Why Don't Poor Families Move? A Spatial Equilibrium of Parental Decisions with Imperfect Information*

Suzanne Bellue†

October 4, 2022
Click here for the latest version

Abstract

United States parents shape children's economic opportunities by choosing their neighborhood quality. But most children raised in bottom-quality neighborhoods tend to choose low-quality neighborhoods in adulthood. I develop a quantitative spatial model of parental decisions that incorporates a novel mechanism: community learning about the skill formation technology. Segregation generates information frictions that systematically distort parents' subjective beliefs and behavior. The calibrated model helps understand parental behavior across socioeconomic groups. Under perfect information, inequality decreases by 1%, and social mobility increases by 13%. Housing vouchers improve neighborhood quality and earnings of eligible children. However, at scale, the policy backfires, increasing inequality.

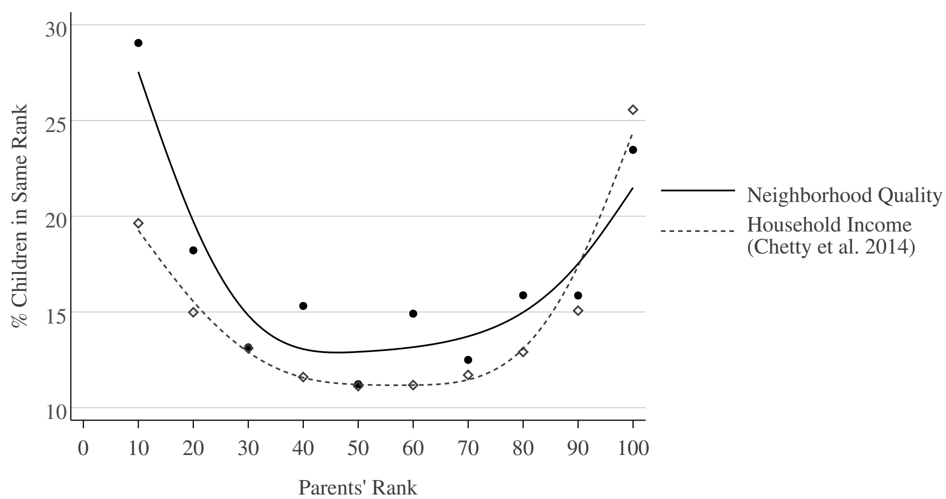
*I am indebted to Michèle Tertilt for her continued and invaluable support and guidance in this project. In addition, I am very grateful to Klaus Adam, Antoine Camous, Antonio Ciccone, Anne Hannusch, Jamie Hentall MacCuish, Georgi Kocharkov, David Koll, Tsung-Hsien Li, Giacomo Ponzetto, José Víctor Ríos Rull, Jan Sun, Minchul Yum and seminar and conference participants at the XXV Workshop on Dynamic Macroeconomics 2022 (Vigo), the Summer School in Urban Economics 2022, the SMYE 2022, the CRC retreat 2022, the ENTER Jamboree 2022, UCL, the University of Mannheim for helpful discussions and suggestions. I gratefully acknowledge financial support by the German Academic Exchange Service (DAAD) and the German Research Foundation (through the CRC-TR-224 project A03).

†University of Mannheim

1 Introduction

In the United States, childhood neighborhood quality shapes adulthood economic opportunity (Chetty and Hendren, 2018b).[1] But many parents born in low-quality neighborhoods choose to raise their children in those types of neighborhoods. Figure 1 shows that while less than 15% of United States children raised in middle-range quality neighborhoods remain in those neighborhoods in adulthood, this number rises to almost 30% for bottom-quality neighborhood children (solid line). To put this number in perspective, the probability that a child is born and stays in a bottom-income household in adulthood is ten points lower (Figure 1, dashed line, Chetty et al. (2014)). Given the benefits of escaping low-quality neighborhoods, why do families stay?

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 quality-rank neighborhood as in their childhood. The sample is restricted to the 100 biggest commuting zones in the United States and interviewees who do not live in their parent's houses in adulthood. The dots are data points, and the solid line is a smooth interpolation—data source: National Longitudinal Study of Adolescent to Adult Health. For comparison, diamonds and dashed line represents the share of children who, in adulthood, have the same household income rank as their parents—data source: Chetty et al. (2014).

[1] I use "quality" to refer to neighborhoods' characteristics such as median household income, low poverty rates, low crime rates, and high performing schools that correlate with place effects measured by Chetty and Hendren (2018a).

Based on the extensive subjective beliefs literature, I propose a new mechanism to help understand parental behavior across socioeconomic groups. Suppose individuals' success is a function of past parental decisions –including neighborhood quality– and idiosyncratic ability, which is random and can be interpreted as a form of luck. Assume people are unaware of the returns to parental decisions and must learn about them before making those decisions. Young adults learn through community learning; by observing how successful older people around them are. But suppose they don't see abilities. They can't disentangle whether success is due to past parental decisions or abilities. Imagine then that they suffer from a cognitive bias. They think people around them are of average ability; in other words, they observe a representative sample of the population.[2] But since there is residential segregation, delusion about the returns to parental decisions arises. Relatively low-ability people surround children raised in low-quality neighborhoods; young adults in those neighborhoods underestimate the returns and choose to stay. Delusion across generations is persistent. Parents' subjective beliefs influence their residential choices, affecting their children's subjective beliefs.

I develop a quantitative spatial model of residential and parental time decisions to study the effects of housing vouchers on the economy. Crucially, this model incorporates a novel mechanism: community learning about the technology of skill formation. Once calibrated to the average commuting zone in the United States, the model matches targeted and non-targeted residential mobility patterns. Segregation generates information frictions that distort parental subjective beliefs and decisions, increasing inequality. I use the calibrated model to study the effects of a housing voucher policy on inequality and social mobility. I run a field experiment within the model and find that housing vouchers induce eligible parents to move to higher-quality neighborhoods, increasing their children's future income. However, the policy backfires when scaled up: it decreases social mobility and increases inequality. Failure to consider parental subjective beliefs responses leads to misleading policy recommendations.

In addition to building on the subjective belief literature, I provide empirical evidence of the community learning mechanism. To do so, I use the National Longitudinal Study of Adolescent to Adult Health, a nationally representative panel survey of 20,000 students in the United States. I derive two testable implications of the community learning mechanism: (a) parental decisions concerning their child's education reflect unobserved parents'

[2]This cognitive bias called "selection neglect" or "assortativity neglect." Enke (2020) provides empirical evidence of it.

subjective beliefs and are correlated, and (b) childhood neighborhood quality influences later parental decisions through community learning. I proxy for parental time by the number of parent-child activities and for neighborhood quality by census tract household median income. Both measures predict college graduation probability. After controlling for all relevant observable characteristics, including income and race, I find that (a) parental time and neighborhood quality are positively correlated, and (b) childhood neighborhood quality positively correlates with adulthood neighborhood quality more than 20 years later. Both evidence suggests that childhood neighborhood quality shapes parental subjective beliefs.

Motivated by this evidence, I incorporate community learning into a quantitative spatial overlapping generations model with residential and parental time decisions to evaluate a counterfactual housing voucher policy. 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 prices that 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 luck, as children are born with different and unobserved abilities. Crucially, I depart from perfect information and introduce community learning. Suppose agents do not know the returns to parental decisions: neighborhood quality and parental time. Children inherit subjective beliefs from their parents and update them by observing older neighbors' outcomes and history. Since agents don't observe abilities, young agents must approximate average abilities among their neighbors to infer the returns. In addition, suppose they assume people around them are, on average, of average ability. Then, when surrounded by "surprisingly" high-ability neighbors, children implicitly attribute too much of the observed human capital to past parental decisions and overestimate the returns to neighborhood quality and parental time. Conversely, when surrounded by surprisingly low-ability neighbors. Residential segregation, a form of spatial sorting partly based on ability, generates systematic biases in the estimation across socioeconomic groups and persistence in subjective beliefs within families. Children of high-subjective beliefs and wealthy parents are likely to live in high-quality neighborhoods –composed of relatively high-ability residents– overestimate the elasticity parameter and become wealthy parents next period, conversely for children of low-subjective beliefs and low-income parents. Agents differ in their human capital—primarily determined by their parents–and in their subjective beliefs—determined mainly by their childhood neighborhood. Given community learning, there are multiple critical equilibrium objects: the distribution of human capital, subjective beliefs, and local prices, 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 from computed from the ACS 2000 and NHGIS 2000 datasets. In addition, it targets causal places' 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 patterns in the ATUS survey and neighborhood quality choices from AddHealth. Even though the model doesn't 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 heterogeneous preferences across places of birth and education. To see this, I first re-calibrate the model shutting down the subjective beliefs channel. Since 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 under perfect information, agents born in bottom-quality neighborhoods must like their place of birth thirty times more than the others. This necessary feature contradicts Bergman et al. (2019) empirical findings. The authors compare low-income housing voucher holders who 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. If it matches residential mobility by construction, the calibrated perfect information model with preference heterogeneity fails to generate a college gap in parental time that is large enough.

