Opportunity & Inclusive Growth INSTITUTE

FEDERAL RESERVE BANK OF MINNEAPOLIS

INSTITUTE WORKING PAPER
No. 47

The Geography of Opportunity: Education, Work, and Intergenerational Mobility Across US Counties

Revised April 2024

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DOI: https://doi.org/10.21034/iwp.47
Keywords: Spatial economics; Intergenerational mobility; Regional labor markets
JEL classification: E24, E62, R12, R23, R76, I24, I28

The Geography of Opportunity: Education, Work, and Intergenerational Mobility Across US Counties*

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First Version: November 2017
This Version: April 2024

Abstract

Neighborhoods have a profound and lasting impact on children's economic outcomes later in life, challenging the equality of opportunity promised by the American Dream. We develop a dynamic spatial equilibrium model in which children's education choices are shaped by the costs and returns to education in their childhood location. Local returns depend on the moving-cost-adjusted education wage premia in all locations and local costs on the per-student school funding raised from local taxes. In the calibrated model, equalizing school funding across all students decreases differences in education outcomes across US counties and increases intergenerational mobility. However, the reform reduces the supply of educated workers in locations where the demand for them is highest, lowering aggregate output. Policies that instead broaden access to counties with good education outcomes increase intergenerational mobility without reducing output.

Keywords: Spatial Economics, Intergenerational Mobility, Regional Labor Markets
JEL Codes: E24, E62, R12, R23,R75, I24, I28

*Corresponding author: Tatjana Kleineberg, tkleineberg@worldbank.org. We thank our advisors Giuseppe Moscarini, Samuel Kortum, Michael Peters and Fabrizio Zilibotti. We owe special thanks to Rucker Johnson for providing additional estimation results and to Gilles Duranton, Nir Jaimovich, Jessie Handbury, and Juan Herreño for advice. We are also grateful to Joseph Altonji, Costas Arkolakis, Lorenzo Caliendo, Ed Glaeser, Nathan Hendren, Costas Meghir, Mark Rosenzweig, Sharon Traiberman, and Aleh Tsyvinski. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent. This paper was previously circulated as "Saving the American Dream? Education Policies in Spatial General Equilibrium."

INTRODUCTION

The American Dream promises equality of opportunity to all children, regardless of their place of birth and parental background. However, childhood neighborhoods profoundly impact children's educational prospects and economic outcomes later in life. Policymakers have proposed various policies in response to these disparities. Proposals include allocating more school funding to under-performing neighborhoods or enabling more families to access well-performing neighborhoods through subsidies or housing policies. Such proposals typically neglect to consider that the geography of education choices is an equilibrium outcome, which changes in response to policies.

In this paper, we develop a spatial equilibrium model in which children's educational choices in each location depend on the local costs and returns to education, which are equilibrium outcomes. We estimate the model with novel US data on county-level education outcomes. We use the estimated model for an equilibrium evaluation of policies that are commonly proposed to reduce the opportunity gap across neighborhoods and parental backgrounds. We find that a budget-neutral school funding equalization across students reduces the dispersion in education outcomes across US counties and parental backgrounds. However, general equilibrium forces substantively mitigate the policy's direct effects. In addition, the policy distributes funding away from locations with a high demand for educated workers, which creates a mismatch between the local skill demand and skill supply and reduces aggregate output. Alternative policies, which expand access to locations with good education outcomes, manage to improve intergenerational mobility without reducing aggregate output.

The model has a dynastic structure in which agents live for a childhood and adulthood period. Children choose their education in their location of birth. Later on, they choose an adulthood location based on idiosyncratic preferences, wages, residential rents, moving costs, and the future utility each destination offers their own children. Education decisions and residential choices jointly determine the supply of educated workers in each location. Local production technologies differ in productivity and skill-intensity and determine the local demand for educated workers.

The novelty in our model is that education choices vary endogenously across neighborhoods due to differences in the local returns and costs of education. Local returns to education are summarized by a labor market access term that captures the moving-cost-adjusted education wage premia in all possible destinations. Local costs of education depend on the amount of per-student school funding, which is partly funded from local property taxes. To capture other determinants of the local costs of education, we include an exogenous "education productivity" term that differs by neighborhood and parental education. In an extended version of the model, we additionally include peer effects as an endogenous determinant of local education outcomes.

Relative to existing spatial models, our framework has three new parameters that shape local education decisions: a parental altruism parameter, that measures the weight parents place on their children's utility relative to their own when making residential choices, the variance of children's idiosyncratic preference shocks over education levels, and the effect of local school funding on local education outcomes. To calibrate these parameters, we use US county-level data on children's college education rates by parental background and childhood county, per-student school funding by funding source, and residential stocks of workers by education level and by presence of children in the household.

We identify these new parameters from the differential residential sorting of parents and non-parents across counties and by mapping existing micro-estimates to our model. The extent to which parents sort more than non-parents toward counties which offer their children higher overall utility identifies the altruism parameter. The extent to which parents sort on the cost-adjusted returns to *all* education levels–as opposed to just one education level–identifies the variance of idiosyncratic education taste shocks. Intuitively, if the variance is zero, all children in a location choose the education level that offers the highest cost-adjusted return. The higher the variance, the more returns to *all* education options matter. We obtain the effect of school funding on education outcomes by mapping estimates of the causal effect of school funding on college education rates from Jackson, Johnson, and Persico (2016) to our model. We infer the education productivity for each county and parental background, so that the model exactly matches the corresponding data on college education rates, after accounting for school funding and local education returns.

We use the estimated model to evaluate three policies commonly proposed to reduce differences in education outcomes across locations and parental backgrounds. First, we implement a budget-neutral equalization of per-student school funding that removes the link between local tax revenues and local school funding by raising all funds from federal taxes. Second, we offer a subsidy to low-education parents conditional on living in locations that are in the top two deciles of education outcomes. Last, we expand housing supply in the same set of locations as a reduced-form way of modeling a relaxation of zoning restrictions.[1] The equilibrium effects of these policies depend on the joint distributions of productivities, skill intensities, amenities, and education productivities

[1] All three policies have received attention from policymakers and academics in the US. The funding of schools from local property taxes and the resulting disparities in funding across locations have led to many contentious debates and even numerous lawsuits during the past decades. Moving disadvantaged families to locations with good education outcomes was proposed by the well-known Moving to Opportunity experiment, studied in Katz, Kling, and Liebman (2001) and Chetty, Hendren, and Katz (2016). Many policymakers and scholars have advocated for relaxing zoning restrictions, for example, in Hsieh and Moretti (2019).

across counties that we recover from the data.

We find that the school funding equalization and the subsidy reduce differences in college education rates across locations. The school funding equalization leads to a convergence in education outcomes because it redistributes funding from locations with high initial education outcomes to those with low education outcomes. The subsidy attracts low-education parents into subsidized locations where initial education outcomes are high. Average education outcomes therefore decrease in these locations because children of low-education parents have, on average, lower education outcomes than children from high-education parents. The housing expansion increases the population size of targeted locations without changing their demographic composition, leaving the spatial distribution in education outcomes largely unchanged.

All policies increase intergenerational upward mobility by raising the average college education rate for children from non-college-educated parents. The increase is 1.4 percentage-points (pp) for the school funding equalization, 0.5 pp for the housing expansion, and 0.2 pp for the subsidy. The direct effects of these policies on intergenerational mobility are even larger; however, responses in residential sorting and in the costs and returns to education mitigate their effects in equilibrium.

The mechanisms underlying the equilibrium adjustments are specific to each policy. For the school funding equalization, effects are smaller in general equilibrium, because low-education families leave locations that receive more funding due to the reform. They do so because rental prices increase in these locations and because low-education parents are more sensitive to rents than other demographic groups. Effects of the subsidy are mitigated in general equilibrium because education outcomes decrease in subsidized locations, as the large inflow of children reduces the school funding amount that is available for each student. In addition, only low-education parents are eligible for the subsidy, making it more attractive to be low-educated and therefore reducing returns to obtaining high-education.

By changing the geography of the supply of educated workers, the policies also affect aggregate output. Equalizing school funding reduces the supply of educated workers in locations where funding is high prior to the reform. We find that these locations have highly productive and skill-intensive production technologies, so that the policy creates a spatial mismatch between the supply and demand of educated workers and lowers aggregate output by 0.5%. The subsidy and housing expansion target counties with high initial education outcomes, which we find to also have more productive and more skill-intensive production technologies compared to non-targeted locations. Therefore, both policies increase the number of workers in productive locations which raises aggregate output by 0.7% for the housing expansion and by 0.1% for the subsidy. Effects on output are smaller for the subsidy because it specifically attracts low-education workers, reducing the college share among workers in skill-intensive locations.

