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

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**Abstract**

In the U.S., beliefs about parenting and parental choices differ across socioeconomic groups. This paper develops an overlapping generations model with social learning, where young adults form beliefs about parenting by observing neighbors but may make inference mistakes due to selection neglect—imperfect correction for selection. In equilibrium, residential segregation generates information frictions that foster heterogeneous beliefs and distort parenting decisions. When calibrated to the U.S., the model suggests these beliefs reduce equity and efficiency, and housing vouchers can enhance both social mobility and aggregate income. In contrast, a model that replaces beliefs with fixed preference heterogeneity predicts income losses.

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

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

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# Introduction

Parental input decisions—such as time spent with children or the quality of the neighborhood—and beliefs about their relevance for children's future opportunities vary among U.S. parents.[1] Since Cunha et al. (2013), a growing body of evidence suggests that lower-income parents tend to underestimate parental input relevance, leading to lower levels of inputs and a larger socioeconomic gap in parental inputs, potentially dampening social mobility.[2]

Because the effects of parenting on children's future opportunities are not immediately observable, social learning—learning from the observations of others' outcomes—appears a natural key channel for shaping beliefs about parenting. When individuals exhibit a selection neglect bias, a well-documented cognitive bias in the behavioral and psychological literature that reflects a limited ability to account for selection, social learning can generate belief heterogeneity across environments.[3] This theoretical learning framework can rationalize, for instance, why the absence of successful role models in disadvantaged areas may reduce motivation and educational engagement.[4]

In this paper, I incorporate social learning and selection neglect into a spatial overlapping generations model of human capital accumulation. Young adults inherit beliefs from their parents and form their own view of the relevance of parental inputs by observing older individuals in their neighborhood, but are prone to errors due to a selection neglect bias. Learning occurs during pre-adulthood, a period of intensive cognitive and social development, and within neighborhoods that implicitly shape young adults' social networks—e.g., through schools and shared public spaces. In equilibrium, residential segregation introduces

[1]The literature documents disparities in time investment between more- and less-educated parents in the U.S. and beyond (see Doepke et al. (2023) for a review).

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

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

[4]See, Durlauf (2011); La Ferrara (2019)) for a discussion. Among others, Alan et al. (2019); Huillery et al. (2025); Breda et al. (2023); Guyon and Huillery (2020); Nguyen (2008); Beaman et al. (2012) study the effects of successful role models on beliefs and educational inputs.

information frictions: young adults in low-income neighborhoods tend to underestimate the relevance of parental inputs—because successful role models have left their neighborhoods—while those in high-income neighborhoods tend to overestimate it. Because beliefs shape parenting choices—neighborhood quality—which in turn generate belief-consistent signals across generations, social learning leads to a self-reinforcing equilibrium with a persistent and stable distribution of beliefs.

The quantitative model features altruistic parents who choose two parental inputs—the quality of their neighborhood and parental time—under budget and time constraints. Children's future human capital depends on these inputs, on parental human capital, and on an idiosyncratic, unobserved ability shock, which can be interpreted—to some extent—as luck. Motivated by Cunha et al. (2013)'s evidence, agents are unaware of the elasticity of human capital with respect to parental inputs and form beliefs about it through social learning. Young adults infer this elasticity by observing the average outcomes and past inputs of their neighbors—the average adult in the neighborhood thus serves as a proxy for the social network accessible to youth. However, due to selection neglect, they fail to fully account for selection on unobserved ability shocks, leading to inference mistakes. As a result, parents differ in their beliefs, but also family history, human capital, and education status—which influence their budget, labor supply, and time constraints. Given the model structure and perfectly competitive land developers, there are multiple critical equilibrium objects: the distribution of human capital and education, neighborhood choices and local rents, and beliefs, which are endogenously determined as fixed points.

The model is solved numerically and calibrated to match a set of critical moments from several United States representative datasets. It comprises ten quality-ranked neighborhoods and is calibrated to replicate residential segregation and family earnings dispersion in the average commuting zone, based on data from the 2000 American Community Survey (ACS) and the National Historical Geographic Information System (NHGIS).[5] In addition, I target

[5]Ruggles et al. (2023); Manson et al. (2022). I proxy neighborhood "quality" with neighborhoods' median household income that correlates with places' effects measured by Chetty and Hendren (2018b), as well as

causal estimates of neighborhood effects on children's future income and social mobility from the literature.[6] Parents' working time is computed from the American Time Use Survey (ATUS) and neighborhood choice from the panel data Add Health.[7] Finally, I discipline the model's beliefs using the estimates from Cunha et al. (2013). Eliciting the beliefs about parenting of disadvantaged mothers, the authors find that shifting median beliefs to the lowest estimated elasticity would boost parental inputs by 3.6% to 24.3%, with an average increase of 11.6%.

First, the model's predicted distribution of parental inputs closely mirrors observed patterns in parental time use and neighborhood quality choices across socioeconomic groups, despite these patterns not being directly targeted. In contrast, when ignoring beliefs about parenting prevents, the model fails to replicate these empirical patterns. Explaining the data under a perfect information framework instead requires assuming large preference heterogeneity across childhood neighborhoods and education status. However, such an assumption—particularly a higher preference for deprived neighborhoods—appears inconsistent with existing empirical evidence and has important implications for policy recommendations.[8]

Second, beliefs about parenting affect both aggregate measures of equity and efficiency. To quantify their impact, I simulate a counterfactual economy in which all parents have perfect information and solve for the new steady state. Providing information prompts parents in the bottom income quartile to increase their parental input by 11.3%, while parents in the top quartile revise their beliefs downward and reduce their input. However, the reduction at the top is smaller in magnitude than the increase at the bottom, resulting in a net rise of 4.6% in aggregate parental input. As a result, eliminating misinformation reduces the intergenerational rank-rank coefficient—a measure inversely related to social mobility—by 12.3%, lowers the income Gini index by 2.4%, and raises aggregate income by

with low poverty and crime rates, and access to high-performing schools.

[6]Estimates are taken from Chetty and Hendren (2018b) and Chetty et al. (2014).

[7]Hofferth et al. (2020) and Harris et al. (2019).

[8]When comparing low-income families randomly incentivized to move to higher-quality neighborhoods, empirical studies tend to find higher satisfaction rates and willingness to stay among families living in higher-quality neighborhoods (see, for instance, Bergman et al. (2024)).

3.8%, improving consumption-equivalent welfare by 4.9%. Overall, distorted beliefs about parenting both widen inequality and lower economic efficiency, disproportionately harming low-income families while reducing aggregate income.

Third, I use the calibrated model to study the effects of housing vouchers on the U.S. economy. Two frictions motivate this policy intervention. The first is standard in overlapping generations models: parents cannot borrow against their children's future income, so housing vouchers help relax the budget constraints of low-income families. The second is model-specific: information frictions stemming from residential segregation, which housing vouchers can help mitigate in general equilibrium.

As a first step, I conduct three field experiments within the model and compare the partial equilibrium effects with empirical estimates from Jacob et al. (2015); Chetty et al. (2016); Bergman et al. (2024). The first experiment targets young adults below the tenth income percentile, the second augments this intervention by providing information about the role of neighborhood quality in shaping children's future human capital, and the third focuses on young adults below the fifth income percentile. Although the model predicts slightly higher mobility than observed empirically, likely due to the younger age of the recipients, the partial equilibrium effects of correcting beliefs and improving neighborhood quality closely align with the empirical findings.

When scaling up a range of housing voucher policies to all eligible families and accounting for general equilibrium effects, the model indicates that a more generous policy than those implemented in empirical studies yields the largest welfare gains. Over the long run, such policies can simultaneously increase income and social mobility. However, when the policy is evaluated using an alternative model that replaces endogenous belief formation with preference heterogeneity, the predicted welfare gains are smaller and come with a decline in aggregate income.

This paper contributes to the macroeconomics literature that studies household heterogeneity and its consequences for aggregate outcomes.[9] It builds upon the literature pioneered by Aiyagari et al. (2002); Becker and Tomes (1986); Loury (1981) that models human capital accumulation and parental input decisions. Many subsequent analyses use this framework in quantitative models to study the consequences of parental input decisions for macroeconomic outcomes.[10] This paper not only analyzes the consequences of parental decisions for macroeconomic outcomes but also introduces the environment as a possible driver of parental decisions' heterogeneity. In that sense, it closely relates to Agostinelli et al. (2024), who study parental behavior responses to changes in peer quality in the United States, and to Kim et al. (2024), who rationalize very high education spending in South Korea through a status externality in which parents value their children's education relative to the education of other children. This paper's model includes direct peer quality effects and its key novel ingredient, social learning within neighborhoods.[11]

This paper connects residential segregation and social mobility by introducing social learning in a spatial model, contributing to the quantitative spatial economics literature.[12] Several recent quantitative studies underline the relationship between residential segregation and inequality through direct peer effects or local school funding (see, for instance, Chyn and Daruich (2022); Eckert and Kleineberg (2024); Fogli and Guerrieri (2019); Gregory et al. (2022)).[13] Adding to this literature, this paper endogenizes residential sorting and

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

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

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

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

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

social learning, resulting in heterogeneous valuations of neighborhood amenities—through beliefs about parenting—, contributing to the growing literature that considers endogenous neighborhood amenities.[14]

The notion that a neighborhood's demographic composition can influence educational outcomes through social learning has long been discussed (see, for instance, Durlauf (2011)). This paper's contribution lies in developing and calibrating a quantitative model of human capital accumulation that incorporates a social learning process, resulting in a self-fulfilling equilibrium with systematic bias in beliefs.[15] The social learning process primarily builds on Fogli and Veldkamp (2011), who explain geographical and historical variation in the increase of female labor supply by a change in local beliefs. Nonetheless, the authors abstract from residential decisions and, hence, systematic and persistent bias in beliefs that this model generates. In a different context, abstracting from residential segregation, Piketty (1995) develops a self-fulfilling equilibrium of effort and social mobility. The author posits that individuals' past experiences shape their beliefs about the relevance of effort for upward mobility, which in turn affects their effort levels. Heterogeneous biased beliefs are stable if they lead individuals to exert effort levels that result in the believed probabilities of upward mobility. Similarly, my model generates a self-fulfilling equilibrium across generations, as parents' residential decisions, on average, provide confirming signals to their children.

Finally, the microfoundations of the model are grounded in a broad body of empirical evidence. The inclusion of beliefs about parenting reflects a widely shared view in the literature: that such beliefs significantly influence parental decisions and vary across socioeconomic groups, whereas the technology of skill formation itself remains largely constant.[16] The model's biased learning channel is motivated by empirical evidence showing

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

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

[16] See, for example, Attanasio and Kaufmann (2014); Attanasio et al. (2019); Boneva and Rauh (2016, 2018); Cunha et al. (2013); Belfield et al. (2019); Caucutt et al. (2017); Dizon-Ross (2019); Jensen (2010);

that heterogeneous beliefs often arise from variation in whom individuals observe.[17] In particular, several studies suggest that the absence of successful role models among older peers in low-income areas contributes to lower levels of motivation and educational effort.[18] The technical features of the model learning process are informed by insights from several strands of research. First, social learning plays a crucial role when outcomes are not immediately observable (Frick et al., 2022). Second, younger individuals are more likely to update their beliefs in light of new information than older individuals.[19] Third, individuals tend to make systematic inference errors due to their inability to account for selection on unobservables—a phenomenon known as selection neglect bias (Enke, 2020).

The remainder of the paper proceeds as follows. Section I presents the spatial overlapping generations model. Section II explains the model calibration and presents some quantitative results. Section III uses the model for policy analysis, and Section IV concludes.

# 1 The Model

Consider one commuting zone composed of a finite number of heterogeneous neighborhood types. The economy is populated by a continuum of heterogeneous families, each consisting of one parent and one child. Time is discrete, and agents live for two periods: childhood and parenthood. During parenthood, individuals make two key decisions that influence their child's future human capital: the type of neighborhood in which to raise their child and the amount of time to spend with their child—parental time. One of the key and novel model mechanisms resides in parents' imperfect information about the technology of skill

Kaufmann (2014); Wiswall and Zafar (2021). An exception is Attanasio et al. (2019), who finds no socioeconomic gradient in beliefs in the UK context.

[17]For example, in rural Ghana, Conley and Udry (2010) show that small farmers' adoption of fertilizer increases after observing unexpectedly successful peers.

[18]See, for example, Alan et al. (2019); Huillery et al. (2025); Breda et al. (2023); Guyon and Huillery (2020); Nguyen (2008). More recently, Chetty et al. (2022) find that the share of high-socioeconomic-status friends in a ZIP code is the strongest predictor of upward income mobility in the United States, proposing social learning as a key mechanism.

[19]From the neuroscience literature, see, for instance, Eppinger et al. (2008); Hämmerer et al. (2011); Mell et al. (2005); Nassar et al. (2016); Weiler et al. (2008).

formation and the social learning process. Learning occurs during childhood—a period of intensive cognitive and social development—using information at the neighborhood level.[20] As such, neighborhoods shape both children's future human capital and beliefs by influencing their social networks through schools and everyday interactions.

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

## 1.1 Social Learning and Technology of Skill Formation

**Technology of Skill Formation:** Children's next period human capital $h'$ primarily depends on their parent, as it is determined by childhood neighborhood quality $m$—which reflects factors such as school quality, cultural amenities, environmental conditions, and safety—parental time $\tau$, and parental human capital $h$. Idiosyncratic variation in future human capital is captured by an unobserved ability shock $\varepsilon'$. The functional form is as follows:

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

where parameters $\alpha,\ \beta,\ \gamma \in (0,1)$, and $\bar{A}$ a scaling parameter. Ability shocks $\varepsilon'$ are drawn from a normal distribution $\mathcal{N}(\mu_{\varepsilon}, \sigma_{\varepsilon})$.[21]

By assumption, parental human capital $h$ enhances the productivity of the two parental inputs. This feature seeks to capture that high-human-capital parents are better at building

[20] The neuroscience literature shows that younger individuals are more likely to update their beliefs and learn than older individuals (see, for instance, Mell et al. (2005); Eppinger et al. (2008); Weiler et al. (2008); Hämmerer et al. (2011); Nassar et al. (2016)).

[21] By assuming uncorrelated ability shocks across generations, I abstract from modeling genetics. However, the main results would still hold if genetic factors were included, as the relative importance of $h$ in the technology of skill formation already partially captures genetic influences.

child skills and that environmental factors, such as in-utero experiences correlated with parental human capital, influence children's skills (Cunha and Heckman (2007, 2009); Cunha et al. (2010); Heckman and Mosso (2014)). Following the literature, I assume a nested CES function for the skill formation technology, with one of the elasticities set to unity, which imposes a parsimonious Cobb-Douglas outer form.[22] Finally, parental time $\tau$ is normalized by its baseline unconditional mean ($\overline{\tau}$) to achieve unit independence and computational stability following Jang and Yum (2023).

Crucially, the elasticity of adulthood human capital with respect to the combination of parental inputs $\alpha$ is unknown, and ability shocks $\varepsilon'$ are unobservable.

