Zoning Out Opportunities: The Intergenerational Impact of Housing Supply Restrictions

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Abstract

This paper evaluates the welfare effects of housing supply restrictions through the lens of an equilibrium model that incorporates neighborhood effects on child development. We develop a general equilibrium overlapping-generations framework with endogenous housing supply, neighborhood quality, location choice, and skill formation. Housing regulations are modeled as convex construction costs that limit supply and raise prices. The model is estimated using U.S. data and validated against reduced-form evidence from the Moving to Opportunity experiment.

Reducing housing regulations to levels observed in less restrictive U.S. cities generates substantial welfare gains. Intergenerational dynamics are central to this result: when parental altruism is excluded from welfare calculations, gains for adults alive at the time of reform fall by a factor of forty, and political opposition rises from 17 to 52 percent. These findings suggest that standard frameworks abstracting from intergenerational linkages substantially understate the benefits of housing deregulation.

Keywords: Neighborhood effects, housing supply, intergenerational mobility, child development, spatial equilibrium.
JEL Codes: J13, R13, R23, R31, I31.

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1 Introduction

Where children grow up matters for their long-run economic outcomes. Recent experimental and quasi-experimental evidence demonstrates that neighborhoods have causal effects on children's earnings, educational attainment, and other outcomes that persist into adulthood. Chetty et al. (2016) find that young children whose families received housing vouchers through the Moving to Opportunity (MTO) experiment and relocated to lower-poverty neighborhoods experienced substantial earnings gains as adults. Chyn (2018) documents similar long-run benefits for children displaced from public housing through demolitions. More broadly, Chetty and Hendren (2018) estimate that each year of childhood exposure to a better neighborhood improves adult outcomes, with effects that cumulate over time. A crucial factor in designing successful neighborhood-based policy interventions is understanding the elasticity of housing supply (Chyn and Daruich, 2025). This paper investigates the effects of housing supply restrictions by integrating neighborhood effects into a general equilibrium overlapping-generations model that accounts for endogenous housing supply, neighborhood quality, location choice, and child development.

Housing supply restrictions—including zoning regulations, building codes, and permitting delays—vary substantially across U.S. cities and have been linked to high housing costs in productive metropolitan areas (Saiz, 2010; Gyourko and Krimmel, 2021). A growing literature examines the aggregate consequences of these restrictions. Hsieh and Moretti (2019) estimate that housing constraints in high-productivity cities like New York and San Francisco lowered aggregate U.S. GDP growth by 36 percent between 1964 and 2009 by limiting labor mobility. Glaeser and Gyourko (2018) review the evidence and argue that the implicit tax on development created by housing regulations likely exceeds any negative externalities from new construction. Favilukis et al. (2023) develop a spatial equilibrium model to evaluate housing affordability policies in New York, finding welfare gains from relaxing zoning in the city center.

A limitation of existing quantitative work on housing supply restrictions is that it abstracts from intergenerational linkages. Standard spatial equilibrium models feature either infinitely-lived households or life-cycle agents without parental altruism toward children. Welfare assessments therefore focus on effects operating through housing costs, labor market access, and wealth accumulation—but not through child development. Yet if neighborhoods causally affect children's outcomes, and if parents value their children's welfare, then housing policies that expand access to better neighborhoods may generate benefits that existing frameworks fail to capture.

A separate literature uses spatial equilibrium models to study neighborhood sorting and child development. Foundational theoretical work by Benabou (1996*a*), Benabou (1996*b*), Durlauf (1996), and Fernandez and Rogerson (1996, 1997, 1998) established the importance of local spillovers and residential sorting for inequality and intergenerational mobility. More recent quantitative contributions include Fogli et al. (forthcoming), who study how segregation amplifies inequality; Fogli et al. (2025), who analyze the dynamic and welfare effects of desegregation policies; Zheng and Graham (2020) and Eckert and Kleineberg (2021), who evaluate education finance reforms; Chyn and Daruich (2025), who analyze housing vouchers and place-based subsidies; Gregory et al. (2024), who examine racial segregation and college attainment; and Bellue (2024), who study barriers to mobility among poor families. A common feature of these spatial-macro models with endogenous child human capital is that the housing supply elasticity is treated as a fixed parameter. This limits their ability to study policies that directly affect housing supply, such as zoning reform.

This paper develops and estimates a general equilibrium model designed to quantify these intergenerational effects of housing supply restrictions. The framework builds on Chyn and Daruich (2025) while introducing two key innovations. First, we endogenize the housing supply elasticity by modeling how local regulations affect construction costs. This is crucial because Chyn and Daruich (2025) show that optimal neighborhood policies depend importantly on housing supply elasticities, which are exogenous in their framework and in all other models of neighborhood effects on children. Second, we extend the spatial structure from two to three neighborhoods, allowing us to distinguish effects in middle-income versus top-income areas and to evaluate policies implemented in only some neighborhoods—which may induce households to relocate across neighborhood types.

Parents in our model are altruistic and invest in their children through both time and neighborhood choice. Children's skill formation follows the technology estimated by Cunha et al. (2010), with neighborhood quality entering as an input that complements parental time investments. Housing is produced by a competitive construction sector subject to convex costs that capture the effects of local housing regulations. These regulations vary across neighborhoods, with more restrictive rules limiting supply and raising prices in higher-income areas.

We estimate the model using U.S. data on income dynamics, neighborhood characteristics, housing costs, and child outcomes. The estimation targets moments related to parental time investments, neighborhood income differentials, and the relationship between childhood neighborhood and adult earnings. To validate the model, we simulate a housing voucher program similar to MTO and compare the predicted effects on children's earnings to the site-specific treatment effects documented in the experimental literature. The model's predictions align closely with the reduced-form evidence, providing confidence in using the framework for policy evaluation.

The main policy experiment reduces housing supply regulations from levels observed at the

75th percentile of U.S. cities (similar to Los Angeles) to levels at the 25th percentile (similar to St. Louis). This change lowers house prices by approximately 10 percent on average and allows more children to grow up outside the most disadvantaged neighborhoods. The share of children in the bottom-decile neighborhood declines by 2 percentage points. While the influx of lower-income families reduces neighborhood quality in middle- and high-income areas, the net effect on child skill development is positive, and both consumption inequality and intergenerational persistence of income decline.

Welfare gains from housing deregulation are substantial. Under the veil of ignorance, a newborn would be willing to give up a meaningful fraction of initial wealth to live in the deregulated steady state rather than the regulated one. Adults alive when the policy is introduced also gain on average. Gains are largest for low-wealth households in disadvantaged neighborhoods, who benefit both from lower housing costs and from improved prospects for their children. High-wealth households generally experience welfare losses due to declining house prices, though these losses are partially offset by gains accruing to their descendants.

A central finding of the paper is that intergenerational dynamics are quantitatively essential for understanding the welfare effects of housing policy. To demonstrate this, we compute welfare gains under an alternative specification that excludes parental altruism from welfare calculations. Without altruism, average welfare gains for adults at the time of reform fall by a factor of nearly forty. This dramatic difference reflects the fact that, from the perspective of current adults, the direct effects of housing deregulation on their own consumption are modest: housing costs decline, but so does housing wealth. The large welfare gains in the baseline model arise because parents value the improved neighborhood access and skill development that deregulation provides for their children and grandchildren.

The political economy implications are equally notable. With intergenerational altruism, only 17 percent of adults would oppose housing deregulation based on their individual welfare effects. Without altruism, opposition rises to 52 percent—a shift from a broad majority in favor to a narrow majority against. This reversal occurs because, absent concern for children's gains, the policy becomes primarily a redistribution from housing-asset holders to renters, with limited aggregate benefits to compensate the losers.

These results contribute to the literature on housing policy by highlighting a channel that existing quantitative work has largely overlooked. Models in the tradition of Hsieh and Moretti (2019) and Favilukis et al. (2023) provide valuable insights into the labor market and wealth effects of housing supply restrictions, but they do not capture the intergenerational benefits that arise when deregulation improves children's access to high-opportunity neighborhoods. Our findings suggest that accounting for these benefits substantially increases both the estimated welfare gains from reform and the political coalition that might support it.

The paper also connects to a broader literature on the macroeconomic effects of policies targeting children. Research on early childhood education and education reform (e.g., Restuccia and Urrutia, 2004; Abbott, 2021; Abbott et al., 2019; Lee and Seshadri, 2019; Caucutt et al., forthcoming; Daruich, forthcoming) has emphasized that policies affecting child development can have large long-run effects that justify substantial upfront costs. Housing deregulation operates through a similar logic: the immediate effects on housing markets are relatively modest, but the cumulative benefits from improved child outcomes are large when properly valued.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 describes the estimation strategy, data sources, and validation exercises. Section 4 analyzes the effects of reducing housing supply restrictions. Section 5 examines the importance of intergenerational dynamics for welfare conclusions. Section 6 concludes.

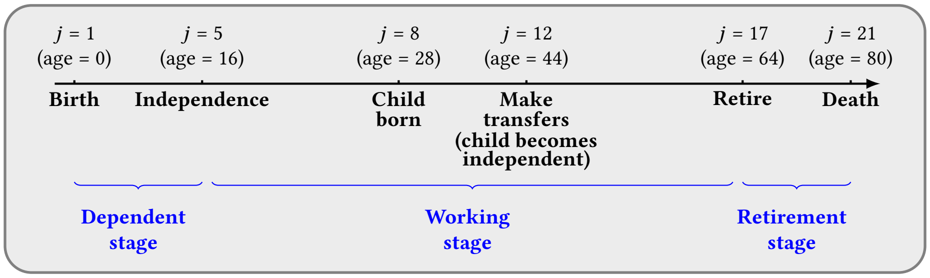
2 Model

The model has three main building blocks. First, children's long-term outcomes are influenced by parental choices, as individual earnings depend on childhood-acquired skills. Parents build their children's skills through neighborhood and time investments, with local spillovers increasing skill accumulation in higher-income areas. Second, the economy is framed within a general equilibrium life-cycle model with income uncertainty and incomplete markets. A representative firm produces final goods using labor and capital. Importantly, an endogenous amount of these final goods is converted into housing by a competitive construction sector. Third, the government taxes consumption, labor, capital, and property to fund transfers and retirement benefits. Housing regulations reduce supply and raise prices, and policy changes require adjusting property taxes to balance the budget.

2.1 Households

The household problem is based on Chyn and Daruich (2025). Within this dynastic model, life is segmented into three primary phases: childhood, working adulthood, and retirement, extending over 20 age-periods. Figure 1 illustrates an individual's life cycle. Each period spans four years. We use j to indicate the age within each period (e.g., $j = 1$ refers to ages 0–3). During periods $j = 1$ to $j = 4$, children reside with their parents in neighborhood n and do not make any decisions. In our stylized model, individuals attain adulthood and independence at the onset of $j = 5$ (age 16). Upon reaching independence, state variables for the individual are the residential neighborhood n, wealth a (deriving from parental transfers), and skills θ.

Figure 1: Model Timeline: A Dynastic Framework with Three Stages



Notes: This figure illustrates key events and the three main stages of life for an agent in the model.

Each period consists of two parts. In the first, the agent selects a neighborhood, each with a rent $p_{r,n}$ and possibly a moving cost. After choosing a neighborhood, the second part unfolds. In their youth, individuals work, facing idiosyncratic, uninsurable risks affecting their stochastic labor income, leading them to decide on savings and consumption. They can borrow up to a certain limit and save via a non-stage-contingent asset. At $j = 8$, individuals become parents and must make additional decisions. For four periods, up to their child's 16th year, they decide on time invested in child development. Both time investment and neighborhood choice shape a child's skills. Finally, parents make a transfer before the child gains independence. Upon reaching $j = 17$, agents transition to retirement, relying on savings and government retirement benefits for income.

2.1.1 Working Stage Decisions

During the working stage, individuals consume c and save a' in the second part of each period. These choices depend on the individual's level of assets a, level of skills θ, current neighborhood location n (which is chosen previously during the first part of each period as detailed below), and a stochastic income shock η. Formally, the value function during the working stage when individuals do not have children is given by:

$$V_j\left(a,\theta,n,\eta\right) = \max_{c,a'}\left\{u\left(c\right) - \bar{v}_n + \beta\mathbb{E}\left[\widehat{V}_{j+1}\left(a',\theta,n,\eta'\right)\right]\right\}, \tag{1}$$

$$c\left(1+\tau_c\right) + p_{r,n} + a' - \left(y - T\left(y\right)\right) - \omega = \begin{cases} a\left(1 + r\left(1-\tau_a\right)\right) & \text{if } a \geq 0 \\ a\left(1+r^-\right) & \text{if } a < 0 \end{cases}$$

$$y = wE_j\left(\theta,\eta\right), \quad a' \geq \underline{a}_j, \quad \eta' \sim \Gamma_j(\eta).$$

People derive flow utility from consumption via the function $u(c)$ and gain additional utility from their neighborhood's constant (exogenous) amenity value $\bar{v}_n$. They can borrow up to an age-specific limit $\underline{a}_j$ at interest rate r^-, while savings yield rate of return r. As further explained in

Section 2.2, the decentralized equilibrium leads to uniform wages across neighborhoods since the interest rate is taken as given. Labor income is then adjusted by the age-specific function $E_j(\theta, \eta)$, which depends on individual skills θ and unique labor efficiency η. Additionally, individuals pay linear taxes on consumption (τ_c) and capital income (τ_a), face a progressive non-linear tax on labor income ($T(y)$), and receive the lump-sum government transfer ω.