Our analysis shows that the effectiveness of policies to improve welfare and to restore equality of opportunity across locations and parental backgrounds is mitigated in equilibrium by responses in local wages, rents, and residential sorting. In addition, such policies can have unintended output costs by creating a spatial mismatch between demand and supply of educated workers. Taken together, we find that the housing expansion increases welfare by an equivalent of 3.6% of baseline income, compared to an increase of 0.5% for the school funding equalization, and a decrease of 0.2% for the tax-funded subsidy.

Related Literature We contribute to the large literature on neighborhood effects. Early work was mostly theoretical and studies how residential sorting, local school funding, and local education outcomes affect income inequality and aggregate growth.[2] The last decade has seen an expansion of applied work that quantifies the causal impact of neighborhoods on children's long-run outcomes.[3] Our paper develops a quantitative spatial framework to study the mechanisms behind these estimated neighborhood effects and to evaluate large-scale policies while accounting for general equilibrium effects.

Our paper relates to an emerging quantitative literature studying the sorting of heterogeneous workers across cities (see, e.g., Diamond, 2016; Rossi-Hansberg, Sarte, and Schwartzman, 2019; Giannone, 2016) and across neighborhoods within cities (see, e.g., Couture, Gaubert, Handbury, and Hurst, 2019; Almagro and Dominguez-Iino, 2022; Vitali, 2023; Miyauchi, Nakajima, and Redding, 2021). Within cities, most papers attribute residential sorting to differences in house prices, commuting access, and observable measures of school quality, such as test scores (see, e.g., Bayer, Ferreira, and McMillan, 2007; Nechyba, 2006). In our paper, neighborhoods differ in their dynamic education production which is similar to an endogenous amenity (see, Almagro and Dominguez-Iino, 2022 or Diamond, 2016), but which additionally has a lasting effect on individuals by affecting their education level throughout their lifetime.

To the best of our knowledge, this is the first paper to introduce local education choices into a dynamic quantitative spatial framework (see, Redding and Rossi-Hansberg, 2017 for a general review and Caliendo, Dvorkin, and Parro, 2019 for a dynamic version).[4] Our model incorporates the idea of "locations as an asset," introduced in Bilal and Rossi-

[2] See, e.g., Benabou (1993, 1996), Durlauf (1996a, 2004) and Fernandez and Rogerson (1996, 1997). Fernandez and Rogerson (1998) pioneered early quantitative study that evaluates the effects of a school funding equalization in a two location model. We benchmark our findings to theirs in the counterfactual analysis.

[3] See, e.g., Altonji and Mansfield (2018, 2021); Chetty, Hendren, Kline, and Saez (2014) and Chetty and Hendren (2018a,b)).

[4] The quantitative spatial literature highlights the role of market access in determining the location choices of workers (cf., Redding and Venables, 2004, Desmet, Nagy, and Rossi-Hansberg, 2018, and Bryan and Morten, 2019). Our model highlights how labor market access additionally affects the return to education and forward-looking education choices.

Hansberg (2021). Parents move to locations with better child opportunities to invest in their children's education incurring higher rents and lower consumption today. Location choices therefore emerge as a means of investing and transferring consumption across generations.

A handful of contemporaneous papers study the link between education outcomes and residential choices. A first set of papers uses more stylized macro models which consider residential choices between a small number of synthetic neighborhoods (Fernandez and Rogerson, 1998; Fogli and Guerrieri, 2019; Zheng and Graham, 2022; Agostinelli, Doepke, Sorrenti, and Zilibotti, 2020). Two recent papers use static quantitative spatial models to study the effects of school transportation programs on school access in one specific US county (Agostinelli, Luflade, and Martellini, 2021) and to study the effects of a school construction program in Indonesia (Hsiao, 2023). Relative to these papers, our framework models education choices as a dynamic and forward-looking decision and explicitly accounts for the long-run interactions between the geography of skill demand and skill supply. In addition, we incorporate local labor and housing markets, which are both important determinants for agents' educational and residential choices by affecting the geography of costs and returns to education in equilibrium.

The paper proceeds as follows. Section 1 presents our theory. Section 2 discusses the calibration of our model. In Section 3, we use the estimated model to evaluate a set of policy counterfactuals.

1. Theory

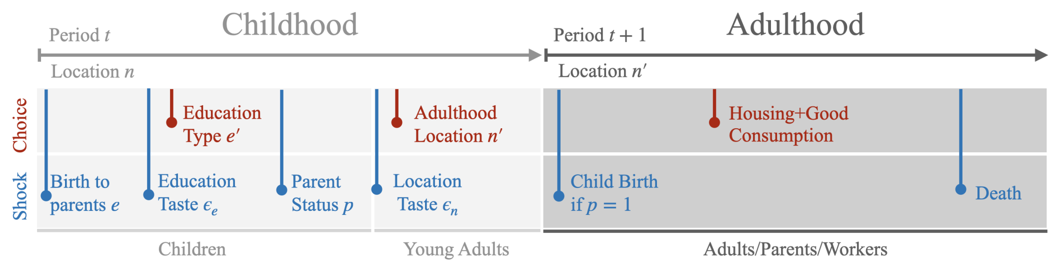
In this section, we develop a dynamic spatial equilibrium model of educational and residential choice that incorporates local labor and housing markets which are separated by moving costs. We suppress time subscripts when presenting the static elements of the theory.

1.1 Model Environment

The economy consists of a discrete set of labor markets indexed by $m \in \mathbb{M}$. Each labor market nests a discrete set of residential neighborhoods indexed by $n \in \mathbb{N}_m$. Time is discrete and indexed by t. In each period, the economy is inhabited by a mass C_t of children and a mass L_t of adults.

Timeline. Figure 1 shows the timeline of our model. Individuals live for two periods, childhood and adulthood. At the beginning of a period t, children are born into neighborhood n to parents who have either low- or high-education levels ($e = l, h$). Each child i receives idiosyncratic education-preference shocks, $\{\epsilon_e^i\}_e$. After learning the realization of these shocks, children choose to attain either a low-education ($e = l$) or a high-education ($e = h$) status.

FIGURE 1: MODEL TIMELINE



Notes: This figure shows a timeline of an agent's life in our model. Choices are marked in red. The timing of idiosyncratic shocks is marked in blue.

After children finish their education, they learn their "parent status" p, which takes a value of 0 for "non-parents" and 1 for parents. Next, these young adults–who already chose an education e and learned their parent status p, but sill live in their childhood neighborhood n–learn the realization of a vector of idiosyncratic location-preference shocks $\{\epsilon_n^i\}_n$ and then choose an adulthood neighborhood n'. The arrival in the adulthood neighborhood and its associated labor market marks the beginning of a new period $t+1$, which implies the former adult generation dies and former children become the adults of the next generation.

In period $t+1$, the new generation of adults lives in their chosen neighborhoods n', where they work and choose optimal quantities of housing and final-good consumption. Children grow up and choose their education in the neighborhood n' that their parents chose for them. Education and location choices depend on a range of neighborhood characteristics that we now describe.

Local Labor Markets. In each labor market, a representative firm produces a freely traded homogeneous consumption good using the following location-specific CES technology:

$$Y_m = \mathcal{Z}_m \left(\mathcal{S}_m^l \left(L_m^l \right)^{\frac{\rho-1}{\rho}} + \mathcal{S}_m^h \left(L_m^h \right)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{1}$$

where $\mathcal{Z}_m$ denotes labor productivity and $\mathcal{S}_m^l$ and $\mathcal{S}_m^h$ are education-type-specific productivity shifters.[5] L_m^l and L_m^h denote the firm's labor demand for workers with low- and high-education levels, and the parameter ρ is the elasticity of substitution between workers of each education level. We denote the market-clearing wage for workers with education e in labor market m by w_m^e. The price of the consumption good serves as the

[5]While these productivity shifters could result from directed technological change (Acemoglu, 2002), we take it as given.

numeraire.

Moving Costs. Young adults who move from childhood neighborhood n to adulthood neighborhood n' incur a bilateral moving cost, $C^{ep}_{nn'}$, denominated in utils and indexed by education type and parent status.

Neighborhood Rental Market and Education Index. Residential amenities, $\mathcal{A}^{ep}_n$, differ across neighborhoods, education groups, and parent status. Housing supply in each neighborhood $\mathcal{H}_n$ is fixed and local rental rates, r_n, adjust to equate housing demand and supply.[6]

Neighborhoods further differ in an "education index" $\mathcal{E}^e_n$ that measures the ease with which local children attain high-education. The education index varies by parental education e, reflecting that parents' education level may affect their children's education outcomes directly–through nature or nurture–or indirectly by affecting the degree to which children can capitalize on educational resources in a given neighborhood. We parameterize the education index of neighborhood n for children with parents of education level e as:

$$\mathcal{E}^e_n = \mathcal{Q}^e_n + \gamma^e \log f_n, \tag{2}$$

where f_n denotes local school funding per student and γ^e measures the weight of school funding in the education index. The term $\mathcal{Q}^e_n$ is an exogenous local education productivity shifter that captures all remaining local characteristics that determine local education indices. Such local characteristics can include teacher quality, classroom size, or any neighborhood exposure effects through peers, role models, culture, crime, or others.