**Social Learning:**

Let's now turn to one of the key features of the model: the learning process about the elasticity parameter $\alpha$. Following Fogli and Veldkamp (2011), learning happens in the first period of life, a period of intensive cognitive and social development, before making parental decisions.[23] Prior to entering parenthood, young agents update inherited beliefs ($\tilde{\alpha}$) using neighborhood-based inference ($\hat{\alpha}_m$), through a form of Bayesian learning that allows for partial forgetting. Specifically, their updated belief is given by:

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

where parent's beliefs $\tilde{\alpha}$ serve as the prior, and the inference drawn from local information $\hat{\alpha}_m$ acts as the signal. The parameter $\mu \in (0, 1)$ governs the relative weight young agents put on their own experience ($\hat{\alpha}_m$) versus inherited beliefs ($\tilde{\alpha}$). Formally, $\mu$ represents the ratio of the prior variance to the sum of the prior and signal variances, capturing the perceived reliability of personal experience relative to inherited knowledge. A constant $\mu$ implies that the reliability of personal experience does not vary across neighborhoods and that each

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

[23]Evidence from the neuroscience literature suggests younger individuals are more likely to update their beliefs in light of new information than older individuals, see, for instance, Eppinger et al. (2008); Hämmerer et al. (2011); Mell et al. (2005); Nassar et al. (2016); Weiler et al. (2008)

generation evaluates their parent's beliefs with a fixed degree of uncertainty, consistently treating them as informative but not definitive.

Young agents make their own inference $\hat{\alpha}_m$ through social learning using information available at the neighborhood level.[24] Specifically, they observe local aggregates of outcomes and past inputs of their peers' parents to assess the relevance of parental inputs.[25] It is reasonable to assume that young adults have a reliable sense of neighborhood averages through daily interactions and exposure to local media. The average adult in a neighborhood thus serves as a proxy for the average social network accessible to a young individual. Observable characteristics—such as educational attainment, socioeconomic background, and parental input—can be directly observed or discussed.[26] In contrast, ability shocks, which, by definition, reflect factors such as innate ability or luck, are largely unobservable, and young agents can only imperfectly perceive them. Following Bénabou and Tirole (2005)'s modeling, the perception of the average ability shock in neighborhood $m$, $\tilde{\varepsilon}_m$, is given by:

$$\tilde{\varepsilon}_m = \overline{\varepsilon}_m + \pi(\mu_\varepsilon - \overline{\varepsilon}_m),$$

where $\overline{\varepsilon}_m$ represents the actual average ability shock in neighborhood $m$ and $\mu_\varepsilon$ the average ability shocks in the economy. The parameter $\pi \in [0, 1]$ governs the strength of selection neglect, a cognitive bias empirically documented (Enke, 2020).[27] Intuitively, young agents think of the sample of adults they observe as a more representative sample of the population than it is. Notice that $\pi = 0$ implies no selection neglect as young agents can perfectly observe the local aggregate of ability shocks, and $\pi = 1$ implies full selection neglect with

[24]Social learning plays a crucial role when outcomes are not immediately observable (Frick et al., 2022).

[25]Social learning could also encompass the exchange of information and mutual belief sharing. However, starting from correct priors, this process does not generate heterogeneous beliefs. With exogenous heterogeneity in priors, this process would eventually converge to a mass point distribution, with all agents holding the same belief.

[26]Notice that results hold if young agents could only imperfectly perceive past input and human capital.

[27]Using bounded signal is a way to micro-found the parameter $\pi$ as in Jehiel (2018). Alternatively, the selection neglect bias could be modeled via learning costs, with $\pi$ as an equilibrium outcome. Costly learning leads agents to optimally weight their beliefs toward the population average—implicitly assuming this average as the optimal guess and thus reflecting selection neglect.

young agents thinking of their neighbors as a representative sample of the population.[28]

By assumption, young agents know the log-linear form of the skill formation technology (1), but the parameter $\alpha$ representing the relative importance of parental inputs.[29] Formally, the signal observed by young agents in neighborhood $m$ is then given by:[30]

$$\hat{\alpha}_m = \frac{\overline{\log h}_m \; - \; \beta \, \overline{\log h^0}_m - \tilde{\varepsilon}_m}{\overline{\log i(\tau^0, m^0)}_m},$$

where $\overline{\log h}_m$ denotes the average log human capital of current parents in neighborhood $m$, $\overline{\log i(m^0,\ \tau^0)}_m \geq 0$, represents the average log of past parental inputs, and $\overline{\log h^0}_m$, refers to the average log of past parental human capital, both in the neighborhood $m$.

Young agents' inference is downward biased when local ability shocks are lower than what they perceive (i.e., $\bar{\varepsilon}_m \leq \mu_\varepsilon$), leading them to mistakenly attribute the "surprisingly" low observed human capital to low parental input effectiveness. Conversely, when local ability shocks are higher than perceived (i.e., $\bar{\varepsilon}_m \geq \mu_\varepsilon$), they overestimate the effectiveness of parental inputs, interpreting "surprisingly" high outcomes as evidence of high parental input effectiveness.

This learning framework is consistent with empirical evidence showing that heterogeneous beliefs often arise from variation in whom individuals observe. A substantial body of research documents such mechanisms in various contexts. For instance, in rural Ghana, Conley and Udry (2010) show that small farmers' adoption of fertilizer increases after ob-

[28] As in Fogli and Veldkamp (2011), if there were no residential sorting or if young agents could observe all neighborhoods, the selection neglect bias would irrelevant and beliefs would eventually converge toward the truth.

[29] The parameter $\beta$ is assumed to be known. This can be justified by widespread information on individuals' incomes and family backgrounds through national media, history books, and the internet. Young adults can relatively easily observe and correlate patterns of past and present human capital for representative individuals in the economy, enabling them to infer the value of $\beta$. A similar argument is proven in Piketty (1995). With learning within the family, individuals have richer observations of human capital than effort levels, enabling them to perfectly infer the value of the equivalent of $\beta$.

[30] Results go through if agents observe all their neighbors and run an OLS regression as in Fogli and Veldkamp (2011). An alternative approach would have agents observe a subset of neighbors and estimate outcomes via OLS based on their social network. While this would add realism by requiring an explicit network structure, it would not alter the core intuition: on average, a young agent in neighborhood $m$ observes the average adult in that neighborhood.

serving unexpectedly "successful" peers. In the domain of education, several studies suggest that the absence of successful role models among older peers in low-income neighborhoods dampens younger students' motivation and effort, while interventions that increase exposure to successful examples in schools tend to enhance both.[31] More recently, Chetty et al. (2022) find that the share of high-socioeconomic-status friends in a ZIP code is the strongest predictor of upward income mobility in the United States, suggesting social learning as a key mechanism.

## 1.2 Economic Environment

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

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

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

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

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

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

**Education Status**: I introduce education status to connect the model outputs to the data. Each child has a positive probability of entering and graduating from college. The college graduation probability $g(h', \hat{y}, s)$ depends on the parent's education status $s$, the

[31] See, for example, Alan et al. (2019); Huillery et al. (2025); Breda et al. (2023); Guyon and Huillery (2020); Nguyen (2008).

parents' income $\hat{y}$, and the child's accumulated human capital $h'$. The agent's education status $s'$ equals one if the agent graduated from college; it is zero otherwise.

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

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

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

**Parents' Preferences**: Parents consume and enjoy leisure and their environment. In addition, they are altruistic as their child's value enters their utility function. Preferences of a parent raised in childhood neighborhood quality $m^0$, and with beliefs about parenting $\tilde{\alpha}$ can be summarized by the following utility function:

$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa\, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \delta\, rank_m + \iota\, \mathbb{1}_{m^0=m} + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right) | \tilde{\alpha}\right],$$

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

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

**Aggregate Rent:** Rents are assumed to be used to pay housing costs such as capital depreciation and maintenance.

## 1.3 Parents' Problem

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

$$\begin{aligned}\mathcal{V}\left(h, s, m^0, \tilde{\alpha}\right) = \max_{c,\tau,m}\{ \log\left(c\right) + \frac{\left(1 - \overline{\ell_s} - \kappa\,\tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} \\ +\ \delta\ rank_m +\ \iota\ \mathbb{1}_{m^0=m} +\ \nu\varepsilon_m +\ b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right]\}\end{aligned} \tag{4}$$

subject to:

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

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

$$h' = f(\tau,\ m,\ h,\ \varepsilon'|\tilde{\alpha}), \quad \varepsilon' \sim \mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon)$$

$$p(s'=1) = g(h', \hat{y}, s),$$

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

### 1.4 Housing Market

Let $U = E(\mathcal{V})$ denote the expected lifetime utility of a representative parent with respect to the vector of idiosyncratic neighborhood taste shocks $\varepsilon_m$. Let $V\left(h, s, m^0, \tilde{\alpha}, m|r_m\right) = \log\left(c^*_m\right) + \frac{(1-\overline{\ell_s}-\kappa\ \tau^*_m)^{1-\frac{1}{\psi}}}{1-\frac{1}{\psi}} +\ \delta\ rank_m +\ \iota\ \mathbb{1}_{m^0=m} +\ b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \tilde{\alpha}\right)|\tilde{\alpha}\right]$ the utility derived from living in neighborhood $m$ abstracting from the neighborhood taste shock, with $c^*_m$ and $\tau^*_m$ the optimal parent's choices given the neighborhood $m$ and the rent price $r_m$.

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

$$U\left(h, s, m^0, \tilde{\alpha}\right) = \nu \log \sum_m \exp\{\frac{1}{\nu}\ V\left(h, s, m^0, \tilde{\alpha}, m|r_m\right)\}.$$

The share of parents who choose to locate in neighborhood quality $m$ among parents with human capital $h$, graduation status $s$, raised in neighborhood quality $m^0$ and with beliefs $\tilde{\alpha}$ is :

$$\lambda_m(h, s, m^0, \tilde{\alpha}|r_m) = \frac{\exp\{\frac{1}{\nu}\, V\,(h, s, m^0, \tilde{\alpha}, m|r_m)\}}{\sum_n \exp\{\frac{1}{\nu}\, V\,(h, s, m^0, \tilde{\alpha}, n|r_n)\}}.$$

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

$$\sum_{m^0} \sum_{s} \int \int \lambda_m(h, s, m^0, \tilde{\alpha}|r_m) F(h, s, m^0, \tilde{\alpha})\; dh\; d\tilde{\alpha} = \zeta_m {r_m}^{\eta}, \tag{5}$$

with $F(h, s, m^0, \tilde{\alpha})$ the joint distribution of human capital, graduation status, childhood neighborhood, and beliefs about parenting.

## 1.5 Equilibrium

The key objects of the equilibrium in the steady state are the endogenous distribution of human capital, education status, childhood neighborhood, beliefs, and rent prices. For a given initial human capital, graduation status, neighborhood of birth, and parental belief distribution $F_0(h, s, m^0, \tilde{\alpha})$, an equilibrium is characterized by a sequence of residential and parental time choices, $\{m\}$ and $\{\tau\}$, a sequence of rents $\{r_m\}$ for each neighborhood, and a sequence of distributions $\{F(h, s, m^0, \tilde{\alpha})\}$, such that the following four conditions are satisfied:

1. agents solve (4).

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

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

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

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

# 2 Calibration

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

## 2.1 Preliminaries

First, I let the discrete distribution for ability shocks to approximate a normal distribution $\varepsilon \sim \mathcal{N}(\mu_\varepsilon, \sigma_\varepsilon)$, which I discretize using Tauchen (1986), with a fifteen-point grid. Then, I assume the technology of skill formation has constant returns to scale, $\beta = 1 - \alpha$.

I use multiple data sources to compute the relevant moments to calibrate the model. Earnings distribution moments come from the American Community Surveys (ACS) from 2000 (Ruggles et al., 2023). I use the information at the census tract level from the National Historical Geographic Information System (NHGIS) dataset in 2000 (Manson et al., 2022) to construct neighborhood sociodemographic characteristics. I aggregate census tract information at the commuting zone level using a county-to-commuting zone crosswalk. Neighborhood choices and college graduation probabilities are estimated using data from the AddHealth survey described in Appendix Section C.1.2 (Harris et al., 2019).[32] Finally, parents' time use information is taken from the American Time Use Survey (ATUS) 2003 (Hofferth et al., 2020).[33]

### 2.1.1 Geography

The model is calibrated to the average commuting zone in the United States, matching neighborhoods' impact estimated by Chetty and Hendren (2018a) in the 100 biggest commuting

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

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

zones. To be consistent, I only use the top 100 commuting zones in NHGIS 2000. I set the number of neighborhoods $N$ in the model to ten, representing a synthetic decile census tract in the data. Specifically, in each of the 100 commuting zones of the NHGIS 2000, I sort census tracts by median household income and form ten synthetic neighborhoods from the deciles of this distribution.[34] I then create one average commuting zone by computing the population-weighted average characteristics of each of the ten neighborhoods.[35]

## 2.2 Empirically Estimated Parameters

**Housing Markets**: Rental prices are determined in equilibrium given the supply function: $\mathcal{H}_m = \zeta_m r_m^\eta$, where $r_m$ is the equilibrium rent in the neighborhood $m$, and $\eta$ is the price elasticity of housing supply. Saiz (2010) estimates population-weighted average price elasticity in the average metropolitan area of the U.S. to be 1.75, so I set $\eta = 1.75$. The remaining parameters $\zeta_m$ can be estimated directly from the synthetic neighborhood density and median rents.[36]

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

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

where $g(h', \hat{y}, s)$ is the binary outcome of either graduating college or not in the data,

[34] 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%.

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

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

$s = 1$ 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 $rank_{\hat{y}} \in \{1, 2, ..., 10\}$ is the household income decile in 1994-1995.[37]

## 2.3 Externally Calibrated Parameters

The term $1/\psi$ governs the curvature of the utility function with respect to leisure. I set the intertemporal elasticity of substitution $\psi$ to 0.5, as is standard in the literature. The parameter that governs the progressivity of the marginal tax rate is set to $\tau_y = 0.18$ (Heathcote et al., 2017). I assume agents have an endowment of one unit of time corresponding to sixteen hours per day in the data.[38] The fraction of time allocated to market work by education comes from ATUS 2003, as described in Appendix Section C.1.1. The wage rate $w$ are normalized to 1, and the normal distribution of the shocks is centered at zero ($\mu_\varepsilon = 0$). I assume the exogenous neighborhood quality component is distributed according to $\bar{m} \sim \mathcal{N}(\mu_{\bar{m}}, \sigma_{\bar{m}})$. The average exogenous neighborhood quality component $\mu_{\bar{m}}$ is set to one as parental time is normalized to 1 in (1), and $\bar{A}$ is set to 1.5 to guarantee a positive local aggregate log-parental inputs for the learning process. Appendix Table A6 summarizes the externally calibrated parameters.

## 2.4 Internally Calibrated Parameters

Table 1 lists the fifteen parameters I calibrate by minimizing the sum of squared percentage differences between data and model-generated moments. The targeted moments include measures of earnings dispersion, social mobility, parental behavior, segregation, place-based and beliefs effects.[39] Due to the complexity of eliciting beliefs, there is no representative data on beliefs about parenting across neighborhoods or education status. To discipline the

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

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

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

model's beliefs, I then use the estimates from Cunha et al. (2013) for the lowest income quartile of parents. Eliciting the beliefs about parenting of disadvantaged African American mothers, the authors find that shifting median beliefs to the lowest estimated elasticity would boost parental inputs by 3.6% to 24.3%, with an average increase of 11.6%.