In the first part of each period, individuals choose where to live taking into account their expected utility value (which depends on their current state variables and rent costs, as represented above), location preference shocks, and moving costs. We allow for age-specific moving costs—this assumption will help the calibrated model to capture the fact that younger individuals are more likely to live in lower-income neighborhoods. Given the neighborhood location n in the period when $j = 4$ (chosen by one's parents), the value function determining agent's first location choice at independence (i.e., age-period $j = 5$) is given by:

$$\widehat{V}_{j=5}\left(a, \theta, n, \eta\right) = \mathbb{E}_{\varepsilon^n}\left[\max_{n' \in \{1,2,3\}} \left\{V_{j=5}\left(a, \theta, n', \eta\right) + \varepsilon^{n'} - \kappa_{j,n'} 1(n' \neq n)\right\}\right],$$

where $\kappa_{j,n'}$ is the utility cost of moving to neighborhood n' and $\varepsilon^{n'}$ is the location preference shocks, which are independently, identically distributed, and drawn from an extreme value distribution with shape parameter σ_ε. Of course, the moving cost $\kappa_{j,n'}$ is only incurred when an individual chooses a new neighborhood (i.e., $n' \neq n$). From $j = 6$ until retirement (which starts at $j = 17$), the individual's optimization problem in the first part of each period (except for parenthood as described below) is similar to Equation 1. Note that, in addition to location preference shocks, wage shocks (i.e., η) can induce workers to move.

2.1.2 *Parental Investment and Child Development*

The household's problem changes when a child is born at the exogenously given fertility age-period $j = 8$ (age 28). We assume each person has one child. As described in Barro and Becker (1989), parents are altruistic, valuing their child's welfare with weight $\tilde{\beta}$. Children inherit skills θ_k, which might correlate with parental skills. Parents build their child's skills during early years ($j = 8 - 11$). Consistent with findings from Cunha (2013), skills consist of both cognitive $\theta_{c,k}$ and non-cognitive $\theta_{nc,k}$ elements. Throughout the parenting period ($j = 8 - 11$), parents decide the amount of time τ dedicated to enhancing the child's skill set. Children's skill development is influenced not only by time investment but also by neighborhood quality. We represent neighborhood quality with an index s_n. This influence is assumed to be driven by the total income per adult (combining capital and labor) of residents in neighborhood n.

Our focus on income captures several common theoretical frameworks believed to influence neighborhood effects. Higher-income areas usually boast better-quality schools due to local funding of public education (Howell and Miller, 1997; Hoxby, 2001; Biasi, 2019).[1] Moreover, children often gain from being around highly productive adults, serving as role models (Wilson, 1987). Using earnings to proxy local externalities effects is also in line with existing studies that use local income or poverty rates as indicators of neighborhood quality (Kling et al., 2007; Chetty and Hendren, 2018). Similarly, Chyn and Daruich (2025) illustrates that the effects of two neighborhood-targeted policies (rent vouchers and place-based subsidies) remain largely consistent regardless of using neighborhood spillovers based on education levels or tax income, as these policies show an almost perfect correlation in their impacts on income per capita and corresponding effects on education and tax revenues.

We represent skill development θ_k using two nested constant elasticity of substitution (CES) functions that capture the roles of parental time and neighborhood spillovers. Based on Cunha et al. (2010), the outer CES function relates a child's future skills θ_k' to their current skills, parents' skills θ, parental investments I, and a random shock v. Meanwhile, the inner CES function, which calculates I, explicitly includes τ and s_n.

Formally, we assume that the problem of parents in age-periods $j = 8 - 11$ is:

$$V_j\left(a, \theta, n, \eta, \theta_k\right) = \max_{c,a',c_k,\tau} u\left(c\right) - \bar{v}_n + \tilde{\beta} u\left(c_k\right) - v\left(\tau\right) + \beta \mathbb{E}\left(\widehat{V}_{j+1}\left(a', \theta, n, \eta', \theta_k'\right)\right), \quad (2)$$

$$\left(c + c_k\right)\left(1 + \tau_c\right) + p_{r,n} + a' - \left(y - T(y)\right) - \omega = \begin{cases} a\left(1 + r\left(1 - \tau_a\right)\right) & \text{if } a \geq 0 \\ a\left(1 + r^-\right) & \text{if } a < 0 \end{cases}$$

$$y = wE_j\left(\theta, \eta\right), \quad a' \geq \underline{a_j}, \quad 0 \leq \tau \leq 1, \quad \eta' \sim \Gamma_j(\eta)$$

$$\theta_{q,k}' = \left[\alpha_{1,q,j}\theta_{c,k}^{\rho_{q,j}} + \alpha_{2,q,j}\theta_{nc,k}^{\rho_{q,j}} + \alpha_{3,q,j}\theta_{c}^{\rho_{q,j}} + \alpha_{4,q,j}\theta_{nc}^{\rho_{q,j}} + \alpha_{5,q,j}I^{\rho_{q,j}}\right]^{1/\rho_{q,j}} e^{\nu_q}$$

$$\nu_q \sim N(0, \sigma_{q,j,\nu}), \quad q \in \{c, nc\}$$

$$I = \bar{A}_j\left[\alpha_{I,j} f\left(s_n\right)^{\gamma} + (1 - \alpha_{I,j})\tau^{\gamma}\right]^{1/\gamma}$$

In addition to investing time, parents also choose their children's consumption c_k, which is assumed to be valued by the same utility function as adults' consumption, adjusted by the altruism parameter $\tilde{\beta}$. For the skill development function, the parameter $\rho_{q,j}$ defines how substitutable the inputs are in the outer CES function for $q \in \{c, nc\}$. The degree to which parental time investments and neighborhood quality can be substituted is specified by γ in the inner CES function.

As in other periods, people can move at the beginning of each period. Distinct from previous

[1] However, research points out that schools are only one factor producing neighborhood effects. (Chetty et al., 2018) highlight considerable variations in child outcomes across Census tracts within identical school areas, with schools accounting for under half of the variance within a county.

periods, however, the value function for that choice incorporates the children's skills θ_k:

$$\widehat{V}_j\left(a,\theta,n,\eta,\theta_k\right)=\mathbb{E}_{\varepsilon^n}\left[\max_{n'\in\{1,2,3\}}\left\{\mathbb{E}(V_j\left(a,\theta,n',\eta,\theta_k\right)+\varepsilon^{n'}-\kappa_{j,n'}\,1(n'\neq n)\right\}\right].$$

2.1.3 Child Independence

Before the parent reaches age-period $j=12$, equivalent to reaching age 44, they choose a monetary transfer $\hat{a}$ for the child. We model this as occurring in a sub-period before the child turns independent at age 16, defining the agent's corresponding value as V_{Transfer}:

$$V_{\text{Transfer}}\left(a,\theta,n,\eta,\theta_k\right)=\max_{\hat{a}}\widehat{V}_{j=12}\left(a-\hat{a},\theta,n,\eta\right)+\tilde{\beta}\mathbb{E}_{\eta_k,\kappa}\left(\widehat{V}_{j'=5}\left(\hat{a},\theta_k,n,\eta_k,\kappa\right)\right), \tag{3}$$

$$\hat{a}\geq 0,\quad \kappa\sim N(\bar{\kappa},\sigma_\kappa),\quad \eta_k\sim\Gamma_{j'=5}.$$

Importantly, the transfer $\hat{a}$ must be non-negative, as parents cannot pass on debt to their children or leverage their child's future earnings. In making this decision, the parent is informed about their own income shock η but unaware of the child's income shock η_k and the random location preference shocks ($\varepsilon^{n'}$) affecting both themselves and their child. Unlike as in Equation 2, the value function at this stage incorporates the child's continuation value $\widehat{V}_{j'=5}$, where j' represents the child's age period. As the problem is structured recursively, this ensures that throughout all preceding periods where parental choices impact the child, the utility of the child and future generations is considered, reflecting the motive of parental altruism. Upon the child's independence, the parent's problem reverts to that described by Equation 1.

2.1.4 Retirement

When reaching $j=17$ (age 64), an individual retires and relies on two income sources: their savings a and public retirement benefits π. To simplify, retirement benefits are considered to vary based on the individual's skill level and are taxed under the same labor tax function $T(.)$. The formal problem at the retirement age is:

$$V_j\left(a,\theta,n\right)=\max_{c,a'}u\left(c,0\right)-\bar{v}_n+\beta\widehat{V}_{j+1}\left(a',\theta,n\right), \tag{4}$$

$$c\left(1+\tau_c\right)+p_{r,n}+a'-\omega-\left(\pi(\theta)-T\left(\pi(\theta)\right)\right)=\begin{cases}a\left(1+r\left(1-\tau_a\right)\right) & \text{if } a\geq 0\\ a\left(1+r^-\right) & \text{if } a<0\end{cases}$$

$$a'\geq \underline{a_j}.$$

As in other periods, the individual can move at the beginning of each period:

$$\widehat{V}_j\left(a,\theta,n\right)=\mathbb{E}_{\varepsilon^n}\left[\max_{n'\in\{1,2,3\}}\left\{V_j\left(a,\theta,n'\right)+\varepsilon^{n'}-\kappa_{j,n'}\,1(n'\neq n)\right\}\right].$$

2.2 *Final Goods Production*

We assume that there is a representative firm in each neighborhood n, operating with a production technology given by $Y_n = AK_n^{\alpha}H_n^{1-\alpha}$, where A represents total factor productivity, K_n denotes the total physical capital in neighborhood n, and H_n describes the total efficiency units in that neighborhood. Capital depreciates at rate δ every period. Firms operate in a perfectly competitive market, resulting in zero profits, and they compensate labor based on its marginal product. In this open economy, the interest rate r is fixed externally, while the equilibrium wage is $w_n = (1-\alpha)A(K_n/H_n)^{\alpha}$—as determined by the capital's first-order condition. Given that r is independent of the neighborhood, H_n/K_n must also be equal across neighborhoods. Thus, $w = (1-\alpha)A\left(\frac{A\alpha}{r+\delta}\right)^{\alpha}$.

2.3 *Housing Markets*

For simplicity, we assume there are three neighborhoods denoted $n = \{1, 2, 3\}$.[2] Without any loss of generality, we assume that neighborhoods are ranked in terms of their amenity values, with $n = 1$ as the disadvantaged neighborhood with lowest amenity (we make the normalization such that $\bar{v}_3 = 0$). We estimate the model such that 10 percent of all households reside in the disadvantaged area $n = 1$ in the initial steady state. This choice is motivated by the empirical evidence that suggests that there are substantial gains from reallocating children away from these areas. We also map the top neighborhood $n = 3$ to an area of equivalent size but at the very top of the income distribution. This is motivated by an upcoming exercise in which we aim to evaluate a housing policy change that is blocked in high-income areas but approved in the rest of the city—a pattern commonly observed in practice (e.g., Einstein et al., 2019; Hankinson, 2018).