I use the calibrated model with community learning to understand parents' residential-quality choices and to conduct policy experiments. The first finding is that community learning explains a large share of the socioeconomic gap in parental decisions. Segregation generates informational frictions that systematically distort parents' subjective beliefs con-

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

cerning the technology of skill formation. Providing information would improve low-income parents' subjective beliefs by 37% and decrease high-income parents' ones by 15%. Children born in bottom-quality neighborhoods would be half as likely to remain in those neighborhoods in adulthood, and non-college parents would spend more time with their children than college parents. Social mobility would improve by 13% and inequality decrease by 1%.

Motivated by the evidence that housing vouchers improve the neighborhood quality of eligible families, I use the quantitative model to study their effects on the United States economy. I 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 in neighborhood quality above the bottom decile, up to a unique rent ceiling. Eligible households are parents from the bottom decile of the income distribution. The rent ceiling is defined as the 40th percentile rent in the commuting zone. I first run a randomized control trial. The housing voucher program induces eligible parents to move to higher-quality neighborhoods, positively affecting their children's earnings. The results are in line with Chetty et al. (2016)'s empirical findings. Subjective beliefs play a substantial role, as neighborhood quality-rank would increase by 19% under perfect information.

The second finding is that, when implemented at scale, a housing voucher policy with a unique rent ceiling for the commuting zone decreases social mobility and increases inequality. Housing voucher holders bunch in neighborhoods below the rent ceiling, increasing local rents and crowding-out low-income-non-eligible households who cannot afford to live there anymore. In addition, eligible households tend to concentrate in similar quality neighborhoods. Despite a decrease in segregation, housing vouchers have the unintended effect of worsening subjective beliefs among low-income families, decreasing social mobility, and increasing inequality. Failure to consider parental subjective beliefs responses leads to different policy recommendations.

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 models community learning about the technology of skill formation and contributes to the subjective beliefs literature. Since Cunha et al. (2013), a large body of research documents 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); Cunha (2014); Kaufmann (2014); Wiswall and Zafar (2016); Caucutt et al. (2017); Boneva and Rauh (2018); Belfield et al. (2019); Dizon-Ross (2019)).[4] While systematic differences in subjective beliefs are not driven by actual differences (Cunha et al., 2013; Boneva and Rauh, 2016), they are often linked to community learning: we learn by observing how successful people around us are. Community learning often relates to technology adoption, but there is also evidence of it in education.[5] However, in education, because people sort depending on whether they are successful or not is not, community learning effects often relate to selection. The idea that low-income people, mainly because of segregation, lack successful role models, which dampens their effort, is consensual (Nguyen, 2008; Alan et al., 2019; Breda et al., 2019; Algan et al., 2020; Guyon and Huillery, 2020). Community learning is one likely explanation for Chetty et al. (2022)'s recent findings that upward income mobility in the United States is best predicted by the share of high socioeconomic status friends in a ZIP code. However, if Durlauf (2011) develops the idea of neighborhood effects through community learning, very few papers have linked heterogeneous subjective beliefs and residential choices. Roemer et al. (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 community learning and endogenous subjective beliefs.

Second, this paper proposes a quantitative spatial model of human accumulation, with community learning and endogenous subjective beliefs as the main novelty. By doing so, I contribute to the quantitative family macroeconomics literature. Human capital accumulation is modeled following recent macroeconomic papers such as Daruich (2018); Jang and Yum (2021); Kim et al. (2021); Yum (ming); Chyn and Daruich (2021). The learning process is inspired by Fogli and Veldkamp (2011), who model female labor supply over time and space in the United States. However, the model introduces residential choices, which generates heterogeneous subjective beliefs without convergence. 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

[4]One exception is Attanasio et al. (2019) in the UK who doesn't find a socioeconomic gradient in beliefs.

[5]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.

macroeconomics, individual subjective beliefs are usually ignored.[6]

Finally, the paper quantitatively links segregation and inequality and contributes to the urban economics literature. I use methods from the quantitative spatial economics literature reviewed in Redding and Rossi-Hansberg (2017). The model displays exogenous amenities motivated by recent evidence of a causal relationship between exogenous neighborhoods and child's skills (Nakamura et al., 2016; Chyn, 2018; Chetty and Hendren, 2018a,b; Hwang, 2022). As in Fogli and Guerrieri (2019); Eckert et al. (2019); Chyn and Daruich (2021); Gregory et al. (2022), neighborhoods' environment quality directly affects children's future human capital. By having endogenous valuations of neighborhood quality through individuals' 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 (2021) 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 tests two of the community learning implications. Section 3 presents the spatial overlapping generations model. Section 4 explains the model calibration and presents some quantitative results. Section 5 uses the model for policy analysis, and Section 6 concludes.

2 Neighborhood Quality and Parental Time in the United States

In addition to the extensive subjective beliefs literature, I build on evidence from the National Longitudinal Study of Adolescent to Adult Health (AddHealth). This section tests for two implications of community learning. First, parents' decisions that concern their children are driven by unobserved subjective beliefs. This statement entails a positive correlation parental time and neighborhood quality. Second, childhood neighborhood quality affects later parental decisions through community learning. I expect childhood neighbor-

[6]One major exception is Fogli and Veldkamp (2011).

hood quality to correlate with adulthood neighborhood quality. The data support these intuitions.

2.1 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.[7]

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.[8] Parental time is approximated to the number of parent-child activities over the past four weeks measured in 1994-1995.[9]

As a first step, I verify the two constructed variables correctly proxy for two parental inputs of the child's skill production function. Columns (1) and (2) of Table 1 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 proxies for parental time and neighborhood quality as two forms of parental investment.[10]

[7] Appendix Section B provides robustness checks using data in 2008 (Wave IV).

[8] 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).

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

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

2.2 Correlation between Time and Neighborhood

Let's assume parents' neighborhood choices are driven by their perceived value of the elasticity of child skills with respect to parental investments. All else equal, parents with low (high) subjective expectations 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 1 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.[11] Note that in both regressions of Column (3) and (4) of Table 1, 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 in parents' education in the United States (see Doepke et al. (2022) for a review).[12] This observed correlation could solely be driven by a neighborhood composition effect. In Column (4) of Table 1, I control for three variables measuring households' socioeconomic status: parents' highest level of education, family income, and parent's marital status.[13] The sample size shrinks to 12,633 observations due to missing values in household characteristics variables, but the relationship remains significant at a one percent level. The coefficient remains positive, suggesting that the correlation between the two forms of parental investments is not simply due to a composition effect.

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 about this relationship.[14]

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

[12]In Appendix D.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.

[13]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.

[14]To match parental time patterns across neighborhoods, Chyn and Daruich (2021) assume complementarity between time and neighborhoods, but Agostinelli (2018) and Agostinelli et al. (2020)'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).

Table 1: 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.

2.3 Childhood Neighborhood and Adulthood Parental Investment Choices

Let's now test for the second implication, which is childhood neighborhood, and later parental investment choices are positively correlated due to community 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 is positively correlated with later neighborhood choices.

Column (5) of Table 1 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 1, 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.[15] 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.[16]

Motivated by this evidence, the following section details the quantitative model in which I introduce community learning.

3 The Model

Consider a commuting zone composed of a finite number of neighborhoods characterized by quality. Suppose it is populated by a continuum of families consisting of a parent and a child. Time is discrete, and each generation lives for two periods: childhood and parenthood. At the beginning of each period, parents decide in which neighborhood quality to raise their child and how much time to spend on their child's education. A child's next period human

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

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

capital depends primarily on her parents as it is a function of her childhood neighborhood quality, parental time, parental human capital, and of a ability that is uncorrelated with parental characteristics and unobserved. Heterogeneity in parental decisions comes from the fact that parents differ in their human capital and income and their subjective beliefs about the technology of skill formation.

One key feature is community learning. Assume agents don't know the returns to neighborhood quality and parental time. They must learn about it before making parental decisions. As in Fogli and Veldkamp (2011), they have two sources of information: their inherited parent's subjective beliefs and the observation of their neighbors' outcomes and history. However, because young agents do not observe abilities, they can't perfectly infer the returns. Suppose young agents know the average ability at birth and use this value as a proxy for average neighbors' abilities.[17] Because of residential choices, young agents' inference suffers from a selection bias. Young agents do not interact with a representative sample of the economy as a whole but with a selected sample of neighbors.[18] In neighborhoods composed of parents with relatively high-abilities and hence high earnings, young agents implicitly attribute too much of the observed human capital to parental decisions and overestimate the elasticity parameter. The opposite happens in neighborhoods composed of relatively low-ability parents. As those neighborhoods correspond to high-quality and low-quality neighborhoods in a steady state, community learning generates a stable distribution of subjective beliefs positively correlated with earnings.