Table 1: Internally Calibrated Parameters

| Parameter | Description | Moment | Data | Model |
|---|---|---|---|---|
| **Skill Formation** | | | | |
| $\alpha = 0.74$ | Parental inputs elasticity | Rank-rank coefficient (IGE) | 0.341 | 0.345 |
| $\gamma = 0.2$ | Parental time share | Neighborhood effect (75th pct.) | 0.046 | 0.048 |
| $\varphi = 0.208$ | Substitutability | Income gradient in parental time | 0.140 | 0.131 |
| $\sigma_\varepsilon = 0.695$ | Ability shock variance | Income Gini | 0.333 | 0.336 |
| **Labor Market and Preferences** | | | | |
| $\omega = 0.02$ | College wage premium | Income ratio non-college - college | 0.554 | 0.552 |
| $\lambda_y = 0.67$ | Tax function scalar | Avg. marginal income tax rate | 0.351 | 0.353 |
| $b = 0.4$ | Altruism | Average rent over income | 0.117 | 0.118 |
| $\kappa = 0.335$ | Parental time disutility | Parental time non-college parents | 0.075 | 0.075 |
| $\iota = 0.0015$ | Place of birth preference | Residential mobility (D1-D1) | 0.302 | 0.304 |
| **Neighborhoods** | | | | |
| $\sigma_m = 0.088$ | Neighborhood quality | Neighborhood effect (25th pct.) | 0.062 | 0.059 |
| $\nu = 0.022$ | Taste shock variance | Census tract Gini | 0.221 | 0.216 |
| $\xi = 0.065$ | Demographics effects | Explained share place-based effects | 0.24 | 0.24 |
| $\delta = 0.008$ | Amenities | Rent price gradient | 54.2 | 54.6 |
| **Social Learning Process** | | | | |
| $\mu = 0.55$ | Update weight | Neighborhood quality correlation | 0.417 | 0.415 |
| $\pi = 0.45$ | Cognitive bias strength | Beliefs effects on parental input Q1 | 0.116 | 0.118 |

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

Table 1 outlines a correspondence between the calibrated parameters and the data moments. While all parameters influence each moment, certain moments exhibit greater sensitivity to specific parameters.[40] Understanding these intuitive links is informative about the underlying model mechanisms.

The technology of skill formation parameters $\varphi$, $\gamma$, $\alpha$, and $\sigma_a$ influence human capital

[40] Appendix Figure A2 illustrates the percentage change in each moment resulting from a 10% level increase in each parameter.

accumulation, earning dispersion, and parental choices, affecting most targeted moments. Because $\varphi$ governs the substitutability between a monetary (neighborhood type) and a non-monetary (time) parental input, I associate it with the parental time difference across income groups. Here, I use the regression coefficient of parental time on household income quartiles.[41] The parental timeshare parameter $\gamma$ captures the respective parental inputs' influence on human capital. I map this parameter with the causal effect of neighborhood quality for a child born in the 75th percentile of the household income distribution estimated by Chetty and Hendren (2018b).[42] It determines how much children's future income rank would increase if they had been growing up in one standard deviation better neighborhood. The parental human capital share parameter $1-\alpha$ mechanically increases the income correlation between parents and children. Thus, I use the rank-rank coefficient between parental and child labor earnings estimated by Chetty et al. (2014), an inverse measure of social mobility that captures the pre-tax income correlation between parents and children, as the relevant moment. Finally, the ability shock standard deviation $\sigma_\varepsilon$ captures any income variation not explained by parental choices and human capital. Data moments include two measures of household income dispersion within commuting zones computed from the ACS 2000: the Gini coefficient of household earnings and the income ratio of non-college and college households. Both are weighted population averages across the 100 biggest commuting zones.[43] I map the income Gini with the ability shock standard deviation $\sigma_\varepsilon$ and the earnings gap between college and non-college parents with the college wage premium $\omega$. More straightforward is the tax function scalar $\lambda_y$ that is tightly linked to the average marginal tax rate.[44]

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

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

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

[44] I use a 35.1 percent average marginal income tax rate estimated by the Urban & Brookings Tax Policy Center. See `https://www.taxpolicycenter.org/`

The preference parameters $b$, $\kappa$, and $\iota$, together with the neighborhood parameters $\sigma_m$, $\nu$, and $\xi$, and $\delta$ govern parents' input choices and the model geography—which are also affected by the skill formation technology parameters. The parental time disutility parameter $\kappa$ directly affects parental time choice. It is pinned down by the fraction of time allocated to parental time by non-college parents computed from ATUS.[45] The altruism parameter $b$ affects all parental choices, including the share of income spent on rent, so I include the average rent price over the average household income as a targeted moment. The preference for place of birth $\iota$ influences the share of adults who live in the neighborhood type they grew up in. It is pinned down by a moment labeled "residential immobility (D1)". It is defined as the fraction of children born in the worst synthetic neighborhood who choose to live in the same synthetic neighborhood in adulthood.

Regarding the model geography, the standard deviation $\sigma_m$ affects the exogenous part of the neighborhood quality distribution ($\{m\}$) that directly enters the child skill production function. Consequently, it influences how much a child's earnings are affected by neighborhood choices. I use a similar moment for calibrating $\gamma$, namely the causal effect of neighborhood quality for a child born in the 25th percentile of the household income distribution measured by Chetty and Hendren (2018b). The taste shock variance $\nu$ controls residential moves orthogonal to neighborhood quality and directly affects residential segregation that I measure by the Gini coefficient across the ten neighborhoods in the NHGIS 2000 dataset. How much the neighborhood quality changes with a change in the demographic composition depends on $\xi$, calibrated by matching the share of the variance in causal placed-based effects explained by observable characteristics estimated by Chetty and Hendren (2018b) (24%).[46] Finally, additional neighborhood amenities drive parental moves through $\delta$, disciplined by the slope in monthly rent prices across neighborhood types.

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`model-estimates/baseline-effective-marginal-tax-rates-allocatedjuly-2016/t16-0114-effective-marginal-tax`.

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

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

Lastly, I discipline the belief parameters $\mu$ and $\pi$ using additional parental behavior moments. The parameter $\mu$ governs the correlation between parents' and children's beliefs. A higher $\mu$ generates lower persistence in beliefs and parental behavior within families but a higher influence of neighborhoods on future choices through beliefs. I associate this parameter with the intergenerational neighborhood correlation. Finally, to discipline the strength of the selection neglect bias ($\pi$), I include the average estimated effect of beliefs on parental inputs among low-income mothers from Cunha et al. (2013). I compute the corresponding model moment by solving for the partial equilibrium effect of providing information to parents below the first quartile of the income distribution.

## 2.5 Non-Targeted Moments

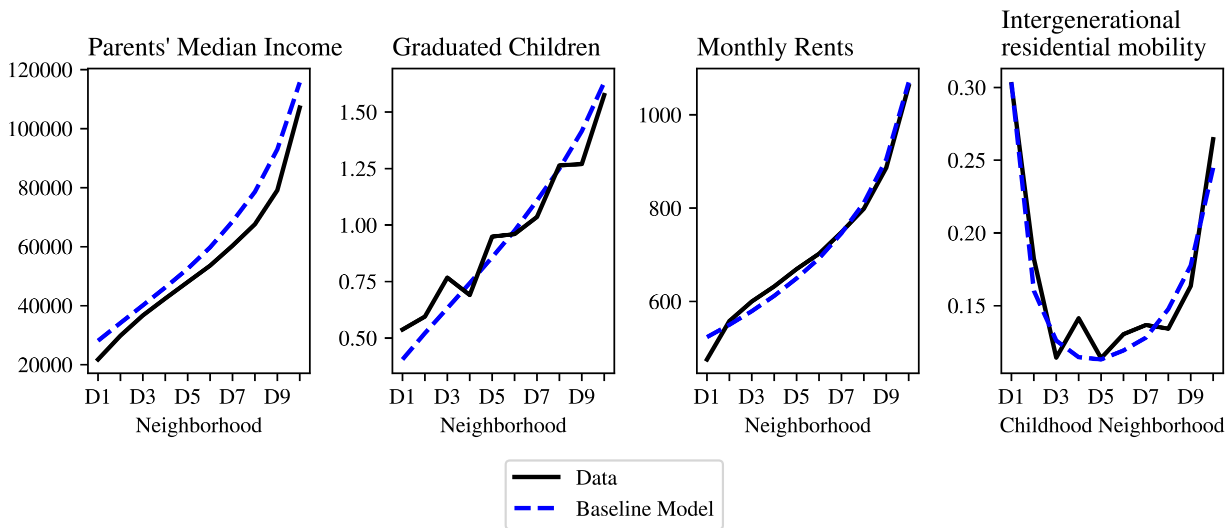
In addition to closely matching the targeted moments, the calibrated model successfully reproduces untargeted patterns observed across neighborhoods and socioeconomic groups.

Despite neighborhood quality and parental time being substitutes in the child skill production function ($\varphi > 0$), and despite college-educated parents working longer hours, the model predicts that college-educated parents spend more time on parenting than non-college-educated parents. This largely reflects the positive correlation between beliefs about parenting and education. Quantitatively, the model predicts a parental time gap of 1.23 between college- and non-college-educated parents, close to the empirical estimate of 1.33.

Figure 1 shows non-targeted moments across neighborhoods. The first, second, and third panels of Figure 1 represent median income, the share of graduated children, and monthly rents per neighborhood, respectively. Although none of these moments were directly targeted, income segregation, social mobility, place-based causal effects, and the slope in rents are. Moreover, the housing supply function is empirically estimated. While a good fit of those moments is not entirely surprising, it validates the model's internal and empirical consistency.

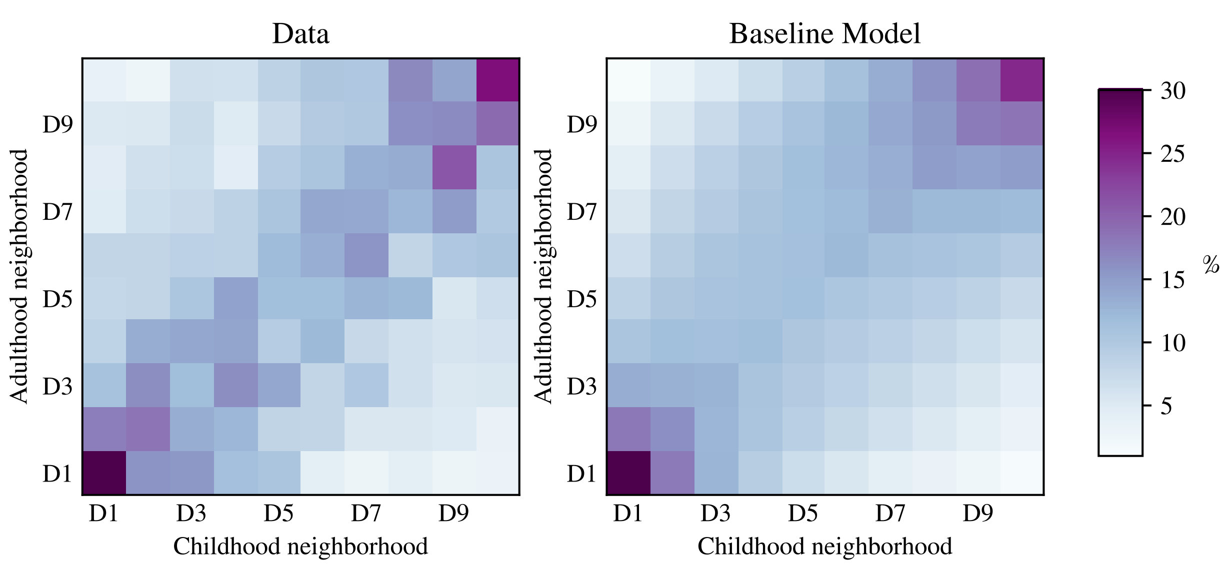
The last panel of Figure 1 shows the share of children who, as adults, live in the same

FIGURE 1: Non-Targeted Moments by Neighborhood




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

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




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

type of neighborhood as their parents. Among the statistics displayed, only the first point is directly targeted. Yet, the model closely reproduces the observed U-shaped pattern in the data. To further illustrate intergenerational mobility, Figure 2 presents a frequency matrix of all possible neighborhood transitions, where each cell represents the likelihood of a given move. Darker cells indicate higher probabilities. For example, a child born in Neighborhood D1 is likely to remain in D1 or move to D2, but is unlikely to reach D7 or higher. Once again, the calibrated model (right panel) closely mirrors the empirical pattern observed in the data (left panel), capturing both the direction and strength of mobility across neighborhood types.

It is important to note that the model does not explicitly incorporate wealth accumulation. However, in the U.S., wealth is highly concentrated, and for most households, it primarily consists of housing, an asset explicitly modeled here. Rodriguez et al. (2002) report that, as of 1998, the bottom 80% of households collectively held less than 20% of total wealth, while the top 10% controlled approximately 70%. Using historical data from the Survey of Consumer Finances, Kuhn et al. (2020) describe the bottom 50% of households as holding very little wealth, over 80% of which consists of housing and other nonfinancial assets. Even among households in the 50th to 90th percentiles, two-thirds of wealth is similarly concentrated in nonfinancial assets. Reflecting this pattern, large inter vivos financial transfers are rare for most families. Lee et al. (2020) find that the probability of receiving a parental transfer exceeding USD 5,000 between the ages of 25 and 44 is about 15% for those in the top wealth quartile, and below 6% for all others. These figures suggest that the absence of a wealth accumulation channel may partly explain the model's limited ability to capture the high persistence of neighborhood quality at the top of the distribution—last point of Figure 1 and upper right corner of Figure 2. However, because housing is modeled explicitly and the calibration targets neighborhood causal effects that encompass all forms of neighborhood influence—including in-kind transfers, such as "rent" for adult children living with their parents—this omission likely has little impact on the rest of the distribution.[47]

## 2.6 Comparison with a Perfect Information Alternative Model

This section calibrates an alternative model that ignores beliefs about parenting, replacing them with preference heterogeneity. It then compares the resulting parameters and underlying assumptions to those of the baseline model.

To make a fair comparison, I modify the model to have the same number of free parameters and targeted moments. I replace the beliefs target with parental time for college-educated parents, and add two parameters that closely relate to parental time by education and neighborhood choices across generations: heterogeneous preferences regarding the parental time disutility ($\kappa_s$) and quadratic moving costs ($\tilde{\iota}$). The parental time disutility parameter depends on the college education status $s$, capturing a—non-empirically documented—difference in time valuation by education, leading to a difference in parental time choices by education. The quadratic moving suggests a homophily bias for neighborhood quality types. Two parents of similar earnings and taste shocks could have different preferences for living in a neighborhood, depending on how close their childhood neighborhood quality type was compared to the current one. This last feature mechanically creates a U-shape in residential mobility and a smooth gradient in the frequency matrix of intergenerational residential moves. However, once calibrated, this alternative version of the model misses untargeted intergenerational residential mobility moments (Panel 4, Figure 3), suggesting a need for additional preference heterogeneity.[48] I thus introduce additional free parameters capturing a preference for neighborhood that varies by childhood neighborhood type ($\iota_{m^0}$) and include as targeted moments the data points in the last panel of Figure 1. The alternative model fit now resembles the baseline model.[49]

Notice that while introducing preference heterogeneity can help match the data, it lacks

[47] For consistency, social mobility and inequality moments do not incorporate wealth.
[48] See Appendix Section D.1 for the fit of targeted moments.
[49] See Appendix Section D.2 for the fit of targeted moments.

empirical grounding. There is no evidence that parental time disutility systematically varies by education level, and the assumption of quadratic moving costs appears somewhat ad hoc. Moreover, the alternative model predicts a preference for childhood neighborhood that is more than forty times higher in the lowest-quality neighborhood compared to middle-tier ones, which contradicts empirical evidence. In reality, the most disadvantaged neighborhoods tend to exhibit high crime rates, elevated poverty, limited opportunities for children, and high resident dissatisfaction.

