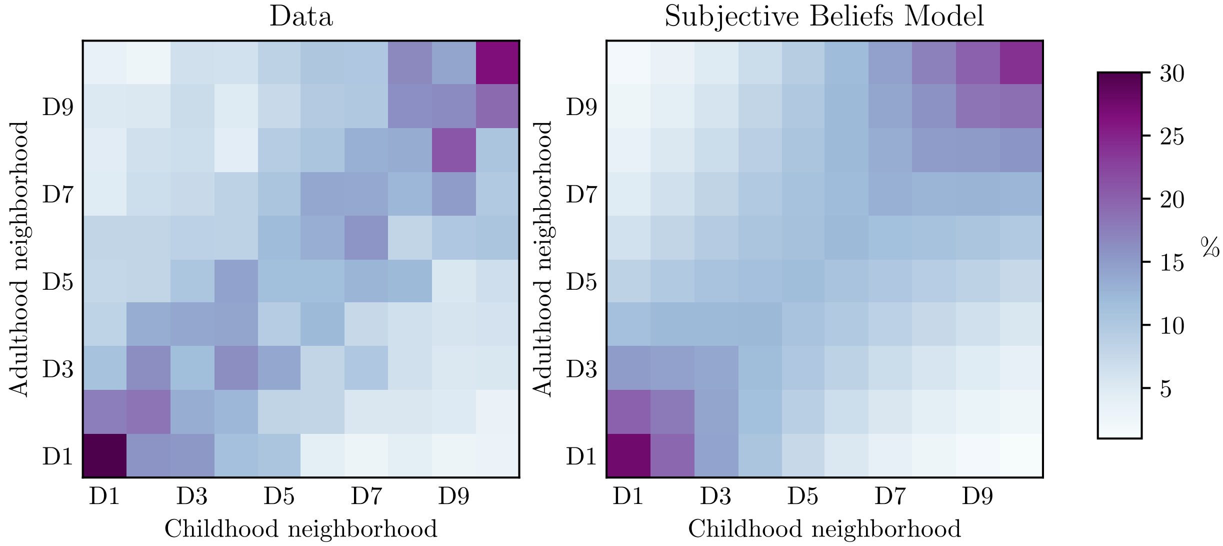
interpolation between the dots which are data moments. The blue dashed line represents model simulated analogs. While the first synthetic neighborhood statistic is a targeted moment, the others are not. The model generates a U-shape that is very close to the data. To go further, Figure 3 illustrates 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 very unlikely to live in neighborhood six or above. The calibrated model (right panel) matches the data patterns (left panel) remarkably well.

Figure 2: Non-targeted Moments: Residential Mobility



Notes: This Figure shows the share of children who still live in their childhood neighborhood quality when they are adults. The dots and solid line are data moments; the baseline model simulated analogs in blue long-dashed-line, and the perfect information model in green dashed-line—data source: Add Health, see Appendix for details of data construction.

Figure 3: 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 for details of data construction.

3.6 The Role of Subjective Beliefs

The model is calibrated under the assumption of imperfect information and social learning at the neighborhood level. Natural questions are: What does the endogenous distribution of subjective beliefs do? And how well would the model match the moment under perfect information?

I first shut down the subjective beliefs channel to understand the role that subjective beliefs play in the economy by assuming parents know the returns to parental input (α). Table 3 presents the effects of subjective beliefs on the economy. In the bottom quartile of the income distribution, parents underestimate the returns to neighborhood quality and parental time by 17% while parents in the top quartile of the income distribution overestimate them by 7%. These numbers are of a reasonable order of magnitude. Cunha et al. (2013), who elicits disadvantaged African American mothers' subjective beliefs about the elasticity of child development with respect to parental investments, finds greater differences between the truth and their subjective beliefs. As a result, low-income parents spend too little time with their children, while high-income parents spend too much time. Providing information to parents would, in the long run, increase low-income households' parental time by 31% and decrease high-income households' one by 5%. Under perfect information, aggregate parental time increases by 7%. Parents' subjective beliefs decrease social mobility—negative rank-rank coefficient—and earnings by 12% and 3% respectively and increase inequality and poverty by 3% and 17%. The Green dashed line in Figure 2 shows that subjective beliefs double the share of children born in bottom-quality neighborhoods who choose to remain in adulthood. These findings imply that a relatively modest level of delusion, coherent with micro-studies, has large effects on the economy.

Table 3: Effects of Subjective Beliefs

		Household Income quartile			
	All	1st	2nd	3rd	4th
Subjective Beliefs	-2.8%	-17.5%	-5.9%	+0.2%	+7.4%
Parental Time	-7.5%	-30.9%	-9.9%	-2.5%	+4.8%
Earnings	-2.5%	-6.4%	-5.8%	-4.7%	-2.2%
Rank-rank coefficient	+11.8%				
Census tract Gini (Segregation)	+0.6%				
Income Gini (Inequality)	+2.7%				
Absolute poverty	+16.9%				

Notes: This table displays percentage differences in model generated moments between the baseline calibrated model with and without subjective beliefs.

How would a model do without subjective beliefs? I calibrate the same model shutting down subjective beliefs to see how well this alternative version of the model matches targeted and non-targeted moments. Appendix Table S7 shows the fit of the perfect information model version. As expected, to generate a positive correlation between income and parental time, time and neighborhood quality are complement inputs in the technology of skill formation ($\varphi < 0$). In addition, to have 30% of children born in the bottom-quality neighborhood who stay there in adulthood, the preference parameter ι needs to be much larger than in the subjective beliefs version of the model. However, this feature reduces mobility in all other neighborhoods.[28] Under perfect information, the model, misses all the

[28]Appendix Figures S4 and S5 show non-targeted simulated moments. In the mobility matrix under perfect information, not only is the diagonal off but all the squares off-diagonal are of similar color, which is at odds with the data.

intergenerational residential mobility moments despite a good match of social mobility and inequality moments.

Since, the model fails to match important non-targeted moments without subjective beliefs, I augment it with heterogeneous preferences and moving costs. I now assume a quadratic moving cost function and preferences for childhood neighborhoods that vary by place of birth to capture the mobility matrix. Parents' preferences take the following forms:

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

Appendix Table S8 shows the fit of the perfect information model version augmented with preference heterogeneity. To reproduce the U-shape patterns in residential mobility, the preference for place of birth needs to be about thirty times higher in the bottom-quality neighborhood than in the middle-quality ones. This feature is at odds with Bergman et al. (2019)'s empirical findings. The 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. Those parents are more likely to move and to be satisfied and willing to stay in their neighborhood than those in the control group. The model with perfect information and heterogeneous preferences across places of birth fits residential mobility patterns by construction but misses parental time patterns across socioeconomic groups.[29] The data shows a steep parental time gradient in education. The model does not capture the income gradient well–it is 0.09 instead of 0.14 despite $\varphi = -5$ being very negative–and generates a too small education parental time gap –0.93 instead of 0.75. There is intuitive reasoning behind this result. Parental time and neighborhood quality are complements inputs of the technology of skill formation ($\varphi < 0$), which, combined with income segregation, generates a strong positive correlation between parental time and income and a smaller one with education. However, college parents work more hours than non-college parents. This feature decreases the correlation between parental time and education. College parents are also better at teaching their children than non-college parents. This feature has an ambiguous effect on the correlation between parental time and education. Overall, parental time is weakly correlated with education. Additional sources of heterogeneity are needed to fully match the parental behavior and understand why college parents spend more

[29] Appendix Figures S6 and S7 show the fit of residential mobility moments by this alternative version of the model.

time with their children than non-college parents despite working more hours.[30]

While preference heterogeneity can help match the data, its origin is difficult to justify. Do parental time preferences systematically differ by education status? How does it transmit to children? Is a quadratic moving costs function credible? Why would children born in the bottom neighborhood be so much more attached to their neighborhood quality given all the negative features it has: high-crime rates, high-poverty rates, a low opportunity for children?[31] Discrimination or a homophily bias could motivate some of these modeling assumptions. However, in Table 9, I find that race is not the primary driver of intergenerational residential mobility once controlled for childhood neighborhood quality. In addition, Bergman et al. (2019) find higher satisfaction levels of low-income families who moved to higher-quality neighborhoods which suggests that if they face discrimination once installed, it does not make them want to move back to low-quality neighborhoods.