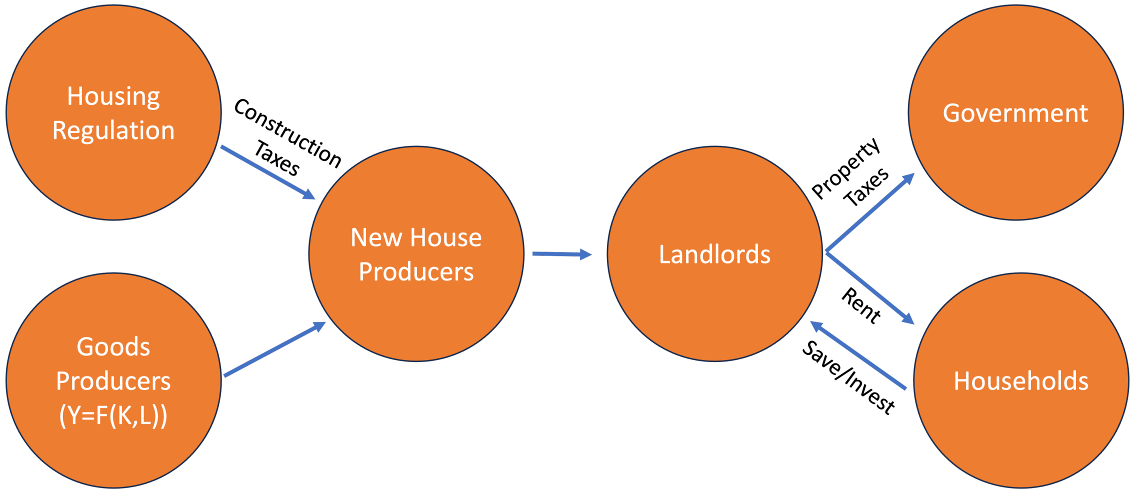
New housing is produced by a simple construction sector that transforms final goods into houses using the production function:

$$H_n = (1+\alpha)^{\frac{1}{1+\alpha}}\,A_n^{\frac{\alpha}{1+\alpha}}Q_n^{\frac{1}{1+\alpha}}, \tag{5}$$

where Q_n are units of the final good and A_n is a measure of the productivity of the housing sector. However, they must abide by housing regulations, which introduce an increasing construction

[2]Our approach is similar to prior studies that simplify the number of neighborhoods in order to incorporate intergenerational dynamics in human capital development (e.g., Fogli et al., forthcoming; Chyn and Daruich, 2025; Aliprantis and Carroll, 2018).

Figure 2: The Housing Sector



Notes: This figure illustrates the flow of resources in the housing sector. Construction firms transform final goods into new housing, subject to regulation-induced construction taxes. Landlords purchase housing, pay property taxes to the government, and rent to households. Households save by investing in the landlords' portfolio.

tax $\tau_n^C(H_n) = \left(\frac{H_n}{T_n}\right)^{\varepsilon_n} - 1$. Notice that the larger ε_n is, the more this tax increases with housing production. Thus, this helps proxy a situation in which regulation limits the amount of housing (e.g., multifamily housing like apartment buildings or small-lot housing) produced in a neighborhood. T_n, instead, relates to the scale of construction taxes in general. The benefit of this parametrization is that it leads to a simple expression for total housing production cost:

$$\frac{1}{1+\alpha}\frac{1}{A_n^{\alpha}T_n^{\varepsilon_n}}H^{1+\varepsilon_n+\alpha}. \tag{6}$$

Notice that the housing supply elasticity is then given by $\frac{1}{\alpha+\varepsilon_n}$, which clearly shows that there are two things that lead to lower elasticities. First, α relates to technological features that make housing production more costly as the amount of housing produced increases. Second, ε_n relates to housing regulations that make producing more housing units more costly.

New houses are then sold to landlords at price $p_{H,n}$, who rent them to the households at rent price $p_{r,n}$. Landlords, however, also need to pay property taxes $\tau_{H,n}$, which may vary by neighborhood. Moreover, houses depreciate at rate δ_H. Importantly, households themselves are the ones who indirectly own housing by investing in the landlords' portfolio. In order to be indifferent between the landlords portfolio and the owning capital stock that is used by the final goods producers, a no-arbitrage condition must hold. This defines the housing rent price:

$$\underbrace{p_{r,n}}_{\text{Rent}} = \underbrace{\underbrace{p_{H,n}}_{\text{House Price}} \times \Big[\underbrace{\tau_H}_{\text{Prop. Taxes}} + \underbrace{r - \delta}_{K \text{ Return}} + \underbrace{\delta_H}_{\text{House Depreciation}} \Big]}_{\text{User Cost of Capital}} - \underbrace{(1 - \delta_H)\Delta p_{H,n}}_{\text{Capital Gains}} \tag{7}$$

For the non-arbitrage condition to hold, the sum of the rent income and capital gains need to compensate home owners for the user cost of capital, which includes property taxes, the opportunity cost of using that money instead to own capital (which for which the firms would pay r), and housing depreciation. Note that the housing is subject to capital gains as housing might change prices outside a steady state. For example, if house prices are going to increase ($\Delta p_{H,n} > 0$) rent prices today will be lower.

2.4 *Definition of Stationary Equilibrium*

The model includes J_d overlapping generations and is solved numerically to characterize the stationary equilibrium allocation. Stationarity implies an equilibrium in which the cross-sectional distribution for any given cohort of age j is invariant over time periods. Particularly important is that the distribution of initial states is determined by the choices of the older generations. The equilibrium allocation requires that: households choose location, consumption, parental time investments, and parental transfers to maximize expected utility; firms maximize profits; prices (wages and rents) clear labor and housing markets; and neighborhood quality s_n equals average income per capita in each neighborhood.

Note that we do not require that the government budget is balanced. The government may have other non-modeled expenses G. Hence, G will be defined in the initial steady state as a residual. However, to evaluate policies (e.g., housing regulation changes), we do assume that any net additional expenses must be offset by additional revenue (e.g., property tax revenue).

3 Estimation

This section outlines our approach to parameterizing and estimating the model. Using the simulated method of moments, we match both standard and novel moments to U.S. data from the 2000s, focusing on parental investments and neighborhood income disparities. Some parameters are calibrated externally, while others are estimated internally through model simulations. For the latter, we compute the economy's steady state, obtain the ergodic distribution, and calculate the relevant moments. Post-estimation, we validate the model against reduced-form estimates from prior experimental and quasi-experimental studies.

3.1 Preliminaries

Overview of Data and Samples: The model's parameters are estimated using two types of data. Initially, individual-level statistics are derived from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY). Subsequently, neighborhood-level moments concerning income, housing costs, time spent with children, and children's long-term outcomes are constructed using various Census data, the ATUS, and the Opportunity Atlas from Chetty et al. (2018). Lastly, the housing supply restrictions are mapped to the estimates from Saiz (2010). This section continues with a detailed description of all data sources and the key measures used.

Labor Earnings and the Return to Skill: At age j, a household's labor income equals the product of the wage w and efficiency units $E_j(\theta, \eta)$.[3] Efficiency units combine an age profile ι_j and an idiosyncratic component $\psi_j(\theta, \eta)$, so that $E_j = \iota_j \psi_j(\theta, \eta)$. The idiosyncratic component depends on cognitive skills θ_c and a productivity shock η_j:

$$\log(\psi_j) = \Upsilon \log(\theta_c) + \eta_j, \tag{8}$$

where η_j follows an AR(1) process: $\eta_j = \rho_\eta \eta_{j-1} + \xi_j$, with $\xi_j \sim N(0, \sigma_{\xi,j})$. The initial shock η_0 is drawn from $N(0, \sigma_{\eta_0})$.

We estimate this income process in two steps. First, we estimate the age profile ι_j from PSID data using a second-order polynomial in age:

$$w_t = \beta_0 + \beta_1 \text{Age}_t + \beta_2 \text{Age}_t^2 + \beta_3 X_t + \Pi_t + \psi_t,$$

where Π_t captures year fixed effects and X_t controls for selection into work via a Heckman correction.[4] We use the PSID rather than the NLSY because its representative cross-section in each year prevents cohort effects from confounding age effects. Data are aggregated into four-year periods to match the model's timing. Appendix Table A1 reports the estimates.

Second, we estimate the return to skill Υ using the NLSY, which contains skill measures (AFQT scores) unavailable in the PSID. We compute the residual ψ_t using the PSID-estimated age profile and regress it on log cognitive skills. The AR(1) parameters for η are estimated via minimum distance (Rothenberg, 1971). Our estimates are similar to those in related work (e.g., Abbott et al., 2019; Daruich and Fernández, 2020).

[3]Wages per efficiency unit are identical across neighborhoods due to the exogenous interest rate.

[4]We estimate the participation equation using the number of children and year-region fixed effects to compute Inverse Mills ratios.

Neighborhoods: There are three neighborhoods delineated in the model. To align this with data, U.S. Census tracts are sorted into three groups, matching neighborhoods $n = 1$, $n = 2$, and $n = 3$.[5] We proceed in three steps. First, we use tract-level data to compute population-weighted percentiles of median household income within each commuting zone (CZ).[6] In each CZ, tracts below the 10th percentile of median income are classified as neighborhood $n = 1$ (least advantaged and with lowest amenity). Those above the 90th percentile fall into $n = 3$ (most advantaged with highest amenity). The remaining tracts are grouped as $n = 2$, reflecting an average non-poor city neighborhood.[7] Different neighborhood definitions could be used, but we prefer this approach as it highlights the importance of moving children out of the poorest neighborhoods. For example, it aligns with real-world policies targeting disadvantaged urban neighborhoods, like the MTO voucher and place-based EZ investments (Kling et al., 2005; Busso et al., 2013).[8] The top neighborhood $n = 3$ is included to capture high-income neighborhoods that may resist housing regulation changes. Second, we calculate averages of tract characteristics (detailed below) for those assigned to each n in each CZ. Finally, we compute population-weighted averages of these statistics across CZs.

This methodology allows us to consolidate various local area attributes, assessed at the Census tract level, into the three synthetic neighborhoods within our model. Table 1 presents the summary statistics pertinent to the neighborhood features central to our study. Columns 1–3 display the summary statistics for each neighborhood. The numbers between brackets in column 2 refer to the percentage change between $n = 1$ and $n = 2$, while those in column 3 are the equivalent for the percent change between $n = 2$ and $n = 3$.

The following tract-level characteristics are key to our model: per capita income, home value, property taxes, and expected child outcomes. The income and housing-related measures come from the 2012-2016 American Community Survey (ACS). Housing value and property tax statistics are available at the tract and CZ level, respectively. We impute tract-level property taxes in two steps. First, we use CZ-level data and regress property taxes on median household income. Second, we return to tract-level data and use the CZ-level regression estimates to predict property taxes based on the median household income in a given tract. We divide this number by the average number of adults in a household to obtain a per individual estimate. The measures of ex-

[5]Census tracts are geographic divisions with an average population of 4,250.

[6]Commuting zones are county aggregations similar to metropolitan statistical areas, but they cover the entire country.

[7]In our baseline model, neighborhood $n = 2$ averages characteristics akin to those of the fifth decile in income distribution.

[8]For instance, the EZ program analyzed by Busso et al. (2013) aimed investments at disadvantaged areas covering 10 percent of the city's population.

pected child outcomes come from Chetty et al. (2018). Specifically, we rely on tract-level statistics on the expected income for children who have parents at the 25th, 50th, and 75th percentile of the income distribution.

Table 1: Neighborhood Summary Statistics

	(1)	(2)		(3)	
	Bottom 10%	**Middle 80%**		**Top 10%**	
Income					
Mean Individual Income	$14,844	$28,162	(+89.7%)	$51,515	(+82.9%)
Child's Mean Income at Age 26 by Parental Income					
25th Percentile	$18,600	$22,674	(+21.9%)	$26,730	(+17.9%)
50th Percentile	$24,696	$28,795	(+16.6%)	$29,493	(+2.4%)
75th Percentile	$28,103	$32,354	(+15.1%)	$33,091	(+2.3%)
Housing					
Median Home Value	$100,944	$138,572	(+37.3%)	$260,094	(+87.7%)
Avg. HH Size	2.79	2.73	(-2.1%)	2.83	(+3.7%)

Notes: This table reports neighborhood summary statistics for three types of neighborhoods. The threshold for a bottom neighborhood is based on whether median household income in the area is in the bottom 10 percent. The threshold for a top neighborhood is based on whether median household income in the area is in the top 10 percent. When possible, we report summary statistics based on tract-level data. Due to data limitations, we also rely on summary statistics based on commuting zone (CZ) level data. CZs are geographical aggregations of counties that are similar to a metro area but cover the entire United States (including rural areas). We convert the CZ-level statistics to tract-leave measures to match the two neighborhoods in our model. Yearly housing costs are estimated combining tract-level home values and CZ-level statistics on property taxes, as explained in the main text. Housing, demographic, and income statistics are from the 2012-2016 ACS. Child outcome statistics are from the Opportunity Atlas (Chetty et al., 2018).

Table 1 shows that there are substantial differences between the less and more advantaged neighborhoods that we study. For example, the average individual income and median home values are 108 and 67 percent higher in the more advantaged neighborhood. Most importantly, the summary statistics are consistent with a model that features sorting and causal neighborhood effects: children who grow up in the more advantaged neighborhood have higher later-life incomes. This is particularly true for children from low-income households (i.e., those with parents at the 25th percentile of the national income distribution) whose incomes are 30 percent higher.