It is straightforward to allow for additional endogenous determinants of the education index. A natural addition is to allow for "peer effects" in education by including moments of the endogenous distribution of workers across locations and education types, such as the local share of workers with high-education. We provide this model extension in Appendix C.

School funding in each neighborhood consists of contributions from local, state, and federal governments, which are raised through taxes. States s are mutually exclusive groups of labor markets or neighborhoods. Federal and state governments tax wage income at rates t^w_f and t^w_s and distribute the revenue across neighborhoods according to specific allocation rules, δ^n_f and δ^n_s, which measure the share of federal or state tax revenue allocated to each neighborhood n. Local neighborhood governments impose a tax t^r_n on rental income, and their tax revenue flows entirely into local schools.

Indirect Utility. Households have Cobb-Douglas preferences over housing and final good consumption. The indirect utility of a worker with education e and parent status p

[6] In Appendix C, we present a model extension with elastic housing supply.

in neighborhood n is given by:

$$U_n^{ep} = \mathcal{A}_n^{ep} + \log Y_n^e - \alpha^{ep} \log r_n, \tag{3}$$

where α^{ep} is the housing-expenditure share, r_n is the local rental rate of housing, and Y_n^e is disposable after-tax income. Following Caliendo et al. (2019), we assume all after-tax rent payments are sent to a national real estate fund which then pays the entire rental income out to all workers as a proportion D of their wage income. As a result, disposable after-tax income for a worker with education e in neighborhood n is given by $Y_n^e = (1 - t_f^w)(1 - t_s^w)w_m^e + Dw_m^e$.

1.2 Dynamic Education and Location Choices

In this section, we derive the dynamic education and location choices for each type. Young adults choose their adulthood neighborhood n' to maximize their destination utility net of moving costs. The expected utility of young adults with education e, parent status p, and childhood neighborhood n prior to learning their idiosyncratic location taste shocks is therefore given by:

$$V_t(e, p, n) = E_{\epsilon_{n'}} \max_{n'} \{\sigma_N \epsilon_{n't}^i + U_{n't}^{ep} - C_{nn't}^{ep} + \beta^p O_{t+1}(e, n')\}, \tag{4}$$

where the expectation is taken over the idiosyncratic location taste shocks ϵ_n and incorporates the utility-maximizing behavior of workers. U_n^{ep} is the indirect utility of each type which depends on local disposable income, rents, and amenities. The parameter β^p is parents' altruism which indicates the weight that parents place on their children's future utility. Altruism takes a value of 0 for non-parents. The parameter σ_N is the weight that agents place on idiosyncratic moving motives relative to local characteristics that are equally valued by all agents of a given type. We refer to the term $O(e, n)$ as a neighborhood's "child opportunity value." The term captures the expected utility of children who have parents with education e and grow up in neighborhood n.

The child opportunity value incorporates the utility-maximizing education choice and can be written as:

$$O_t(e, n) = E_{\epsilon_{e'}} \max_{e'} \{\sigma_E \epsilon_{e't}^i + 1_{e'=h} \mathcal{E}_{nt}^e + \bar{V}_t(e', n)\}, \tag{5}$$

where the expectation is taken over children's idiosyncratic education taste shock ϵ_e. $\mathcal{E}_n^e$ is the local education index, which captures a utility cost that children with parents of education e who grow up in neighborhood n must pay to attain high-education. Because education is a binary choice, we normalize the education index to zero when choosing low-education. Hence, we multiply the index with an indicator that is equal to 1 when a child chooses high-education. The term $\bar{V}(e, n)$ is the expected continuation value that childhood neighborhood n offers young adults who have chosen education e but who have not yet learned their parent status or their idiosyncratic location taste shocks. The continuation value takes the expectation over future parent status p, so it is equal to $\bar{V}(e,n) = \sum_p \phi^{ep} V(e,p,n)$, where ϕ^{ep} are the probabilities of parenthood (or non-parenthood) for adults with education level e.

1.3 Aggregation and Equilibrium

We now solve and aggregate the dynamic education and location choices and use the resulting analytic expressions to define market clearing and the equilibrium of the economy.

Aggregating Individual Decisions. For aggregation purposes, we make the following assumption on the distribution of idiosyncratic preference shocks:

Assumption 1. *Each worker i draws a separate idiosyncratic taste shock for each neighborhood, $\{\epsilon_n^i\}_n$, and education level, $\{\epsilon_e^i\}_e$, in an i.i.d. fashion from the following type-I extreme value distribution:*

$$F(z) = \exp(\exp(-z-\bar{\gamma})),$$

where $\bar{\gamma} \equiv \int_{-\infty}^{\infty} x \exp(-x - \exp(x))dx$ is the Euler-Mascheroni constant.

The parameters σ_N and σ_E pre-multiply idiosyncratic shocks in all equations and hence flexibly parameterize the effective variance of each shock.[7] Under Assumption 1, we can derive analytical expressions for the value functions and for the share of agents of each type who make a given discrete choice.

Among the children who grow up in neighborhood n with parents of education e, the share $\pi_n^{ee'}$ who chooses education level e' is equal to

$$\pi_n^{ee'} = \frac{\exp\left(1_{e'=h}\mathcal{E}_n^e + \bar{V}(e',n)\right)^{\frac{1}{\sigma_E}}}{\sum_{e'} \exp\left(1_{e'=h}\mathcal{E}_n^e + \bar{V}(e',n)\right)^{\frac{1}{\sigma_E}}}. \tag{6}$$

The opportunity value (that is, expected utility) for children who grow up in neighborhood n with parents of education e, prior to the realization of idiosyncratic shocks, is given by

$$O(e,n) = \sigma_E \log\left[\sum_{e'} \exp\left(1_{e'=h}\mathcal{E}_n^e + \bar{V}(e',n)\right)^{\frac{1}{\sigma_E}}\right]. \tag{7}$$

Among the young adults with education e, parent status p, and childhood neighbor-

[7] The type-I extreme value distribution in Assumption 1 has zero mean and variance of $\pi^2/6$.

hood n, the share $\lambda^{ep}_{nn'}$ who moves from their childhood neighborhood n to adulthood neighborhood n', is equal to

$$\lambda^{ep}_{nn'} = \frac{\exp\left(U^{ep}_{n'} - C^{ep}_{nn'} + \beta^p O(e,n')\right)^{\frac{1}{\sigma_N}}}{\sum_{n'} \exp\left(U^{ep}_{n'} - C^{ep}_{nn'} + \beta^p O(e,n')\right)^{\frac{1}{\sigma_N}}}. \tag{8}$$

Last, the expected utility of young adults with education e, parent status p, and childhood neighborhood n, before knowing their neighborhood taste shocks, is given by

$$V(e,p,n) = \sigma_N \log\left[\sum_{n'} \exp\left(U^{ep}_{n'} - C^{ep}_{nn'} + \beta^p O(e,n')\right)^{\frac{1}{\sigma_N}}\right]. \tag{9}$$

The Aggregate Law of Motion. Individuals' dynamic choices jointly determine how the distribution of workers across neighborhoods and education levels evolves over time. The law of motion is given by:

$$L^{e'p'}_{n't+1} = \sum_n \lambda^{e'p'}_{nn't} \phi^{e'p'} \sum_e \pi^{ee'}_{nt} C^e_{nt}, \tag{10}$$

where C^e_{nt} denotes the mass of children born at time t in neighborhood n to parents of education e. A share $\pi^{ee'}_n$ of them chooses education e'. Summing across parental education yields the mass of children with education e'. Fertility shocks ϕ^{ep} determine the share of these individuals who become parents. To hold population size constant, we assume each parent with education e has $1/\phi^{e1}$ children so that $C^e_{nt} = L^{e1}_{nt-1}/\phi^{e1}$. After finishing education and learning their parent status, a fraction $\lambda^{ep}_{nn'}$ of young adults moves from their childhood neighborhood n to the chosen adulthood neighborhood n'. Summing across childhood neighborhoods n yields the distribution of adults across education levels e', parent status p', and adulthood neighborhoods n' at time $t+1$.