Alternative mechanisms—such as discrimination or homophily—could motivate other modeling choices.[50] However, findings from Bergman et al. (2024), who compare low-income families randomly induced to move to higher-quality neighborhoods or not, show that families who moved reported higher satisfaction. This suggests that if discrimination exists in better neighborhoods, it does make the families systematically want to return to low-quality neighborhoods.[51] Alternatively, introducing stronger complementarity between parental human capital and parental inputs in the child skill production function could help generate differences in parental time by education. However, the empirical support for such a mechanism is mixed. If anything, the direct productivity effects of parental human capital on child skill formation appear to be limited to very early childhood.[52]

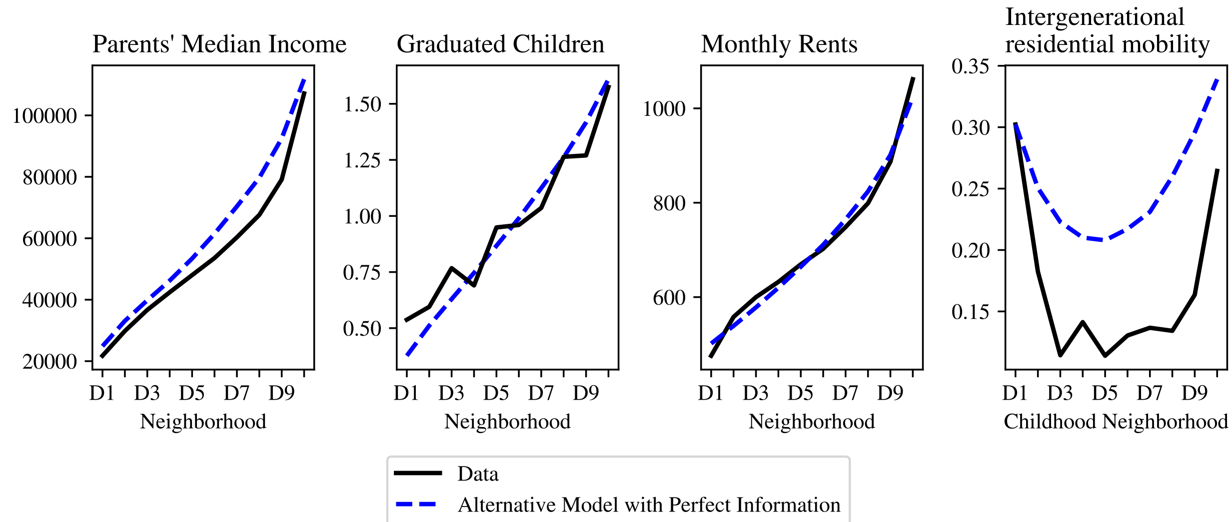
The baseline and alternative models offer contrasting explanations for the parental input gap across socioeconomic groups. In the alternative model, without beliefs, the calibration requires an education-specific disutility of parental time and a complementarity between parental inputs ($\varphi < 0$), the latter consistent with Chyn and Daruich (2022). Since college-educated parents both work more and spend more time with their children, only a combination of input complementarity and education-specific time disutility can replicate observed

[50]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.

[51]In Appendix Table A10, I find that while childhood neighborhood quality is correlated with adulthood neighborhood quality, once controlled for childhood neighborhood quality, race is not the primary driver of intergenerational residential mobility.

[52]See, for example, Caucutt et al. (2020), who find no significant effects for children aged 5–12.

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




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

patterns.[53] Furthermore, large heterogeneity in preference for childhood neighborhood type is needed to match the intergenerational persistence in residential sorting. In contrast,the baseline model, which incorporates beliefs about parenting, implies that neighborhood quality and parental time are substitutes in the child skill production function ($\varphi > 0$), in line with findings from Agostinelli (2018) and Agostinelli et al. (2022). In this case, the gradient of parental time by education flattens due to input substitutability and differences in work hours, but steepens with beliefs that are positively correlated with income. Importantly, this model fits the data without requiring education-specific time disutility or heterogeneous neighborhood preferences.

[53] As discussed in Guryan et al. (2008), the theoretical effect of higher returns to parental inputs for higher-human-capital parents on parental time choices is ambiguous.

## 2.7 The Impact of Beliefs about Parenting

This section evaluates the macroeconomic impact of beliefs about parenting. Using the baseline calibrated model, I simulate a counterfactual scenario in which young adults receive accurate information about parenting in every period—effectively shutting down social learning—and compare the resulting steady state to the baseline.

Table 2 shows that providing information would prompt parents in the bottom income quartile to revise their beliefs upward, leading to an 11.3% increase in overall parental input, and closing the parental time gap by education.[54] In contrast, parents in the top quartile would adjust their beliefs downward, resulting in a reduction in parental input. However, this decline is smaller in magnitude than the increase observed among low-income parents. As a result, aggregate parental input rises by +4.6%, leading to a 3.8% increase in aggregate income.

Distorted beliefs about parenting thus lead to systematic patterns of under- and over-investment. Ensuring perfect information improves social mobility by 12.3% and dampens income inequality and absolute poverty by 2.4% and 19.3%, respectively.[55] Under perfect information, aggregate welfare—defined by the consumption equivalence under the veil of ignorance in the baseline economy, given parents' beliefs, relative to the counterfactual economy—would increase by 4.9%.[56]

In summary, beliefs about parenting have substantial implications for both equity and efficiency. They disproportionately harm lower-income households while also diminishing aggregate income. As a result, improving the accuracy of beliefs about parenting would lead to welfare gains, even when accounting for the fact that, at baseline, parents optimize given their beliefs, and are, in a sense, "happily wrong."

[54] Appendix A9 reports percentage differences by income quartile, based on the baseline definition of these groups.

[55] Social mobility is measured by the negative income rank-rank coefficient; income inequality by the Gini index; and poverty by the share of households below the baseline 10th percentile of the income distribution.

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

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

| | All | Income quartile 1st | 2nd | 3rd | 4th |
|---|---|---|---|---|---|
| Beliefs about parenting | +12.3 | +51.8 | +19.2 | +4.6 | -8.3 |
| Parental input | +4.6 | +11.3 | +6.4 | +3.3 | -0.5 |
| Parental time | +10.7 | +39.8 | +15.8 | +4.9 | -7.7 |
| Neighborhood rank | +1.7 | +2.8 | +4.4 | +2.4 | -0.1 |
| Social mobility | +12.3 | | | | |
| Segregation | -2.1 | | | | |
| Income inequality | -2.4 | | | | |
| Absolute poverty | -19.3 | | | | |
| Income | +3.8 | +7.7 | +6.5 | +4.7 | +2.4 |
| Welfare | +4.9 | +11.7 | +7.3 | +3.7 | -0.2 |

*Notes*: This table reports the percentage changes in model-generated moments resulting from providing information, based on the baseline calibrated model. *Social mobility* is measured by minus the income rank-rank coefficient, *Segregation* by the neighborhood Gini coefficient, and *Inequality* by the income Gini coefficient.

# 3 Housing Voucher Policies

The baseline model displays two main frictions that motivate policy interventions: first, a friction common to overlapping generation models, parents cannot borrow against their children's future earnings, and second, model-specific frictions, information frictions arising from residential segregation. This model, therefore, offers a new rationale for information-based interventions—such as role model programs—and for housing voucher policies, which provide subsidies to low-income families. In this framework, housing vouchers serve not only as a redistributive tool but also as a means to reduce residential segregation and alleviate the resulting information frictions.

In this section, I use the quantitative model to assess the macroeconomic effects of providing housing vouchers to low-income young adults in the United States. The model policy targets individuals with income below a relative poverty threshold, defined as the tenth percentile of the income distribution. Eligible individuals receive the housing voucher upon reaching the age of independence, when they move out of their parental home. The voucher covers the difference between a fraction of the neighborhood's median rent $\Gamma_r$ and a fraction of the recipient's income $\Gamma_y$, thereby requiring recipients to contribute at least $\Gamma_y$ of their income toward rent. Accordingly, the effective rent faced by a parent with income $y(h, s)$ residing in neighborhood $m$ is given by:

$$\begin{aligned} \hat{r}_{m,h,s} &= r_m - \max(\Gamma_r \, r_m - \Gamma_y \, y(h,s),\ 0) \\ &= \min(\Gamma_y \, y(h,s) + (1-\Gamma_r) \, r_m,\ r_m). \end{aligned}$$

## 3.1 Partial Equilibrium Effects of Housing Vouchers

As a first step, I conduct three field-style experiments within the model and compare the results to the empirical estimates by Jacob et al. (2015); Chetty et al. (2016); Bergman et al. (2024). Field experiments typically affect too few participants to influence equilibrium prices or distributions. Therefore, I compute partial equilibrium effects in the model, holding constant all parental and neighborhood characteristics, including beliefs and rents. To closely match the experimental settings, I assume that eligible parents must contribute at least 30% of their income toward rent ($\Gamma_y = 0.3$). I also calibrate the policy to generate mobility rates comparable to those observed in Chetty et al. (2016), which implies setting $\Gamma_r = 0.75$. Under these assumptions, the voucher covers the difference between 30% of family income and 75% of the neighborhood median rent. The first experiment targets families with incomes below the tenth percentile of the distribution. The second experiment replicates this approach but also provides information about the relevance of neighborhood quality for children's future human capital. The third experiment focuses on families with incomes below the fifth percentile of the distribution.

Panel A of Table 3 contains the partial equilibrium effects of the first experiment and highlights slightly higher mobility rates of eligible families in the model than in the empirical study. While the model predicts that families eligible for housing vouchers experience an increase in neighborhood quality, with an average improvement of +0.8 neighborhood ranks, Jacob et al. (2015) find no effect of housing vouchers on the neighborhood quality of

Table 3: Partial Equilibrium Effects of Three Housing Voucher Interventions

| | Data | | Model | |
|---|---|---|---|---|
| | Control Mean | Treatment Effect | Baseline | Treatment Effect |
| *Panel A: Housing vouchers for families with income below the 10th pct* | | | | |
| *Jacob et al. (2015) - Housing vouchers for low-income families in private housing* | | | | |
| Neighborhood rank$^{(a)}$ | 1 | 0 | 2.2 | +0.8 |
| Child's future earnings (percentile)$^{(b)}$ | na | 0 | 32 | +0.6 |
| % in top 3 neighborhoods | na | na | 0 | +3.2 |
| *Panel B: Information to families receiving a housing voucher (income below the 10th pct)* | | | | |
| *Bergman et al. (2024) - Information to low-income families receiving a housing voucher* | | | | |
| Neighborhood rank$^{(a)}$ | 3 | 0 | 3.0 | +0.6 |
| Child's future earnings (percentile) | na | na | 33 | +0.4 |
| % in top 3 neighborhoods$^{(c)}$ | 13 | +8.9 | 3 | +2.2 |
| *Panel C: Housing vouchers for families with income below the 5th pct* | | | | |
| *Chetty et al. (2016) - Experimental vouchers for low-income families in public housing* | | | | |
| Neighborhood rank$^{(a)}$ | $\leq$1 | +1.0 | 1.8 | +1.1 |
| Child's future earnings (percentile)$^{(d)}$ | 29 | +3.2 | 30 | +3.1 |
| % in top 3 neighborhoods | na | na | 0 | +3.1 |

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

beneficiaries.[57] Consistently, the authors who study the housing voucher lottery in Chicago report no significant impact on measurable child outcomes such as achievement test scores or high school graduation.[58] In contrast, the model predicts a positive impact of housing vouchers on children's future earnings, with an improvement of 0.6 percentiles.

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

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

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

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

to families with a housing voucher. The top 3 neighborhoods represent the high-opportunity areas. The model's predictions align with the empirical findings. In Bergman et al. (2024), the information treatment increases the share of families who moved to high-opportunity areas by a not statistically significant 8.9 pp relative to the control group. In the model, the information treatment leads to a 2.2 pp increase. These relatively small effects of information in both the model and the empirical study indicate that factors beyond beliefs hinder housing voucher holders from moving to the highest opportunity areas.

Finally, Panel C contains the empirical estimates of Chetty et al. (2016). The authors evaluate experimental housing vouchers' effects on extremely low-income households living in public housing at baseline. The eligible families in this study are poorer, with household heads less likely to be employed and residing in more disadvantaged areas than in previous studies.[59] The average household earnings of children in the control group between 2008-2012 is \$12,702, placing them at the 29th percentile of the household earnings distribution at age 26 in 2015 dollars.[60] In the model, I focus on extremely poor parents with incomes below the fith percentile to align children's future earnings with the 30th percentile at baseline.[61] As treated families are incentivized to move to low-poverty areas, Chetty et al. (2016) find an effect of a 10 pp reduction in census tract poverty rates or an improvement of about one neighborhood rank, which generates an increase of about \$2,230 (with a \$771 standard error) or 3.2 percentiles (with a 1.05 standard error) in children's future earnings.[62] The model's predictions are close to those estimates and fall within their confidence intervals. Young families with a housing voucher move to a +1.1 higher neighborhood rank, which translates into a +3.1 income percentiles for children.

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

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

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

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

To conclude this section, although the model predicts slightly higher mobility than observed in empirical studies, likely due to the younger age of the recipients, the partial equilibrium effects of correcting beliefs and improving neighborhood quality align with the empirical literature's estimates. While not shown here, the alternative model with perfect information yields effects of similar magnitude—except, of course, in the second experiment—which comforts the validity of its calibration.

## 3.2 General Equilibrium Effects of Housing Vouchers

This section analyzes scaled-up housing voucher policies by comparing steady states with and without policy intervention, both in the short run and the long run. I define the short-run effects as the impact on the first generation of parents who benefit from the policy, as observed along the transition path.[63] The short-run comparison with the baseline highlights the general equilibrium effects of the policy on housing prices, capturing market responses. The long-run steady-state comparisons additionally reflect shifts in population distributions, including the evolution of beliefs about parenting.

When scaled-up, I will assume the housing voucher policy is financed through property taxes, which adds two terms to the household budget constraint:

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

where $\tau_r$ is the tax rate and $\hat{r}_{m,h,s}$, is the effective rent households face, which depends on their income. This policy is fully financed so that:

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

I begin by evaluating the long-run general equilibrium effects of various housing voucher policy designs to identify the one that maximizes welfare. The policies considered target

[63] At each generation along the transition path, the housing market is assumed to clear, with neighborhood quality adjusting accordingly. Appendix A.2 provides further details on how transition paths are computed.