Table 1 reveals significant disparities between the neighborhoods we examine. For instance, average individual income almost doubles from $n = 1$ to $n = 2$ as well as from $n = 2$ to $n = 3$. Crucially, these summary statistics align with a model indicating sorting and causal neighborhood impacts: children raised in more advantaged areas achieve higher incomes in adulthood. This is especially evident for children from low-income families (those with parents at the 25th percentile nationally). Although children of middle- and high-income parents do exhibit approximately 15% higher-income when they grow up in $n = 2$ rather than $n = 1$, there are almost no differences between such children who grow in the middle and top neighborhoods.

Lastly, it is instructive to highlight that variations in neighborhood income and demographic composition influence and affect the main parameters governing relocation decisions within our framework. As detailed in Section 2, the model features i.i.d. heterogeneous preference shocks (ε_n) drawn from an extreme value distribution with a shape parameter σ_ε. This parameter is estimated based on the income disparities observed across neighborhoods. Essentially, as preference shocks increase in significance, income's role in determining location choice decreases. Furthermore, our model includes a common relative (dis)utility for living in the less advantaged neighborhood (i.e., $n = 1$) along with moving costs between areas. The relative utility is set to reflect that in the initial steady state, 10 percent of households reside in $n = 1$ and $n = 3$ each. To simplify the estimation, we parametrize the amenities of each neighborhood as:

$$\bar{v}_n = \sum_{\hat{n}=n}^{3} \nu_{\hat{n},}$$

where ν_3 is normalized to zero such that the amenity value of the top neighborhood is zero as well ($\bar{v}_3 = 0$).[9]

We parametrize moving costs to depend on the age of individuals and the destination of their move,

$$\kappa_{j,n'} = \bar{\kappa} \times \exp\left[\alpha_\kappa \left(\bar{v}_{n'} - \bar{v}_2\right)\right],$$

which is normalized such that moving costs to the largest neighborhood ($n = 2$) are only given by common factor $\bar{\kappa}$. $\bar{\kappa}$ is estimated to match the share of people in the largest neighborhood ($n = 2$) that did not live in that same neighborhood in the previous period (i.e., the share of movers). We estimate this using Census data but, due to data limitations, we can only do this at the PUMA level.[10] Empirical results suggest that 7.75% of households in that neighborhood did not live there 5 years before. Finally, α_κ is estimated to match the relative income differences between $n = 3$

[9]This helps the estimation as it will easily guarantee that $\bar{v}_1 \geq \bar{v}_2 \geq \bar{v}_3$, as long as $\nu_n \geq 0$ for all n.

[10]PUMAs are also statistical geographic areas created by the U.S. Census Bureau. They are include approximately 100,000 people and are built from groups of contiguous Census Tracts (they nest within states but can span multiple counties). We perform a similar analysis to the one done at the PUMA level, we rank PUMAs by income and group them into synthetic neighborhoods. We then use this information to calculate moving rates.

and $n = 2$ versus $n = 2$ and $n = 1$. Intuitively, the larger α_κ is, the more moving costs will increase with the utility obtained from moving to a given neighborhood. Given that this utility cost is independent of income, it is more likely that only higher-income individuals will move and, hence, income differences will increase.

Parental Time Investment: The differences in child outcomes across areas documented in Table 1 could be due to both neighborhood effects and parental investments. Our model captures the latter by allowing for time investments. Ideally, we would estimate the relationship between parenting time and neighborhood choice directly. Unfortunately, existing time-use survey data does not provide detailed information on the neighborhood of respondents. We follow the strategy in Chyn and Daruich (2025) and estimate the relevant parameters using two moments from their empirical estimates. The first two moments relate the amount of time that parents spend with children. Young children (ages 0–3) spend about 25.6 weekly hours of quality time with their parents. This moment is informative about the disutility of spending time with children, relative to leisure. As children age they also spend less time with theirs parents. Those between 4 and 15 years old spend approximately 41% less quality time with their parents. This moment will be informative about the relative importance of time at different stages of development (i.e., $\frac{\alpha_{I,j>8}}{\alpha_{I,j=8}}$).[11]

Child Skill Development: We estimate children's future skills as a function of current skills, parental skills, and an investment index, which is determined by neighborhood quality and parental time. As outlined in Section 2, we assume the child development function has a nested CES structure. For the outer CES, we apply the parameter estimates from Cunha et al. (2010), derived from a representative sample (see Appendix B1). These parameters differ according to the child's age, denoted as age-period j. A significant insight from their research is that skills are more flexible when children are younger, as indicated by a larger substitution elasticity $\rho_{q,j}$ at younger ages. In line with Cunha et al. (2010), we consider skills as a combination of cognitive and non-cognitive aspects. Cunha et al. emphasize that ignoring these dual skill types can lead to underestimations of how productive investments for low-skill children are. Thus, θ and θ_k represent vectors with entries for each skill type.

The initial skill distribution is influenced by parental skills via a distinct AR(1) model for

[11]Note that we allow $\alpha_{I,j}$ to vary between the periods when children are the youngest ($j = 8$) and subsequent age-periods ($j = 9 - 11$). To simplify the estimation, we impose that $\alpha_{I,j>1} = \alpha_{I,j=1} \times \delta_{\alpha_I}$. Since $\alpha_{I,j}$ varies, we similarly allow the investment scaling parameter $\bar{A}_j$ to take different values between the periods when children are the youngest ($j = 8$) and in the later periods ($j = 9 - 11$). Specifically, we assume that $\bar{A}_{j>1} = \bar{A}_{j=1} \times \delta_{\bar{A}}$.

cognitive and non-cognitive skills

$$log(\theta_{k,q}) = \hat{\rho}_q log(\theta_q) + \epsilon_{\theta_{k,q}}, \quad q \in \{c, nc\},$$

where $\epsilon_{\theta_{k,q}}$ represents a shock that is uncorrelated across skill types. The persistence factor $\hat{\rho}_q$ is defined as $\rho_k \times \left[\frac{Var(log(\theta_{k,q}))}{Var(log(\theta_q))}\right]^{0.5}$, with ρ_k being the correlation between $log(\theta_{k,q})$ and $log(\theta_q)$. We directly apply variance estimates from Cunha et al. (2010) to compute $\hat{\rho}_q$. The skill shock variance is given by: $\epsilon_{\theta_{k,q}} = Var\left(log(\theta_{k,q})\right) - \hat{\rho}_q^2 Var\left(log(\theta_q)\right)$.

We consider the following functional form for neighborhood spillovers. As previously indicated, the impact of neighborhood quality on children in our primary estimation is represented by the total of capital and labor income per adult: $s_n = \overline{y}_n + (r+\delta)\overline{a}_n$, where $\overline{y}_n$ and $\overline{a}_n$ show the (per adult) labor income and wealth in neighborhood n. To parametrize neighborhood effects, we define $f(s_n) = A\exp(\zeta \log(s_n))$. Essentially, different values of the parameter ζ will imply that neighborhoods differences can have either a smaller or greater influence on child development. , and that such impact may be non-linear (if $\zeta_2 \neq 0$).

In this framework, there are three sets of parameters governing investments. We internally estimate the parameters $\alpha_{I,j=8}$ and ζ to match two key moments for the average difference in child outcomes between neighborhoods: the difference in average incomes for middle-income children (i.e., have parents at the 50th percentile of the income distribution) between $n = 2$ and $n = 1$ as well as between $n = 3$ and $n = 2$.[12] We set the neighborhood parameter γ to match the elasticity of 0.25 between parental time investments and other educational inputs in children's development (e.g. Caucutt et al., forthcoming; Abbott, 2021).[13]

Taxes, Lump-sum Transfers, and Pension Benefits: Our model incorporates multiple taxation forms. For the labor income tax, we define $T(y) = y - \lambda y^{1-\tau_y}$. The parameter τ_y indicates the progressivity of the marginal tax rate, and we adopt $\tau_y = 0.18$ from Heathcote et al. (2017). We estimate λ to match an average effective marginal labor tax rate of 35 percent.[14] Besides labor taxes, both consumption and capital income are taxed. Following Trabandt and Uhlig (2011), we set $\tau_a = 0.36$ and $\tau_c = 0.05$.

The model also features a lump-sum transfer ω that we estimate to match a measure of income

[12]This second moment is transformed into its difference with respect to the first moment. This transformation is useful (given the finite amount of estimations) as it highlights that ζ is particularly related to how much the neighborhood impact changes as their characteristics change.

[13]Note that, without loss of generality, we set the scaling parameter A such that the weighted average quality of neighborhoods is normalized to one in the baseline steady state.

[14]See https://www.taxpolicycenter.org/model-estimates/baseline-effective-marginal-tax-rates-july-2016/t16-0114-effective-marginal-tax. The model's average labor income tax rate is 23.6 percent.

redistribution—the ratio of the variance of pre-tax total (i.e., labor and savings) income to after-tax total income—to capture the disposable income available at the bottom of the income distribution. We find that ω=\$2,425 on an annual basis. Note that lump-sum transfers are a standard feature in equilibrium models such as ours. The justification for this stems from the observation that low-income households tend to have higher after-tax income than what would be predicted based on a tax function without a lump-sum component (e.g., Figure 1 of Heathcote et al., 2017).

Lastly, our model incorporates pension benefits following the U.S. federal program for Old Age, Survivors, and Disability Insurance. As explained in Appendix B2, we estimate the average lifetime income using skills to calculate the replacement benefit.

Preferences: We specify that the period utility function for consumption is:

$$u(c,h) = \frac{c^{1-\sigma_c}}{1-\sigma_c},$$

where we follow the literature and specify $\sigma_c = 2$. When parents choose their time to spend with children, the disutility is assumed to be linear: $v(\tau) = \xi\tau$. The parameter ξ is estimated to match the average time spent with children. Finally, the altruism factor $\tilde{\beta}$ in Equation 3 is estimated to match the intergenerational persistence of income from Chetty et al. (2014).

Prices: In the model, labor income is normalized such that the mean annual labor earnings at age 48 are 1. According to the PSID data, this corresponds to \$36,575. The interest rate r is fixed at an annualized value of 4%.

Aggregate Production Function for Final Goods: There is, as previously stated, a representative firm in neighborhood n operates with the production function $Y_n = AK_n^{\alpha}H_n^{(1-\alpha)}$. Here, α is set to 1/3 and the capital depreciation rate is $\delta = 0.065$.

Housing Markets: Rental prices are determined in equilibrium given the landlords housing supply and individuals housing demand. Housing supply in each neighborhood is given by the non-depreciated amount in the previous period plus the new amount purchased from the new house producers:

$$S_{n,t} = (1-\delta_H)\, S_{n,t-1} + H_{n,t}.$$

For a given price $p_{H,n}$ for new housing, the rent price is pinned down by the non-arbitrage condition (7). If the demand is too low (high), $p_{H,n}$ (and, consequently, rent price $p_{r,n}$) will decrease (increase) until the markets clear. Following Davis and Heathcote (2005), we set the housing depreciation rate $\delta_H = 0.015$.

As explained in Section 2.3, the new housing supply elasticity in neighborhood n is given by $\frac{1}{\alpha+\varepsilon_n}$, where α relates to technological features that make housing production more costly as the amount of housing produced increases while ε_n relates to housing regulations that make producing more housing units increasingly more costly. Given the general evidence that lower-income neighborhoods tend to have less strict housing regulations (e.g., Gyourko and Krimmel, 2021; Song, 2025), we assume that $\varepsilon_1 = 0$. For simplicity as well as for lack of detailed enough evidence, we assume that the amount of regulation is similar in the other two neighborhoods (i.e., $\varepsilon_2 = \varepsilon_3$). Following Saiz (2010), we map housing regulations to the Wharton Land Use Regulation Index (Gyourko et al., 2008). Using the estimates from Saiz (2010) on how much the supply elasticity changes when the regulation increases, we estimate the average regulation to be $\varepsilon_2 = \varepsilon_3 = 0.327$.[15] Given that the total elasticity estimated by Saiz (2010) is 1.75, we can then back out that $\alpha = 0.275$. Having calibrated ε_n, T_n determines how much regulation increases housing costs. While empirical estimates are varied, we set T_n such that housing production costs increase by 25% in the equilibrium as this number is in line with various relevant estimates (e.g., Quigley and Raphael, 2005; Quigley and Rosenthal, 2005; Glaeser et al., 2005).

Lastly, following the standard urban economics literature, we set the housing production productivity parameter (A_n) to match the observed housing quantities and prices in each neighborhood.