Definition of Equilibrium. The economy is characterized by two sets of parameters. First, a set of structural parameters: the elasticity of substitution between workers of different education levels in the production function ρ, the dispersion measures of education and location taste shocks σ_E, σ_N, altruism β^p, fertility rates ϕ^{ep}, housing expenditure shares α^{ep}, and the effectiveness of school funding γ^e. Second, a set Ω_t of location-specific parameters that can vary over time: locations' total factor productivity $\mathcal{Z}_m$, education-level-specific productivity shifters $\mathcal{S}^e_m$, moving costs $C^{ep}_{nn'}$, housing supply $\mathcal{H}_n$, residential amenities $\mathcal{A}^{ep}_n$, education productivity $\mathcal{Q}^e_n$, tax rates t^w_f, t^w_s, t^r_n, and school-funding allocation rules for federal and state governments δ^n_f, δ^n_s.

Given a path of location-specific parameters $\{\Omega_t\}^{\infty}_{t=0}$ and an initial distribution of workers L^{ep}_{n0}, the sequential competitive equilibrium is a sequence of (i) residential and education choices $\{\lambda^{ep}_{nn't}, \pi^{ee'}_{nt}\}^{\infty}_{t=0}$, (ii) value functions $\{V_t(e,p,n)\}^{\infty}_{t=0}$, (iii) distributions of workers across education levels, parent status, and neighborhoods $\{L_{nt}^{ep}\}_{t=0}^{\infty}$, and (iv) local factor prices $\{w_{mt}^{e}, r_{nt}\}_{t=0}^{\infty}$ such that:

1. Residential and education choices maximize each type's utility as derived in equations (6) and (8);
2. Value functions are consistent with equations (7) and (9);
3. The distribution of workers across education levels, parent status, and neighborhoods is consistent with the law of motion in equation (10);
4. Wages for each worker type clear each labor market m;
5. Rental prices per housing unit clear the housing market in each neighborhood n.

A stationary equilibrium of the model is a sequential competitive equilibrium such that $\{V(e,p,n), \lambda_{nn'}^{ep}, \pi_{n}^{ee'}, L_{n}^{ep}, w_{m}^{e}, r_{n}\}_{t=0}^{\infty}$ are constant for all t, e, p, and n. A *stationary equilibrium* in this economy is a situation in which no aggregate variable changes over time and location-specific parameters are constant for all t. In the stationary equilibrium, agents still move from one state (education, parent status, neighborhood) to another, but inflows and outflows balance so that the distribution of adult workers across education levels, parent status, and neighborhoods is constant over time. With this definition, it is possible that certain locations consistently experience a net outflow of educated young adults if they produce more educated workers than they can retain for their workforce. Hence, locations can experience either brain drain or brain gain in the steady state.

1.4 Key Model Properties

The introduction of local education choices into an otherwise standard quantitative spatial model generates a set of new model properties. We now briefly describe three of these properties.

Education outcomes differ across neighborhoods. Education choices in each neighborhood are equilibrium outcomes because they depend on local returns and local costs of education. The following equation illustrates this property nicely, by linking the odds of choosing high- relative to low-education for a child with parents of education e who grows up in childhood neighborhood n to the local returns and costs of education:

$$\underbrace{\log \frac{\pi_n^{eh}}{\pi_n^{el}}}_{\text{High-Edu Odds}} = \underbrace{\frac{1}{\sigma_E}\left(\bar{V}(h,n) - \bar{V}(l,n)\right)}_{\text{Return to Education}} + \underbrace{\frac{\gamma^e}{\sigma_E}\log f_n}_{\text{Funding}} + \underbrace{\frac{1}{\sigma_E}\mathcal{Q}_n^e}_{\text{Educ. Productivity}}. \tag{11}$$

Returns to education measure the expected utility premium that a given childhood neighborhood offers young adults with high- relative to low-education. Education returns are endogenous because they depend on the moving-cost-adjusted education wage premia in all locations, which respond in equilibrium to changes in the local demand and supply of educated workers. We model local costs of education (that is, local ”education indices”) as a function of local school funding which is endogenously determined by tax revenues from local wages and local rents.[8] To capture other determinants of the local costs of education, we include an exogenous education productivity shifter that differs across neighborhoods and parental background.

Residential choices affect education outcomes. Because neighborhoods differ in their education outcomes, the distribution of parents across neighborhoods is crucial for the local and aggregate production of educated workers. Residential sorting and housing markets are therefore key determinants for education outcomes and equality of opportunity.

Local education outcomes affect aggregate output. Education decisions and moving choices jointly determine the spatial distribution of the *supply* of educated workers. Local production technologies, which can differ in productivity and skill-intensity, determine the local *demand* for educated workers. Changes in local education outcomes affect the allocation of educated workers across labor markets, which can create a mismatch between local skill demand and skill supply, and impacts aggregate output.

2. Quantifying the Model

In this section, we describe our data set and discuss how we select the structural and location-specific parameters of the model.

2.1 Data Sources

For most of the calibration, we use data moments for 2010. We further rely on data from the 1980, 1990, and 2000 cross sections for one estimation step. The Online Appendix provides a more comprehensive description of the data sources and data preparation.

Spatial Units. We map labor markets m in the model to commuting zones (CZs) as defined in Tolbert and Sizer (1996), which partition the territory of the US into 741 units. We map model neighborhoods n to counties in the data and from now on refer to two interchangeably. The US has approximately 3,100 counties, each of which belongs to precisely one CZ. We choose counties to define neighborhoods because they represent the most disaggregated spatial level at which we can obtain all data moments that we need for the model estimation.[9]

[8] In a model extension, we include peer effects as an additional endogenous determinant of local education outcomes. Endogenizing other determinants is simple in the theoretical framework. However, the quantification is challenging because it requires detailed data and an identification strategy for the causal effect of the variable in question on education outcomes.

[9] Information on children’s college-education rates by parental background and childhood location are not available at the sub-county level.

Education and Parent Status. We map ″low-education″ to individuals with at most a high-school diploma in the data, and ″high-education″ to all other education levels. Hereafter, we use the terms high-education and college-educated as well as low-education and non-college-educated interchangeably. We define the parent status of $p = 1$ in the model as having at least one child under 18 in the household. We assign parent status $p = 0$ to all other individuals in the data. We refer to the two parent statuses as ″parents″ and ″non-parents.″

To construct the relevant data moments for our model quantification, we restrict the sample to individuals ages 35 to 50. We choose this age group because adults in this age range are plausibly ″old enough″ to have finished their education and to have children–if they will have any–but ″young enough″ to still have school-age children who live in their household.[10]

Wages by Education Level. We use microdata from the US Decennial Census and the American Community Survey (ACS) to compute wage levels for college- and non-college-educated workers at the CZ level. The census and ACS provide information about respondents' wage income and their current Public Use Microdata Area (PUMA) of residence which we map to CZs.

Local Rental Rates. We use data from the National Historic GIS database (NHGIS) to construct county-level estimates of rental rates per housing unit. The data include information on rent payments and housing characteristics at the block-group level. We estimate hedonic price regressions to adjust for differences in housing size and quality across locations, providing us with quality-adjusted rental-rate indices at the county level. The Online Appendix provides the full description of this procedure.

School Funding per Student by Funding Source. We use data from the National Center for Educational Statistics (NCES) to compute school funding amounts per student by funding source. The financial surveys of the NCES provide information about the school-funding amounts from federal, state, and local governments and the number of students for each school district which we aggregate to the county level.

College-Education Rates by Childhood Neighborhood. We obtain information about children's college-education rates by parental income percentile and county of childhood residence from the replication files of Chetty and Hendren (2018a,b). The underlying data comes from the Internal Revenue Service, which allows linking children to their parents and their childhood county for all children born between 1981 and 1988. The large sample size of the administrative data allows measuring these data moments separately for each county for the entire territory of the US.

[10] In Appendix D, we show our results are robust to using the full sample of working-age individuals between 25 and 64 years.

Moving Flows and Population Stocks by Agent Type. The US Census and ACS microdata provide information on respondents' current PUMA residence and their PUMA of residence five (or one) years ago. We use these data to construct a matrix of cross-CZ moving flows by education and parent status.

To capture residential choices of each worker type within CZs, we obtain data on population stocks for each county, separately by age, education, and parent status from the "Education Demographic and Geographic Estimates" (EDGE) program of the "National Center of Education Statistics" (NCES). The data further allows us to distinguish between households whose children are enrolled in public versus private schools.

2.2 Calibration and Estimation of Parameters.

We now describe how we choose the parameters of our model. First, we calibrate a set of parameters to observed data moments. We then estimate another set of parameters by matching model-implied estimating equations to the corresponding data moments. Last, we recover a set of parameters with a simulated method of moments estimator. Table 1 lists all model parameters, the estimated values, and data targets.

2.2.1 Calibrating Parameters

We first calibrate housing expenditure shares and the probability of parenthood by setting them directly to observed data moments.