4 Housing Voucher Policies

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

In this section, I use the quantitative model to study the effects of housing vouchers. The Housing Choice Voucher program is the U.S. Department of Housing and Urban Development largest housing assistance program and its primary mechanism for promoting the mobility of low-income families.[32] The model provides a new rationale for this policy. In addition to addressing redistribution concerns, this policy can improve information about the child skill technology in the economy by reducing segregation.

In the model, housing vouchers are financed through property taxes, which adds two terms to the household budget constraint:

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

[30] Differences by education in the altruism parameter b are not sufficient to fit the data.

[31] 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.

[32] `https://www.huduser.gov/quarterly_update/update_June2015.html`

where τ_r is the tax rate and $r^{hv}_{m,h,s}$, is the rent faced by households once the housing voucher policy is implemented. The government budget constraint is balanced such 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 Housing Voucher Policy

The Housing Choice Voucher program rule imposes that seventy-five percent of families who receive housing vouchers each year have "extremely low incomes," defined as incomes up to the poverty line. The others' income may not exceed 50% of the median income for the metropolitan area where the family chooses to live. The voucher generally covers the difference between 30 percent of the family income and the rent, up to a limit based on Housing and Urban Development's fair market rent estimates at the metropolitan area level.

I consider a housing voucher policy closely designed as the Housing Choice Voucher program. Housing vouchers are offered to young parents, before they make their residential choice. They cover 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. Eligible households are those below the poverty threshold, defined as the income level at the tenth percentile of the income distribution. Let r_{m40} the 40th percentile rent in the commuting zone, then the rent price in neighborhood m for a parent of income $y(h,s)$ who receives the housing voucher is:

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

As a first step, I investigate the impact of housing vouchers in a randomized control trial and compare them to empirical estimates by Chetty et al. (2016). These are partial equilibrium results as few people are treated. Then, I scale up the policy without changing the eligibility criterion and consider steady-state comparisons, which helps gauge the long-run implications.

4.1.1 Randomized Control Trial Within Model

Column 4 Table 4 shows the positive effects of housing vouchers on eligible households. The housing voucher policy improves neighborhood quality by 1.5 points for treated households, improving children's earnings at age 26 by $663. The predicted effect on children's earnings falls 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, Chetty et al.

(2016) evaluate housing vouchers' effects on low-income households who already live in public housing in deprived neighborhoods. The average family earnings at age 26 of children in the control group is \$12,702 in the data, while in the model, it is \$20,917. The share of families who live in bottom-quality neighborhoods in the data is 100%, while it is 40% in the model. Nevertheless, the predicted effect on children's earnings falls within Chetty et al. (2016)'s estimated confidence interval (\$1,452 with a standard error of 736). In both cases, the policy induces an extra 62% of families to move out of bottom-quality neighborhoods.

Parental subjective beliefs are part of why not all low-income families move to high-quality neighborhoods. In Column 5 Table 4, families know the returns to neighborhood quality. The neighborhood income rank improves by an additional 0.4 points and the share of families who choose to live in the worse neighborhood drops to 9%. As a result, perfect information further improves children's adulthood earnings by an additional \$132.

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

	Data		Model		
	Control	Housing Vouchers	Control	Housing Vouchers	Housing Vouchers + Info
	(1)	(2)	(3)	(4)	(5)
% in bottom-quality neighborhood	100%	[-62%; -70%]	40%	-62%	-76%
Children's future earnings	\$12,702	[+\$11;+\$2,893]	\$20,917	+\$663	+\$795
Neighborhood rank			2.14	+1.5	+1.9
Parental time (min./day)			57	+1	+1

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).

4.1.2 Scaling-up Housing Vouchers

General equilibrium responses in local prices and subjective beliefs amplify housing voucher effects. Column 2 of Table 5 shows the effects of a scaled-up housing voucher policy on eligible households. Compared to partial equilibrium, eligible households' parental time and neighborhood rank increase, further increasing eligible children's earnings by \$1,008 per year (\$1,671 - \$663) . I fix the information friction at the baseline level to see whether this amplification effect is due to housing market responses or a change in subjective beliefs (Column 4). In this case, eligible households' neighborhood rank increases but not parental time, further increasing eligible children's earnings by $207 per year ($870 - $663). This suggests that general equilibrium responses in parental subjective beliefs account for 80% of the amplification effect on eligible households.

Table 5: The Effects of Scaling-up Housing Vouchers

	Small Field	Large Scale and Long Run			
	Baseline model	Baseline model		Baseline model without change in social learning	
Households	Eligible (1)	Eligible (2)	All (3)	Eligible (4)	All (5)
% in neighborhood D1	-62%	-58%	-3%	-69%	-1%
Children's future earnings	+$663	+$1,671	+$277	+$870	-$57
Neighborhood rank	+1.5	+1.6	+0.0	+1.9	+0.0
Parental time (min./day)	+1	+9	+2	+0	-1
Inequality			-0.8%		+0.0%
Poverty			-6.3%		+1.3%
Earnings			+0.9%		-0.2%
Rank-rank coefficient			-3.8%		+0.5%

Notes: This table shows the effects of scaling-up housing vouchers within the calibrated baseline model.

The policy also positively affects the economy. Column 3 of Table 5 shows the housing voucher policy effects on all households. Inequality and poverty decrease while earnings and social mobility increase. However, ignoring subjective belief responses lead to opposite conclusions (Columns 5 of Table 5). If only long-run responses in local prices are considered, inequality and poverty increase while earnings and social mobility decrease. Figure 4 and Table 6 help understand subjective beliefs' role in the policy effects. With the housing voucher policy, parents' subjective beliefs improve in the long run, particularly those of low-income parents. This leads to a change in parents' behavior. Low-income parents spend more time with their children despite an increase in neighborhood quality (remember that neighborhood quality and parental time are substitute inputs in the technology of skill formation). The change in subjective beliefs decreases the share of parents in the bottom-quality neighborhood and improves the share of parents in higher-quality neighborhoods (Figure 4). As a result, social mobility improves, and inequality decreases. However, all those positive effects are absent when ignoring the change in subjective beliefs.

A striking result of the policy is the increase in high-income households' subjective beliefs

Table 6: The Effects of Scaling-up Housing Vouchers by Income Quartile

		Household Income quartile			
	All	1st	2nd	3rd	4th
Subjective Beliefs	+2.8%	+7.1%	+3.3%	+2.2%	+0.2%
Parental Time	+2.6%	+8.0%	+2.2%	+1.2%	+1.3%
Earnings	+0.9%	+0.7%	+2.3%	+3.5%	+2.3%

Notes: This table shows the effects of scaling-up housing vouchers by income group.

(Column 5 Table 6). A decrease in segregation should improve information, decreasing the subjective beliefs of high-income parents who overestimate them. However, the policy has a unique rent ceiling for the commuting zone, which creates a bunching at the rent limit. This bunching is illustrated by the peak in neighborhood 5 in Figure 4 and observed in the data by Collinson and Ganong (2018). As a result, low-income households don't move to the highest-quality neighborhoods, and information does not improve in those neighborhoods. Since there is a debate concerning the unique rent feature of the Housing Choice Voucher program, I now evaluate a housing voucher policy with rent limits set at the neighborhood level instead of at the commuting zone level.