The next describes the economic environment, the parents optimization problem, the housing market and community learning; the novel mechanism. Then is gives the equilibrium definition.

3.1 Economic Environment

Geography and Amenities: Consider one labor market with a finite number of neighborhoods. Each neighborhood $m \in \mathbb{M}$ is characterized and indexed by an exogenous quality $\{m\}_{m \in \mathbb{M}}$. As wages do not vary across neighborhoods, neighborhood quality is the only

[17] For instance, because they play with their neighbors' children, who are a representative sample of the population by assumption.

[18] Frick et al. (2022) show this form of misperception (assortativity neglect or selection neglect) is the only one that can persist in any environment, Jehiel (2018) links selection problems in belief updating to investment decisions. For empirical evidence that people's choices are affected by selection bias, see Enke (2020).

exogenous amenity.

Families: Consider an economy populated by a continuum of families composed of one parent and one child. Each agent lives for two periods: childhood and parenthood. Parents choose in which neighborhood quality to raise their child and parental time. Families are heterogeneous concerning four parental characteristics: accumulated human capital, college graduation status, place of birth, and subjective beliefs about the technology of skill formation.

In the following, primed letters correspond to children's next period variable, and lower case 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 a'. The functional form is as follows:

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

where $\alpha,\ \beta,\ \gamma \in (0,1)$ and the child's ability a' is uncorrelated with parental characteristics and drawn from a normal distribution $\mathcal{N}(0, \sigma_a)$.[19]

By assumption, parental human capital h enhances the productivity of education investments. 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 initial 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.[20] Following Kim et al. (2021), the pa-

[19]By assuming uncorrelated abilities across generations, I abstract from modeling genetics. If one added it, incentives to invest would be distorted as high human capital parents would expect their child to have high abilities already. However, the main results of the paper would go through. In particular, the share of h in the human capital production function captures part of a genetic effect.

[20]For similar modeling assumptions, see for instance Chyn and Daruich (2021); Jang and Yum (2021); Yum (ming).

rameter $\underline{i} > 0$ 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, time investment τ is divided by its average in the economy ($\overline{\tau}$) to achieve unit independence as in Fuchs-Schündeln et al. (2020).

College Graduation Probability: 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.

Parents' Earnings: Parents' earnings are a function of accumulated human capital h and exogenous working time $\overline{\ell_s} > 0$. Exogenous working time depends on the schooling 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 next period utility enters their utility function. Preferences of a parent of accumulated human capital h, schooling status s, childhood neighborhood quality m_0, and subjective beliefs $\tilde{\alpha}$ can be summarized by the following utility function:

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

where b is a measure of direct 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 $-\frac{1}{\psi}$, and ψ can be interpreted as a Frisch elasticity of labor supply. 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 $\mathrm{E}_{\tilde{\alpha}}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)\right]$ is the expected child lifetime utility given the parent's subjective beliefs $\tilde{\alpha}$.

Housing Supply: There are perfectly competitive land developers using the final good to produce housing on a unit endowment of land with an isoelastic production function: $\mathcal{H}_m = z r_m^k$. Equilibrium rents per housing unit $\{r_m\}_{m \in \mathbb{M}}$ are determined by rental market clearing, such that housing demand equals housing supply in each neighborhood: $\mathcal{H}_m = \mathcal{L}_m$.

Aggregate Rent Rebates: Rents are reimbursed to all families proportionally to their earnings. Every household receives a rebate from aggregate rent payments equal to $y * R$, where y is the parent's earnings and R is the ratio of the economy's total rent payments to total earnings.

3.2 Parents' Problem

Parents are the only decision-makers in the economy. They make two decisions 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 without observing their child's ability. The maximization problem is the following:

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

subject to:

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

where r_m is the equilibrium rent of neighborhood m. 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.

3.3 Housing Market Flows

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

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

$$
U\,(h, s, m_0, \tilde{\alpha}) = \nu \log \sum_{m \in \mathbb{M}} \exp\{\frac{1}{\nu}\ V\,(h, s, m_0, \tilde{\alpha}, m)\}
$$

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 :

$$
\lambda_m(h, s, m_0, \tilde{\alpha}) = \frac{\exp\{\frac{1}{\nu}\ V\,(h, s, m_0, \tilde{\alpha}, m)\}}{\sum_{n \in \mathbb{M}} \exp\{\frac{1}{\nu}\ V\,(h, s, m_0, \tilde{\alpha}, n)\}}
$$

3.4 Community Learning

One key feature of the model is community learning. I assume agents don't know the value of α, the elasticity of child's skills with respect to parental time and neighborhood quality.

They must form expectations about its value before making parental decisions.

Following Fogli and Veldkamp (2011), young agents have two sources of information: they inherit their parent's subjective beliefs about α and observe their adult neighbors' outcomes and history.

Young agents see their neighbors' human capital and earnings and know about past parental choices. They use this information to learn about the value of α. But since they do not observe abilities, they do so only imperfectly. As in Fogli and Veldkamp (2011), I assume young agents use the average value of abilities in the economy as a proxy for the local one. This assumption requires young agents to know the average value of abilities in the economy and makes them "naive intuitive statisticians."[21] Assume they know the average value because they have access to national media and play with children in their neighborhood. Since children's ability is independent of parental characteristics, in every neighborhood, children's average ability is equal to its analog in the economy. Under this approximation, young agents' inferences suffer from a selection bias.[22] Indeed, adult neighbors are not a representative sample of the population but parents who choose to live in given neighborhood quality. The incorrect mental model of a young adult in a given neighborhood m is the following:

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

where T and M represent past parental choices and H, past parental human capital.[23]

Young agents observe local averages.[24] Agents cannot observe individual outcomes and history of all their neighbors, but, by talking to neighbors, they have a good sense of local

[21]As this value is zero, this is equivalent to assuming that agents ignore abilities when learning about α.

[22]See Enke (2020) for empirical evidence of the selection bias. Jehiel (2018) and Frick et al. (2022) develop a theoretical framework in which the selection neglect persists.

[23]If young adults ignored abilities, the mental model would be

$$h_j = (i(\mathrm{T}_j, M_j) + \underline{i})^{\alpha} \;\; H_j^{\beta} \;, \quad j \in m$$

.

[24]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.

averages. Every agent in a neighborhood quality m makes the following estimation:

$$\hat{\alpha}_m = \frac{\overline{\log(h)}_m \; - \; \beta \, \overline{\log H}_m}{\overline{\log\left(i(\mathrm{T}, M) + \underline{i}\right)}_m} \tag{3}$$

Young agents update their subjective beliefs using a weighted average of the local estimate and the inherited subjective beliefs.

$$\tilde{\alpha}' = \mu\hat{\alpha}_m + (1-\mu)\tilde{\alpha} \tag{4}$$

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

In equilibrium, community learning generates a persistent delusion about the value of α because of residential sorting.[25] In neighborhoods where the local average of parents' abilities is above the average in the economy, young adults attribute too much of the observed human capital to past parental choices and overestimate the value of α. Conversely, in neighborhoods where the local average of parents' abilities is below the average in the economy.[26] There is also persistence in subjective beliefs within families. Children of wealthy and high-subjective beliefs parents are raised in high-quality neighborhoods, observe their neighbors, and are comforted in their inherited subjective beliefs. Because of their parents, those children will likely become wealthy parents and have high-subjective beliefs next period. The opposite happens for children of low-income and low-subjective beliefs parents.

3.5 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, place of birth and prior belief distributions $F_0(h, s, m_0, \tilde{\alpha})$, an equilibrium is characterized by a sequence of residential and parental time choices, $\{m\}$ and $\{\tau\}$, a sequence of rents $\{r_m\}_{m\in\mathbb{M}}$ 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' optimization: taking subjective beliefs, graduation status, place of birth and earnings as given, consumption, parental time, and neighborhood quality decisions maximize expected utility subject to the constraints. Expectation is conditioned on

[25]Without residential sorting, there is convergence. This is the case in Fogli and Veldkamp (2011).

[26]This phenomenon can be thought of as a form of "illusion of control".

subjective beliefs $\tilde{\alpha}$.

2. housing market clearing: $\{r_m\}_{m \in \mathbb{M}}$ ensures housing demand equals supply in every neighborhood $\mathcal{H}_m = \mathcal{L}_m$.

3. beliefs update: young agents update their inherited beliefs by observing local averages in their neighborhood.

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.

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

4 Calibration

I numerically solve the model as detailed in the 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.