Housing Expenditure Shares. With Cobb Douglas preferences, individuals with education e and parent status p spend a constant share α^{ep} of their disposable income on housing. We calibrate these parameters to data from the 2010 Consumer Expenditure Survey, which provides individual-level data on housing expenditure, education, and the presence of children in the household. We find that housing expenditure shares are 33% (34%) for non-parents with (without) college education and 36% (38%) for parents with (without) college education (cf. Panel A.1 of Table 1). Hence, non-college-educated parents have the highest housing expenditure share and are therefore more sensitive to rental prices than the other demographic groups.

Probability of Parenthood. We set the probability of parenthood for each education level to the share of individuals between ages 35 and 50 who live with a child under 18 in the same household, which we observe in the census data. The fraction of so-defined parents is equal to 56% for adults without college education and 63% for adults with college education.

2.2.2 Estimating Parameters and Recovering Location-Specific Characteristics

We next estimate a set of structural parameters and regional characteristics by fitting model-implied estimating equations to the corresponding data moments. This procedure does not require us to solve for the model's steady state, so we do not impose that the data are in a steady state.

To identify key structural parameters, we use a two-step procedure that follows Berry, Levinsohn, and Pakes (2004), Artuç and McLaren (2015), and Diamond (2016). In the first step, we estimate a gravity equation of moving flows to estimate moving costs and the average utility that each type attributes to each location. In the second step, we use these estimates and an IV strategy to decompose locations' average utility values into the weights that each type places on local rent-adjusted real income and different components of the child opportunity values. These weights identify the altruism parameter and the dispersion parameters of the idiosyncratic education and location taste shocks. To simplify notation, we normalize utility by the dispersion of the location taste shocks σ_N. We denote re-normalized objects with lower case letters, for example, $o(e,n) := O(e,n)/\sigma_N$.

Gravity Estimation for Moving Costs and Local Utility Values. To estimate the gravity equation, we need data on bilateral moving flows, which are available across CZs but not across counties (cf. section 2.1). We therefore make the following assumption:

Assumption 2. *Moving across CZs incurs costs, whereas moving within CZs is free, so that,* $C^{ep}_{nn'} = C^{ep}_{mm'} \forall n \in \mathcal{N}_m, n' \in \mathcal{N}_{m'}, \forall m \neq m'$ *and* $C^{ep}_{nn'} = 0 \forall n \in \mathcal{N}_m, n' \in \mathcal{N}_{m'}, \forall m = m'$.

Given Assumption 2, we use equation (8) to aggregate moving flows to the cross-CZ level:

$$\lambda^{ep}_{mm'} = \frac{\overbrace{\exp\left(-c^{ep}_{mm'}\right)}^{\text{Bilateral Mov. Cost}} \overbrace{\sum_{n' \in \mathbb{N}_{m'}} \exp\left(u^{ep}_{n'}\right)}^{\text{Destination-FE}}}{\underbrace{\sum_{n'' \in \mathbb{M}} \exp\left(u^{ep}_{n''} - c^{ep}_{mm''}\right)}_{\text{Origin-FE}}} = \frac{\exp\left(u^{ep}_{m'} - c^{ep}_{mm'}\right)}{\sum_{m''} \exp\left(u^{ep}_{m''} - c^{ep}_{mm''}\right)}, \tag{12}$$

where $c^{ep}_{mm'}$ are normalized moving costs, u^{ep}_{n} is average county utility, and u^{ep}_{m} is the corresponding average CZ utility. Average utility values depend on local amenities, wages, rents, and child opportunity values.

Equation (12) implies the following gravity estimating equation:

$$\lambda^{ep}_{mm'} = \exp\left(\delta^{ep}_{m} + \psi^{ep}_{m'} - \iota^{ep} X_{mm'}\right) + \tilde{\epsilon}^{ep}_{mm\prime}, \tag{13}$$

where δ_m^{ep} are origin fixed effects and ψ_m^{ep} are destination fixed effects. We parameterize the normalized moving costs as $c_{mm'}^{ep} := \iota^{ep} X_{mm'} + \epsilon_{mm}^{ep}$, where $X_{mm'}$ are observable characteristics that vary across CZ pairs. For each pair of CZs, we include their bilateral distance and dummies, which are equal to 1 if two CZs lie in different states, in different Census divisions, or have different urban/rural status. The parameter vector ι^{ep} measures the importance of each bilateral characteristic for explaining observed moving flows, which can vary across types. The residual term $\tilde{\epsilon}_{mm}^{ep}$ captures measurement error.

We estimate equation (13) separately for each education level and parent status via poisson pseudo-maximum likelihood (PPML), following Silva and Tenreyro (2006). We use the estimated coefficients $\hat{\iota}^{ep}$ to construct each type's normalized moving-cost matrix $\hat{c}_{mm'}^{ep}$. The estimated destination fixed effects, identified up to a constant of normalization, correspond to the mean utility that each type attributes to each CZ.

Using Assumption 2, we can compute county-utility values using the estimated CZ-utility values and the share of the CZ population that lives in the given county as follows:

$$\exp\left(u_n^{ep}\right) = \frac{L_n^{ep}}{L_m^{ep}} \exp\left(u_m^{ep}\right). \tag{14}$$

Estimating Elasticities, Parental Altruism, and Amenities. Next, we estimate the dispersion of location and education taste shocks and parents' altruism parameter.

To do so, we use another model-implied estimating equation that relates average county utility values to neighborhood characteristics as follows:

$$u_n^{ep} = a_n^{ep} + \frac{1}{\sigma_N} \log I_n^{ep} + \beta^p o(e,n), \tag{15}$$

where a_n^{ep} are normalized amenities, $o(e,n)$ are normalized child opportunity values, and $I_n^{ep} = Y_n^{ep} / r_n^{\alpha^{ep}}$ are disposable real incomes adjusted for rents.

The inverse of the dispersion of location taste shocks σ_N is the weight that agents place on local characteristics that are equally valued by all agents of their type. This parameter is commonly estimated in the spatial literature. Estimates range from 0.18 in Diamond (2016) to 0.3 in Monte, Redding, and Rossi-Hansberg (2018). To estimate σ_N, we restrict the sample to *non-parents* for whom the expression of county-utility values simplifies because they do not value local child opportunities (that is, $\beta^0 = 0$) so that their residential choices solve a static maximization problem. In this case, an identification challenge arises due to amenities that act as an unobserved residual and can correlate with disposable real incomes and rents. We follow Diamond (2016) and estimate equation (15) in changes while using Bartik-like local labor demand shocks and their interaction with local housing-supply elasticities as instruments for changes in real disposable income that are plausibly exogenous to changes in local amenities. To do so, we use three cross sections of data for 1990, 2000, and 2010. Appendix A.2 describes the IV estimation in more detail. Our estimates yield similar values for σ_N as the literature. Based on our results and the estimates from the literature, we set $\sigma_N = 0.25$ in our baseline calibration and perform robustness around this estimate.

Using this estimate of σ_N, we recover local amenities for non-parents as a structural residual from equation (15).[11]

The remaining parameters to estimate are parents' altruism and the dispersion of education taste shocks. These parameters shape local education choices and are novel in the quantitative spatial literature. To identify them, we make the following identifying assumption:

Assumption 3. *Local amenities for parents are a scaled version of those for non-parents, so that* $a_n^{e1} = \theta a_n^{e0}$.

Given Assumption 3, we can write equation (15) for *parents* as follows:

$$u_n^{e1} - \frac{1}{\sigma_N} I_n^{e1} = \theta a_n^{e0} + \beta \bar{v}(l, m) - \beta \frac{\sigma_E}{\sigma_N} \log \pi_n^{el}, \tag{16}$$

which expresses the child opportunity values $o(e, n)$ as a function of local continuation values of non-college-educated young adults and local probabilities of choosing non-college education. The Online Appendix presents the derivation of this expression. All terms in equation (16) are known from the data or previous estimates, except the parameters of interest θ,β, and σ_E. We compute continuation values of young adults from the fixed-effect and moving-cost estimates that we obtain in the gravity estimation, using the mapping shown in equation (9).[12]

We then estimate equation (16) via ordinary least squares (OLS) using our estimates of county-utility values, (non-parent) amenities, and continuation values, as well as data on education rates and real income. Importantly, we can now include our amenity estimates from non-parents directly into the regression, which removes the omitted-variable bias that occurs when excluding typically unobserved amenities.

We find parents place a weight of $\theta = 0.9$ on the amenity estimates that we recovered from the residential choices of non-parents. This finding makes intuitive sense: amenities are relatively less important for parents' location decisions than for non-parents, because parents also value the opportunity values that locations offer their children. We find an

[11] In Appendix B, we show these recovered structural residuals are highly correlated with observable proxies of local amenities, which we compute by extending data sources used in Diamond (2016) and Lee and Lin (2018). Appendix Table B.1 shows the results of regressing the amenities that we recover in the model on data of observable amenity proxies. The R-squared of the regression is 0.75 for amenities of low- and high-education types.