3.2 Simulated Method of Moments: Results

There are 16 parameters of the model that we estimate using simulated method of moments: $\tilde{\beta}$, ξ, $\bar{v}_1$, $\bar{v}_2$, $\bar{\kappa}$, σ_ε,α_κ, $\bar{A}_{j=8}$, δ_A, $\alpha_{I,j=8}$, δ_{α_I}, ζ, λ, and ω. Specifically, we use a Sobol sequence in order to solve and simulate the model in a seventeen-dimensional hypercube in which parameters are distributed uniformly and over a "large" support. This provides a global method to find combinations of parameters.

Table 2 reports estimated parameters as well as the corresponding moments in data (Column 5) and the simulated economy (Column 6). Overall, the model provides a good fit of the data. Given our purposes, we highlight that the simulated moments related to the skill formation parameters are close to their empirical counterparts. Moreover, the simulated moments that are informative for the neighborhood value parameter and costs are also close to the ones observed in the data.

[15] Saiz (2010) estimates the impact of a normalized version of the Wharton Land Use Regulation index on the inverse of the elasticity to be 0.268. The mean and minimum values of the original regulation index are approximately zero and minus two, respectively. Saiz adds three to the original index to ensure that the log is always positive. Combining these elements, the mean and minimum value of the log-regulation-index are log(3) and 0, respectively. Thus, we obtain that $\varepsilon_2 = \varepsilon_3 = \frac{0.268 \times \log(3)}{0.9} = 0.327$.

Table 2: Estimation Parameters and Moments

Parameter	Value	Description	Moment	Data	Model
Preferences					
$\tilde{\beta}$	0.30	Altruism	Income Persistence	0.34	0.32
ξ	0.17	Parent disutility of time with children	Avg. weekly hours with child (age 0-3)	25.6	27.0
Neighborhood Value and Moving Costs: $\kappa_{j,n'} = \bar{\kappa} \times \exp\left[\alpha_\kappa \left(\bar{v}_{n'} - \bar{v}_2\right)\right]$					
v_1	0.24	Exogenous disutility of $n = 1$	Share in $n = 1$	10.0%	10.2%
v_2	0.26	Exogenous disutility of $n = 1$ and $n = 2$	Share in $n = 3$	10.0%	9.9%
$\bar{\kappa}$	1.05	Moving cost	Share of movers in $n = 2$	7.8%	6.4%
σ_ε	0.29	Preference shock variance	Income Ratio ($n = 2$ vs. $n = 1$)	1.90	1.88
α_κ	-2.87	Location dependent moving cost	Income Ratio p.p. Difference (3−2 minus 2−1)	-0.10	-0.08
Skill Formation: $I = \bar{A}\left[\alpha_{I,j} f\left(\bar{y}_n\right)^\gamma + \left(1 - \alpha_{I,j}\right)t^\gamma\right]^{1/\gamma}$; $\alpha_{I,j>1} = \alpha_{I,j=1} \times \delta_{\alpha_I}$; $\bar{A}_{j>1} = \bar{A}_{j=1} \times \delta_{\bar{A}}$					
$\bar{A}_{j=1}$	0.90	Returns to investments	Average log-skills (age 4)	0.00	0.00
$\delta_{\bar{A}}$	2.72	Returns to investments	Average log-skills growth (age 16 minus age 4)	0.00	0.00
$\alpha_{I,j=1}$	0.69	Neighborhood share of investments	Child inc. diff.: 50 pct. parents, $n = 2$ vs. $n = 1$	16.6%	14.0%
ζ	3.07	Neighborhood curvature	Child inc. diff.: 50 pct. parents, $n = 3 - 2$ -. $n = 2 - 1$ (p.p.)	-12.1	-16.6
δ_{α_I}	0.89	Time share of investments	Avg. hours with child age-ratio $\left(\frac{\text{age 4–15}}{\text{age 0–3}}\right)$	0.59	0.66
$\hat{A}$	1.25	Neighborhood scaling	Neighborhood $n = 2$ normalization	1.00	1.00
Government					
λ	0.76	Tax function scalar	Aggregate marginal labor income tax rate	35.0%	34.5%
ω	0.07	Lump-sum transfer	Income variance ratio: Disposable to pre-gov	0.61	0.62

Notes: This table reports estimates of the model parameters as well as the observed and simulated moments associated with each parameter estimate. See text for definitions and data sources.

3.3 Validation Exercises

After estimating the model, we validate it through two exercises. First, we compare non-targeted moments from the model to their empirical counterparts. Second, we verify that the model's key elasticity—the effect of neighborhood quality on children's outcomes—aligns with reduced-form experimental evidence. (The elasticity of housing supply to regulation was already disciplined by the estimation of ε_n and T_n.)

3.3.1 Non-Targeted Moments

Table 3 summarizes the first validation results, i.e., those from non-targeted moments. With regards to capital accumulation forces in the model, Table 3 shows that the capital-output ratio (annualized) is 2.7 in the model, which is in line with the typical estimate of 3 (e.g., Inklaar and Timmer, 2013). With regards to its portfolio distribution, the model predicts that housing stock's value accounts for about 61% of the total wealth. In the flow of funds data, this share fluctuates around 50%. Lastly, a relevant measure of how feasible it is for the government to introduce new expenses (and taxes), is the size of the government (Heathcote and Tsujiyama, 2021). The model's estimated taxes and transfers lead to government expenses being 16.6% of GDP, in line with the empirical estimates of around 18%.

Table 3: Validation: Non-Targeted Moments

Moment	Data	Model
Aggregates		
Capital-output ratio (annualized) (Inklaar and Timmer, 2013)	≈ 3	2.7
Housing share of households' assets (Flow of Funds)	~50%	61%
Gov. Expenditures (G) over GDP (Heathcote and Tsujiyama, 2021)	18%	16.6%
Income Inequality (PSID)		
Labor Income: 1st Quintile	4.6%	9.0%
Labor Income: 2nd Quintile	12.0%	13.2%
Labor Income: 3rd Quintile	17.4%	17.8%
Labor Income: 4th Quintile	23.7%	23.1%
Labor Income: 5th Quintile	42.2%	36.9%
Intergenerational Mobility (Chetty et al., 2014)		
Prob. of child born in bottom 20% exiting bottom 20%	66.3%	71.0%
Prob. of child born in top 20% exiting top 20%	63.5%	67.3%
Parental Transfers (Daruich and Fernández, 2020)		
Avg. parental transfers as a share of avg. annual labor income	1.44	1.48

Notes: This table compares non-targeted moments from the model to their empirical counterparts. Panel A reports aggregate statistics: capital-output ratio, housing share of wealth, and government expenditure as a share of GDP. Panel B reports labor income shares by quintile. Panel C reports intergenerational mobility statistics. The probability of exiting the bottom quintile is calculated as the share of children born to parents in the bottom quintile of the income distribution who have income above the bottom quintile as adults. See text for data sources.

We can also examine a variety of inequality measures to see how well the model performs in this important dimension. The second panel shows how the model performs in terms of labor income inequality. The model does a good job of replicating labor income shares by quintile, though the shares at the bottom and top in the model suggest lower inequality than in the data.

Turning to intergenerational mobility, the third panel uses the same income measures for parents and children that we employed to construct the rank-rank measure of intergenerational mobility in the targeted moments. The probability of a child born to either the bottom or top quintile of the income distribution of exiting such quintile matches the data well.

Lastly, we study monetary transfers by using the PSID estimates from Daruich and Fernández (2020). They estimate the total transfer received on average by children between the ages of 17 and 30. This yields an estimate of \$46,956 per child, equivalent to 144% of average annual labor income. This estimate is similar to the one of \$44,897 from Johnson (2013), based on NLSY data. Transfers from parents to child as a share of labor income is well matched in the model. This is important as this is also an informative moment on how altruistic parents are (e.g., Daruich, forthcoming).

3.3.2 Comparing Simulations with Experimental Estimates of Housing Voucher Effects

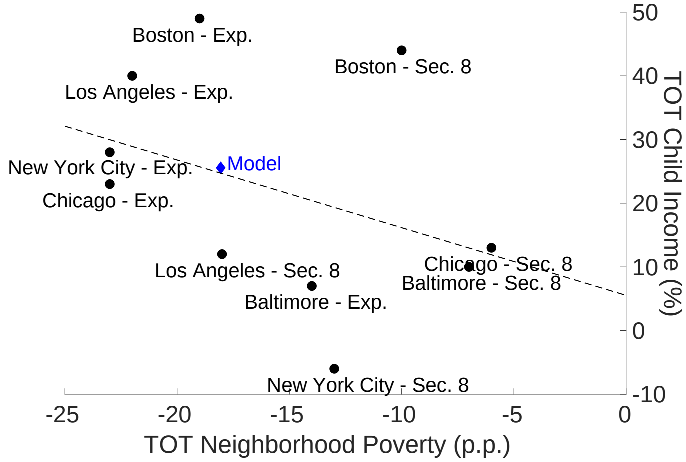
We use credible estimates from the literature to test one of the key mechanisms of our model: how neighborhoods impact child development. Chetty et al. (2016) investigated the Moving to Opportunity (MTO) study, which offered housing vouchers to low-income families with children residing in poor neighborhoods in Baltimore, Boston, Chicago, Los Angeles, and New York. These families were randomly assigned to one of three groups: an "experimental" group, a Section 8 comparison group, and a control group. The experimental group was provided with housing vouchers that were restricted to being used in Census tracts with poverty rates under 10 percent. The Section 8 comparison group received vouchers without any geographic limitations. The control group did not receive vouchers through this experiment. Earlier research on the MTO program indicates it decreased the chances of living in high-poverty areas and positively influenced children's long-term outcomes. Chetty et al. (2016) report that participation in MTO resulted in a \$3,500 increase in earnings for children who relocated. These findings align with a model like ours in which exposure to "better" environments enhances long-term outcomes.

We use our model to simulate a policy akin to the MTO voucher program. Starting from the steady state, the government provides rent-subsidy vouchers to low-income families with children residing in disadvantaged neighborhoods, allowing them to move to the middle-income area ($n = 2$). Vouchers cannot be used in the highest-income area ($n = 3$), consistent with the MTO design. Our simulation follows the program rules, limiting eligibility to those earning less than half the median income and requiring families to contribute 30% of their labor income towards rent.[16] Importantly, we assume that rental prices and neighborhood quality remain unchanged,

[16]We do not model the work disincentives created by the income-based contribution rule, as endogenizing labor supply is computationally infeasible in our framework.

consistent with the expectation that a small-scale RCT does not affect local equilibrium conditions.

Figure 3: Validation: Comparing MTO Site-Specific Effects to Model Simulation



Notes: This figure compares results from the Moving to Opportunity (MTO) housing voucher experiment and simulation results based on our calibrated model. The MTO experiment took place in five cities: Baltimore, Boston, Chicago, Los Angeles and New York. Families were randomized into one of three groups: an experimental group, a Section 8 comparison group, and a control group. The solid (black) dots plot the treatment effects on long-run earnings of children (y-axis) and the change in neighborhood poverty for each site and voucher group (x-axis). Since there were five sites and two vouchers arms (Section 8 and Experimental, respectively), there are 10 solid dots. The solid (blue) diamond plots the simulated effect on long-run earnings of children and associated change in poverty rates from moving to the middle-income neighborhood ($n = 2$). The dashed line shows predictions from a linear regression of the treatment effects on long-run child income (as a percent effect relative to the control group mean) on the reductions in poverty rates.

The main result of this validation exercise is that the simulated voucher program produces effects on children's earnings comparable to those observed in the MTO experiment. We assess the simulated impact on children's earnings in their late 20s against MTO site-specific treatment effects (Ludwig et al., 2013; Chetty et al., 2016). Figure 3 illustrates the treatment effects as black dots for both unrestricted (standard Section 8) and experimental voucher groups across the five MTO cities. It is evident that treated households in the experimental group witnessed more substantial drops in neighborhood poverty. Correspondingly, the treatment effect on children's earnings tends to rise with greater neighborhood quality improvements, indicated by lower neighborhood poverty rates. The dashed line represents a linear regression prediction through these site-specific estimates. The blue diamond marks our simulation results.[17] Encouragingly, our simulation closely matches the linear prediction derived from site-specific MTO findings.

[17] The model considers neighborhood poverty using data from three hypothetical neighborhoods, averaging tract-level Census data as detailed in Section 3.1.

4 Policy Analysis

4.1 Steady-State Effects

The main objective of this paper is to evaluate the intergenerational effects of reducing housing supply regulations. We focus on empirically plausible changes calibrated to observed variation in U.S. cities. Following our estimation strategy, we use the Wharton Land Use Regulation Index to calculate potentially feasible amounts of regulation in the US. Table 4 shows the steady-state results of reducing regulations in three different amounts. The first row reduces regulations (i.e., ε_n) by the difference between the 75th (similar to Los Angeles' estimated regulation) and the 50th percentile (similar to Minneapolis) and is approximately equal to $\Delta\varepsilon_n = -0.055$. The next two rows refer to cases that reduce regulations by the amount between the 75th and the 25th (similar to St. Louis, $\Delta\varepsilon = -0.117$) percentiles and between the 75th and the 10th (similar to Dayton, $\Delta\varepsilon = -0.193$) percentiles, respectively.