4.1 Preliminaries

As mentioned in Section 3, I assume standard logarithmic utility for consumption; consequently, child and adult equivalence scale parameters are irrelevant to the problem. I let the discrete distribution for a to approximate a normal distribution $a \sim \mathcal{N}(0, \sigma_a)$ which I discretize using Tauchen (1986), with a ten-point grid. Finally, I assume the technology of skill formation has constant returns to scale, $\beta = 1 - \alpha$.

I use multiple data sources to compute the relevant moments to calibrate the model. Earnings distribution moments come from the American Community Surveys (ACS) from 2000. I use the information at the census tract level from the National Historical Geographic Information System (NHGIS) dataset in 2000 (Manson et al., 2022) to construct neighborhood sociodemographic characteristics. I aggregate census tract information at the commuting zone level using a county to commuting zone crosswalk. Neighborhood choices and college graduation probabilities are estimated using data from the AddHealth survey described in Section 2.1.[27] Finally, parents' time use information is taken from the American Time Use Survey (ATUS) from 2003.[28]

4.1.1 Geography

The model is calibrated to the average commuting zone in the United States, matching neighborhoods' impact estimated by Chetty and Hendren (2018a) on 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 sort census tracts by median household income and form ten synthetic neighborhoods from the deciles of this distribution.[29] I then create one average commuting zone by computing the population-weighted average characteristics of each of the ten neighborhoods.[30]

4.2 Empirically Estimated Parameters

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 (2020) 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.[31]

[27] See Appendix Section D.3 for more details on those statistics.

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

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

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

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

Housing Markets: Rental prices are determined in equilibrium given the supply function: $\mathcal{H}_m = zr_m^k$, where r_m is the equilibrium rent price in the neighborhood m and k is the price elasticity of housing supply. k and z can be estimated directly from the synthetic neighborhood density and rents.[32,33,34]

4.3 Externally Calibrated Parameters

The parameter ψ can be interpreted as a Frisch labor supply elasticity. Since the model's labor supply is exogenous, this interpretation is irrelevant. Still, it allows me to use a direct standard analog in the literature: 0.5. 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 each neighborhood quality $m \sim U(\underline{m}, \overline{m})$. Table 2 summarizes the parameters that are externally calibrated.

Table 2: 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

Notes: The table shows all the externally calibrated parameters.

4.4 Internally Calibrated Parameters

The remaining 11 parameters to calibrate are listed in Column (1) Table 3. I calibrate them by minimizing the sum of squared percentage differences between data and model moments.

[32] Without loss of generality, the numeraire is the average household earnings in the economy.

[33] Appendix Figure S1 summarizes the log-relationship between density (Column (5) Table S4) and rents across the ten synthetic neighborhoods.

[34] Note that in the literature, z is sometimes neighborhood specific (z_m). In this context, there is an almost linear log relationship between density and rent prices (see Appendix Figure S1); I choose to have the same z value across neighborhoods.

The data moments include two measures of household earnings dispersion within commuting zones computed from the ACS 2000: the mean over the median household earnings and the income ratio of non-college and college households. Both are weighted population averages across the 100 biggest commuting zones, and the first one measures inequality. In addition, I ensure income and college graduation 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 ($\{m\}_{m\in\mathbb{M}}$) 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). I add a Gini coefficient across the ten neighborhoods computed from the NHGIS 2000 dataset to match residential segregation. The place of birth preference parameter is calibrated by matching a moment labeled residential immobility. It is defined as the fraction of children born in a given 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 investment behavior.[35]

Table 3 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 parental investment behavior. 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 immobility in the first neighborhood, the fraction of children who remain in the same type of neighborhood when adults. I use the first neighborhood as a reference point and compare the other neighborhood moments from the model to the data to further validate the model. 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

[35]Moments construction and data sources are detailed in Appendix Section D.4.

Table 3: Internally Calibrated Parameters

Parameter	Description	Moment	Data	Model
Preferences and Labor Market				
$b = 0.7$	Altruism	Ratio share college parents Q1 to Q4	0.102	0.108
$\kappa = 0.76$	Parental time disutility	Parental time non-college parents	0.075	0.07
$\iota = 0.0001$	Place of birth preference	Residential immobility (D1)	0.295	0.283
$\omega = 0.01$	College wage premium	Earnings ratio non-college - college	0.554	0.541
Neighborhoods				
$\sigma_m = 0.21$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.056
$\nu = 0.019$	Taste shock variance	Census tract Gini	0.265	0.218
Skill Formation: $h' = \left(\left(\gamma \ \left(\frac{\tau}{\overline{\tau}}\right)^{\varphi} + (1-\gamma)\, m^{\varphi}\right)^{\frac{1}{\varphi}} \ + \ \underline{i} \right)^{\alpha} \ h^{1-\alpha} \ \exp(a') \text{ with } a' \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0.765$	Elasticity of investments	Rank-rank coefficient (IGE)	0.341	0.335
$\gamma = 0.38$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.048
$\varphi = 0.56$	Substitutability	Parental time income coeff.	0.099	0.117
$\sigma_a = 0.58$	Ability shock variance	Mean over median income	1.247	1.242
Belief Updating Process				
$\mu = 0.8$	Update weight	Parental time education coeff.	0.245	0.215

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

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.

The child's skill formation parameters are most relevant for this paper. In particular, as it is standard in the literature, the substitutability parameter φ is calibrated by matching the childcare time difference across income groups, but controlling for education; here, I use the regression coefficient of parental time on household income quartiles controlling for college graduation status.[36] With subjective beliefs and community 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. (2020)). 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 variance captures any income variation not explained by parental choices and human capital, it is calibrated by matching a measure of household earnings inequality.

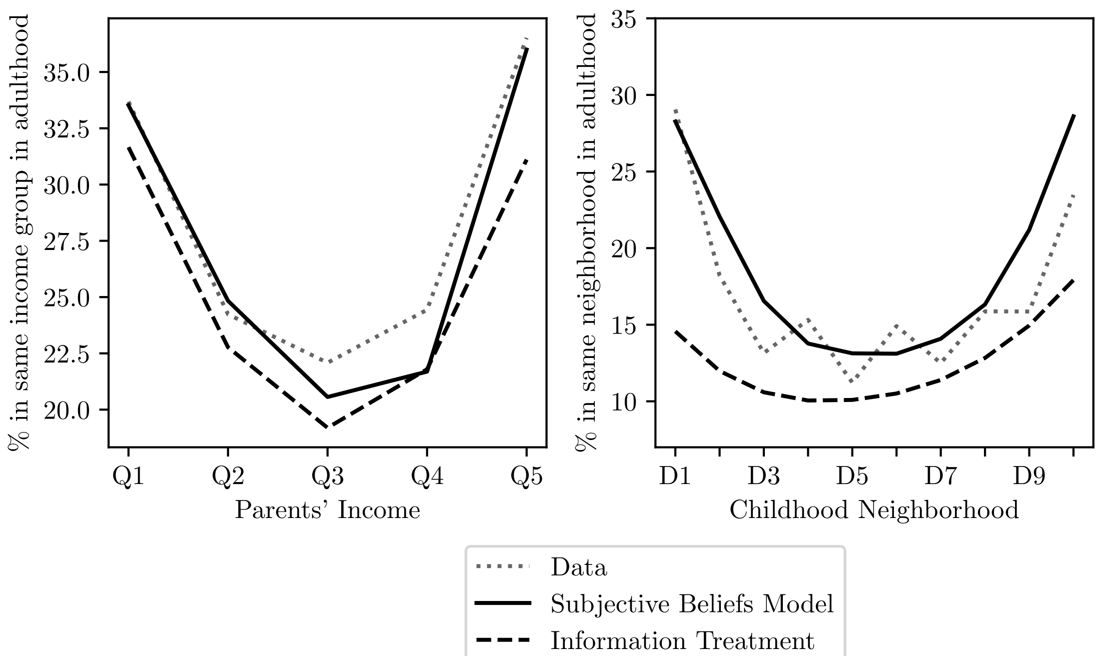
Finally, the correlation between parental and children's subjective beliefs is governed by μ and affects the persistence of beliefs and hence, parental behavior within families. Since there is also persistence in earnings and schooling status within families, I discipline this parameter by matching parental time across socioeconomic groups. Specifically, I simultaneously regress childcare time on education and income quartiles and use the regression coefficient of parents' education. Because time and neighborhood are substitutes input in the production function, parental time gradients in income and education result from two opposing forces. Misconception about the technology of skill formation, if correlated with earnings, increases the two gaps, but the substitution force decreases the income one because of income segregation.