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

| | Short-Run | | Long-Run | |
|---|---|---|---|---|
| Households | All<br>(1) | Eligible<br>(2) | All<br>(3) | Eligible<br>(4) |
| Beliefs about parenting | 0.0 | 0.0 | +12 | +51 |
| Parental input | -1.2 | +8.7 | +3.1 | +22 |
| Parental time | -7.0 | -12 | +1.8 | +24 |
| Neighborhood rank | +2.9 | +133 | +4.4 | +152 |
| Segregation | -53 | | -62 | |
| Future social mobility | +17 | | +24 | |
| Future income inequality | -0.6 | | -3.1 | |
| Future income | -0.9 | +0.5 | +2.3 | +8.4 |
| Welfare | +2.4 | +15 | +5.8 | +27 |

*Notes*: This table presents the general equilibrium effects of the optimal housing voucher policy, using the calibrated model. The considered policy targets the bottom 25% of households, which vouchers covering the gap between 10% of income and 85% of the median rent. Columns (1)-(2) contain short-run effects that reflect percentage changes for the first generation of parents who receive the vouchers, and Columns (3)-(4) present long-run effects that capture percentage changes between the baseline and the counterfactual economy steady states.

households between the 10th and 35th percentiles of the income distribution and cover the difference between 10–30% of household income and 65–95% of the neighborhood median rent. Appendix Figure A6 shows the predicted steady-state percentage changes in welfare, inequality, and income. The model reveals increasing welfare gains as policy generosity expands and the optimal design provides vouchers to households in the bottom 25th percentile of the income distribution, covering the difference between 10% of household income and 85% of the neighborhood median rent.[64]

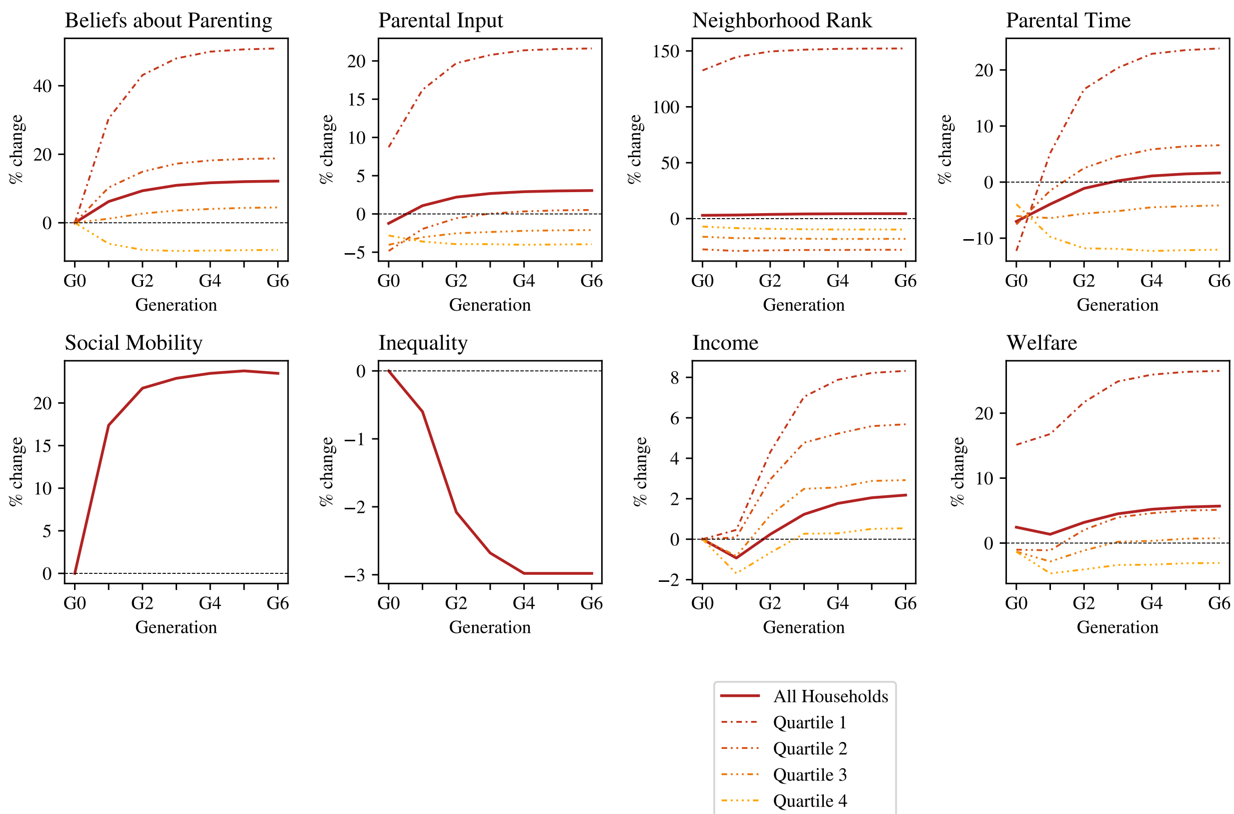
Table 4 reports the percentage changes in key outcomes in the very short run and long run resulting from the optimal policy. By construction, the policy does not affect beliefs in the short run, as it considers the first generation of parents who receive the voucher (Columns (1) and (2)). In the short run, eligible parents benefit from improved neighborhood quality, which mechanically raises their level of parental input while allowing them to reduce parental

[64]Consistent with the partial equilibrium analysis, the model predicts modest short- and long-run effects of the policy shown in the first two panels of Table 3, on segregation, parental behavior, and, consequently, welfare outcomes.

time, given the substitutability of inputs. In contrast, ineligible parents—particularly those in the second income quartile—experience a decline in neighborhood quality, leading to a reduction in their parental input. These opposing effects result in slightly lower aggregate parental input (-1.2%) and future income (-0.9%). Nevertheless, the policy improves future social mobility and reduces inequality, ultimately leading to a net gain in welfare of 2.4% in consumption-equivalent units.

In the long run, general equilibrium shifts in population distributions amplify the short-run effects of the housing voucher policy (Columns (3)–(4) vs. (1)–(2) in Table 4). Welfare gains reach 5.8% in consumption-equivalent units, accompanied by lower income inequality (–3.1%), higher social mobility (+23%), and, in contrast to the short-run effects, an increase in average income (+2.3%). Figure 4 illustrates the transition dynamics following the implementation of the optimal housing voucher policy. While neighborhood rank and residential segregation remain largely stable across generations, beliefs about parenting steadily improve—except among parents in the top income quartile, whose beliefs decline. As a result, both parental time and parental input increase over time for households in the bottom half of the income distribution. Households in the third income quartile, despite stronger beliefs, face rising housing costs and reduce their parental input. Among top earners, the combination of declining beliefs and higher housing prices leads to a further reduction in input. These shifts in beliefs and parental behavior contribute to sustained improvements in social mobility, reductions in inequality, and an eventual rise in average income above its baseline level, ultimately increasing welfare for most parents.

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




*Notes*: The figure shows the transition dynamics of eight outcomes under the optimal housing voucher policy.

Using the alternative model with perfect information to evaluate the policy yields similarly modest short-run effects on aggregate outcomes but markedly different long-run results.[65] In the short run, the main distinction from the baseline model is the positive response of parental time among eligible households, driven by the complementarity between parental input and neighborhood quality. However, since both models are calibrated using the same strategy, aggregate parental input responses remain broadly comparable. In the long run, however, the alternative model predicts a decline in parental input and a gradual decrease in aggregate income. While social mobility improves and inequality declines—albeit to a lesser

[65] Appendix Figure A8 illustrates the transition dynamics under the alternative model with perfect information.

extent than in the baseline model—overall welfare gains remain limited and are concentrated among eligible households, with welfare falling over time for ineligible groups.

This pattern holds across a broad range of housing voucher policy designs.[66] Although the alternative model also exhibits increasing welfare gains with greater policy generosity, these gains are more modest—remaining below 2% in consumption-equivalent units—and are accompanied by a growing equity-efficiency tradeoff absent in the baseline model: as policies become more generous and social mobility improves, aggregate income losses become more pronounced.

# 4 Conclusion

In this paper, I develop an overlapping generations model that incorporates beliefs about parenting and social learning within neighborhoods. In equilibrium, residential segregation gives rise to information frictions, resulting in heterogeneous beliefs and distorted parental choices: low-income parents tend to under-invest in their children, while high-income parents tend to over-invest. Calibrated to the U.S., the model explains two key patterns: the tendency of parents raised in disadvantaged neighborhoods to select similar environments for their own children, and the fact that college-educated parents, despite working longer hours, devote more time to their children than non-college-educated parents.

These belief-driven distortions have significant macroeconomic implications. They amplify income inequality, hinder social mobility, and depress aggregate income, thereby reducing welfare as measured by consumption equivalence. While one could reproduce these patterns by imposing substantial preference heterogeneity across socioeconomic groups, such an approach lacks empirical support.

The model's frictions provide a new rationale for implementing housing voucher policies. I assess these policies in both partial and general equilibrium. In partial equilibrium, the

[66] Appendix Figure A7 shows the predicted steady-state percentage changes in welfare, inequality, and income across a range of policy designs using the alternative model with perfect information.

results closely align with empirical findings. In general equilibrium, the model suggests that a more generous policy than those implemented in empirical studies yields the highest welfare gains, with increases of up to nearly 6% in consumption-equivalent units. Over the long run, such policies can simultaneously enhance income and social mobility. Importantly, when the policy is evaluated using an alternative model that replaces endogenous belief with preference heterogeneity, the predicted welfare gains are smaller, below 2% in consumption-equivalent units, and accompanied by a loss in aggregate income.

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# Appendix

# A Equilibrium and Transition Path Computation

## A.1 Equilibrium Computation

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

1. Make an initial guess for the distribution $F(h, s, m^0, \tilde{\alpha})$, the share of families $(h, s, m^0, \tilde{\alpha})$ in each neighborhood ($\lambda_m(h, s, m^0, \tilde{\alpha})$ for every $m$) and value function $U(h, s, m^0, \tilde{\alpha})$.

2. Given $U(h, s, m^0, \tilde{\alpha})$, compute the policy function $\tau(h, s, m^0, \tilde{\alpha}, m)$ and the corresponding $V(h, s, m^0, \tilde{\alpha}, m)$

3. Make an initial guess for rent prices $\{r_m\}_{m\in\mathbb{M}}$

4. Given $V(h, s, m^0, \tilde{\alpha}, m)$, $\tau(h, s, m^0, \tilde{\alpha}, m)$ and $\{r_m\}_{m\in\mathbb{M}}$, compute the share of families $(h, s, m^0, \tilde{\alpha})$ in each neighborhood ($\lambda_m(h, s, m^0, \tilde{\alpha})$ for every $m$).

5. Compute $\{r_m\}_{m\in\mathbb{M}}$ given the share of families in each neighborhood.

6. Iterate 3 to 5 until $\{r_m\}_{m\in\mathbb{M}}$ converges.

7. Given $\{r_m\}_{m\in\mathbb{M}}$, compute the expected value function $U(h, s, m^0, \tilde{\alpha})$ and based on it, obtain the policy function for time investment $\tau(h, s, m^0, \tilde{\alpha})$.

8. Compute the distribution $G(H, \mathrm{T}, m^0, h, m)$ given $\lambda_m$, and obtain updated beliefs in each neighborhood $\tilde{\alpha}(\tilde{\alpha}, m)$.

9. Compute the time-invariant distribution $F(h, s, m^0, \tilde{\alpha})$, based on the initial guess, the policy functions for neighborhoods $\lambda_m(h, s, m^0, \tilde{\alpha})$, and $\tau(h, s, m^0, \tilde{\alpha}, m)$, and on beliefs updating $\tilde{\alpha}(\tilde{\alpha}, m)$ obtained above.

10. Iterate from 1 to 9 until $F(h, s, m^0, \tilde{\alpha})$ converges.

## A.2 Transition Path Computation

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

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

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

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

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

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

   (b) Given $V_t(h, s, m^0, \tilde{\alpha}, m)$, $\tau_t(h, s, m^0, \tilde{\alpha}, m)$ and $\{\{r_m\}_{m\in\mathbb{M}}\}_t$, compute the share of families $(h, s, m^0, \tilde{\alpha})$ in each neighborhood $(\lambda_{m,t}(h, s, m^0, \tilde{\alpha})$ for every $m$).

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

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

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

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

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

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

# B Welfare Measure

## B.1 Aggregate Welfare Measure

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

$$V^P(h, s, m^0, \tilde{\alpha}, \Delta) = \mathbb{E}^P \ \log\left(c^{*P}(1+\Delta)\right) + \frac{\left(1 - \overline{\ell_s} - \kappa \ \tau^{*P}\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \ \delta \ rank_m$$
$$+ \ \iota \ \mathbb{1}_{m^0 = m^{*P}} + \ \nu \varepsilon_{m^{*P}} + \ bV^P\left(h', s', m^{*P}, \tilde{\alpha}, \Delta\right).$$

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

$$V^P(h, s, m^0, \tilde{\alpha}, \Delta) = (1 + \ b) \ \log\left(1 + \Delta\right) \ + \ \mathcal{V}^P(h, s, m^0, \tilde{\alpha}).$$

The average welfare is:

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

where $\Lambda^P$ is the distribution of initial states $\{h,s,m^0,\tilde{\alpha}\}$ in the economy $P$.

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

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

Which can be written as:

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

## B.2 Welfare Measure by Income Quartile

Consumption equivalence by income quartile, denoted $\Delta_i$, represents the percentage change in consumption that makes individuals indifferent between being born in income quartile $q(y)_i$, for $i \in \{1,2,3,4\}$, in the baseline economy ($P=0$) and in a counterfactual economy where policy $P \neq 0$ is implemented. Let $Q_i^P = \{h,s \mid y(h,s) \in q(y)_i\}_P$ denote the set of human capital and education pairs that define income quartile $q(y)_i$ in economy $P$. Denote by $V_i^P(h,s,m^0,\tilde{\alpha},\Delta i)$ the lifetime welfare of an agent in income quartile $q(y)_i$, conditional on their initial state $(h,s,m^0,\tilde{\alpha})$, if their consumption (and that of their descendants) is scaled by $(1+\Delta_i)$. Welfare can be written as in the previous section, and the average welfare in the income quartile $i$ is:

$$\bar{V}_i^P(\Delta_i) = \sum_{s \in Q_i^P, m^0} \int_{h \in Q_i^P, \tilde{\alpha}} V^P(h,s,m^0,\tilde{\alpha},\Delta)\Lambda^P(h,s,m^0,\tilde{\alpha}),$$

where $\Lambda^P$ is the distribution of initial states $\{h,s,m^0,\tilde{\alpha}\}$ in the economy $P$.

The consumption equivalence $\Delta_i^P$ makes the average individual in income quartile $i$ indifferent between being born in the baseline economy $P=0$ and one in which policy $P \neq 0$

is in place, such that:

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

Which can be written as:

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

# C Data and Additional Information on the Calibration

## C.1 Data Description

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

### C.1.1 The American Time Use Survey (ATUS)

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

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

I restrict the sample to individuals in a two-parent household, defined as married individuals whose youngest child is under age 18.[67] As all the other datasets are from 2000, I use the earliest ATUS survey year, 2003. In 2003, 5,597 married parents were interviewed, 2,168 of whom had a college degree.[68] Table A1 describes how married couples with a child below 18 in the household in the United States allocate their time in 2003.

[67] 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.

[68] Parent's education is defined as the highest level of education of the respondent. Using the highest education level of both parents or the mother doesn't change the numbers in Table A3. I removed 255 observations that have less than 23 hours of activity a day reported. 92% of the remaining observations have precisely 24 hours of activity a day reported.