Reducing housing regulations (ε) has the expected effect of reducing house prices, as shown by column 2. Prices fall by 5 to 13 percent which, compared to the price differences across cities at these regulation percentiles, represents approximately one-tenth of the observed variation. As shown by columns 3–5, this allows more children to move away from the most disadvantaged neighborhood and, instead, grow up in neighborhoods $n = 2$ and $n = 3$. While this exposes more children to these better neighborhoods, the influx of relatively lower-income families also leads to a reduction in neighborhood quality in those neighborhoods (see columns 7–8). Thus, while children who would have otherwise grown up in $n = 1$ are now more likely to have higher skills, those who would have grown up in $n = 2$ and $n = 3$ are not. This explains why there is a relatively small impact on average skills (column 9) but a larger impact on inequality.[18] Consumption inequality (measured as the variance of log consumption) is reduced by between 2.6 and 6.1%, and intergenerational mobility increases by 1 to 3%.[19] Column 12 uses the wealth equivalence measure (under the veil of ignorance) to summarize the welfare effects of the policy change. Children would need to start adulthood (at age $j = 5$) with between \$9,600 and \$23,000 more in assets in the initial steady state to be indifferent with being born in the steady state with lower housing regulations.[20]

[18] Appendix Table A2 shows the results from performing a Shapley decomposition to evaluate the impact of equilibrium forces. The fact that neighborhood quality decreases is the main driver of the muted impact on average skills. If the neighborhood quality was unchanged, average skills would increase substantially more.

[19] All intergenerational mobility numbers are calculated using parental income averaged over the periods that the child lives with their parents ($j = 8$ to 11) and child's income measured at $j' = 8$. The rank-rank coefficient on gross income (used by Chetty et al. (2014)) is multiplied by -1 so that an increase signifies less dependence on parental income rank.

[20] As highlighted by Conesa et al. (2018) and Herkenhoff and Raveendranathan (2024), this welfare measure is

Table 4: Steady State Results

	Percent Change from Initial Steady State										
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔHousing	**House**	**Share of Kids in (p.p.)**			**Neigh. Qual.**			**Skills**	**Cons.**	**Interg.**	**Welfare**
Regulations	**Values**	$n = 1$	$n = 2$	$n = 3$	$n = 1$	$n = 2$	$n = 3$	θ_c	**Ineq.**	**Mobility**	**($1k)**
$75^{th} \rightarrow 50^{th}$	-5.1	-1.2	0.7	0.5	5.3	-2.2	-1.1	0.1	-2.6	1.2	9.6
$75^{th} \rightarrow 25^{th}$	-9.4	-2.0	1.1	1.0	12.4	-4.1	-2.1	0.1	-4.6	2.4	17.5
$75^{th} \rightarrow 10^{th}$	-12.8	-2.6	1.2	1.3	19.6	-5.5	-2.9	0.0	-6.1	3.1	23.0

Notes: This table reports steady-state effects of reducing housing supply regulations. Each row corresponds to a different reduction in the regulation parameter ε_n, calibrated to the difference between the 75th percentile of the Wharton Land Use Regulation Index and the 50th, 25th, and 10th percentiles, respectively. Column 1 reports the change in ε_n. Column 2 reports the percent change in average house prices. Columns 3–5 report percentage point changes in the share of children residing in each neighborhood. Columns 6–8 report percent changes in neighborhood quality (average income per capita). Column 9 reports the percent change in average skills. Columns 10–11 report percent changes in consumption inequality (variance of log consumption) and intergenerational mobility (negative of the rank-rank coefficient). Column 12 reports welfare gains under the veil of ignorance, measured as the wealth equivalent transfer in dollars that would make a newborn indifferent between the initial and new steady states.

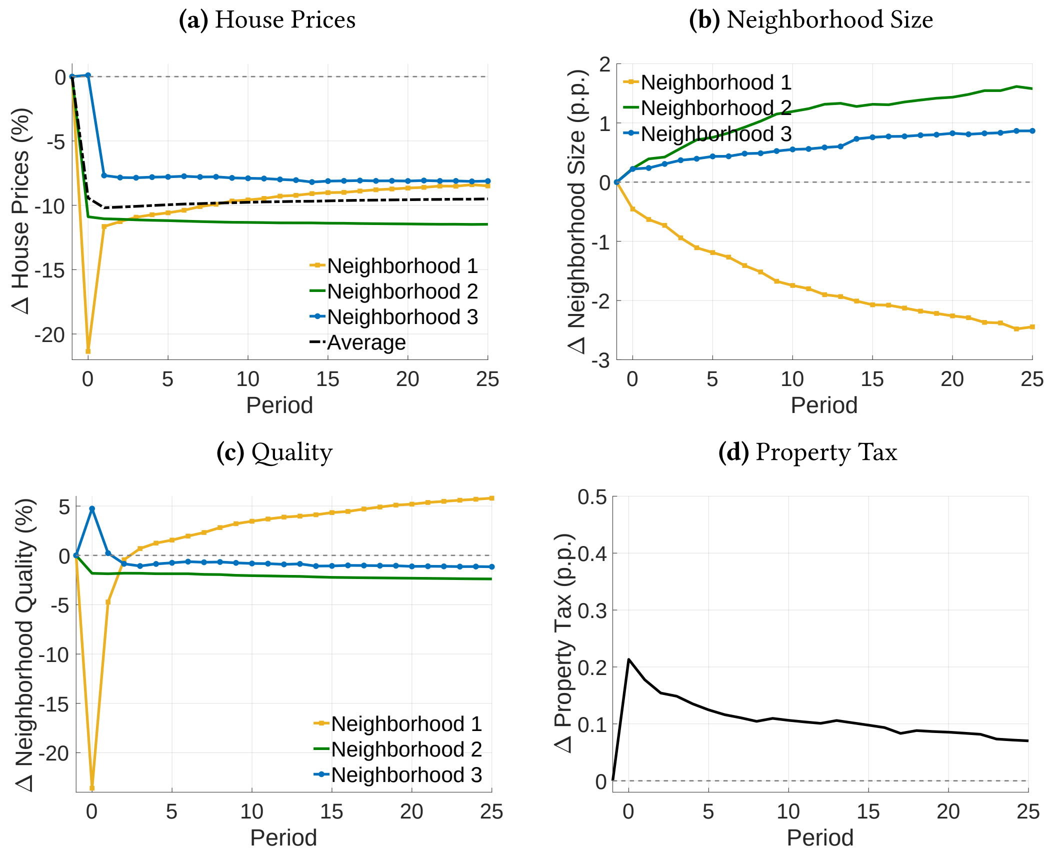
The rest of the results focus on the case in which housing regulations are reduced within the interquartile range (i.e., from the 75th to the 25th percentiles). Given the monotonicity of results in Table 4, we focus on this case for brevity.

4.2 Transition Dynamics

We assume the policy is introduced unexpectedly at the beginning of period $t = 0$, after individuals have received their shocks for that period (labor income, child skill, and taste shocks) and parents have made transfers, but before households make their consumption and location decisions. We examine the dynamic consequences of such a policy, analyzing how it affects inequality and the welfare of different cohorts by taking into account intergenerational dynamics as well as general equilibrium effects through prices, neighborhood quality and property taxes.

useful for several reasons. First, it is easy to calculate even in computationally complicated models as it is implicitly already described by the value functions values at different amounts of assets. Second, it also has the benefit that it can be aggregated across individuals. Lastly, it allows for a scenarios in which individuals can reoptimize their decisions once the transfer is received. While this does not take into account general equilibrium effects from everyone receiving such transfers, we are closer to evaluating a counterfactual in which we can compensate individuals such that everyone is better off (if the sum of all welfare gains is positive) – a fact that we will exploit in Section 5. This would not be possible using the standard consumption equivalence measure.

Figure 4: Transition Dynamics: Aggregates



Notes: This figure shows the transition dynamics following a reduction in housing supply regulations from the 75th to the 25th percentile of the Wharton Land Use Regulation Index. The policy is introduced unexpectedly at period $t = 0$. Panel (a) plots the percent change in house prices by neighborhood relative to the initial steady state. Panel (b) plots the change in neighborhood population shares in percentage points. Panel (c) plots the percent change in neighborhood quality (average income per capita). Panel (d) plots the change in property tax rates in percentage points. All panels show dynamics until the economy converges to the new steady state.

Figure 4 shows the effects of the housing deregulation policy on a series of key variables and outcomes over the transition to the new steady state. As shown in panel (a) of Figure 4, house prices decline in all neighborhoods. However, the initial decline is larger in the lowest-income neighborhood, where demand falls the most. Instead, as shown by panel (b), the other two neighborhoods see an increase in demand which then requires an increase in new housing supply to achieve an equilibrium. Although construction costs have declined, house prices in the top-income neighborhood must remain temporarily elevated to equilibrate higher demand, which itself reflects anticipated future price declines. As shown by panel (b), the economy slowly converges to its new size distribution over the next 20 periods (at which point it has mostly stabilized). Panel (c) shows that the outflow of individuals from the poorest neighborhood and its associated housing price decline leads to substantially negative effect on its neighborhood quality. However, this recovers over time as housing prices recover once new housing supply is needed to replace depreciated stock. Importantly, as housing prices decline (on average by about 10%), property taxes need to increase to balance the government budget. The initial increase is of 0.2 percentage points (from an initial value between 1.7 and 2.9 percentage points depending on the neighborhood) but this is reduced to around 0.1 percentage points as individuals move to neighborhoods with already higher initial property tax rates.

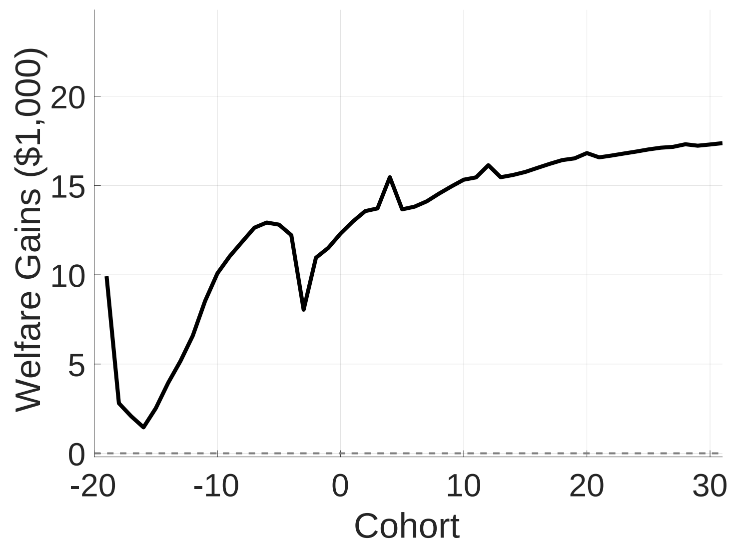
4.3 Welfare Effects

We now turn to welfare effects. We summarize welfare using wealth equivalence: the asset transfer that would make an individual indifferent between the two steady states. Figure 5 reports average welfare gains by cohort where the y-axis measures the average wealth transfer by which the deregulation policy is preferred to the original steady state. Cohort 0 is the first cohort born when the policy is introduced. Cohorts to the left of zero (that is, until negative 19) are the cohorts who were already alive when the policy was introduced; cohorts to the right of zero are those born after the policy is introduced. For adult cohorts (those strictly to the left of -3) we show average welfare gains by cohort. For all other cohorts, we calculate welfare gains under the veil of ignorance.[21]

Housing deregulation has (on average) positive welfare consequences for all cohorts, both those alive when the policy is introduced and those born later. Given the choice between being born in the initial steady state or in the one with lower housing regulation, an individual would need to be given a transfer of $17,000 (which is about 41% of the average initial amount of assets) to remain in the non-deregulated economy. Agents who are adults when the policy is introduced (i.e, those of period age $j = 5$ to 20) have an average welfare gain of approximately $5,000.

[21]Note that cohorts -1 to -3 are alive when the policy is introduced. To reduce the computational burden, we calculate their welfare change under the veil of ignorance (i.e., under the assumption that the agent obtains a random draw from the equilibrium distribution of the state variables $(\theta, \hat{a}, n)$, which varies by cohort).