[12] We assume parents are naive and that their children's continuation values are the same as the current values, so that $\bar{v}_{t+1}(e, m) = \bar{v}_t(e, m)$.

estimate of $\beta = 0.23$ for altruism.[13] For the dispersion of education taste shocks, which measures the extent to which local education choices depend on local costs and returns of education as opposed to idiosyncratic reasons, we find an estimate of $\sigma_E = 0.32$. All estimates are statistically significant at the 1% significance level. Table A.1 in the Appendix presents the regression results.

The intuition behind our estimation strategy is that non-parents' residential choices identify the general attractiveness (that is, unobserved amenities) of locations. Differences in residential choices between parents and non-parents then identify parents' valuations for the different components of local child opportunity values.[14] The extent to which parents sort more towards places with better overall child opportunities than non-parents identifies their altruism parameter β (cf. equation (15)). The extent to which parents sort on the cost-adjusted returns to *all* education levels–as opposed to just one education level–identifies the variance of idiosyncratic education taste shocks σ_E. To gain intuition about the identification of the variance, note that all children in a location would choose the education level with the highest cost-adjusted return if the variance was zero. The higher the variance, the more the returns to all education options matter. In equation (16), the cost-adjusted returns to both education levels are captured by the local probability of choosing non-college education, given that the equation already controls for the return to low-education.[15]

The assumption that parents and non-parents value amenities proportionally across locations is necessary to relate differences in residential choices between parents and non-parents to local child opportunities. The regression in equation (16) has a very good fit with an R-squared of 0.97, which aligns with this assumption. In Appendix A.3, we further allow for the possibility that parents and non-parents can value *observable* local amenities differentially. To do so, we construct proxies for observable amenities from multiple data sources that build on Diamond (2016) and Lee and Lin (2018) and we then include these variables directly in our estimating equation (16), allowing the weights on these observable amenities to differ across education and parent groups. Appendix Table A.1 presents the results of these regressions and shows our parameter estimates change only slightly with the inclusion of these observable amenity proxies.

[13] Our estimate of altruism is comparable to the literature. Daruich (2023) finds, for example, an estimate of 0.475, whereas Abbott, Gallipoli, Meghir, and Violante (2019) find values of 0.518 for males and 0.470 for females. Compared with these papers, we do not model children's utility and consumption during childhood, so our altruism parameter only captures parental preferences over their children's future utility once children become adults. These differences could explain why our estimates are slightly lower.

[14] We restrict the sample to individuals of ages between 35 and 50 years to rule out that differences in residential sorting between parents and non-parents are driven by an age effect. In addition, we condition on parents whose children are enrolled in public schools to avoid capturing different residential choices of parents whose children attend private schools.

[15] To see this explicitly, note that the local probability of choosing non-college education can be written as: $\log \pi_n^{el} = -\log\left(1 + \exp\left[\frac{1}{\sigma_E}\bar{v}(h,m) + \frac{1}{\sigma_E}\mathcal{E}_n^e - \frac{1}{\sigma_E}\bar{v}(l,m)\right]\right)$.

Location-Specific Parameters. Similar to amenities, we infer the remaining location characteristics as structural residuals by fitting model predictions to the corresponding data moments, following Redding and Rossi-Hansberg (2017). Panel B of Table 1 lists these parameters and the corresponding data moments. Appendix A.1 describes the inference in more detail and shows the model-implied equations for all location-specific characteristics.

In a nutshell, we recover labor markets' total factor productivity and skill-intensity as well as neighborhoods' housing supply to match observed data on local rents, wages, and worker stocks by education level.

Local Education Productivity. The novel location characteristic in our model is education productivity, $\mathcal{Q}_n^e$, which captures the components of local education indices that are not endogenized in our model. We infer local education productivity by parental education and childhood neighborhood to match the observed data on local college education rates using the following model-implied equation based on equation (11):

$$\mathcal{Q}_n^e = \bar{V}(h,m) - \bar{V}(l,m) + \gamma^e \log f_n - \sigma_E \log \frac{\pi_n^{eh}}{\pi_n^{el}}. \tag{17}$$

Hence, local education productivity is the residual after accounting for local returns to education and for the effects from local per-student school-funding.

School Funding and Tax Rates. To calibrate federal, state, and county-level tax rates, we assume each government balances its budget and uses tax revenues only to provide school funding. With this assumption and for given data on local wages and rents, we can recover each government's tax rate so that its tax revenue matches observed data on school-funding amounts. Appendix A.1 provides more information on the calibration.

We find a federal income tax rate of 0.7% and an average state income tax rate of 2.8%. The average tax rate on rental income across counties is equal to 5.3%. The recovered tax rates are lower than actual tax rates in the US, because we chose them to provide only observed school-funding amounts but no other public goods or transfers.

Each neighborhood uses its entire tax revenue for its own local schools. Federal and state governments use specific allocation rules to distribute their tax revenues across neighborhoods. We calibrate these allocation rules to match observed data on the relative amount of per-student school funding that each neighborhood receives from the federal (or its associated state) government.

Given tax rates and allocation rules, local per-student school funding is endogenously determined by local wages and local rental income.

2.2.3 Simulated Method of Moments

Last, we estimate the elasticity of substitution between low- and high-education workers in the CES production technology and the effect of school funding on education outcomes by simulated method of moments.

Elasticity of Substitution between Low- and High-Education Workers. A large literature provides estimates for the aggregate elasticity of substitution between high- and low-education workers for the US economy. Estimated values range from 1.4 to 1.5 (cf. Katz and Murphy, 1992; Ciccone and Peri, 2005; Acemoglu and Autor, 2011). In our model, the aggregate elasticity of substitution depends on the regional elasticity of substitution and local labor-supply elasticities. We choose the local elasticity of substitution between education types, ρ, so that our model generates values for the aggregate elasticity from previous studies following a procedure outlined in Burstein and Vogel (2017). To do so, we guess a value of ρ and solve for the steady state of our model. We then simulate a small and random education supply shock by perturbing education productivity in all locations and for all parental education types. We use these two model solutions as cross sections of data to compute the aggregate elasticity of substitution:

$$\hat{\rho}_{agg} = \frac{\Delta \log L^h / L^l}{\Delta \log \bar{w}^h / \bar{w}^l}, \tag{18}$$

where $\bar{w}^e$ denotes the average wage of workers with education e.[16] We iterate on the guess of ρ until the aggregate elasticity in our model matches a aggregate elasticity of 1.5 which results in an estimated value of $\rho = 1.43$.

Effectiveness of School Funding. To identify the effect of per-student school funding on local education outcomes, γ^e, we target results from Jackson et al. (2016), who estimate the causal effects of school-funding changes on children's long-run outcomes using exogenous variation in school funding from court-mandated reforms in the US. To match our model equation as closely as possible, the authors provided us additional results (not reported in the published paper) that estimate the effects of school funding on children's probability of attending and graduating from college, separately for children from low- and high-education parents.[17] The estimates show a 10% increase in school funding increases children's probability of attending (and graduating from) college by 7 (4.6) pp for non-college-educated parents. For college-educated parents, children's probability of graduating from college increases by 3.2 pp, and effects on the probability of attending college are not significant.

[16] We use a small-enough perturbation of education productivity, so that the same perturbation in either direction yields the same elasticity estimate.

[17] We are very grateful to the authors, notably Rucker Johnson, for their time and effort in providing these additional results.

Table 1: Parameter Overview

Parameters			Estimation Method
	Description	Value	Panel A.1.: Calibrated Parameters
$\alpha^{l0}, \alpha^{l1}, \alpha^{h0}, \alpha^{h1}$	Housing Expenditure Shares	$(0.34, 0.38, 0.33, 0.36)$	Consumer Expenditure Survey
ϕ^{l1}, ϕ^{h1}	Parenthood Probability	$(0.56, 0.63)$	Micro-data from US Decennial Census and ACS
	Description	Value	Panel A.2.: Estimated Parameters
σ_N	Dispersion: Location Taste Shock	0.25	Literature and Migration Response to Labor Demand Shocks
σ_E	Dispersion: Education Taste Shock	0.32	Parents' Valuation of Local College-Education Rates
β	Parental Altruism	0.23	Parents' Valuation of Local Child Opportunity Values
θ	Parental Amenity Value	0.9	Parents' Valuation of Local Amenities Relative to Non-parents
γ^l, γ^h	Effectiveness of School Funding	$(0.8, 0.49)$	College Education Response to Funding Shock
ρ	Elasticity btw Low- and High-Education Workers	1.43	Target Aggregate Elasticity from Literature
	Description		Panel B: Location-Specific Characteristics
$C^{ep}_{mm'}$	Moving Cost		Moving Flows across CZs
$\mathcal{Z}_m$	Factor Neutral Productivity		Average Wage Level
$\mathcal{S}^h_m$	High-Education Productivity		College Wage Premium
A^{ep}_n	Neighborhood Amenities		Non-Parental Residence Choices
H_n	Neighborhood Housing Supply		Rental Rates
$\mathcal{Q}^e_n$	Education Productivity		College-Education Rates
t^r_n	Local Rent Tax Rate		School Funding Provided by Counties
t^w_s	State Income Rax Rate		School Funding Provided by States
t^w_f	Federal Income Tax Rate		School Funding Provided by Federal Gov.
δ^n_s	State Funding Allocation Rules		School Funding from States to Neighborhoods
δ^n_f	Federal Funding Allocation Rules		School Funding from Federal to Neighborhoods

Notes: The table shows the values for the structural parameters of the model and the corresponding data targets. The parameters of Panel A.1 are model-free and calibrated to values of the literature or the data. The parameters in Panel A.2 are estimated by taking model-implied estimating equations to the data or by simulated methods of moments (ρ and γ^e). The parameters in Panel B are location-specific and inferred as structural residuals by taking model-implied estimating equations to the data. We parameterize bilateral moving costs and recover them from estimating a model-implied gravity equation.