Table A1: ATUS Activity Coding Structure, 2003

| Label | Description | Non-college parents | College parents |
|---|---|---|---|
| | | Hours per day | |
| **Childcare** | | **1.17** | **1.58** |
| Caring for and helping household children | Time spent in caring for or helping household children | 1.17 | 1.58 |
| **Work and Education** | | **4.36** | **4.66** |
| Working and Work-related Activities | Time spent in work activities such as working, doing activities as part of one's job, engaging in income-generating activities (not as part of one's job), and looking for jobs and interviewing. | 4.27 | 4.56 |
| Educational activities | Time spent in non-work education activities, such as taking classes, conducting research and homework, administrative tasks, and extracurricular activities except sports. | 0.10 | 0.10 |
| **Personal leisure** | | **14.39** | **13.64** |
| Personal care | Time spent in personal care activities such as sleeping, grooming, and health-related self care. | 9.05 | 8.66 |
| Eat and drinking | Time spent in activities such as eating and drinking not done as work or a volunteer activity, whether the respondent was alone, with others, at home, at a place of purchase, in transit, or somewhere else. | 1.02 | 1.19 |
| Socializing, relaxing, and leisure | Time spent in personal interest or leisure activities such as communicating with others and attending parties and meetings; and leisure activities such as relaxing, playing (passive) games (unless playing with children only), watching television, playing or listening to music, reading, writing, and all hobbies. | 3.69 | 2.88 |
| Sports, exercise, and recreation | Time spent in sports, exercise and recreational activities such as pleasure boating, throwing a Frisbee, kite flying, or ballooning, and active, participatory outdoor games or activities, such as horseshoes, croquet, and paintball. | 0.25 | 0.33 |
| Religious and spiritual activities | Time spent in work activities such as working, doing activities as part of one's job, engaging in income-generating activities (not as part of one's job), and looking for jobs and interviewing. | 0.14 | 0.17 |
| Volunteer activities | Time spent in volunteer (unpaid) activities done by the respondent for individuals or institutions through formal organizations, such as unpaid performance arts activities, socializing related to volunteering and attending church service as a volunteer activity. | 0.13 | 0.25 |
| Telephone calls | Time spent in telephone communication activities such as talking on phone, waiting for a phone call or Skyping (2011+). | 0.05 | 0.07 |

| | | | |
|---|---|---|---|
| Professional and personal care services | Time spent in activities such as obtaining, receiving, and/or purchasing professional and personal care services provided by someone else. Professional services include child care, financial, legal, medical, and other adult care, real estate, and veterinary. Personal care service activities include massages, haircuts, manicures, and tanning at salons. | 0.07 | 0.09 |
| **Other** | | **4.04** | **4.07** |
| Household activities | Time spent in household activities such as maintaining their household, household management and organizational activities. | 2.13 | 1.94 |
| Caring for and helping household members (except household children) | Time spent in caring for or helping any adult in the respondent's household, regardless of relationship, age, or physical or mental health status. | 0.04 | 0.03 |
| Caring for and helping non-household members | Time spent in caring for or helping any child or adult who is not part of the respondent's household, regardless of relationship, age, or physical or mental health status. | 0.10 | 0.08 |
| Household services | Time spent in activities such as obtaining and purchasing household services provided by someone else. Household services include yard and house cleaning, cooking, pet care, tailoring and laundering services, vehicle and home repairs, maintenance, and construction. Watching someone else perform paid household activities (cooking, cleaning, repairing, etc.) should be coded here, provided "watching" was the respondent's primary activity. | 0.01 | 0.02 |
| Government services and civic obligations | Time spent in activities such as using government services (police, fire, social services), purchasing government-required licenses or paying fines or fees, fulfilling government-required duties (jury duty, parole meetings, court appearances), and participating in activities that assist or impact government processes (voting, town hall meetings). | 0.00 | 0.00 |
| Consumer purchases | Time spent in activities such as purchases and rentals of consumer goods, regardless of mode or place of purchase or rental (in person, via telephone, over the internet, at home, or in a store). | 0.43 | 0.49 |
| Travel | Time spent in travel or transportation activities such as commuting, walking somewhere, or waiting for the bus or train. | 1.33 | 1.51 |
| **Total** | | **24.0** | **24.0** |

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

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

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

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

### C.1.3 National Historical Geographic Information System (NHGIS)

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

### C.1.4 American Community Surveys (ACS) 2000

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

U.S. Census Bureau that has replaced the decennial census as the key source of information about the American population and housing characteristics.

## C.2 Ten Synthetic Neighborhoods

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

Table A2 summarizes the characteristics of these neighborhoods. By construction, median household income increases with neighborhood quality. As expected, so does the fraction of individuals above 25 with a college degree (Column (2)). Note that housing expenditure shares decrease with neighborhood quality (Column (4)), which suggests and motivates non-homothetic preferences.

I use Add Health data and repeat the same exercise to construct the ten synthetic neighborhoods in which the interviewee resided in waves I (1994-1995) and V (2016-2018).[69] The sample is restricted to interviewees who do not live in their parent's houses in adulthood in Wave V. All observations are weighted by the sampling weights of the corresponding wave provided by Add Health. I only use the information at the census tract level available in the Add Health dataset, and due to the sample size, I do it at the U.S. level instead of within commuting zones. Thanks to the panel form of the dataset, I can observe in which synthetic neighborhood an adolescent lived in 1994-1995 and in which synthetic neighborhood she lived during adulthood, in 2016-2018.

[69] In Appendix Section F.3, I also proxy neighborhood quality by the share of residents above 25 with a college degree as a robustness check (Diamond, 2016).

Table A2: Characteristics of Synthetic Neighborhoods

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

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

## C.3 Parental Time

To measure parental time, I use the BLS definition of childcare as ”primary childcare activities” and respect the activity coding structure of ATUS to describe how parents from different socioeconomic groups allocate their time between childcare, leisure, and market work.[70] Market work hours include all hours spent in work-related and education-related activities. The rest of the time is considered leisure time. For informational purposes, I divide this last group into two sub-groups: all personal leisure activities and other activities.[71]

[70]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”.

[71]Personal leisure is composed of eight activities: “eat and drink”, “personal care”, “telephone calls”, “professional and personal care services”, “religious and spiritual activities”, “socializing, relaxing, and leisure”, “sports, exercise, and recreation”, “volunteer activities”. I remove eight hours of sleep needs from ”personal care” that includes sleep time, a standard assumption in the literature. Others are ”household activities,” ”household services,” ”government services and civic obligations,” ”consumer purchases,” ”travel,”’ and ”caring for and helping non-household and [other] household members.” Appendix Table A1 provides detailed information on each activity.

Table A3 summarizes parents' time use in the United States by education. Note that the sample only contains two-parent households, defined as married individuals whose youngest child is under age 18. As standard in the literature, I assume 16 hours of disposable hours and eight hours of sleep are needed per day. I consider an endowment of 16 disposable hours per day in the model and normalize it to one. Parental time patterns are moments to match.

Both parental time and market work time increase in education. Parents with a college degree spend about 1.6 hours per day in childcare activities and 4.7 hours in market work activities, while parents without a college degree spend 1.2 hours in childcare and 4.4 hours in market work.[72] 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.[73]

TABLE A3: Parents' Time Allocation by Education, ATUS 2003

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

*Notes*: This table provides information on time allocation by married parents in the United States. The data source is ATUS 2003. Childcare activity follows the BLS definition of "primary childcare activities." Market work contains all work-related and educational activities. Leisure includes all the other activities. For more details on activity grouping, see Appendix Table A1.

In addition, Add Health survey contains information about ten parent-child activities in 1994-1995.[74] To proxy for time allocated in childcare, I construct a variable that counts

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

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

[74] 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)".

the number of activities that happened over the past four weeks with the mother and the father of the child. I follow the United States Bureau of Labor Statistics (BLS) definition of "primary childcare activities" constructed and exclude two out of the ten events: "shopping" and "went to a religious service or church-related event".[75] The remaining eight activities are: "played a sport", "talked about someone you're dating, or a party you went to", "talked about a personal problem you were having", "had a serious argument about your behavior", "talked about your school work or grades", "worked on a project for school", "talked about other things you're doing in school", "went to a movie, play, museum, concert, or sports event".

## C.4 College Graduation

I use AddHealth to estimate the individual probability of having a college degree conditional on parents and child variables. In the sample, anyone with at least a bachelor's degree in Wave V is considered to have a college degree. To proxy for children's realized human capital, I use an average of Wave II (1996) grades in English, mathematics, social science, and science. Information on parents' highest education level and income comes from the parent survey conducted in 1994-1995. Table A4 contains the estimates of the following weighted logit regression of college completion:

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

where $g(h', \hat{y}, s)$ 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 $rank_{\hat{y}} \in \{1, 2, ..., 10\}$ is the household income rank in 1994-1995.

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

Table A4: Estimated Parameters of the College Graduation Probability

| | College graduation probability | |
|---|---|---|
| $\gamma_1$ | -3.83 | (0.35) |
| $\gamma_2$ | 0.35 | (0.02) |
| $\gamma_3$ | 0.15 | (0.02) |
| $\gamma_4$ | 1.11 | (0.11) |
| Pseudo $R^2$ | 0.28 | |

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

## C.5 Housing Supply

Rental prices are determined in equilibrium given the supply function: $\mathcal{H}_m = \zeta_m r_m^{\eta}$, where $r_m$ is the equilibrium rent price in the neighborhood $m$, and $\eta$ is the price elasticity of housing supply. Saiz (2010) estimates population-weighted average price elasticity in the average metropolitan area of the U.S. to be 1.75, so I set $\eta = 1.75$. The remaining parameters $\zeta_m$ can be estimated directly from the synthetic neighborhood density and rents. Figure A1 summarizes the log-relationship between density (Column (5) Table A2) and rents across the ten synthetic neighborhoods. Without loss of generality, the numeraire is the average household earnings in the economy.

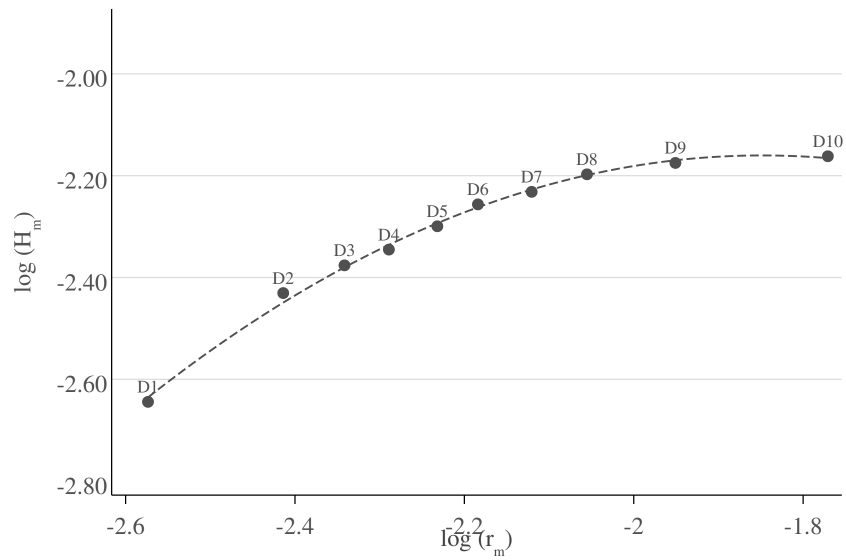
## C.6 Moments

**Intergenerational residential mobility:**

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

**Targeted moments:**

Figure A1: Housing Supply




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

Table A5: Moments Description

| Moment | Description | Data restriction | Source |
|---|---|---|---|
| **Income** | | | |
| Average rent over income | Ratio of average rent over average household income of families. The average rent is computed using the density and the rent prices in each of the ten neighborhoods in Table A2. | 100 biggest commuting zones - families with their own child below 18 | ACS 2000, NHGIS 2000 |
| Income ratio non-college - college | Household income of non-college parents over household income of college parents. | 100 biggest commuting zones - families with own child below 18 | ACS 2000 |
| Income inequality | Families' income Gini, transformed in a 20-year Gini using the 2002 Shorrocks mobility index estimated by Kopczuk et al. (2010). | 100 biggest commuting zones - families with own child below 18 | ACS 2000 |
| Avg. marginal income tax | Average in the population of the marginal income tax that can be written as $1 - \lambda_y * (1 - \tau_y) * y^{-\tau_y}$. | | Urban & Brookings Tax Policy Center. |
| **Residential mobility** | | | |
| Segregation | Gini coefficient across the ten synthetic neighborhoods household median income. | 100 biggest commuting zones - families with own child below 18 | NHGIS 2000 |

| | | | |
|---|---|---|---|
| Neighborhood effect (25th pct.) | For families with below-median income (p = 25). Simulate moves to every neighborhood. Regress children's income on fixed effects for each neighborhood, controlling for origin-by-destination fixed effects. | Tax records covering the U.S. population, spanning 1996-2012. 100 biggest commuting zones (CZ). Within CZ estimates. The authors use income ranks at age 26 because of outliers. In addition, they control for the fraction of childhood spent in a county. | Chetty and Hendren (2018a) |
| Neighborhood effect (75th pct.) | For families with above-median income (p = 75). Simulate moves to every neighborhood. Regress children's income on fixed effects for each neighborhood, controlling for origin-by-destination fixed effects. | Tax records covering the U.S. population, spanning 1996-2012. 100 biggest commuting zones (CZ). Within CZ estimates. The authors use income ranks at age 26 because of outliers. In addition, they control for the fraction of childhood spent in a county. | Chetty and Hendren (2018a) |
| Residential mobility (D1-D1) | Fraction of children born in the first synthetic neighborhood who live in this same neighborhood when they are adults. | 1994-2018. Interviewees who do not live in their parents' houses in adulthood (2018). | AddHealth Wave I and Wave V |
| Explained share place-based effects | One minus ratio of variance of neighborhood effects (25th pct.) without demographics effects over variance of neighborhood effects (25th pct.) with demographics effects. | Variance explanation of neighborhood effects (25th pct.) of all observed demographic factors. Tax records covering the U.S. population, spanning 1996-2012. 100 biggest commuting zones (CZ). Within CZ estimates. The authors use income ranks at age 26 because of outliers. In addition, they control for the fraction of childhood spent in a county. | Chetty and Hendren (2018a) |
| Rent gradient | Regression coefficient of rent on neighborhood rank. | 100 biggest commuting zones | NHGIS 2000 |
| **Social mobility** | | | |
| Rank-rank coefficient | Regression coefficient of child household income rank on parental household income rank. | Tax records covering the U.S. population, spanning 1996-2012. | Chetty et al. (2014) |
| **Parental time** | | | |
| Income gradient in parental time | Regression coefficient of parental time on income quartile of the parents. | Two-parent households with 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 own child below 18. Weighted. | ATUS 2003 |
| **Beliefs** | | | |
| Beliefs effects on parental input Q1 | Partial equilibrium effects of providing information to parents below the bottom quartile of the income distribution on parental input. | Eliciting the beliefs about parenting of disadvantaged African American mothers, the authors find that shifting median beliefs to the lowest estimated elasticity would boost parental inputs by 3.6% to 24.3%, with an average increase of 11.6%. | Cunha et al. (2013) |

*Notes*: This table provides information on targeted moments and their computation.