Figure 5: Transition Dynamics: Welfare Gains

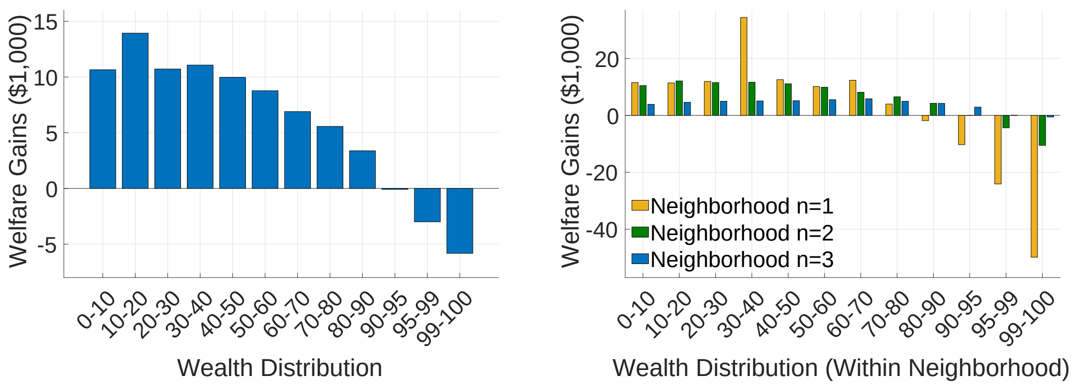


Notes: This figure reports average welfare gains from housing deregulation by cohort. The x-axis denotes cohorts, where cohort 0 is the first cohort born when the policy is introduced, negative values denote cohorts alive at policy introduction, and positive values denote cohorts born after. The y-axis measures welfare as wealth equivalence: the asset transfer (in dollars) that would make an individual indifferent between the initial steady state and the deregulated economy. For adult cohorts (those to the left of -3), welfare is computed using realized state variables. For other cohorts, welfare is computed under the veil of ignorance using the equilibrium distribution of state variables.

We next examine heterogeneity in welfare gains among adults alive when the policy is introduced. For each age group, agents are grouped by percentiles according to their age-adjusted asset holdings. The welfare changes are reported in panel (a) Figure 6. While most wealth groups gain, households in the top 10 percent of the wealth distribution experience losses. These households hold substantial housing wealth and therefore suffer larger capital losses from the price decline. Panel (b) expands on these results by reporting welfare effects by wealth and the initial location where individuals reside. These results show that, within the population of wealthy individuals, it is those originally living in the disadvantaged neighborhood ($n = 1$) who have largest welfare losses since this is area with the largest unexpected housing price decline (and, thus, wealth loss) – as shown in Figure 4. Similarly, the largest welfare gains among those in the bottom 70% of the wealth distribution are generally accrued by those in the poorest neighborhood as well.

Figure 6: Welfare Gains by Wealth and Neighborhood at Policy Introduction

(a) By Wealth **(b)** By Wealth and Initial Neighborhood



Notes: This figure reports welfare gains from housing deregulation for adults alive when the policy is introduced, disaggregated by wealth and initial neighborhood. Panel (a) plots average welfare gains by decile of the age-adjusted wealth distribution. Panel (b) plots welfare gains by wealth decile separately for residents of each neighborhood: $n = 1$ (disadvantaged), $n = 2$ (middle-income), and $n = 3$ (top-income). Welfare is measured as wealth equivalence in dollars. The policy reduces housing regulations from the 75th to the 25th percentile of the Wharton Land Use Regulation Index.

5 Importance of Intergenerational Dynamics

A key feature of our framework is the role of intergenerational altruism in shaping welfare assessments of housing policy. Parents in our model value their children's welfare through the altruism parameter $\tilde{\beta}$, which influences both parental investment decisions and how households evaluate policy changes. In this section, we examine how abstracting from such intergenerational considerations would affect our welfare conclusions.

A substantial literature evaluates the welfare costs of housing supply restrictions using quantitative spatial equilibrium models. Hsieh and Moretti (2019) estimate that housing constraints in high-productivity cities lowered aggregate U.S. GDP growth by 36 percent between 1964 and 2009. Glaeser and Gyourko (2018) review the evidence on housing supply restrictions and discuss welfare implications through housing affordability and labor misallocation channels. More recently, Favilukis et al. (2023) develop a dynamic spatial equilibrium model calibrated to New York to evaluate zoning, rent control, and housing voucher policies. A common feature of these influential contributions is that they abstract from intergenerational linkages: households are either infinitely-lived or follow standard life-cycle patterns without parental altruism toward children. Consequently, welfare assessments focus on effects operating through housing costs, labor market access, and wealth accumulation—but not through child development.

To isolate the contribution of intergenerational dynamics in our framework, we compute welfare gains under an alternative specification in which parents do not internalize benefits accruing to their children—effectively setting $\tilde{\beta} = 0$ when computing welfare. Under this specification, adults still make the same consumption and savings decisions, but their welfare calculations exclude any value placed on their children's outcomes. This exercise quantifies how much of the welfare gain from housing deregulation stems from parents internalizing improvements in their children's future prospects.

Figure 7 compares welfare gains for adults alive at the time the policy is introduced, both with and without intergenerational altruism. Panels (a) and (b) display welfare gains across the wealth distribution, while panels (c) and (d) show welfare gains by age and initial neighborhood.

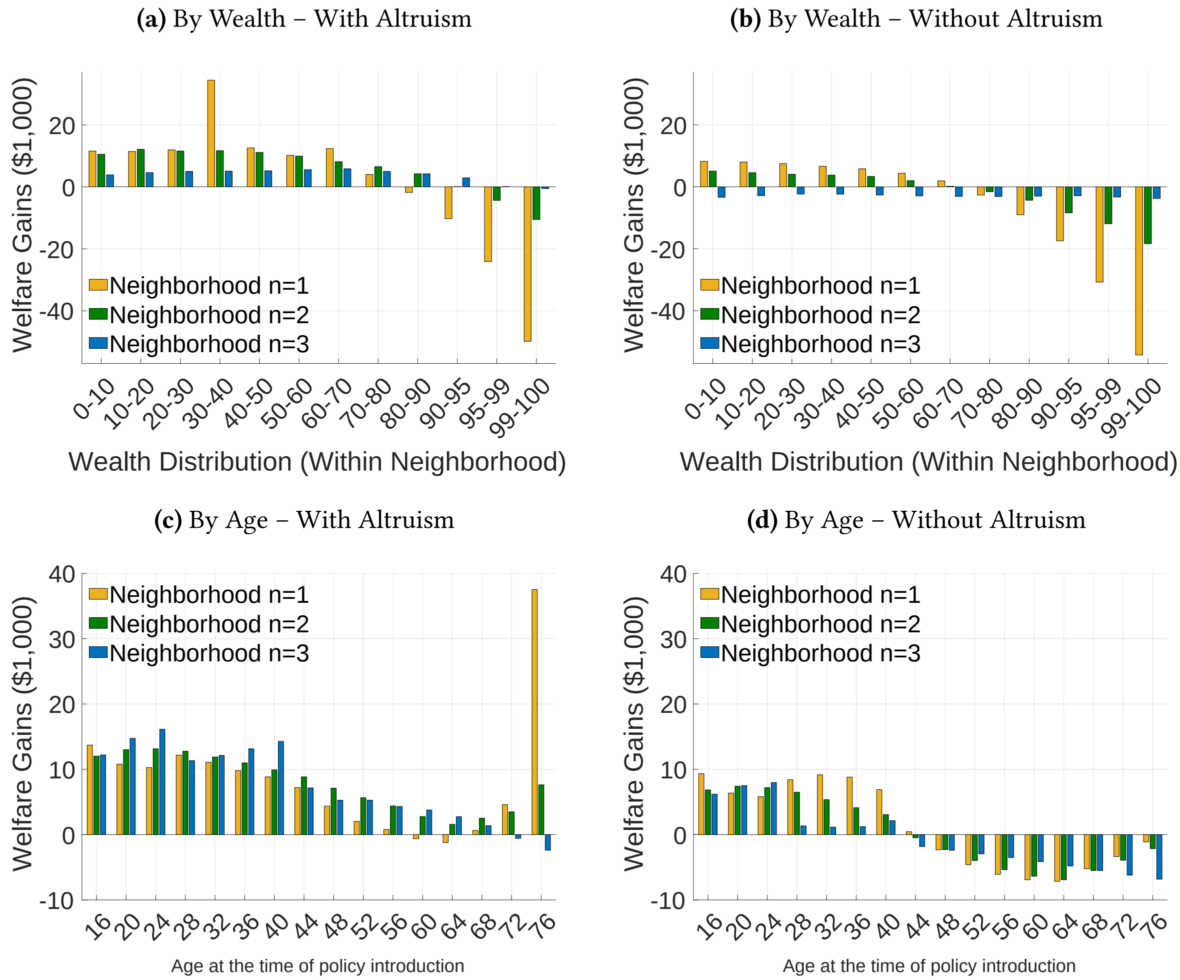
The quantitative implications are substantial. Averaging across all adult cohorts alive when the policy is introduced, the mean welfare gain falls from approximately \$7,900 in the baseline to only \$210 without intergenerational altruism—a reduction by a factor of nearly forty. This dramatic difference reflects the fact that, from the perspective of current adults, the direct effects of housing deregulation on their own consumption are modest. Housing costs decline, but so does the value of housing wealth. Without accounting for the benefits that accrue to children through improved neighborhood access, the net effect on adult welfare is close to zero.

The heterogeneity across wealth groups displayed in panels (a) and (b) reinforces this interpretation. In the baseline model with altruism, low-wealth households in the disadvantaged neighborhood ($n = 1$) experience the largest welfare gains, as they benefit both directly from lower housing costs and indirectly from improved opportunities for their children. Without altruism, this gradient is substantially attenuated because the intergenerational channel is shut down. Meanwhile, wealthy households—particularly those in the poorer neighborhoods who hold housing assets subject to the largest price declines—see their welfare losses become relatively more prominent when the offsetting gains from children's improved prospects are excluded.

Panels (c) and (d) reveal additional heterogeneity by age. While welfare gains decline across all age groups when altruism is removed, the reduction is most pronounced for older individuals. This pattern reflects the fact that older adults have fewer remaining years over which to benefit from lower housing costs, so the direct consumption channel contributes less to their welfare. In the baseline model with altruism, older adults nonetheless experience substantial welfare gains because they value the improved prospects for their children and grandchildren. Once this intergenerational channel is shut down, their welfare gains largely disappear.

The age panels also highlight an important pattern for residents of the top neighborhood ($n = 3$). In the baseline model, these households generally experience positive welfare gains de-

Figure 7: Welfare Gains without Intergenerational Dynamics



Notes: This figure compares welfare gains from housing deregulation with and without intergenerational altruism. Panels (a) and (b) plot welfare gains by wealth decile for residents of each neighborhood; panels (c) and (d) plot welfare gains by age and neighborhood. The left panels include parental altruism ($\tilde{\beta} > 0$) in welfare calculations; the right panels exclude it ($\tilde{\beta} = 0$). In all panels, welfare is measured as wealth equivalence in dollars for adults alive when the policy is introduced. The policy reduces housing regulations from the 75th to the 25th percentile of the Wharton Land Use Regulation Index.

spite facing declines in their housing wealth. This occurs because housing deregulation provides a form of intergenerational insurance: even if their descendants experience negative shocks in the future, those descendants will face an improved opportunity to access high-quality neighborhoods. When altruism is excluded, this insurance value vanishes, and the welfare effects for top-neighborhood residents become negligible or negative.

These differences have important implications for political feasibility. In the baseline model with intergenerational altruism, only 17 percent of adults alive at the time of the policy change would oppose housing deregulation based on their individual welfare effects. However, when altruism is excluded, opposition rises to 52 percent—a shift from a broad political majority in favor to a narrow majority against. This reversal occurs because, without valuing children's gains, the policy becomes primarily a redistribution from housing-asset holders to renters, with limited aggregate benefits to offset the losses of the former group.

These results underscore a broader methodological point. Models that abstract from intergenerational linkages—such as standard spatial equilibrium frameworks or life-cycle models without parental altruism—may substantially understate both the welfare benefits and political viability of policies that improve children's long-term outcomes. Housing deregulation is precisely such a policy: while it generates immediate effects through housing markets, much of its welfare value stems from facilitating access to neighborhoods that promote child development. Failing to account for how parents value these benefits leads to an incomplete and potentially misleading assessment.

6 Conclusion

This paper develops and estimates a general equilibrium overlapping-generations model to evaluate the welfare effects of housing supply restrictions. The framework integrates neighborhood effects on child development, parental altruism, and endogenous housing supply into a unified structure. Housing regulations are modeled as convex construction costs that vary across neighborhoods, allowing the housing supply elasticity to respond to policy changes—a margin that existing spatial equilibrium models with child development treat as fixed. Reducing U.S. housing regulations from levels observed in restrictive cities to those in less restrictive ones generates lower house prices, improved neighborhood access for children in disadvantaged areas, and substantial welfare gains.