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

4.5 Non-Targeted Moments

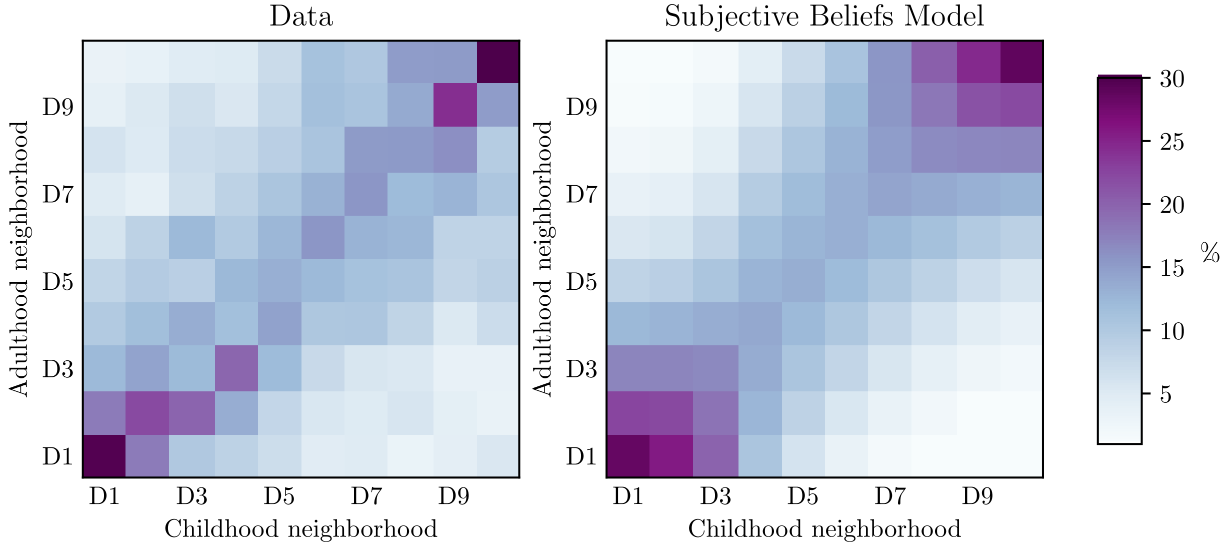
The calibrated model matches targeted moments well but also fits non-targeted residential mobility patterns. Figure 2 presents the share of children who still live in the same neighborhood quality as adults. The dotted line represents the data moments, and the solid line their model simulated analogs. While the first neighborhood statistic is a targeted moment, the others aren't. 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 the neighborhood six or above. The calibrated model (left panel) matches the data patterns (central panel) remarkably well.

Figure 2: Non-targeted Moments: Residential Mobility



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 information treatment in dashed-line.

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.

4.6 The Role of Subjective Beliefs

The model is calibrated under the assumption of imperfect information and community learning. 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. Table 4 presents the effects of providing information to parents. In the bottom of the income distribution, parents' subjective beliefs would increase by 37% while they would decrease by 15% in the top of the income distribution. These number are reasonable. Cunha et al. (2013), who elicits disadvantaged African American mothers' subjective beliefs about the elasticity of child development with respect to investments, finds a greater difference between the truth and their subjective beliefs. As a result, low-income parents spend too little time with their child, while high income parents spend too much time. Providing information to parents would, in the long run, improve low-income households' parental time by 52% and decrease high-income households' one by 11%. Under perfect information, aggregate parental time increases by 12%. Social mobility and earnings would increase by 13% and 3% respectively while inequality and poverty would decrease by 1% and 23% respectively. Right panel of Figure 2 shows that providing information would halve the share of children born in bottom-quality neighborhoods who would choose to live there in adulthood.

Table 4: Effects of Providing Information

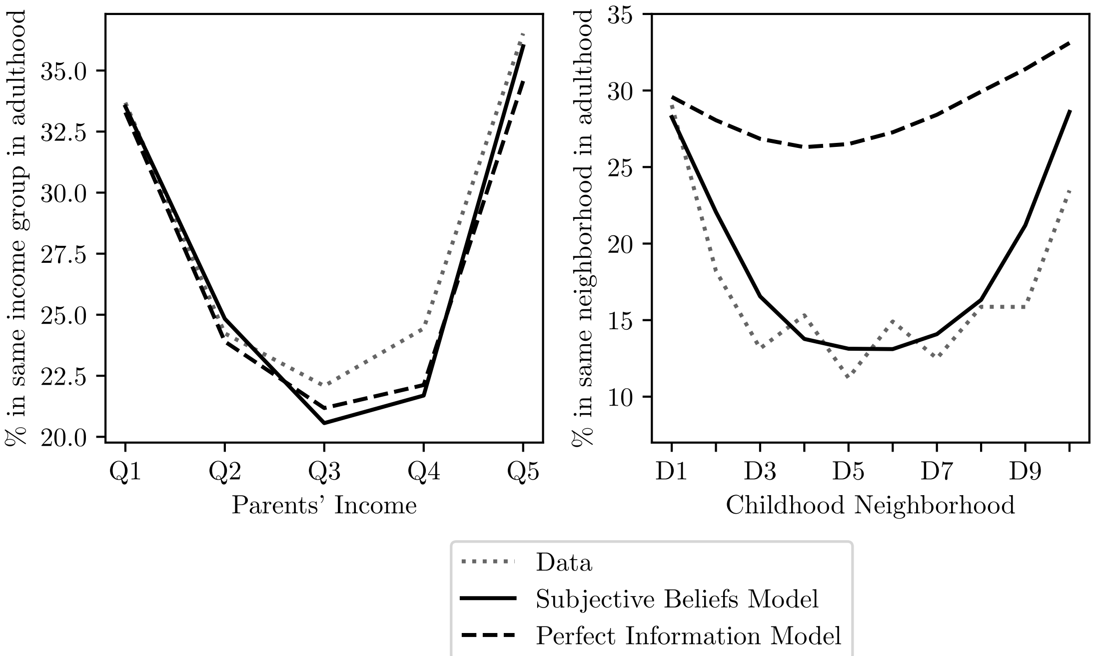
		Income quartile			
	All	1st	2nd	3rd	4th
Subjective Beliefs	+4.8%	+36.9%	+12.0%	-0.8%	-14.8%
Inequality	-1.3%				
Poverty rate	-22.8%				
Rank-rank coefficient	-13.4%				
Neighborhood Gini	+6.4%				
Earnings	+3.1%	+6.4%	+5.6%	+4.3%	+1.8%
Parental time	+12.2%	+51.9%	+19.0%	+3.9%	-11.0%
% of stay	-32.7%	-29.7%	-41.6%	-35.2%	-25.7%
Welfare	+2.1%	+1.5%	+0.4%	+0.2%	-0.0%

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

In a second step, I calibrate the same model shutting down subjective beliefs to see how well it does on 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 induces the other agents to overstay in their neighborhoods. Figure 4 shows non-targeted simulated moments. Under perfect information, despite a good match of social mobility moments (left panel), the model misses the U-shape relationship in intergenerational residential mobility (right panel).[37]

[37] Appendix Figure S2 shows the mobility matrix under perfect information. Not only is the diagonal off,

Figure 4: 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.

Since, without subjective beliefs, the model fails to match important non-targeted moments, 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. 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. Note that the preference for place of birth in the bottom-quality neighborhood is thirty times higher than the middle-quality ones. This feature contradicts Bergman et al. (2019) empirical findings. The authors compare low-income housing voucher

but all the squares off-diagonal are of similar color, which is counterfactual.

holders who 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.

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. In the data, the parental time gradient in education is steeper than in income. In the model, the reverse happens (Column (3) Table 5). 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 child than non-college parents. This feature has an ambiguous effect on the correlation between parental time and education. Overall, I find that parental time is negatively correlated with education after controlling for earnings which contradicts the data (Table 5). Additional sources of heterogeneity are needed to fully match the data and understand why college-parents spend more time with their children than non-college parents despite working more hours.[38]

Table 5: Childcare, Education, and Income

	Data		Model	
	ATUS 2003		Subjective Beliefs	Perfect Information + Heterogeneity
	(1)		(2)	(3)
Education	0.245***	(0.06)	0.215	-0.010
Income Quartile	0.099***	(0.02)	0.117	0.097
R^2	0.24			

Notes: The table shows the regression coefficients of childcare time on parents' education and earnings. In the data, the regression includes child age fixed effects and control for the gender of the respondent, and sampling weights weight all observations. Robust standard errors are in parenthesis. The parents' education coefficient is a targeted moment in the Subjective Beliefs version of the model.

While heterogeneity can help a perfect information model match the data, its origin is difficult to justify. Do parental time preferences systematically differ by education status?

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

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?[39] Discrimination or a homophily bias could motivate some of these modeling assumptions. However, in Table 1, I find that race is not the primary driver of intergenerational residential mobility once controlled for childhood neighborhood quality.