We estimate γ^e so that our model replicates these elasticities. To do so, we guess a value of γ^e and solve for the steady state of our model. We then implement a random shock to local school-funding by perturbing the federal government's school funding allocation rule and we re-solve the model. We use these two model simulations as cross sections of data to estimate the regressions from Jackson et al. (2016); that is, we regress the change in local college-education rates on changes in the log of per-student school funding while controlling for location fixed effects. We estimate the regressions separately for children from college- and non-college-educated parents. We then use the regression coefficients to update our guess of γ^e until the elasticities estimated in the model match those from Jackson et al. (2016).

2.3 Properties of the Calibrated Model

Most of our estimation does not assume that the data is currently in steady state. For our counterfactual policy analysis, we therefore first solve for the baseline steady state holding all policy parameters and local characteristics constant at their calibrated levels. The endogenous outcomes in the baseline steady state resemble closely those in the data, as shown in Appendix Table B.2.

In this section, we present the empirical relationships in the baseline steady state that are central for the effects of policy counterfactuals and we use our estimated model to decompose the spatial variation in education outcomes into variation due to differences in the costs and returns to education.

Joint distribution of productivity, skill-intensity, and school funding. In the steady state of our quantified model, labor markets with high productivity and high skill-intensity also have high levels of per-student school funding. In the data, this is reflected by the fact that per-student school funding positively correlates with wage levels, college wage premia, and workers' college shares across CZs, as shown in Figures 2a and 2b. Hence, labor markets with a high demand for educated workers also invest more resources into education. This finding has important implications for the aggregate effects of policies, as redistributing school funding across locations, or incentivizing workers to change their residential locations, affects the match between local skill supply and skill demand.

Determinants of the local supply of educated workers. In our calibrated model, local education choices and net skill migration jointly determine the supply of educated workers in each location. Figure 2c shows that labor markets with high college wage premia have a larger college share among workers (dotted line) than among local children (solid line), implying that they are net importers of educated workers. Quantitatively, the difference between these two lines is small compared to the total variation in college-education rates across labor markets that we see on the y-axis. Hence, in the baseline

FIGURE 2: SCHOOL FUNDING, WAGES, AND COLLEGE SHARES

(A) FUNDING AND COLLEGE SHARES

(B) FUNDING AND WAGES

(C) COLLEGE SHARE AND WAGE PREMIA

Notes: All of the graphs show data from the baseline steady state. Each scatter point represents one CZ and the size indicates the population size. The lines provide the linear fit. Panel (a) plots college-education rates among children and college shares among workers against per student school funding for each CZ. Panel (b) plots wages for college- and non-college-educated workers against per-student school funding in each CZ. Panel (c) plots college-education rates among children and college shares among workers against the college wage premium in each CZ.

steady state, differences in local education outcomes are more important than net skill-migration to explain differences in the supply of educated workers across locations. This finding is important for policy counterfactuals, because it implies that changes in the local education production can have strong effects on the skill composition of the local workforce.

Decomposing the variance of education outcomes across counties. The average college-education rate for children from college-educated parents is 73% with a standard deviation across counties of 5%. For children from non-college-educated parents, the average is 39% and the standard across counties is 8%. We can use our model structure to additively decompose the variance of the odds of college education across counties into the parts that are due to variation in education returns, school funding, and education productivity, as shown in equation 11. We implement the variance decomposition separately for children from college- and non-college-educated parents.

For children from college-educated parents, we find that variation in education returns explains 28% of the overall variation in the odds of college-education rates. Variation in school funding explains 18% of the variance of education indices. For children from non-college-educated parents, school funding is relatively more important and explain 60% of the variation in education indices. Education returns are relatively less important explaining 18% of the overall variance of the odds of college education rates. This decomposition suggests that changing school funding across locations can have large effects on the observed spatial differences in education outcomes, particularly for children from non-college-educated parents.

3. Policy Counterfactuals

We use the estimated model to evaluate the effectiveness of three policies that are commonly proposed to reduce differences in education outcomes across locations and parental backgrounds. We analyze the long-run effects of policies by comparing baseline and counterfactual steady states.

First, we consider a budget-neutral school-funding equalization that raises all funds with federal taxes, removing the feedback effect between local rents, local tax revenues, and local school funding. The policy is a nationwide and more comprehensive version of school funding reforms that several states implemented in the past decades (see, Jackson et al. (2016)).

Second, we offer a subsidy equal to 25% of wages to low-education parents conditional on living in neighborhoods that lie in the top 20% of education outcomes for children from low-education parents. We fund the subsidy with a lump-sum tax on all workers. The policy reflects a large-scale version of the well-known moving-to-opportunity experiment in which low-income parents received vouchers to move to low-poverty neighborhoods (see, Katz et al. (2001) and Chetty et al. (2016)).

Last, we expand the housing supply by 25% in the same set of neighborhoods, which is a reduced-form way of modeling a relaxation of zoning restrictions advocated by Hsieh and Moretti (2019) and many others.

3.1 Policy Effects on the Spatial Distribution of Education Outcomes

We now discuss how each of the policies affects education outcomes across locations and how these changes affect aggregate output.

Funding Equalization. The school funding equalization decreases per student school funding by 17% in the county at the 10th percentile of changes and increases it by 45% in the county at the 90th percentile. These changes reduce differences in children's college-education rates and in workers' college shares across CZs. Figure 3a shows this convergence by plotting the percentage point changes in both variables against their respective baseline levels for each CZ. The spatial convergence in college education is driven by the fact that CZs with high initial education outcomes also have high levels

TABLE 2: EFFECTS ON COLLEGE SHARES AND WAGES ACROSS CZS

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	1.2	-8.5	-0.7	-8.0	0.7	0.2
College-Share Workers	1.2	-8.8	-0.7	-6.9	0.7	-0.2
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	0.6	-30.5	-1.1	-10.3	0.8	2.1
College Wage	-0.8	10.0	0.8	2.3	0.6	0.5
College Wage Premium	-6.8	42.0	5.6	5.6	-0.6	-0.6
Output	-0.5		0.1		0.7	

Notes: The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

of school funding prior to the reform. The reform therefore redistributes funding from locations with high initial education outcomes to those with low education outcomes. Reducing college-education rates in these locations also decreases the college share among workers because moving is costly and a large share of children stay in the labor market in which they grow up. Overall, the standard deviations of children's college-education rates and workers' college shares respectively decrease by 8.5% and 8.8% across CZs (cf. column 2 of Table 2).

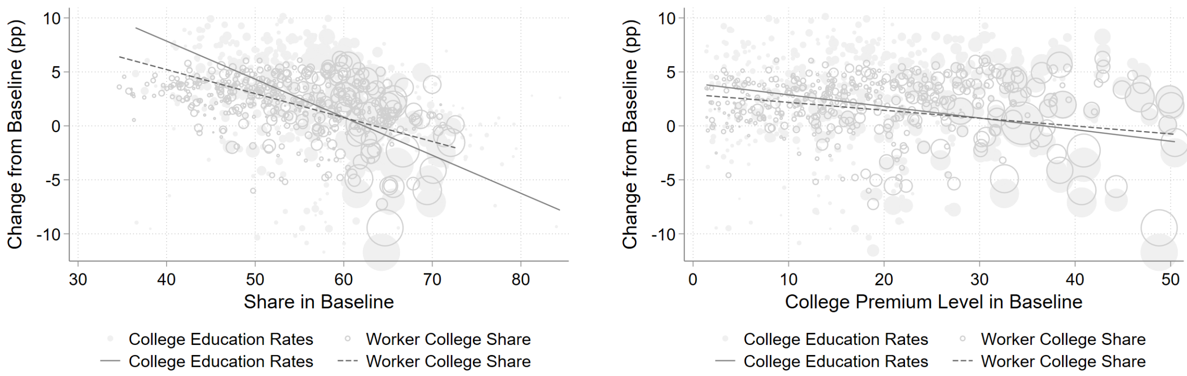
In a given location, the college share of workers tends to change less than children's college-education rate, because net skill migration increases after the reform. This finding can be seen in Figure 3a because the slope is steeper for changes in children's education outcomes (dark grey line) than for changes in workers' college shares (light grey line). The difference between these slopes measures changes in net skill migration after the reform. Hence, locations that produce more college-educated workers after the reform retain some but not all of the additional college-educated workers.