A central finding is that intergenerational dynamics are quantitatively essential for understanding the welfare effects of housing policy. When parental altruism is excluded from welfare calculations, average gains for adults at the time of reform fall by a factor of nearly forty, and political support shifts from a broad majority in favor to a narrow majority against. This result suggests that spatial equilibrium models abstracting from intergenerational linkages—a common feature of the existing literature—may substantially understate both the welfare benefits and political viability of policies that improve children's access to high-opportunity neighborhoods.

The political economy results highlight a potential obstacle to reform: adults who do not fully internalize the benefits accruing to future generations may oppose deregulation due to capital losses on housing wealth. Building political support for housing reform may therefore require compensating adversely affected homeowners. Several mechanisms could achieve this. Temporary reductions in property taxes for existing homeowners would offset some of the capital losses from declining house prices. Phased implementation of deregulation would allow housing markets to adjust gradually, limiting the magnitude of price declines in any given period. Finally, using borrowed funds to be paid by future generations (i.e., the main winners) to provide transfers to current residents in affected neighborhoods could provide direct compensation while maintaining political support for reform.

Our analysis also suggests a promising direction for future research: studying the interaction between housing supply restrictions and demand-side policies. Housing vouchers, place-based subsidies, and zoning reform are often discussed as alternative approaches to improving neighborhood access, but they may be more effective when implemented jointly. Deregulation increases the supply response to voucher-induced demand, potentially amplifying the benefits of both policies while limiting the house price increases that can undermine voucher programs in supply-constrained markets. A framework that evaluates such policy combinations could provide guidance on optimal policy portfolios for promoting intergenerational mobility.

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A Additional Figures and Tables

Table A1: Estimates of Wage Parameters

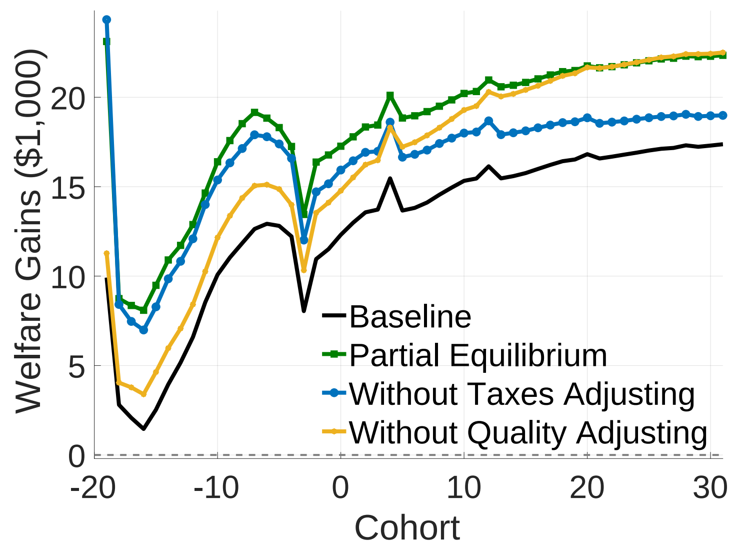
	(1)	(2)	(3)
Age	0.0722***		
	(0.003)		
Age^2	-0.000879***		
	(0.000)		
Inv. Mills Ratio	-0.574***		
	(0.0303)		
Υ		1.486***	
		(0.0223)	
ρ			0.9769***
			(0.000)
σ_z			0.0389***
			(0.000)
σ_{η_0}			0.1001***
			(0.000)
R^2	0.058	0.319	–
# of households	3,576	11,878	11,878
Observations (N)	24,767	28,827	28,827

Notes: This table reports estimates of the parameters of the labor income process in our model. Column 1 reports results for the age profile parameters. This is obtained using a sample constructed from the PSID (1968–2016) and regressing labor income on age, age-squared, and controls for selection into work based on the Inverse Mills Ratio obtained from a Heckman-selection correction approach. The selection estimator is based on estimating an employment participation equation using the number of children and year-region fixed effects. Column 2 reports estimates of the return to skills. This is obtained using a sample from the NLSY and regressing of the idiosyncratic component of labor productivity ψ_j (measured as a residual based on the age profile estimates from Column 1) on the log of cognitive skills as measured by the AFQT score. Column 3 reports estimates of the parameters that govern the AR(1) process that we assume determines the shock η_j which is the idiosyncratic component of labor productivity. These estimates are obtained from the Minimum Distance Estimator developed by Rothenberg (1971). Standard errors are reported in parentheses. Statistical significance is denoted by: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A2: Steady State Results: Shapley Decomposition

Eq. Forces	Percent Change from Initial Steady State										
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	House	Share of Kids in (p.p.)			Neigh. Qual.			Skills	Cons.	Interg.	Welfare
	Values	$n = 1$	$n = 2$	$n = 3$	$n = 1$	$n = 2$	$n = 3$	θ_c	Ineq.	Mobility	($1k)
Without Eq. Forces	-9.2	-2.8	2.0	0.8	0.0	0.0	0.0	1.0	-6.1	2.8	23.0
Neigh. Qual.	-0.2	0.8	-0.9	0.2	12.9	-4.2	-2.2	-0.9	1.3	-0.4	-4.8
Gov. Budget	-0.0	0.0	0.0	-0.0	-0.3	0.1	0.1	0.0	0.3	-0.0	-0.6
With Eq. Forces	-9.4	-2.0	1.1	0.9	12.6	-4.1	-2.1	0.1	-4.6	2.4	17.5

Figure A1: Transition Dynamics: Welfare Gains Decomposition



B Estimation Details

B1 Child Skill Production Function

We rely on estimates from Cunha et al. (2010) for the calibrated model. Specifically, they estimate the following multistage production function for children's cognitive (c) and non-cognitive skills (nc):

$$\theta'_{q,k} = \left[\alpha_{1,q,j}\theta_{c,k}^{\rho_{q,j}} + \alpha_{2,q,j}\theta_{nc,k}^{\rho_{q,j}} + \alpha_{3,q,j}\theta_{c}^{\rho_{q,j}} + \alpha_{4,q,j}\theta_{nc}^{\rho_{q,j}} + \alpha_{5,q,j}I^{\rho_{q,j}}\right]^{1/\rho_{q,j}} e^{v_q}, \qquad v_q \sim N(0, \sigma_{q,j,v})$$

for $q \in \{c, nc\}$. Using a nonlinear factor model with endogenous inputs, their main estimates, which are based on two-year periods, are reported in Table B3 below. We interpret their first stage estimates as referring to the period in which the child is born in our model when the parent's age-period is $j = 8$ and the child's age-period is $j' = 1$, (i.e., 0–3 years old). The second stage is assumed to refer to the last period of skill development when the parent's age-period is $j = 11$ and the child's age-period is $j' = 4$ (i.e., 12–15 years old). We use linear interpolation to obtain the estimates for $j = 9$ and $j = 10$.

Table B3: Child Skill Production Function Estimates from Cunha et al. (2010)

	Cognitive Skills		**Non-Cognitive Skills**	
	1st Stage	**2nd Stage**	**1st Stage**	**2nd Stage**
	($j = 8$)	($j = 11$)	($j = 8$)	($j = 11$)
Current Cognitive Skills ($\hat{\alpha}_{1,q,j}$)	0.479	0.831	0.000	0.000
	(0.026)	(0.011)	(0.026)	(0.010)
Current Non-Cognitive Skills ($\hat{\alpha}_{2,q,j}$)	0.070	0.001	0.585	0.816
	(0.024)	(0.005)	(0.032)	(0.013)
Parent's Cognitive Skills ($\hat{\alpha}_{3,q,j}$)	0.031	0.073	0.017	0.000
	(0.013)	(0.008)	(0.013)	(0.008)
Parent's Non-Cognitive Skills ($\hat{\alpha}_{4,q,j}$)	0.258	0.051	0.333	0.133
	(0.029)	(0.014)	(0.034)	(0.017)
Investments ($\hat{\alpha}_{5,q,j}$)	0.161	0.044	0.065	0.051
	(0.015)	(0.006)	(0.021)	(0.006)
Complementarity parameter ($\hat{\rho}_{q,j}$)	0.313	-1.243	-0.610	-0.551
	(0.134)	(0.125)	(0.215)	(0.169)
Variance of Shocks ($\hat{\sigma}_{q,j,v}$)	0.176	0.087	0.222	0.101
	(0.007)	(0.003)	(0.013)	(0.004)

Notes: Standard errors in parentheses. The first stage refers to the period in which the child is born when the parent's age-period is $j = 8$ and the child's age-period is $j' = 1$ (i.e., 0–3 years old). The second stage refers to the period after the child is born when the parent's age-period is $j = 11$ and the child's age-period is $j' = 4$ (i.e., 12–15 years old).

To go from two-year periods to four-year periods (as in our model), we follow the steps in

Daruich (forthcoming). Using $\hat{\alpha}$ to notate the estimates in Cunha et al. (2010) and α for the values in our model, the two main steps/assumptions for the transformation are: (i) we iterate in the production function under the assumption that the shock v only takes place in the last iteration, i.e., replace $\theta_{q,k}$ by $\left[\alpha_{1,q,j}\theta_{c,k}^{\rho_{q,j}} + \alpha_{2,q,j}\theta_{nc,k}^{\rho_{q,j}} + \alpha_{3,q,j}\theta_{c}^{\rho_{q,j}} + \alpha_{4,q,j}\theta_{nc}^{\rho_{q,j}} + \alpha_{5,q,j}I^{\rho_{q,j}}\right]^{1/\rho_{q,j}}$;[22] and (ii) we assume that the cross-effect of skills (i.e., of cognitive on non-cognitive and of non-cognitive on cognitive) is only updated every two periods.[23] Under these assumptions, the persistence parameter needs to be squared (i.e., $\alpha_{1,c,j} = \hat{\alpha}_{1,c,j}^2$ and $\alpha_{2,nc,j} = \hat{\alpha}_{2,nc,j}^2$), while other parameters inside the CES function need to be multiplied by 1 plus the persistence parameter (e.g., $\alpha_{2,c,j} = \left(1 + \hat{\alpha}_{1,c,j}\right)\hat{\alpha}_{2,c,j}$).

B2 Replacement benefits: US Social Security System

The pension replacement rate is obtained from the Old Age Insurance of the US Social Security System. We use the skill level to estimate a proxy for average lifetime income, on which the replacement benefit is based. Average income at age j is estimated as $\widehat{y}_j\left(\theta_c\right) = wE_j\left(\theta_c, \overline{\eta}\right) \times \overline{h}$ where $\overline{\eta}$ is the average shock (i.e., zero) and $\bar{h}$ are the average hours worked (in the economy). Averaging over j allows average lifetime income $\widehat{y}(\theta_c)$ to be calculated and used in (B1) to obtain the replacement benefits.

The pension formula is given by

$$\pi(\theta_c) = \begin{cases} 0.9\widehat{y}\left(\theta_c\right) & \text{if } \widehat{y}\left(\theta_c, e\right) \leq 0.3\bar{y} \\ 0.9\left(0.3\bar{y}\right) + 0.32\left(\widehat{y}\left(\theta_c\right) - 0.3\bar{y}\right) & \text{if } 0.3\bar{y} \leq \widehat{y}\left(\theta_c\right) \leq 2\bar{y} \\ 0.9\left(0.3\bar{y}\right) + 0.32\left(2 - 0.3\right)\bar{y} + 0.15\left(\widehat{y}\left(\theta_c\right) - 2\bar{y}\right) & \text{if } 2\bar{y} \leq \widehat{y}\left(\theta_c\right) \leq 4.1\bar{y} \\ 0.9\left(0.3\bar{y}\right) + 0.32\left(2 - 0.3\right)\bar{y} + 0.15\left(4.1 - 2\right)\bar{y} & \text{if } 4.1\bar{y} \leq \widehat{y}\left(\theta_c\right) \end{cases} \quad \text{(B1)}$$

where $\bar{y}$ is approximately \$288,000 (\$72,000 annually).

[22]We assume that the variance of the shock in the 4-year model is twice the one in the 2-year model (i.e., $\sigma q, j, v^2 = \hat{\sigma} q, j, v^2$).

[23]Removing this assumption does not change results significantly since the weights corresponding to these elements are very small or even zero in the estimation (in Table B3, see row 2 under columns 1 and 2, as well as row 1 under columns 3 and 4), but it eliminates the CES functional form if $\rho_{c,j} \neq \rho_{nc,j}$.