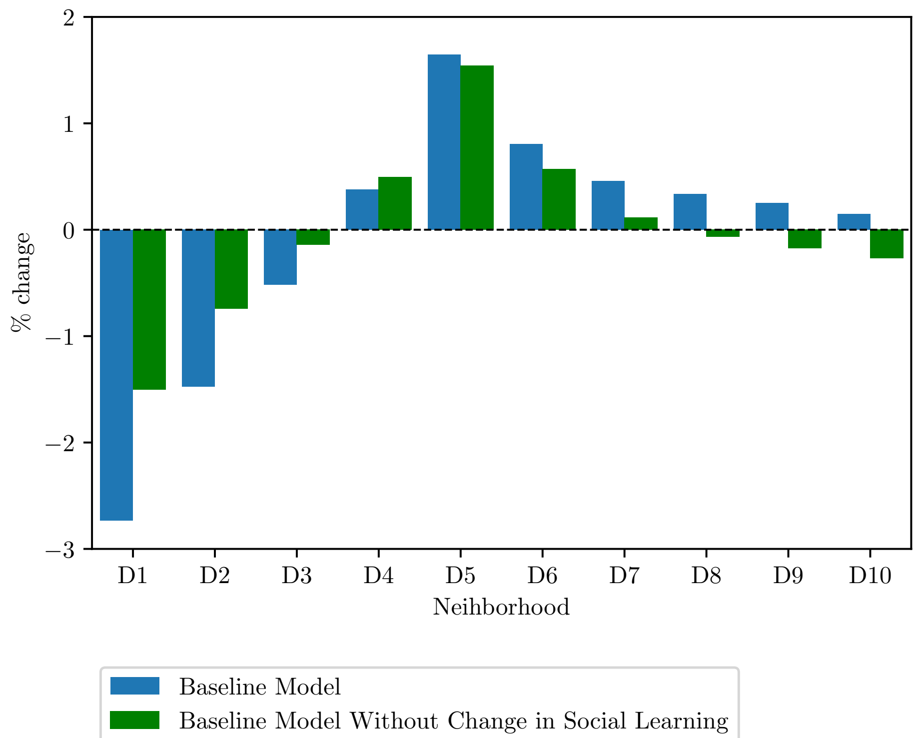
4.2 Housing Voucher Policy with Rent Limits Indexed at the Neighborhood Level

Since Chetty et al. (2016) provided evidence that housing vouchers effectively improve adulthood earnings through improved neighborhood quality, the United States Department of Housing and Urban Development has put additional effort into promoting high-quality mobility. In particular, since 2019, the Department of Housing and Urban Development has allowed housing agencies to set voucher subsidies at local rents rather than at the metro area level.[33] This decision addresses an issue raised about unique rent ceilings: they do "not adequately help families access low-poverty neighborhoods."[34] Indeed, Collinson and Ganong (2018) finds that most rental units below the payment standard are in low-quality neighborhoods and that indexing rent limits to ZIP codes rather than to metropolitan areas improves the share of families who move into higher-quality neighborhoods.

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

[34] https://www.huduser.gov/portal/pdredge/pdr_edge_frm_asst_sec_061515.html

Figure 4: Effects of Housing Vouchers on Neighborhood Density



Notes: This Figure shows the long-run change in neighborhood density due to the scaled-up housing voucher policy.

4.2.1 Housing Voucher Policy with Multiple Rent Limits

I consider a housing voucher policy designed to mimic the Housing Choice Voucher program but with rent limits defined at the neighborhood level. Since the model does not feature heterogeneity in housing prices within neighborhoods, rent limits are determined by the median rent in each neighborhood. As before, eligible households are those below the poverty threshold, defined as the income level at the tenth percentile of the income distribution.

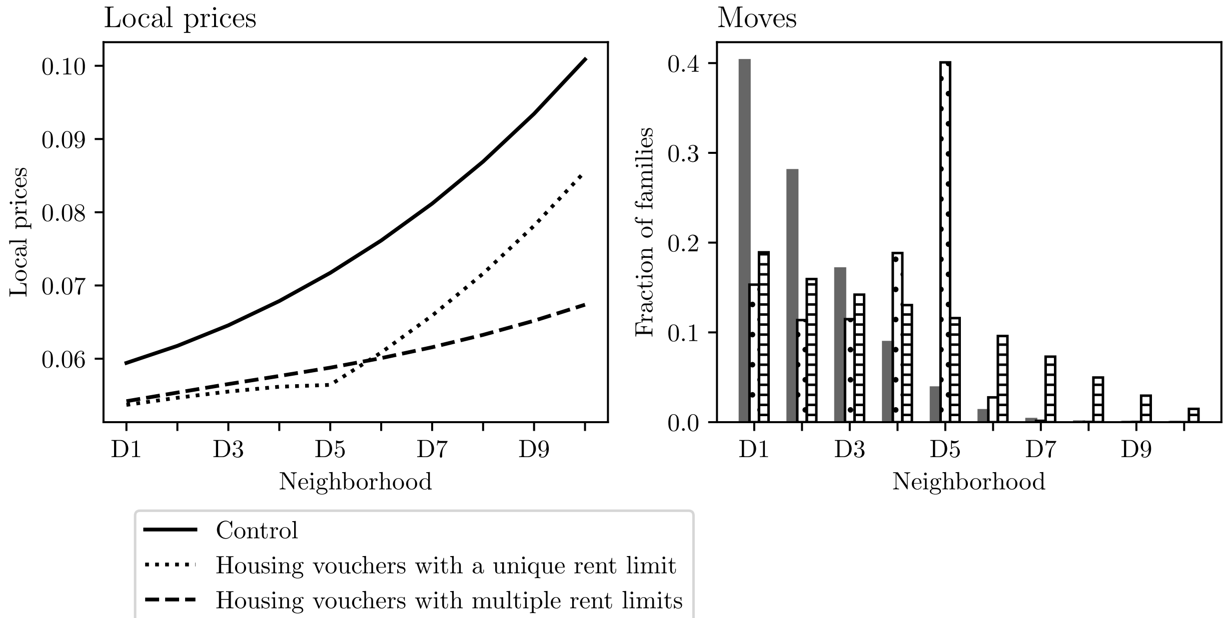
Housing vouchers cover the difference between a fraction of the family's income and a fraction of the median rent in each neighborhood. Those fractions are defined so that, in partial equilibrium, the cost of the policy is the same as the cost of a housing voucher with a unique rent limit and that the rent faced by an average eligible household is the same across the two policies in the first neighborhood. The left panel of Figure 5 illustrates the rent schedule of this new policy for an average eligible household. 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. While under a housing voucher policy with a unique rent limit, the rent schedule has a kink; it is smooth under a housing voucher policy with rent limits set at the neighborhood level.

4.2.2 Effects of a Housing Voucher Policy with Multiple Rent Limits

Partial Equilibrium Effects of the Policy. Consistent with (Collinson and Ganong, 2018)'s empirical findings, I find that a housing voucher policy with multiple rent limits improves the neighborhood rank of eligible households even though more families choose to live in the bottom quality neighborhood (right panel of Figure 5 and Column 2 Table 6). As a result, the effect on children's future earnings is more substantial than under a unique rent limit housing voucher policy, with an increase of $809 per year at age 26.

Large Scale and Long-run Effects of the Policy. Column 3 of Table 8 shows that general equilibrium responses in local prices and subjective beliefs greatly amplify the effects of the policy on eligible households. The neighborhood rank is much higher than under a policy with a unique rent limit (3.3 versus 1.6), increasing children's future earnings by $2,477 per year. The difference in amplification effects between the two policies mainly results from improved housing market access. The attractiveness of the bottom-quality neighborhood decreases even further, as depicted in Figure 6, while the attractiveness of very high-quality neighborhoods increases. However, subjective beliefs of low-income families do not increase more under a housing voucher policy with multiple rent limits than under a housing voucher policy with a unique rent limit (Column 2 of Tables 6 and 8).