5 Housing Voucher Policy

The Housing Choice Voucher (HCV) program is the U.S. Department of Housing and Urban Development (HUD) largest housing assistance program and its primary mechanism for promoting mobility.[40] In 2020, more than two million United States households received housing vouchers.[41] As a rule, seventy-five percent of families who receive housing vouchers each year must 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 HUD's fair market rent estimates at the metropolitan area level. Since (Chetty et al., 2016) provided evidence that housing vouchers effectively improve adulthood earnings through improved neighborhood quality, the HUD has put additional effort into promoting high-quality mobility. In particular, since 2019, the HUD has allowed housing agencies to set voucher subsidies at local rents rather than at the metro area level.[42] This decision addresses an issue raised about unique rent ceilings: they do "not adequately help families access low-poverty neighborhoods."[43] Indeed, Collinson and Ganong (2018) finds that most rental units below the payment standard are in low-quality neighborhoods. Indexing rent limits to ZIP codes rather than to metropolitan areas improves the share of families who move into higher-quality neighborhoods.

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

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

[41] https://www.cbpp.org/research/housing/federal-rental-assistance-fact-sheets Number of families receiving housing vouchers through the Housing Choice Voucher Program.

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

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

In this section, I use the quantitative model to study the effect of a housing voucher policy under the old regime, with a unique rent ceiling. The model predicts that segregation generates heterogeneous subjective beliefs that distort parental investment behavior. As housing vouchers improves neighborhood quality for low-income households, they should decrease segregation, improving subjective beliefs. As a first step, I investigate the impact of these policies in a randomized control trial and compare them to empirical estimates. Then, I scale up the policy and focus on steady-state comparisons, which helps gauge the long-run implications.

5.1 Housing Voucher Policies

I consider housing vouchers that cover for 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. The Housing Voucher (HV) policy is financed through property taxes, which adds two terms to the household budget constraint:

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

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:

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

5.2 Randomized Control Trial

Column 4 Table 6 shows the positive effects of the HV policy on eligible households. The HV policy improves neighborhood quality by 2 points, improving children earnings at age 26 by \$862. Chetty et al. (2016) evaluate housing vouchers' effects on low-income households who live public housing in deprived neighborhoods. Assisted households, in their case, are poorer than those targeted in the model. Average family earnings at age 26 of children in the control group are \$12,702, while in the model, it is \$21,235. The model predicted effect on children's earnings falls within their estimated confidence interval (\$1,452 with a standard error of 736).

Parental subjective beliefs are part of why low-income families don't move to high-quality neighborhoods (Column 5 Table 6). In this exercise, I provide information about the returns to neighborhood quality to eligible parents who receive HV. The neighborhood income rank improves by 0.55 points (13%), and the share of families who choose to live in the worse neighborhood decreases by 5pp, dropping to 0. As a result, the HV policy further improves children's adulthood earnings by 1%.

Table 6: Effects of Policies on Eligible Households

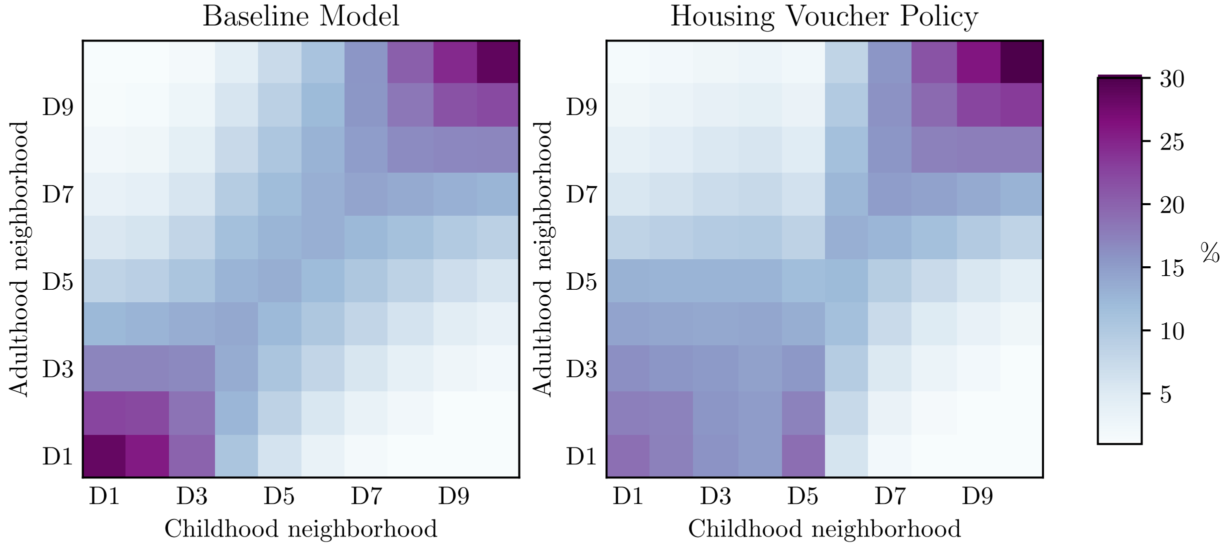
	Data		Model		
		Treatment		Treatment	
	Control	Housing Vouchers	Control	Housing Vouchers	Housing Vouchers + info
Eligible households					
Neighborhood 2-10	0%	+66pp	62%	+33pp	+38pp
Child's future income (at 26)	\$12,702	+\$1,452 (736)	\$21,235	+\$862	+\$1,077
Neighborhood rank			2.16	+2.00	+2.55

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

5.3 Housing Vouchers at Scale

While the model links segregation and inequality, decreasing segregation does not necessarily result in lower inequality. If 10% of households receive housing vouchers, segregation decreases by 8%, but inequality rises by 0.3% (Column 1 Table 7). Figure 5 helps understanding the underlying reasons. Due to the unique rent ceiling feature of the policy, a bunching effect generates pressure on the housing market at the rent limit. This lead non-eligible low-income families to move to lower-quality neighborhoods. As a result, the probability that a child born in neighborhood five lives in a lower-rank neighborhood in adulthood increases. In addition, eligible households concentrate and live in similar quality neighborhoods. When 10% of the population receives a voucher, those flows dampen subjective beliefs among the poorest households in the economy (Column 2 Table 7). Parental time and earnings for this group, but also in the aggregate, decrease. The policy has the unintended effect of dampening social mobility and increasing inequality and poverty (Column 1 Table 7). These findings provide another argument in favor of the current reform of the fair market rent. Rent ceilings defined at a more granular level than at the metro

Figure 5: Effects of Housing Vouchers on Residential Mobility Patterns



Notes: This Figure shows residential mobility between childhood and adulthood in the baseline model (left panel), and if 10% of households receive housing vouchers (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.

area level could avoid the concentration of housing voucher holders (Collinson and Ganong, 2018), avoiding the dampening of subjective beliefs and negative effects on the economy.

I use the calibrated model with perfect information and heterogeneous preferences to understand the importance of considering parental subjective beliefs when evaluating the HV policy. As documented in Section 4.6, this model captures residential mobility patterns but misses parental time across socioeconomic groups. To generate a positive correlation between parental time and household earnings, the perfect information model requires that parental time and neighborhood quality are complementary inputs in the child's skill production function ($\varphi < 0$).

Table 8 shows that considering subjective beliefs or not has significant consequences for policy recommendations. The perfect information model predicts that an HV policy at scale improves social mobility and decreases inequality despite a bunching behavior. Improved neighborhood quality for eligible households mechanically increases parental time ($\varphi < 0$), increasing social mobility. In a model with subjective beliefs, this relationship is more complex. Improved neighborhood quality for eligible households mechanically decreases parental

Table 7: The Effects of Scaling-up Housing Vouchers

	All	Income quartile 1st	2nd	3rd	4th
Subjective Beliefs	-3.9%	-3.8%	-3.3%	-4.0%	-3.9%
Parental Time	-14.6%	-27.2%	-16.1%	-10.2%	-9.0%
Earnings	-3.3%	-3.5%	-3.0%	-2.3%	-2.4%
IGE	-2.1%				
Segregation	-8.3%				
Inequalities	+0.3%				
Poverty	+12.3%				

Notes: This table shows the effects of housing vouchers at scale, predicted by the calibrate model with community learning.

time ($\varphi > 0$) and, depending on the local demographic composition, can improve their subjective beliefs, increasing parental time.

In sum, housing vouchers effectively raise neighborhood quality for eligible households but backfire when scaled up. The policy induces a concentration of very low-income families, decreasing subjective beliefs, earnings, and social mobility while increasing inequality and poverty. The failure to consider subjective beliefs leads to misleading policy recommendations, as a perfect information model would predict a positive effect of the policy on social mobility and a negative impact on inequality.