## C.7 Externally Calibrated Parameters

Table A6: Externally Calibrated Parameters

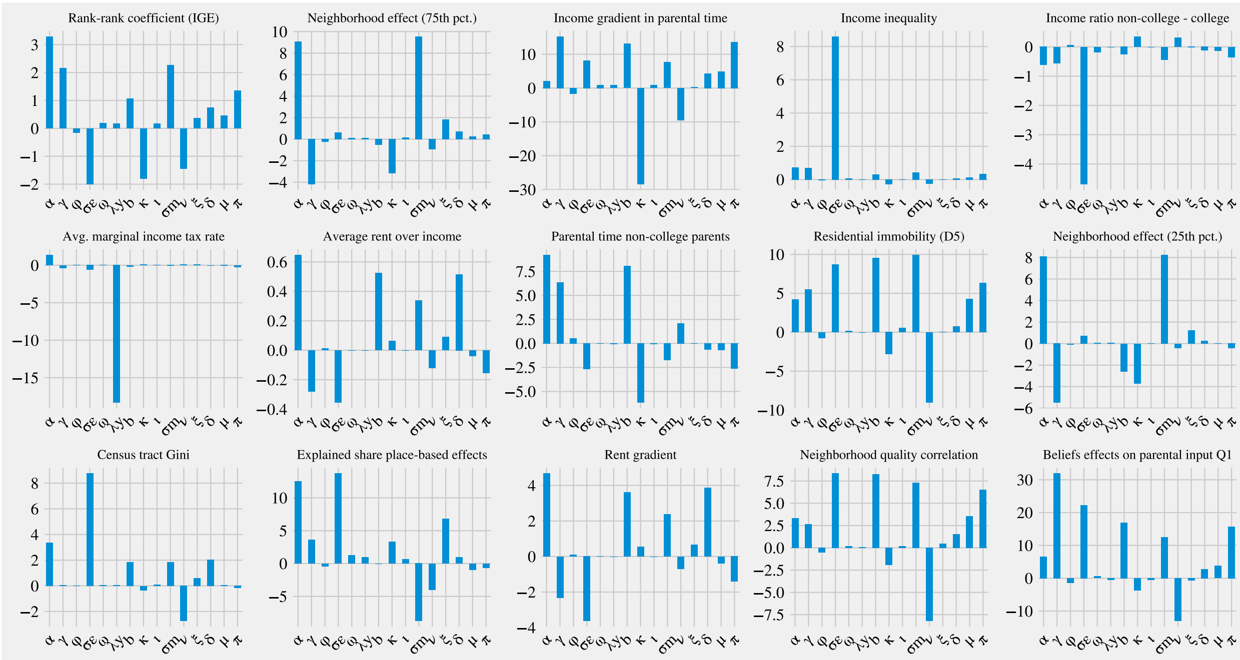
| Parameter | Description | Value | Source |
|---|---|---|---|
| $N$ | Number of neighborhoods | 10 | Deciles NHGIS |
| $\beta$ | Returns on parental human capital | $1-\alpha$ | Constant returns |
| $\psi$ | Intertemporal elasticity of substitution | 0.5 | Standard |
| $w$ | Wage rate | 1 | Normalization |
| $\bar{A}$ | Scaling parameter | 1.5 | Normalization |
| $\mu_{\bar{m}}$ | Average neighborhood quality | 1 | Normalization |
| $\tau_y$ | Tax progressivity | 0.18 | Heathcote et al. (2017) |
| $\eta$ | Price elasticity of housing supply | 1.75 | Saiz (2010) |
| $\zeta_1$ | Housing supply coefficient D1 | 1.859 | NHGIS |
| $\zeta_2$ | Housing supply coefficient D2 | 1.794 | NHGIS |
| $\zeta_3$ | Housing supply coefficient D3 | 1.722 | NHGIS |
| $\zeta_4$ | Housing supply coefficient D4 | 1.661 | NHGIS |
| $\zeta_5$ | Housing supply coefficient D5 | 1.606 | NHGIS |
| $\zeta_6$ | Housing supply coefficient D6 | 1.566 | NHGIS |
| $\zeta_7$ | Housing supply coefficient D7 | 1.479 | NHGIS |
| $\zeta_8$ | Housing supply coefficient D8 | 1.399 | NHGIS |
| $\zeta_9$ | Housing supply coefficient D9 | 1.239 | NHGIS |
| $\zeta_{10}$ | Housing supply coefficient D10 | 0.937 | NHGIS |
| $\overline{\ell_0}$ | Non-college labor supply | 0.275 | ATUS 2003 |
| $\overline{\ell_1}$ | College labor supply | 0.294 | ATUS 2003 |
| $\gamma_1$ | College graduation coeff. - intercept | -3.83 | Add Health |
| $\gamma_2$ | College graduation coeff. - human capital | 0.35 | Add Health |
| $\gamma_3$ | College graduation coeff. - income | 0.15 | Add Health |
| $\gamma_4$ | College graduation coeff. - education | 1.11 | Add Health |

*Notes*: The table shows all the externally calibrated parameters.

## C.8 Model Sensitivity

Figure A2 shows the percentage change in each moment with respect to a 10% level increase in each parameter. The results are computed by comparing steady states.

Figure A2: Model Sensitivity




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

# D Alternative Modeling

## D.1 Alternative Model with Perfect Information

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

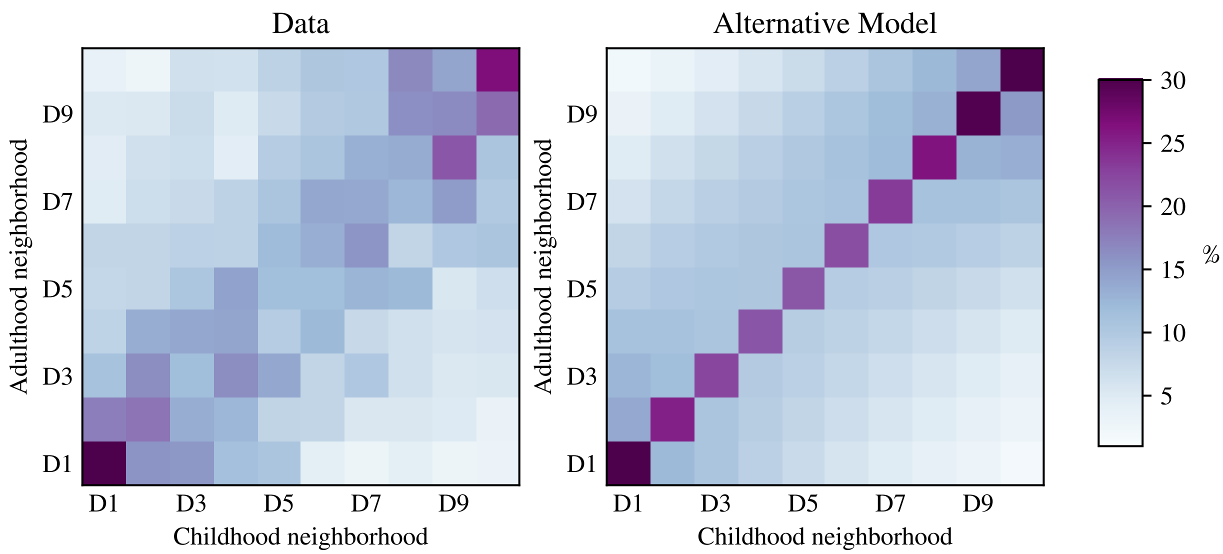
$$\log(c) + \frac{\left(1 - \overline{\ell_s} - \kappa_s\, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \delta\, rank_m + \iota\, \mathbb{1}_{m^0=m} - \tilde{\iota}(m^0 - m)^2 + \nu\varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right].$$

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

| Parameter | Description | Moment | Data | Model |
|---|---|---|---|---|
| **Skill Formation** | | | | |
| $\alpha$ = 0.725 | Parental inputs elasticity | Rank-rank coefficient (IGE) | 0.341 | 0.338 |
| $\gamma$ = 0.3 | Parental time share | Neighborhood effect (75th pct.) | 0.046 | 0.051 |
| $\varphi$ = -1.25 | Substitutability | Income gradient in parental time | 0.14 | 0.123 |
| $\sigma_\epsilon$ = 0.713 | Ability shock variance | Income Gini | 0.333 | 0.340 |
| **Labor Market and Preferences** | | | | |
| $\omega$ = 0.01 | College wage premium | Income ratio non-college - college | 0.554 | 0.548 |
| $\lambda_y$ = 0.67 | Tax function scalar | Avg. marginal income tax rate | 0.351 | 0.355 |
| $b$ = 0.375 | Altruism | Average rent over income | 0.117 | 0.117 |
| $\kappa_0$ = 0.667 | Non college parents' time disutility | Parental time non-college parents | 0.075 | 0.076 |
| $\iota$ = 0.016 | Place of birth preference | Residential mobility (D1-D1) | 0.302 | 0.302 |
| **Neighborhoods** | | | | |
| $\sigma_m$ = 0.082 | Neighborhood quality | Neighborhood effect (25th pct.) | 0.062 | 0.06 |
| $\nu$ = 0.022 | Taste shock variance | Census tract Gini | 0.231 | 0.219 |
| $\xi$ = 0.08 | Demographics effects | Explained share place-based effects | 0.24 | 0.243 |
| $\delta$ = 0.008 | Amenities | Rent price gradient | 54.2 | 54.2 |
| **Others** | | | | |
| $\tilde{\iota}$ = 0.0006 | Quadratic moving costs | Neighborhood quality correlation | 0.417 | 0.44 |
| $\kappa_1$ = 0.319 | College parents' time disutility | Parental time college parents | 0.1 | 0.11 |

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

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




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

## D.2 Extended Alternative Model with Perfect Information

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

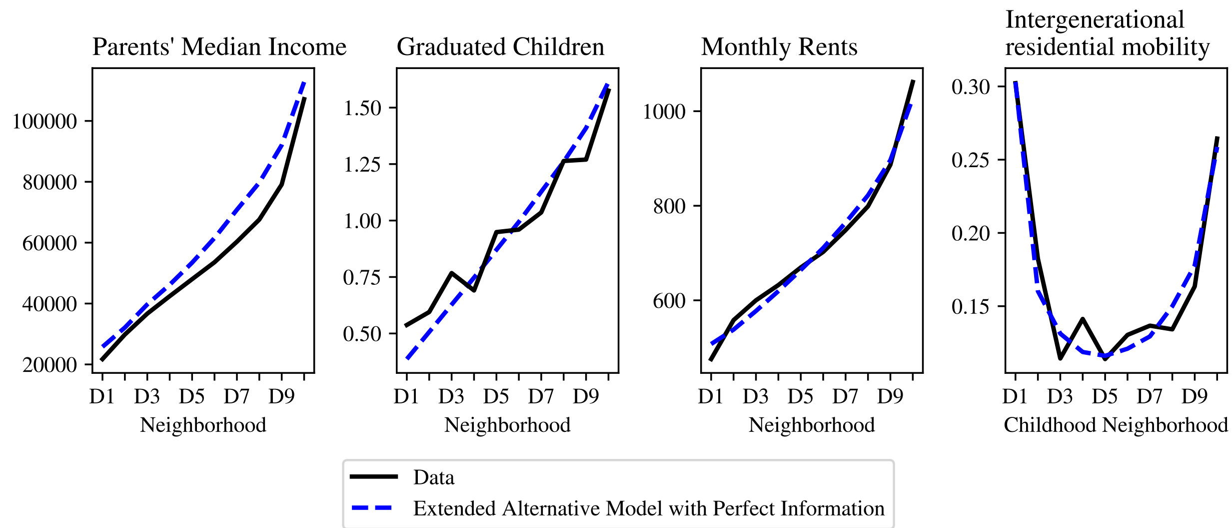
$$\log{(c)} + \frac{\left(1 - \overline{\ell_s} - \kappa_s\, \tau\right)^{1-\frac{1}{\psi}}}{1 - \frac{1}{\psi}} + \delta\; rank_m + \iota_{m^0}\; \mathbb{1}_{m^0 = m} - \tilde{\iota}(m^0 - m)^2 + \nu \varepsilon_m + b\mathrm{E}\left[\mathcal{V}\left(h', s', m, \alpha\right)\right].$$

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

| Parameter | Description | Moment | Data | Model |
|---|---|---|---|---|
| **Skill Formation** | | | | |
| $\alpha$ = 0.725 | Parental inputs elasticity | Rank-rank coefficient (IGE) | 0.341 | 0.338 |
| $\gamma$ = 0.3 | Parental time share | Neighborhood effect (75th pct.) | 0.046 | 0.051 |
| $\varphi$ = -1.25 | Substitutability | Income gradient in parental time | 0.14 | 0.122 |
| $\sigma_\epsilon$ = 0.713 | Ability shock variance | Income Gini | 0.333 | 0.34 |
| **Labor Market and Preferences** | | | | |
| $\omega$ = 0.01 | College wage premium | Income ratio non-college - college | 0.554 | 0.548 |
| $\lambda_y$ = 0.67 | Tax function scalar | Avg. marginal income tax rate | 0.351 | 0.355 |
| $b$ = 0.375 | Altruism | Average rent over income | 0.117 | 0.117 |
| $\kappa_0$ = 0.667 | Non college parents' time disutility | Parental time non-college parents | 0.075 | 0.076 |
| $\iota_1$ = 0.019 | Place of birth pref. 1 | Residential mobility (D1-D1) | 0.302 | 0.303 |
| $\iota_2$ = 0.0017 | Place of birth pref. 2 | Residential mobility (D2-D2) | 0.182 | 0.16 |
| $\iota_3$ = 0.0012 | Place of birth pref. 3 | Residential mobility (D3-D3) | 0.114 | 0.131 |
| $\iota_4$ = 0.0008 | Place of birth pref. 4 | Residential mobility (D4-D4) | 0.141 | 0.119 |
| $\iota_5$ = 0.0008 | Place of birth pref. 5 | Residential mobility (D5-D5) | 0.114 | 0.116 |
| $\iota_6$ = 0.0007 | Place of birth pref. 6 | Residential mobility (D6-D6) | 0.13 | 0.121 |
| $\iota_7$ = 0.0005 | Place of birth pref. 7 | Residential mobility (D7-D7) | 0.137 | 0.129 |
| $\iota_8$ = 0.0005 | Place of birth pref. 8 | Residential mobility (D8-D8) | 0.134 | 0.15 |
| $\iota_9$ = 0.0003 | Place of birth pref. 9 | Residential mobility (D9-D9) | 0.164 | 0.178 |
| $\iota_{10}$ = 0.0066 | Place of birth pref. 10 | Residential mobility (D10-D10) | 0.264 | 0.259 |
| **Neighborhoods** | | | | |
| $\sigma_m$ = 0.082 | Neighborhood quality | Neighborhood effect (25th pct.) | 0.062 | 0.06 |
| $\nu$ = 0.022 | Taste shock variance | Census tract Gini | 0.221 | 0.22 |
| $\xi$ = 0.08 | Demographics effects | Explained share place-based effects | 0.24 | 0.255 |
| $\delta$ = 0.008 | Amenities | Rent price gradient | 54.2 | 53.9 |
| **Others** | | | | |
| $\tilde{\iota}$ = 0.0006 | Quadratic moving costs | Neighborhood quality correlation | 0.417 | 0.403 |
| $\kappa_1$ = 0.319 | College partents' time disutility | Parental time college parents | 0.1 | 0.11 |

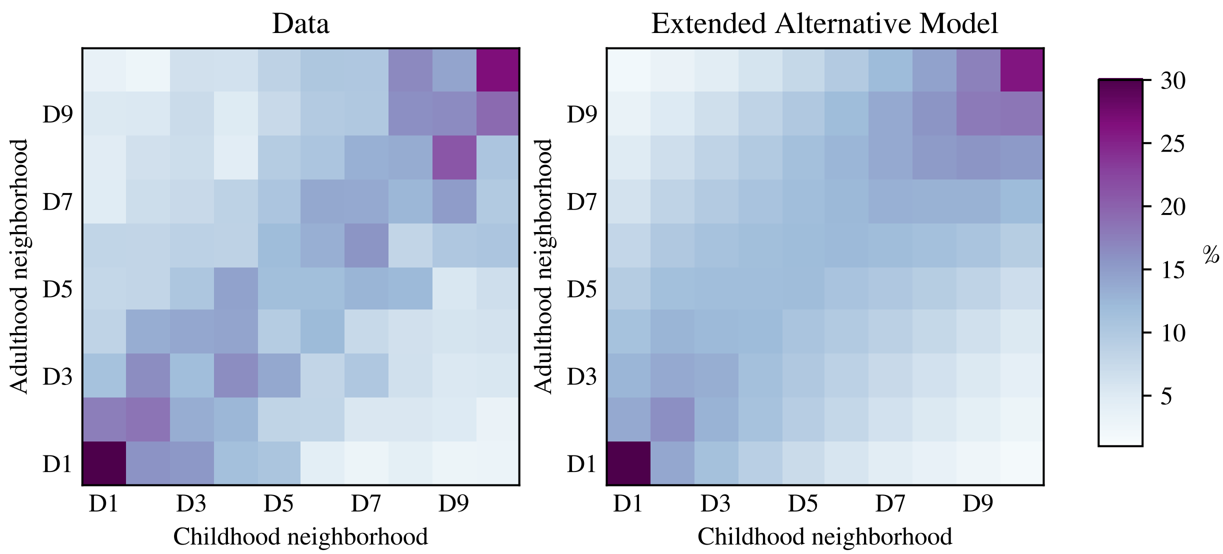
*Notes*: This table reports the internally calibrated parameters of the extended alternative model with perfect information and the observed and simulated moments associated with the parameter estimates. * To improve smoothness and similarity between calibrated models, residential immobility moments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