Figure 5: Design of Housing Voucher Policies - Eligible Households - Partial Equilibrium



Notes: The left panel of this Figure shows the rent schedule for an average eligible household under three scenarios: no policy (control), housing vouchers with a unique rent limit, and housing vouchers with multiple rent limits. The right panel of this Figure shows the residential choices of eligible households under the three scenarios.

Table 7: The Effects of Scaling-up Housing Vouchers with Multiple Rent Limits

	Small Field	Large Scale and Long Run	
	Baseline model	Baseline model	
Households	Eligible (1)	Eligible (2)	All (3)
% in bottom-quality neighborhood	-53%	-69%	-3%
Children's future earnings	+$809	+$2,477	-$1
Neighborhood rank	+1.8	+3.3	+0.0
Parental time (min./day)	+1	+10	-1
Inequality			-1.5%
Poverty			-6.2%
Earnings			-0.0%
Rank-rank coefficient			-8.5%

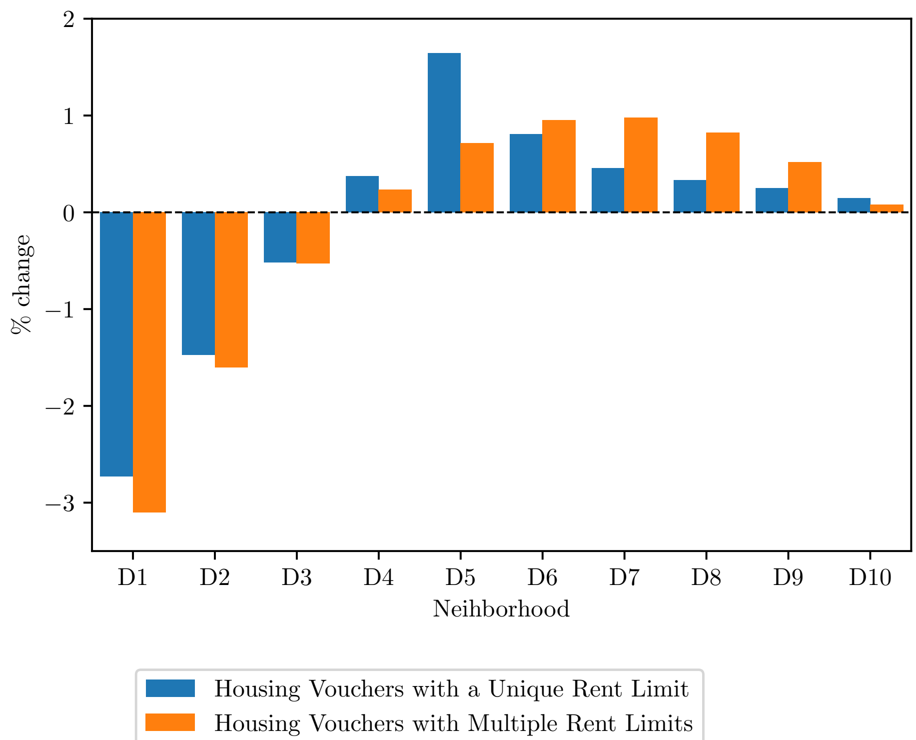
Notes: This table shows the effects of scaling-up housing vouchers with multiple rent limits within the calibrated baseline model.

Table 8: The Effects of Scaling-up Housing Vouchers with Multiple Rent Limits by Income Quartile

		Household Income quartile			
	All	1st	2nd	3rd	4th
Subjective Beliefs	-0.3%	+6.6%	+0.9%	-1.7%	-4.8%
Parental Time	-1.1%	+7.8%	-0.6%	-3.2%	-5.1%
Earnings	-0.0%	+0.7%	+2.2%	+1.9%	-0.6%

Notes: This table shows the effects of scaling-up housing vouchers with multiple rent limits by income group.

Figure 6: Effects of Housing Voucher Policies on Neighborhood Density



Notes: This Figure shows the long-run change in neighborhood density due to the scaled-up housing voucher policies.

The housing voucher policy with multiple rent limits also positively affects the economy. Column 3 of Table 7 shows the policy effects on all households. This policy has stronger effects on inequality and social mobility (-1.5%, +8.5%, respectively). However, the effects on earnings and, consequently, on absolute poverty are weaker. Figure 6 and Table 8 help understand the underlying reasons. Under the housing voucher policy with multiple rent limits, eligible households have better access to all neighborhoods, decreasing segregation and improving information everywhere. In the long run, parents' subjective beliefs become closer to the truth, increasing the subjective beliefs of low-income parents but decreasing those of high-income parents. This leads to a change in parents' behavior across the entire income distribution. Low-income parents spend more time with their children (+8%), and high-income parents spend less time with their children (-5%). As a result, average parental time decreases (-1%), and earnings do not improve. However, the policy greatly affects social mobility and inequality as it mitigates the distorting effects of parents' subjective beliefs.

In sum, a housing voucher policy with multiple rent limits is a better tool to address redistribution concerns and improve information, mitigating the distorting effect of parental subjective beliefs than a housing voucher policy with a unique rent limit. However, this policy does not enhance aggregate income in the long run because it decreases high-income parents' subjective beliefs.

5 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 (AddHealth). In this section I derive and test for two implications of social learning mechanism. None of the implications are rejected which comforts the plausibility of the social learning mechanism.

5.1 Data

The AddHealth 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. In 2016-2018, about 12,300 answered the last follow-up survey. 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 AddHealth 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.[35] Parental time is approximated to the number of parent-child activities over the past four weeks measured in 1994-1995.[36]

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 9 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.[37]

5.2 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) subjective 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.

Columns (3) and (4) of Table 9 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.[38] Note that in both regressions of Column (3) and (4) of Table 9, 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

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

[36] Appendix Section A.1 describes the data and variable construction in more details.

[37] Appendix Table S2 presents the OLS regression coefficients with a different definition of neighborhood quality and parental time variables. Results are robust to definition changes.

[38] The results are robust to the use of alternative proxies for parental inputs. See Appendix Table S2.

(see Doepke et al. (2022) for a review).[39] This observed correlation could be driven by a neighborhood composition effect. In Column (4) of Table 9, I control for three variables measuring households' socioeconomic status: parents' highest level of education, family income, and parent's marital status.[40] 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.

Table 9: Parental Time and Neighborhood Quality, Add-Health 1994-1995 and 2016-2018

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

Notes: This table provides between parental investment choices and college graduation (Columns (1) and (2)) correlations between parental investment choices (Columns (2) and (3)) and between childhood and adulthood neighborhood quality (Columns (5) and (6)). Socioeconomic status variables are family income, highest education level, and marital status. See Appendix Section 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.

While this result is consistent with the assumption of parental beliefs being an omitted variable, it is also compatible with a human capital production function in which neighborhood quality and parental time are complementary inputs. There is no consensus in the

[39] 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.

[40] 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.

literature about this relationship.[41]

5.3 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 9 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 9, 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.[42] 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.[43]

None of the two testable model implications are rejected which, without proving the social learning mechanism, comforts its plausibility.

6 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. Introducing endogenous subjec-

[41] 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).

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

[43] The results are robust to the use of the fraction of adults with a college degree for neighborhood quality. See Appendix Table S2.

tive beliefs helps understand parental behavior across socioeconomic groups. Once calibrated to the average commuting zone in the United States, the model predicts that segregation generates information frictions that shape the subjective beliefs distribution and distort parental investment choices. Low-income parents underestimate the returns to neighborhood quality and parental time, while high-income parents overestimate them. This model provides a rationale for two puzzling parental behaviors: children born in low-quality neighborhoods tend to raise their children in those neighborhoods, and college parents spend more time with their children than non-college parents despite working more hours.