Table 8: The Effects of Scaling-up Housing Vouchers under Perfect Information

	All	Income quartile 1st	2nd	3rd	4th
Subjective Beliefs	0.0%	0.0%	0.0%	0.0%	0.0%
Parental Time	-3.1%	+0.4%	-6.8%	-2.5%	-2.9%
Earnings	-0.8%	-0.3%	-0.2%	-1.0%	-1.6%
IGE	+2.3%				
Segregation	-14.1%				
Inequalities	-0.2%				
Poverty	+2.1%				

Notes: This table shows the effects of housing vouchers at scale, predicted by the calibrate model under perfect information and heterogeneous preferences.

6 Conclusion

In this paper, I present a quantitative spatial model of residential and parental time decisions with community learning about the technology of skill formation. Introducing endogenous subjective beliefs helps understand parental behavior across socioeconomic groups in the United States. Once calibrated to the average commuting zone in the United States, the model predicts that low-income parents underestimate the returns to neighborhood quality and parental time while high-income parents overestimate them. Segregation generates information frictions that shape the subjective beliefs distribution and distort parental investment choices. This model rationalizes two puzzling parental behaviors: children born in low-quality neighborhoods tend to raise their children in those types of 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 has non-intended effects. Once subjective beliefs and general equilibrium price responses are considered, housing vouchers increase inequality and poverty despite a decrease in segregation. A concentration effect due to the unique rent ceiling feature drives this result. If the model links segregation and inequality, this policy evaluation illustrates the complexity of this relationship. Decreasing segregation might not reduce inequality if low-income households remain concentrated at the bottom of the neighborhood quality distribution.

However, using predictions from a perfect information model with heterogeneous preferences and complementary between parental time and neighborhood quality leads to very different policy recommendations. According to this perfect information model, the policy improves social mobility and decreases inequality despite the concentration effect. Correctly pinning down the relationship between parental inputs is critical for accurate policy evaluations considering parental behavior responses. Providing empirical estimates of this relationship would help answer this important question. Finally, since empirical research finds that subjective beliefs matter at the micro level, evaluating their many consequences at the aggregate level is an exciting avenue to pursue in future research.

References

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

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

Agostinelli, F., Doepke, M., Sorrenti, G., and Zilibotti, F. (2020). It takes a village: the economics of parenting with neighborhood and peer effects. Technical report, National Bureau of Economic Research.

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

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

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

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

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

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

Bergman, P., Chetty, R., DeLuca, S., Hendren, N., Katz, L. F., and Palmer, C. (2019). Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice. Technical report, National Bureau of Economic Research.

Bilal, A. (2021). The geography of unemployment. Technical report, National Bureau of Economic Research.

Blandin, A. and Herrington, C. (2020). Family heterogeneity, human capital investment, and college attainment. *Human Capital Investment, and College Attainment (September 14, 2020)*.

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

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

Breda, T., Grenet, J., Monnet, M., and Van Effenterre, C. (2019). Female role models: Are they effective at encouraging girls to study science? Technical report, HAL.

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

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

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

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

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

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

Chyn, E. (2018). Moved to opportunity: The long-run effects of public housing demolition on children. *American Economic Review*, 108(10):3028–56.

Chyn, E. and Daruich, D. (2021). An equilibrium analysis of the effects of neighborhood-based interventions on children.

Collinson, R. and Ganong, P. (2018). How do changes in housing voucher design affect rent and neighborhood quality? *American Economic Journal: Economic Policy*, 10(2):62–89.

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

Cunha, F. (2014). Gaps in early investments in children. *Manuscript, Dept. Econ., Univ. Pennsylvania*.

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

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

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

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

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

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

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

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

Doepke, M., Hannusch, A., Kindermann, F., and Tertilt, M. (2022). The economics of fertility: A new era. *Manuscript in preparation for Handbook of Family Economics.*

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

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

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

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

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

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

Fuchs-Schündeln, N., Krueger, D., Ludwig, A., and Popova, I. (2020). The long-term distributional and welfare effects of covid-19 school closures. Technical report, National Bureau of Economic Research.

Gregory, V., Kozlowski, J., and Rubinton, H. (2022). Local spillovers, segregation, and racial gaps in educational attainment.

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

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

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

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

Hwang, Y. (2022). Neighborhood effects on intergenerational cultural transmission. *Available at SSRN.*

Jang, Y. and Yum, M. (2021). Aggregate and intergenerational implications of school closures: a quantitative assessment. *Available at SSRN 3857687.*

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

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

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

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

Kim, S., Tertilt, M., and Yum, M. (2021). Status externalities in education and low birth rates in korea. *Available at SSRN 3866660.*

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

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

Nakamura, E., Sigurdsson, J., and Steinsson, J. (2016). The gift of moving: Intergenerational consequences of a mobility shock. Technical report, National Bureau of Economic Research.

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

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

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

Roemer, J. E., Wets, R. J., et al. (1994). Neighborhood effects on belief formation and the distribution of education and income. Technical report.

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

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

Wiswall, M. and Zafar, B. (2016). Human capital investments and expectations about career and family.

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

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.

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

Add Health survey contains information about ten parent-child activities in 1994-1995.[45] 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.

[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)".

[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".

The ATUS asked interviewees about their activities the day before the interview–the "diary day." For each activity, respondents are asked how long the activity lasted and, for most activities, where they were and who was with them. After completing the time diary, there are additional questions to identify work, volunteering, eldercare, and secondary childcare activities. Several activity categories are then defined by the United States Bureau of Labor Statistics (BLS), among which one is of particular interest for this research project: "primary childcare activities." This activity category includes time spent providing physical care, playing with children; reading with children; assisting with homework; attending children's events; taking care of children's health needs, and dropping off, picking up, and waiting for children. Passive childcare was included as a primary activity (such as "keeping an eye on my son while he swam in the pool"). However, a child's presence during the training is 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

[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.

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

Socializing, relaxing, and leisure	Time spent in personal interest or leisure activities such as communicating with others and attending parties and meetings; and leisure activities such as relaxing, playing (passive) games (unless playing with children only), watching television, playing or listening to music, reading, writing, and all hobbies.	3.69	2.88
Sports, exercise, and recreation	Time spent in sports, exercise and recreational activities such as pleasure boating, throwing a Frisbee, kite flying, or ballooning, and active, participatory outdoor games or activities, such as horseshoes, croquet, and paintball.	0.25	0.33
Religious and spiritual activities	Time spent in work activities such as working, doing activities as part of one's job, engaging in income-generating activities (not as part of one's job), and looking for jobs and interviewing.	0.14	0.17
Volunteer activities	Time spent in volunteer (unpaid) activities done by the respondent for individuals or institutions through formal organizations, such as unpaid performance arts activities, socializing related to volunteering and attending church service as a volunteer activity.	0.13	0.25
Telephone calls	Time spent in telephone communication activities such as talking on phone, waiting for a phone call or Skyping (2011+).	0.05	0.07
Professional and personal care services	Time spent in activities such as obtaining, receiving, and/or purchasing professional and personal care services provided by someone else. Professional services include child care, financial, legal, medical and other adult care, real estate, and veterinary. Personal care service activities include massages, haircuts, manicures, and tanning at salons.	0.07	0.09
Other		**4.04**	**4.07**

Household activities	Time spent in household activities such as maintaining their household, household management and organizational activities.	2.13	1.94
Caring for and helping household members (except household children)	Time spent in caring for or helping any adult in the respondent's household, regardless of relationship, age, or physical or mental health status.	0.04	0.03
Caring for and helping non-household members	Time spent in caring for or helping any child or adult who is not part of the respondent's household, regardless of relationship, age, or physical or mental health status.	0.10	0.08
Household services	Time spent in activities such as obtaining and purchasing household services provided by someone else. Household services include yard and house cleaning, cooking, pet care, tailoring and laundering services, and vehicle and home repairs, maintenance, and construction. Watching someone else perform paid household activities (cooking, cleaning, repairing, etc.) should be coded here, provided "watching" was the respondent's primary activity.	0.01	0.02
Government services and civic obligations	Time spent in activities such as using government services (police, fire, social services), purchasing government-required licenses or paying fines or fees, fulfilling government-required duties (jury duty, parole meetings, court appearances), and participating in activities that assist or impact government processes (voting, town hall meetings).	0.00	0.00
Consumer purchases	Time spent in activities such as purchases and rentals of consumer goods, regardless of mode or place of purchase or rental (in person, via telephone, over the internet, at home, or in a store).	0.43	0.49
Travel	Time spent in travel or transportation activities such as commuting, walking someplace or waiting for the bus or train.	1.33	1.51

Total			**24.0**	**24.0**

B Robustness checks

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.