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




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

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




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

# E Additional Results

## E.1 The Impact of Beliefs about Parenting

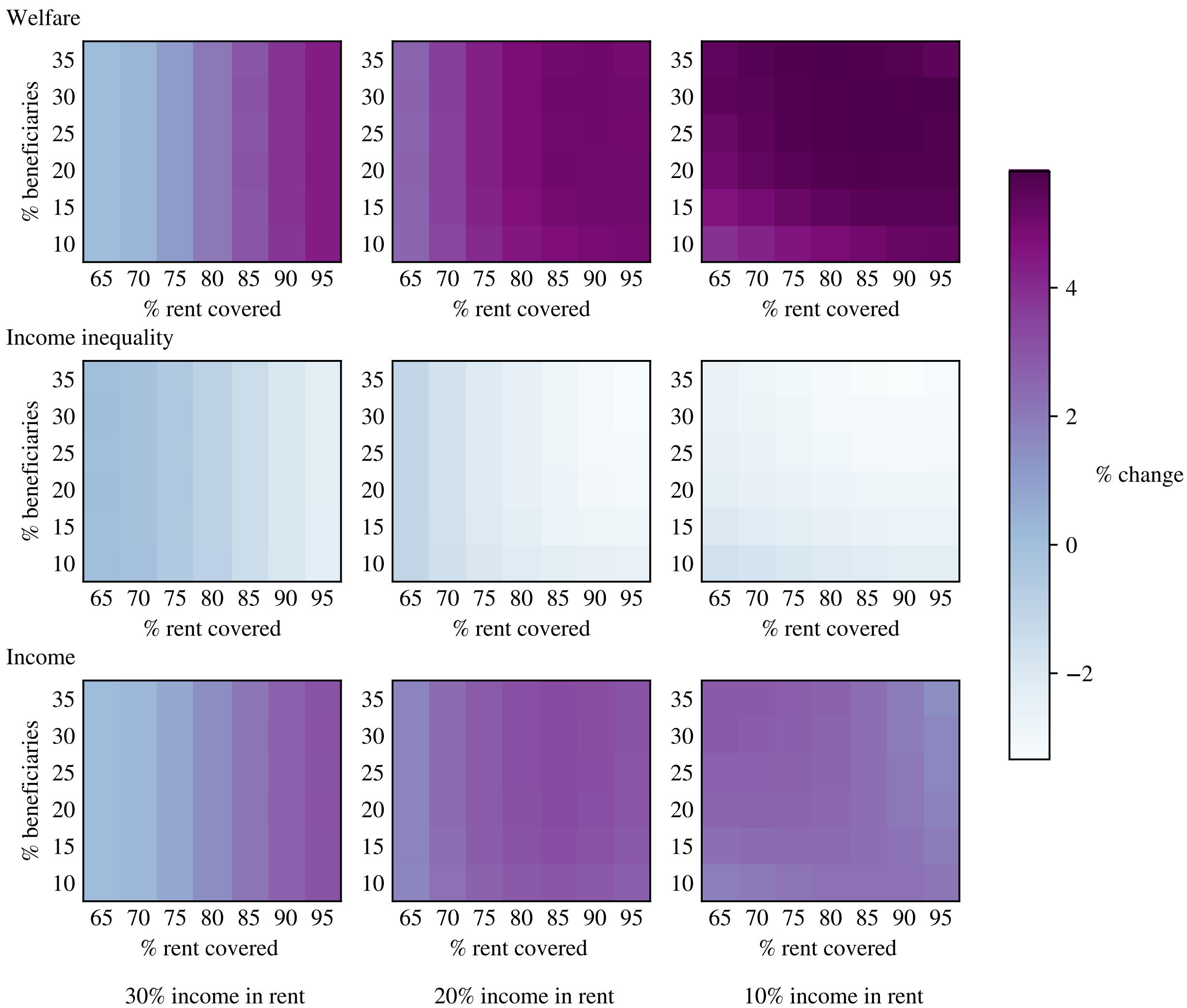
Table A9: General Equilibrium Effects of Providing Information (% changes)

| | | Baseline Income quartile | | | |
|---|---|---|---|---|---|
| | All | 1st | 2nd | 3rd | 4th |
| Beliefs about parenting | +12.3 | +51.8 | +19.2 | +4.6 | -8.3 |
| Parental input | +4.6 | +10.7 | +5.7 | +2.9 | -0.6 |
| Parental time | +10.7 | +40.0 | +15.8 | +5.2 | -7.4 |
| Neighborhood rank | +1.7 | -3.7 | -0.5 | +0.3 | -0.5 |
| Income | +3.8 | +2.0 | +0.2 | +0.1 | +0.1 |
| % | 0.0 | -12.4 | -0.2 | +4.6 | +7.1 |

*Notes*: This table reports the percentage changes in model-generated moments resulting from providing information, based on the baseline calibrated model. Income quartiles are fixed at baseline. *Social mobility* is measured by minus the income rank-rank coefficient, *Segregation* by the neighborhood Gini coefficient, and *Inequality* by the income Gini coefficient.

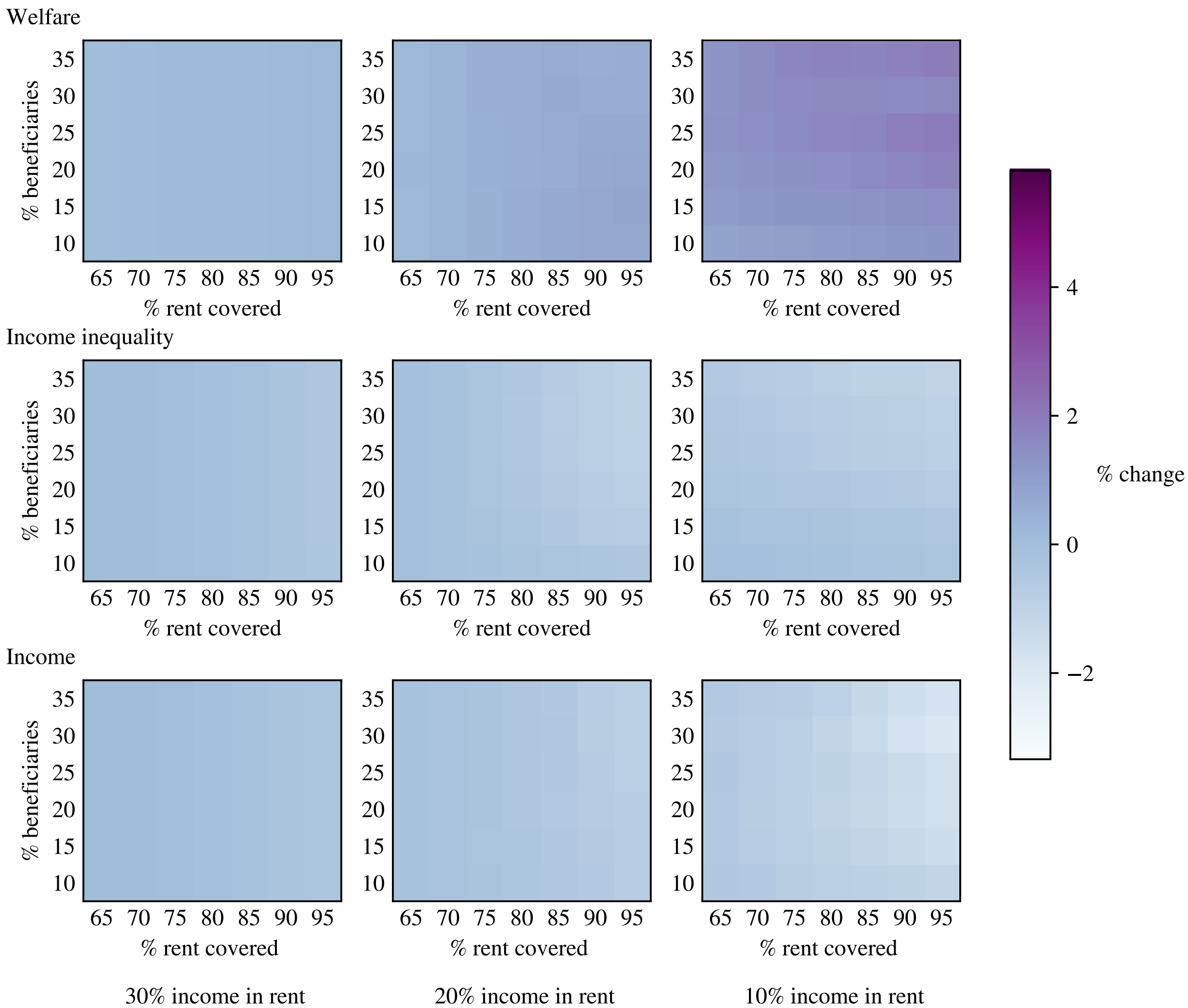
## E.2 General Equilibrium Effects of a Range of Housing Voucher Policy Designs

Figure A6: General Equilibrium Effects of housing voucher policies
(% changes)



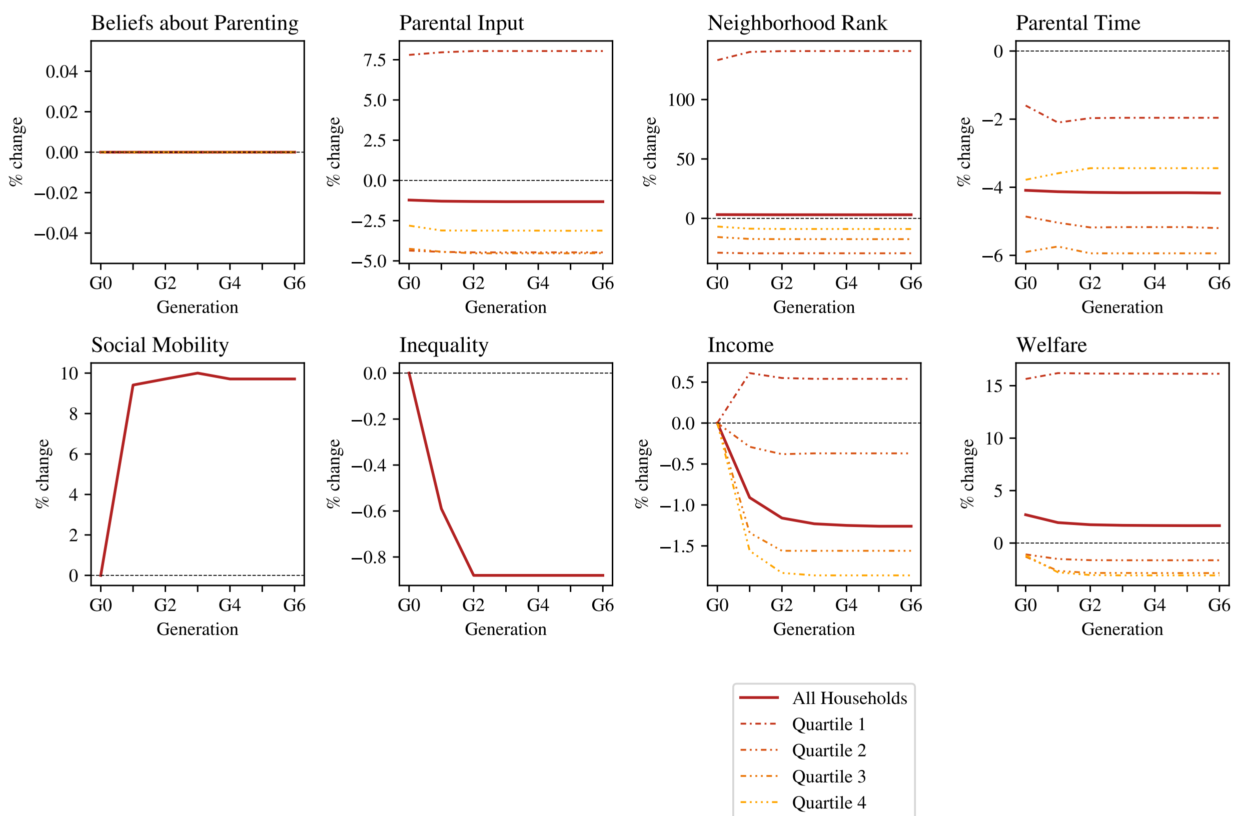

*Notes*: This figure displays the general equilibrium effects on welfare, income inequality, and income of housing voucher policies in percentage change. *Income inequality* by the income Gini coefficient.

Figure A7: General Equilibrium Effects of housing voucher policies
(% changes)
Extended Alternative Model with Perfect Information




*Notes*: This figure displays the general equilibrium effects using the extended alternative model with perfect information on welfare, income inequality, and income of housing voucher policies in percentage change. *Income inequality* by the income Gini coefficient.

Figure A8: Transition Dynamics of the Economy with Optimal Housing Voucher Policy
(% deviation from initial steady state)
Extended Alternative Model with Perfect Information




*Notes*: The figure shows the transition dynamics of eight outcomes under the optimal housing voucher policy using the extended alternative model with perfect information.

# F Neighborhood Quality and Parental Time in the United States

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

## F.1 Correlation between Time and Neighborhood

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

As a first step, using the Add Health datasets, I verify the two parental inputs—parental time measured by the number of parent-child activities done over four weeks and standardized neighborhood quality proxied by household median income—matter for later outcomes.[76] Columns (1) and (2) of Table A10 show that parental time and neighborhood quality positively correlate with later child skills.[77] Conditional on other parents' socioeconomic status (SES), the number of parent-child activities and neighborhood quality co-move with the graduation probability measured twenty-two years later. All coefficients are positive and significant at a one percent level. Motivated by this evidence, I consider the parental time and neighborhood quality variables to be good proxies for parental inputs of the technology of skill formation.[78]

Columns (3) and (4) of Table A10 display a positive and significant correlation between the two parental inputs.[79] Note that in both regressions of Column (3) and (4) of Table A10, I control for school ID fixed effects. A systematic difference in school characteristics is not what drives the correlation. Nevertheless, research finds that parental time increases with parents' education in the United States (see Doepke et al. (2023) for a review). This observed correlation could be driven by a neighborhood composition effect. In Column (4) of

[76]See Appendix section for variable construction.

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

[78]Appendix Table A11 presents the OLS regression coefficients with a different definition of neighborhood quality and parental time variables. Results are robust to definition changes.

[79]The results are robust to the use of alternative proxies for parental inputs. See Appendix Table A11.

Table A10, I control for three variables measuring households' socioeconomic status: parents' highest level of education, family income, and parent's marital status.[80] The sample size shrinks to 12,633 observations due to missing values in household characteristics variables, but the relationship remains positive and significant at a one percent level. This suggests that the neighborhood composition effect does not drive all the correlation between the two parental inputs.

Table A10: Parental Time and Neighborhood Quality, Add-Health 1994-1995 and 2016-2018

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

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

While this result is consistent with the assumption of beliefs about parenting 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

[80] 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.

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

## F.2 Childhood Neighborhood and Adulthood Choices

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

Column (5) of Table A10 displays a positive and significant correlation between childhood (Wave I) and adulthood (Wave V) neighborhood quality. I restrict the sample to interviewees who do not live with their parents and control for commuting zones and age-fixed effects. The correlation remains highly significant even after controlling for household income, marital status, and education status. Other factors might affect residential choices. Racial discrimination and wealth are two of them. In Column (6) of Table A10, 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.[81] 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.[82]

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

[82]The results are robust to the use of the fraction of adults with a college degree for neighborhood quality.

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

## F.3 Robustness checks

As a robustness check, I proxy neighborhood quality by the share of residents above 25 with a college degree (Diamond, 2016). In addition, the proxy of parental time is a count of parent-child activities excluding "went to a movie, play, museum, concert, or sports event".[83] Results are unchanged.

Table A11: Parental Time and Neighborhood Quality, Add-Health 1994-1995 and 2016-2018

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

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

See Appendix Table A11.

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