I investigate the effects of a housing voucher policy that induces low-income households to move to higher-quality neighborhoods. Scaling up the policy amplifies the effects on eligible families and positively impacts the economy as it decreases inequality and poverty and increases social mobility. A change in subjective beliefs mainly drives this amplification effect. Ignoring this change would lead to misleading policy recommendations. Finally, I also find that a housing voucher policy with multiple rent limits within the commuting zone instead of one is a better tool to reduce the distorting effect that social learning and segregation introduce.

This paper shows that a relatively low level of delusion about the technology of skill formation, consistent with micro-studies, has a significant adverse effect on the economy. Estimating subjective beliefs' consequences at the aggregate level and proposing concrete policies that can dampen their negative impacts is an exciting avenue to pursue in future research.

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A Data

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

A.1.1 Description

The National Longitudinal Study of Adolescent to Adult Health (AddHealth) survey is a nationally representative longitudinal survey of adolescents in the United States. In 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 are aged between 12 and 17 years old. In 2016-2018, about 12,300 of them have answered Wave V survey. At the date of the last survey wave, most of the interviewees are aged between 35 and 40 years old. The analysis focuses on the baseline survey in 1994 (Wave I) and the last follow up survey in 2018 (Wave V).

The data set includes detailed information on family background and a rich set of information on neighborhoods 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 neighborhood is available at the census tract level. In addition, AddHealth contains questions on the frequency of a 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

I proxy neighborhood quality by household median income of the census tract.[44] I create ten synthetic neighborhoods by ranking all census tracts by neighborhood quality and grouping them in ten groups of equal size. One synthetic neighborhood represent a decile of the census tracts distribution in the United States. Thanks to the panel 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.[45]

[44] I also use the share of residents above 25 with a college degree as a robustness check of the results (Diamond (2016)).

[45] 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)".

To proxy for time allocated in childcare, I construct a variable that counts the number of activities that happened over the past four week 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 the ten events: "shopping", "went to a religious service or church-related event" and.[46] 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 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,

[46] 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".

there are additional questions to identify work, volunteering, eldercare, and secondary childcare activities. Several activity categories are then defined by the United States Bureau of Labor Statistics (BLS), among which one is of particular interest for this research project: "primary childcare activities." This activity category includes time spent providing physical care, playing with children; reading with children; assisting with homework; attending children's events; taking care of children's health needs, and dropping off, picking up, and waiting for children. Passive childcare was included as a primary activity (such as "keeping an eye on my son while he swam in the pool"). However, a child's presence during the training is 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 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.[47]

Table S1: ATUS Activity Coding Structure, 2003

Label	Description	Non-college parents	College parents
		Hours per day	
Childcare		**1.17**	**1.58**

[47]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.

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**

B Robustness checks

C 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 correspond-

Table S2: Parental Time and Neighborhood Quality, Add-Health 1994-1995 and 2016-2018

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

Notes: This table provides between parental investment choices and college graduation (Columns (1) and (2)) correlations between parental investment choices (Columns (2) and (3)) and between childhood and adulthood neighborhood quality (Columns (5) and (6)). Socioeconomic status variables are family income, highest education level, and marital status. See Appendix Section 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.

ing $V(h, s, m_0, , \tilde{\alpha}, m)$

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 subjective 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.

D Theory Appendix

Let $y|\overline{x} \sim \mathcal{N}(\overline{x}, \sigma_s)$ with $y \in (-c, c)$ and $\overline{x} \in (-c, c)$ where $c > 0$ a real number. Figure S1 illustrates a conditional signal distribution when $\overline{x} > 0$. Let Φ the CDF of the standard normal distribution and ϕ the PDF of the standard normal distribution.

1. If $\overline{x} \geq 0$ then $\mathbb{E}(y|\overline{x}) \geq 0$ and if $\overline{x} \leq 0$ then $\mathbb{E}(y|\overline{x}) \leq 0$.

Proof. Consider $\overline{x} \geq 0$.

The expectation of y conditional on the realization of $\overline{x}$ is:

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

Note that $\phi(u - \overline{x}) = \phi(2 \, \overline{x} - u - \overline{x}) \quad \forall u \geq 0$ and then $\phi(u - \overline{x}) \geq \phi(-u - \overline{x}) \quad \forall u \geq 0$

Then

$$\left| \int_{-c}^{0} \frac{1}{\sigma_s} \, u \, \phi\left(\frac{u - \overline{x}}{\sigma_s}\right) \, du \right| \leq \left| \int_{0}^{c} \frac{1}{\sigma_s} \, u \, \phi\left(\frac{u - \overline{x}}{\sigma_s}\right) \, du \right| \quad \forall u \geq 0$$

and

$$\left(1-\Phi\left(\frac{c-\overline{x}}{\sigma_s}\right)\right) \;\geq\; \Phi\left(\frac{-c-\overline{x}}{\sigma_s}\right) \quad \forall u \geq 0$$

Hence if $\overline{x} \geq 0 \;\Rightarrow\; \mathbb{E}(y|\overline{x}) \geq 0$.

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

2. If $\overline{x} \geq 0$ then $\mathbb{E}(y|\overline{x}) \leq \overline{x}$ and if $\overline{x} \leq 0$ then $\mathbb{E}(y|\overline{x}) \geq \overline{x}$.

Proof. Consider $\overline{x} \geq 0$.

The expectation of y conditional on the realization of $\overline{x}$ is:

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

Note that $\phi(u\;-\;\overline{x}) = \phi(2\,\overline{x}\;-\;u\;-\;\overline{x})$ and $\phi(2\,\overline{x}\;+u\;-\;\overline{x}) = \phi(-\;u\;-\;\overline{x}) \quad \forall u \geq 0$

Then

$$\begin{aligned}
\mathbb{E}(y|\overline{x}) = &\int_{2\,\overline{x}-c}^{c} u\,\frac{1}{\sigma_s}\,\phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\,du \;+\; \int_{-c}^{2\,\overline{x}-c} u\,\frac{1}{\sigma_s}\,\phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\,du \\
&+c\,\left(1-\Phi\left(\frac{2\overline{x}+c-\overline{x}}{\sigma_s}\right)\right) - c\,\Phi\left(\frac{-c-\overline{x}}{\sigma_s}\right) \\
&+c\,\left(\Phi\left(\frac{2\overline{x}+c-\overline{x}}{\sigma_s}\right) - \Phi\left(\frac{c-\overline{x}}{\sigma_s}\right)\right) \\
= \overline{x} \;-\; &\int_{c}^{2\,\overline{x}+c} u\,\frac{1}{\sigma_s}\,\phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\,du \\
&+0 \\
&+c\,\left(\Phi\left(\frac{2\,\overline{x}+c-\overline{x}}{\sigma_s}\right) - \Phi\left(\frac{c-\overline{x}}{\sigma_s}\right)\right) \\
= \overline{x}& \\
&+\underbrace{c\,\left(\Phi\left(\frac{2\,\overline{x}+c-\overline{x}}{\sigma_s}\right) - \Phi\left(\frac{c-\overline{x}}{\sigma_s}\right)\right) \;-\; \int_{c}^{2\,\overline{x}+c} u\,\frac{1}{\sigma_s}\,\phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\,du}_{\leq 0} \\
\leq \overline{x}&
\end{aligned}$$

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

□

3. $\lim_{\sigma_s \to 0} \mathbb{E}(y|\overline{x}) = \overline{x}$ and $\lim_{c \to +\infty} \mathbb{E}(y|\overline{x}) = \overline{x}$.