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

3. Make an initial guess for rent prices $\{r_m\}_{m\in\mathbb{M}}$
4. Given $V(h, s, m_0, \tilde{\alpha}, m)$, $\tau(h, s, m_0, \tilde{\alpha}, m)$ and $\{r_m\}_{m\in\mathbb{M}}$, compute the share of families $(h, s, m_0, \tilde{\alpha})$ in each neighborhood ($\lambda_m(h, s, m_0, \tilde{\alpha})$ for every m).
5. Compute $\{r_m\}_{m\in\mathbb{M}}$ given the share of families in each neighborhood.
6. Iterate 3 to 5 until $\{r_m\}_{m\in\mathbb{M}}$ converges.
7. Given $\{r_m\}_{m\in\mathbb{M}}$, compute the expected value function $U(h, s, m_0, \tilde{\alpha})$ and based on it, obtain the policy function for time investment $\tau(h, s, m_0, \tilde{\alpha})$.
8. Compute the distribution $G(H, \mathrm{T}, m_0, h, m)$ given λ_m, and obtain updated 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 Additional Information on the Calibration

D.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

[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.

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 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.

D.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.

[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.

[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.

D.3 Estimated Parameters: Neighborhood Choices and College Graduation

For two primary purposes, I use the AddHealth survey, detailed in Section 2.1. 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 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%.

[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.

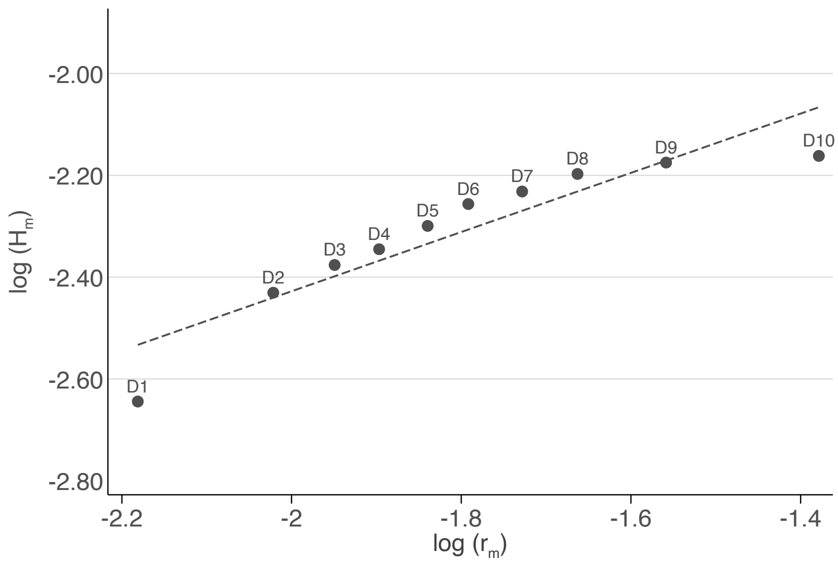
Second, I use AddHealth to estimate the individual probability of having a college degree conditional on parents and child variables. In the sample, anyone with at least a bachelor's degree is considered to have a college degree. Here again, because interviewees are older and more likely to have completed their education in 2016-2018 than in 2008-2009, I use data from Wave V to estimate the highest level of education. To proxy for children's realized human capital, I use an average of Wave II (1996) grades in English, mathematics, social science, and science. Information on parents' highest education level and income comes from the parent survey conducted in 1994-1995.

Table 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 S1: 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.

D.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
Mean over median income [inequality]	Mean household income over median household income	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 (p = 25) income. Simulate moves to every neighborhoods. Regress children's income on fixed effects for each neighborhood controlling for origin-by-destination fixed effects . We estimate the county fixed effects separately by parent income level.	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 and the fraction of childhood spent in a county.	Chetty and Hendren (2018a)
Neighborhood effect (75th pct.)	For families with above-median (p = 75) income. Simulate moves to every neighborhoods. Regress children's income on fixed effects for each neighborhood controlling for origin-by-destination fixed effects . We estimate the county fixed effects separately by parent income level.	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 and 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 househod income rank.	Tax records covering the U.S. population, spanning 1996-2012.	Chetty et al. (2014)
Parental time			

Parental time income coeff.	Income regression coefficient of parental time on income quartile and college graduation status of the parents.	Two-parent households with a own child below 18. Weighted. Additional controls on gender, child age, number of children, and date of interview.	ATUS 2003
Parental time education coeff.	Income regression coefficient of parental time on income quartile and college graduation status of the parents.	Two-parent households with a own child below 18. Weighted. Additional controls on gender, child age, number of children, and date of interview.	ATUS 2003
Parental time non-college parents	Average parental time of non-college parents.	Two-parent households with a own child below 18. Weighted.	ATUS 2003

D.5 Perfect Information Model

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

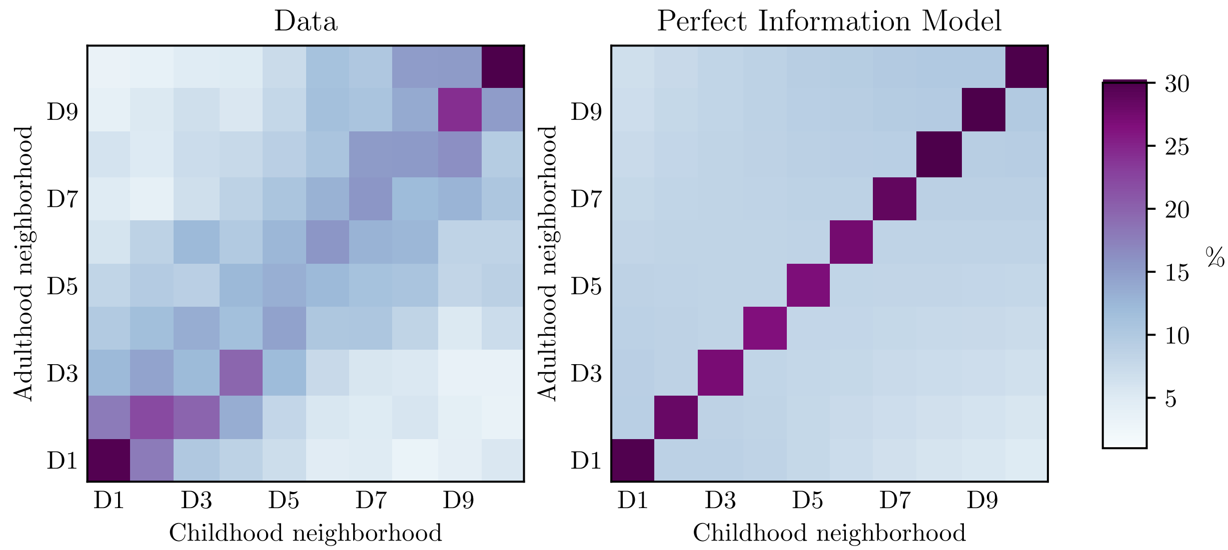
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa\, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \iota\, \mathbb{1}_{m_0 = m} + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right]$$

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	0.118
$\kappa = 0.85$	Parental time disutility	Parental time non-college parents	0.075	0.079
$\iota = 0.024$	Place of birth preference	Residential immobility (D1)	0.295	0.296
$\omega = 0.01$	College wage premium	Earnings ratio non-college - college	0.554	0.558
Neighborhoods				
$\sigma_m = 0.16$	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.061
$\nu = 0.02$	Taste shock variance	Census tract Gini	0.265	0.18
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 $a \sim \mathcal{N}(0, \sigma_a)$				
$\alpha = 0.71$	Elasticity of investments	Rank-rank coefficient (IGE)	0.341	0.345
$\gamma = 0.45$	Parental time share	Neighborhood effect (75th pct.)	0.046	0.057
$\varphi = -5$	Substitutability	Parental time income coeff.	0.099	0.097
$\sigma_a = 0.55$	Ability shock variance	Mean over median income	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 S2: 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.

D.6 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	0.117
κ = 0.8	Parental time disutility	Parental time non-college parents	0.075	0.083
ι_1 = 0.0155	Place of birth preference	Residential immobility (D1)	0.295	0.295
ι_2 = 0.0055	Place of birth preference	Residential immobility (D2)	0.182	0.191
ι_{3-10} = 0.0005	Place of birth preference	Residential immobility (D5)	0.112	0.113
xi = 0.0005	Quadratic moving costs	Residential immobility (D10)	0.235	0.217
ω = 0.01	College wage premium	Earnings ratio non-college - college	0.554	0.558
Neighborhoods				
σ_m = 0.16	Neighborhood quality	Neighborhood effect (25th pct.)	0.062	0.06
ν = 0.02	Taste shock variance	Census tract Gini	0.265	0.179
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 $a \sim \mathcal{N}(0, \sigma_a)$				
α = 0.71	Elasticity of investments	Rank-rank coefficient (IGE)	0.341	0.343
γ = 0.45	Parental time share	Neighborhood effect (75th pct.)	0.046	0.055
φ = -4	Substitutability	Parental time income coeff.	0.099	0.091
σ_a = 0.55	Ability shock variance	Mean over median income	1.247	1.222

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.