Proof. Note $\mathbb{E}(y|\overline{x}) = \ \overline{x} + c\ \left(\Phi\left(\frac{2\ \overline{x}+c-\overline{x}}{\sigma_s}\right) - \Phi\left(\frac{c-\overline{x}}{\sigma_s}\right)\right)\ -\ \int_c^{2\ \overline{x}+c} u\ \frac{1}{\sigma_s}\ \phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\ du$

Note

$$\lim_{\sigma_s\to 0} \Phi\left(\frac{2\ \overline{x}+c-\overline{x}}{\sigma_s}\right) - \Phi\left(\frac{c-\overline{x}}{\sigma_s}\right) = 0$$

similarly,

$$\lim_{\sigma_s\to 0} \int_c^{2\ \overline{x}+c} u\ \frac{1}{\sigma_s}\ \phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\ du = 0$$

then

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

Note

$$\lim_{c\to+\infty} \Phi\left(\frac{2\ \overline{x}+c-\overline{x}}{\sigma_s}\right) - \Phi\left(\frac{c-\overline{x}}{\sigma_s}\right) = 0$$

and

$$\lim_{c\to+\infty} \int_c^{2\ \overline{x}+c} u\ \frac{1}{\sigma_s}\ \phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\ du = 0$$

then

$$\lim_{c\to+\infty} \mathbb{E}(y|\overline{x}) = \overline{x}$$

$\square$

4. $\lim_{\sigma_s\to+\infty} \mathbb{E}(y|\overline{x}) = 0$.

Proof. The expectation of y conditional on the realization of $\overline{x}$ is:

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

Note

$$\lim_{x\to 0} \Phi\left(x\right) = 0.5$$

then

$$\lim_{\sigma_s\to+\infty} c\ \left(1 - \Phi\left(\frac{c-\overline{x}}{\sigma_s}\right)\right) - c\ \Phi\left(\frac{-c-\overline{x}}{\sigma_s}\right) = 0$$

and

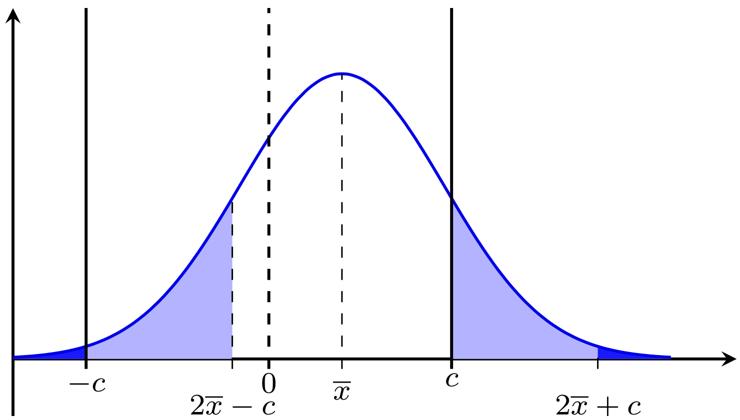
$$\lim_{\sigma_s\to+\infty} \int_{-c}^{c} u\ \frac{1}{\sigma_s}\ \phi\left(\frac{u-\overline{x}}{\sigma_s}\right)\ du = 0$$

Then

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

$\square$

Figure S1: Signal Illustration



Notes: This Figure illustrates a conditional signal distribution with $\overline{x} > 0$.

E Additional Information on the Calibration

E.1 Parental Time

Table S3 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.[48] In 2003, 5,597 married parents were interviewed, among which 2,168 have a college degree.[49,50] 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 activities, while parents without a college degree spend 1.2 hours in childcare and 4.4 hours in market work.[51] 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

[48] 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.

[49] Parent's education is defined as the highest level of education achieved by the mother because it is the most correlated with parental investment (in ATUS) and graduation probability in AddHealth. Using the highest education level of both parents doesn't change the results in Table S3.

[50] 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.

[51] 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.

activities is relatively constant across educational groups.[52] 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 S3: Parents' Time Allocation by Education, ATUS 2003

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

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

E.2 Synthetic Neighborhoods Characteristics

Table S4 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)).[53] Note that housing expenditure shares decrease with neighborhood quality (Column (4)) which suggests and motivates non-homothetic preferences.

E.3 Estimated Parameters: Neighborhood Choices and College Graduation

For two primary purposes, I use the AddHealth survey, detailed in Section 5.1. First, to compute intergenerational residential mobility. To do so, as in the NHGIS data analysis, I create 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

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

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

Table S4: 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.

adolescent lived in 1994-1995 and in which artificial neighborhood she lived during adulthood, in 2008-2009 and 2016-2018. I restrict the sample to people no longer living at their parent's place. Even though, due to attrition, samples are smaller in Wave V than in Wave IV, I use estimates from Wave V.[54] In 2016-2018, interviewees were older, between 35 and 40, and more likely to be married than ten years before.[55] 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%.

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

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

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

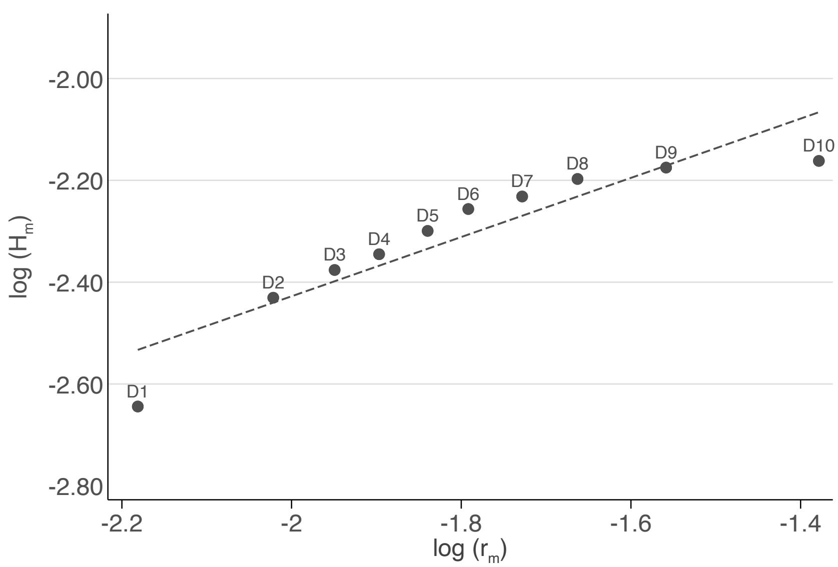
science, and science. Information on parents' highest education level and income comes from the parent survey conducted in 1994-1995.

Table S5: 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

Table S6: Moments Description

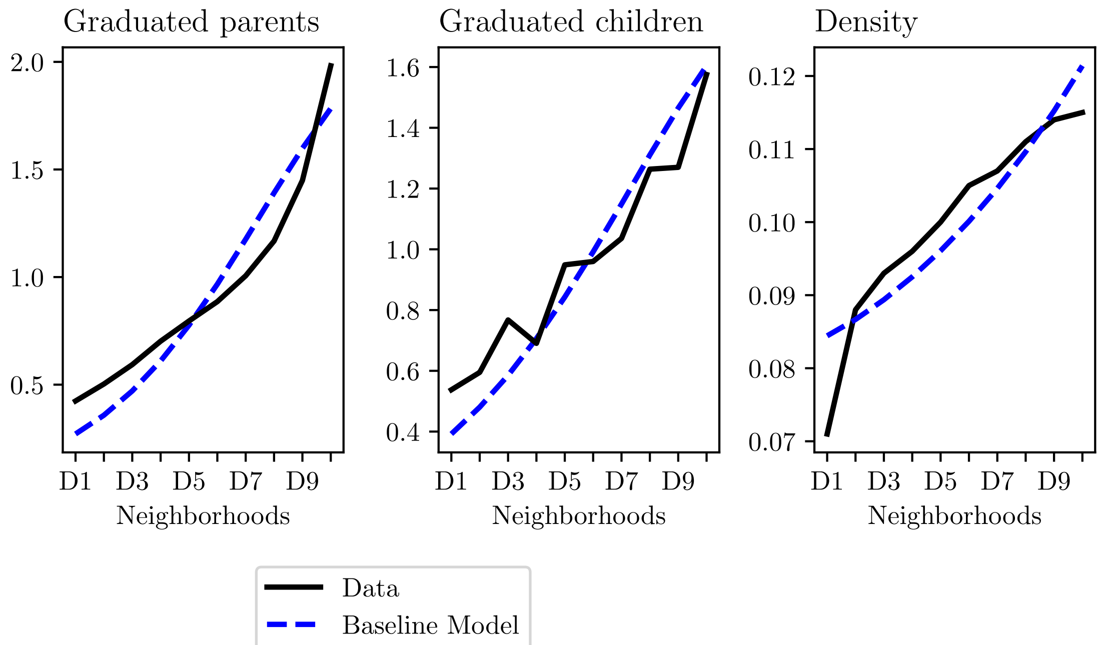
Moment	Description	Data restriction	Source
Earnings			
Share college parents in Q1 over Q4	Fraction of college parents in the first quartile of the income distribution over the fraction of college parents in the fourth quartile of the income distribution.	100 biggest commuting zones - families with a 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.	100 biggest commuting zones. 1994-2018.	AddHealth Wave I and Wave V
Social mobility			
Rank-rank coefficient	Regression coefficient of child household income rank on parental household income rank.	Tax records covering the U.S. population, spanning 1996-2012.	Chetty et al. (2014)
Parental time			

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 Non-Targeted Moments

Figure S3: Non-Targeted Moments by Neighborhood



Notes: .

[ADD QUINTILE MATRIX]

E.6 Perfect Information Model

This section describes the calibration of a model without subjective beliefs. Parents' preferences take the following forms:

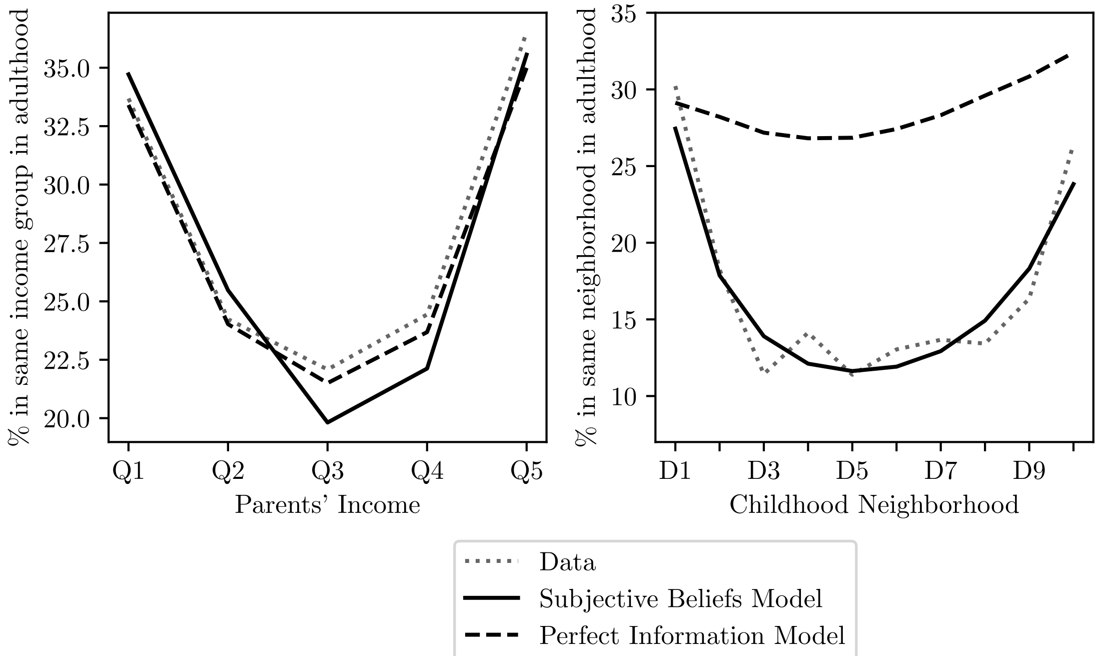
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa\,\tau\right)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} + \iota\,\mathbb{1}_{m_0=m} + \nu\varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right]$$

Table S7: Internally Calibrated Parameters - Perfect Information Model

Parameter	Description	Moment	Data	Model
Preferences and Labor Market				
$b\ =\ 0.65$	Altruism	Ratio share college parents Q1 to Q4	0.102	0.117
$\kappa\ =\ 0.7$	Parental time disutility	Parental time non-college parents	0.075	0.078
$\iota\ =\ 0.024$	Place of birth preference	Residential mobility (D1)	0.295	0.302
$\omega\ =\ 0.01$	College wage premium	Earnings ratio non-college - college	0.554	0.557
Neighborhoods				
$\sigma_m =\ 0.16$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.061
$\nu\ =\ 0.02$	Taste shock variance	Census tract Gini	0.231	0.157
Skill Formation: $h' = \left(\left(\gamma\ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}}\ +\ \underline{i}\right)^{\alpha}\ h^{1-\alpha}\ \exp(a)$ with $a \sim \mathcal{N}(0, \sigma_a)$				
$\alpha\ =\ 0.7$	Elasticity of investments	Rank-rank coefficient	0.341	0.348
$\gamma\ =\ 0.45$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.057
$\varphi\ =\ $-5	Substitutability	Income gradient in parental time	0.140	0.091
$\sigma_a\ =\ 0.55$	Ability shock variance	Income Gini	1.247	1.218

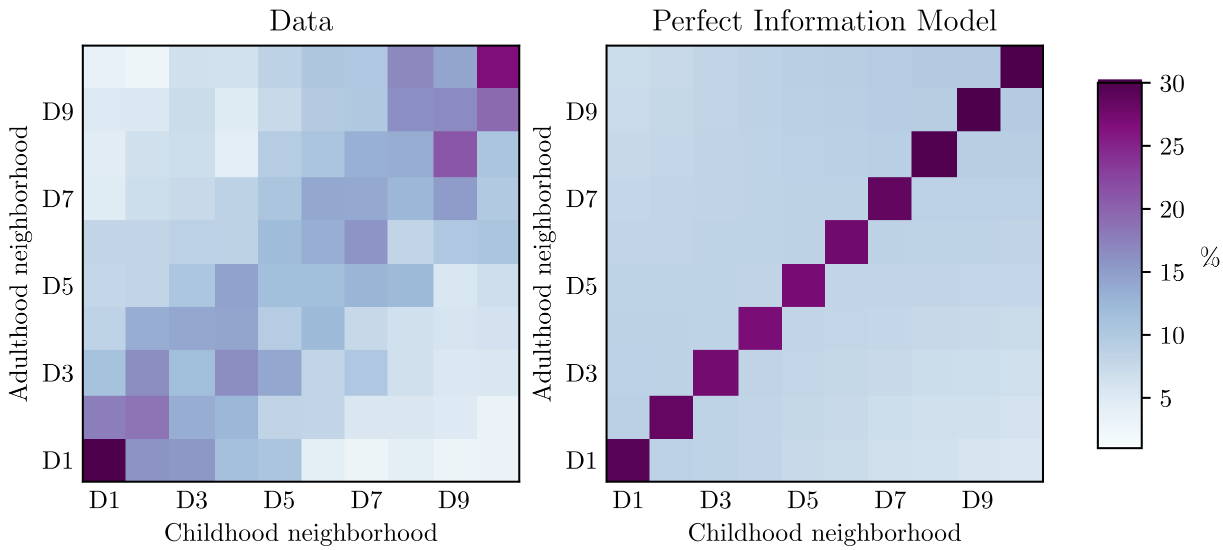
Notes: This table reports the internally calibrated parameters and the observed and simulated moments associated with the parameter estimates. Perfect Information model.

Figure S4: Residential Mobility in a Perfect Information Model



Notes: Left panel shows the share of children who, when they are adults, are in the same household income quintile as their parents. Right panel shows the share of children who still live in their childhood neighborhood quality when they are adults. Data moments are in dotted-line, subjective beliefs model simulated analogs in solid-line, and perfect information model in dashed-line.

Figure S5: Detailed Residential Mobility in a Perfect Information Model



Notes: This Figure shows residential mobility between childhood and adulthood in the data (left panel), and their perfect information 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.

E.7 Perfect Information Model with Heterogeneity

This section describes the calibration of a model without subjective beliefs but with heterogeneous preferences. Parents' preferences feature heterogeneous preferences by place of birth and I assume a quadratic moving cost function. Parents' preferences take the following forms:

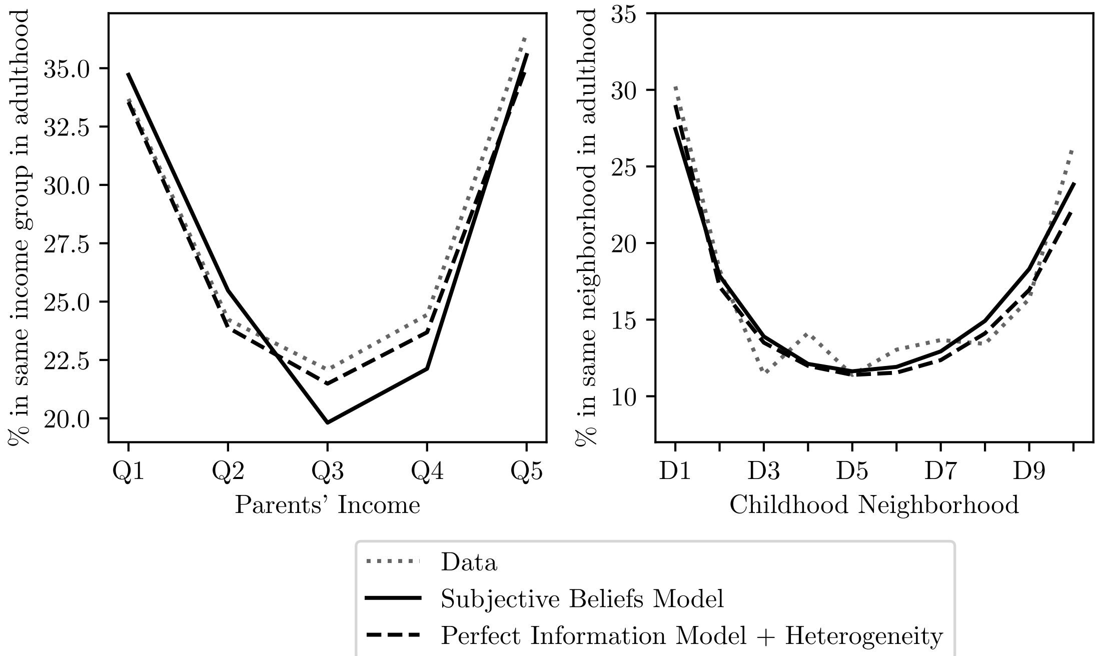
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa\,\tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \iota_{m_0}\,\mathbb{1}_{m_0=m} - \xi(m_0 - m)^2 + \nu\varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right]$$

Table S8: Internally Calibrated Parameters - Perfect Information Model with Preference Heterogeneity

Parameter	Description	Moment	Data	Model
Preferences and Labor Market				
$b = 0.65$	Altruism	Ratio share college parents Q1 to Q4	0.102	0.118
$\kappa = 0.7$	Parental time disutility	Parental time non-college parents	0.075	0.077
$\iota_1 = 0.0135$	Place of birth preference	Residential mobility (D1)	0.295	0.302
$\iota_2 = 0.0015$	Place of birth preference	Residential mobility (D2)	0.182	0.172
$\iota_{3-9} = 0.0005$	Place of birth preference	Residential mobility (D5)	0.112	0.114
$\iota_{10} = 0.0015$	Place of birth preference (D10)	Residential mobility (D10)	0.235	0.223
$xi = 0.0005$	Quadratic moving costs	Correlation neighborhood quality	0.417	0.400
$\omega = 0.0001$	College wage premium	Earnings ratio non-college - college	0.554	0.563
Neighborhoods				
$\sigma_m = 0.16$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.062
$\nu = 0.02$	Taste shock variance	Census tract Gini	0.231	0.154
Skill Formation: $h' = \left(\left(\gamma\ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}} + \underline{i}\right)^{\alpha} h^{1-\alpha}\ \exp(a)$ with $a \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0.7$	Elasticity of investments	Rank-rank coefficient	0.341	0.347
$\gamma = 0.45$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.057
$\varphi = -5$	Substitutability	Income gradient in parental time	0.140	0.090
$\sigma_a = 0.55$	Ability shock variance	Income Gini	0.336	0.328

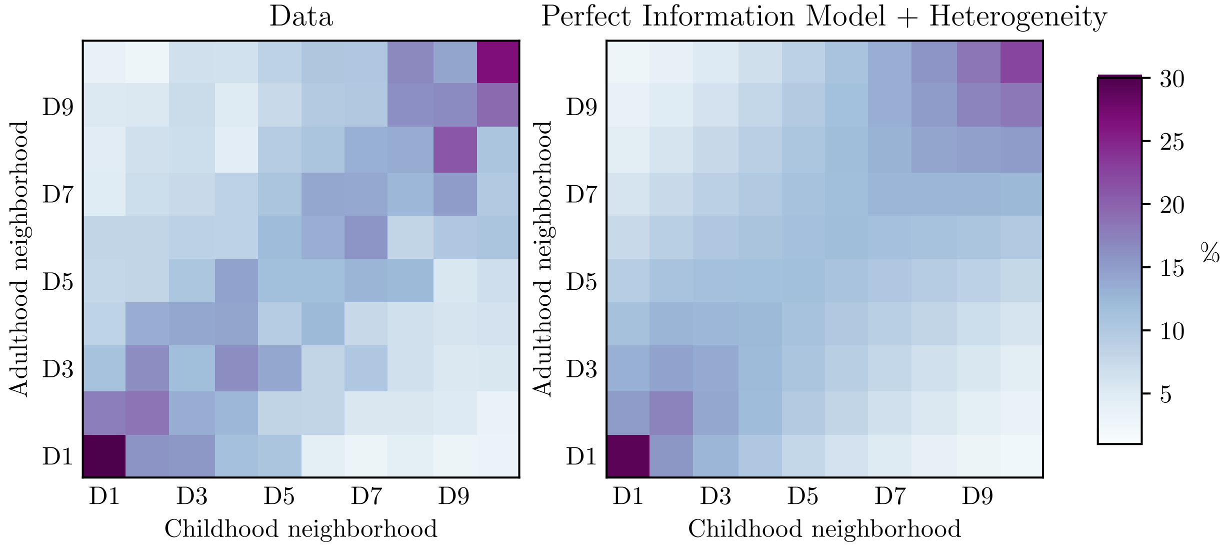
Notes: This table reports the internally calibrated parameters and the observed and simulated moments associated with the parameter estimates. Perfect Information model with preference heterogeneity.

Figure S6: Residential Mobility in a Perfect Information Model with Heterogeneity



Notes: Left panel shows the share of children who, when they are adults, are in the same household income quintile as their parents. Right panel shows the share of children who still live in their childhood neighborhood quality when they are adults. Data moments are in dotted-line, subjective beliefs model simulated analogs in solid-line, and perfect information model with heterogeneity in dashed-line.

Figure S7: Detailed Residential Mobility in a Perfect Information Model with Heterogeneity



Notes: This Figure shows residential mobility between childhood and adulthood in the data (left panel), and their perfect information model with heterogeneity 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.