By changing the allocation of college-educated workers across labor markets, the reform impacts aggregate output. We find that labor markets which had high levels of per-student school funding prior to the reform tend to have productive and skill-intensive production technologies and a high demand for college-educated workers, as evidenced by these locations' high wages and high college wage premia (as discussed in Section 2.3). Equalizing school funding therefore reduces funding, college-education rates, and the supply of college-educated workers in productive and skill-intensive locations. This finding can be seen in Figure 3b which shows that college shares among children

FIGURE 3: EQUAL FUNDING: LABOR MARKET EFFECTS

(A) EDUCATION CHANGES AND INITIAL SHARES

(B) EDUCATION CHANGES AND INITIAL COLLEGE PREMIA



Notes: Panel (a) plots pp changes in college-education rates among children and college shares among workers against the respective shares in the baseline. Changes are computed between the steady state with equalized school funding and the baseline steady state. Each scatter point represents one CZ and the size indicates the population size. The lines provide the linear fit. Panel (b) plots the pp changes in education rates among children and college shares among workers against CZs' initial college wage premia before the reform.

and workers decrease more in locations where college wage premia–and therefore the marginal products of college-educated workers–were high prior to the reform. By depriving centers of skill-intensive production of the excess funding needed to produce large numbers of college-educated workers, the reform creates a mismatch between the local supply and demand of educated workers and decreases aggregate output by 0.5%.

Subsidy. The subsidy reduces spatial differences in children's college education rates and in workers' college shares because it attracts low-education parents into subsidized neighborhoods where initial college education rates are high (cf. column 4 of Table 2). Average college education rates therefore decrease in these locations because children of low-education parents have, on average, lower college education rates than children from high-education parents. Subsidized neighborhoods also tend to be part of productive and skill-intensive labor markets where college shares among workers are high prior to the reform (cf. Section 2.3). The subsidy therefore increases the total number of workers, but reduces the college share in productive and skill-intensive labor markets. Together, the effects increase aggregate output by 0.1%.

Housing Expansion. The expansion of housing has little effect on the spatial distribution of education outcomes and workers' college shares, because it attracts low- and high-education workers in almost equal measure into targeted locations. Aggregate output increases by 0.7% because the total number of workers increases in productive labor markets without decreasing local college shares.

3.2 Effects on Intergenerational Mobility

In this section, we show how each of the policies affects education outcomes by parental background, measuring intergenerational mobility in education.

School-Funding Equalization. The school-funding equalization increases average funding per student by 2.3% for children from non-college-educated parents and decreases it by 1.5% for children from college-educated parents.[18]

TABLE 3: EFFECTS ON INTERGENERATIONAL MOBILITY – CHANGES RELATIVE TO BASELINE

	Equalization		Subsidy		Housing Expansion	
	Direct	GE	Targeted GE	All GE	Targeted GE	All GE
Parental Edu.	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE-SHARE CHILDREN (IN PP)						
No College	3.99	1.43	-2.10	0.15	-0.06	0.49
College	0.18	-0.14	-1.30	-0.58	-0.11	0.13
PANEL B: Δ SCHOOL FUNDING (IN %)						
No College	2.32	2.32	-1.34	0.63	0.35	1.16
College	-1.45	-1.45	-1.11	0.22	0.38	1.17
PANEL C: Δ RETURNS TO EDUCATION (IN %)						
No College	0.00	-2.75	-2.44	-1.01	-0.50	-0.21
College	0.00	-3.49	-2.44	-1.34	-0.50	-0.23

Notes: All numbers in the table represent changes in population-weighted averages between the baseline and counterfactual steady states. Panel A documents percentage point changes in college-education rates for children from low- and high-education parents. Panel B shows percent changes in per-student school funding. Panel C shows changes in returns to education that measure the utility premium between college-educated and non-college-educated workers. Column 1 reports direct effects for the school-funding equalization where we implement only changes in school funding but hold everything else constant. Columns 3 and 5 show changes in full general equilibrium but conditioning only on the sample of neighborhoods that we target in the subsidy and housing-supply expansion. Columns 2, 4, and 6 show changes in full general equilibrium across all neighborhoods.

We first compute the ”direct” effects of the policy by computing changes in college-education rates that occur if only school funding changes without any adjustments in local wages, rents, and residential choices. We find large direct effects: the average college-education rate increases by 4 pp for children from low-education parents, closing the education gap between parental backgrounds by 11% (cf. column 1 of Table 3).

However, these effects are much smaller in general equilibrium where this education

[18]In the model, all students in the same county receive the same amount of school funding. Average school funding in the baseline is higher for children from college-educated parents because they live, on average, in counties with higher per-student funding. Equalizing school funding across students then eliminates all differences across locations and parental backgrounds.

rate increases only by 1.4 pp, closing the education gap between parental backgrounds only by 4.4% (cf. column 2 of Table 3).

Two mechanisms mitigate the direct effect of the reform in general equilibrium. First, returns to education, which measure the utility premium for college- relative to non-college-educated adults, decrease on average. Returns decrease because the average college wage premium declines–in response to an increase in the aggregate supply of college-educated workers–and because non-college-educated parents are better off after the reform since their children receive more school funding and better economic opportunities on average.

A second mitigating factor is that low-education parents shift toward neighborhoods where per-student school funding decreases due to the reform. This change occurs, first, because neighborhoods where school funding decreases experience a decline in college-education rates, which increases the local share of non-college-educated adults due to the presence of moving costs. In addition, rental prices decline in neighborhoods where school funding decreases, which disproportionately attracts low-education parents, who we find to be more sensitive to rental prices. This "gentrification" effect, which shifts low-education families towards neighborhoods with declining education rates and high-education families towards neighborhoods with rising education rates, mitigates the policy's direct effects on intergenerational mobility.

Subsidy. The take-up of the subsidy increases the total share of low-education parents who live in high-opportunity neighborhoods from 25% to 32%. The share of high-education parents in subsidized locations decreases only slightly from 34% to 33.6%, indicating that the total number of residents increases in subsidized locations. Implementing this residential reallocation alone, while holding education rates constant in all locations, increases the average college-education rate by 0.9 pp for children from low-education parents and decreases it by 0.04 pp for children from high-education parents. These effects are lower in general equilibrium, increasing the college education rate by 0.15 pp for children from non-college-educated parents and decreasing it by 0.45 pp for children from college-educated parents (cf. column 4 of Table 3).

In general equilibrium, education outcomes decline in subsidized locations because the subsidy attracts low-education parents into subsidized locations, which increases the ratio of children to total residents. For given local tax rates, this inflow of children reduces the school funding amount that is available for each student. In addition, returns to education decrease because only non-college-educated parents are eligible for the subsidy while all workers have to pay a lump-sum tax to fund the subsidy. The subsidy therefore makes it more attractive to be low-educated relative to higher-educated, lowering the incentives to obtain higher education. Changes in local wages push in the other direction because the inflow of low-education workers increases the college wage premium in subsidized locations. Quantitatively, the former effect dominates, so that average returns to education decrease in subsidized neighborhoods (cf. column 3 of Table 3).

When averaging across all neighborhoods, the subsidy increases average per-student school funding for children from low-education parents by attracting more of them towards subsidized locations, where average per-student school funding is higher than in non-subsidized locations (even after the above-mentioned decline in per-student funding in subsidized locations). Returns to education decrease when averaging across all neighborhoods, because the incentive effects of the subsidy affect expected returns to education also for children who grow up in non-subsidized locations as they have the option value of moving to subsidized locations as adults.

Housing Expansion. Expanding housing supply in neighborhoods with good education outcomes attracts low- and high-education workers and increases the share of children living in these locations by 3.5 pp (compared to 2.4 pp for the subsidy). The policy increases the average college-education rate by 0.5 pp for children from low-education parents and by 0.13 pp for children from high-education parents. Aggregate education outcomes increase because children's average per-student school funding raises, as more families sort into the targeted neighborhoods, which have higher per-student school funding prior to the reform (cf. column 6 of Table 3).

College education rates remain largely unchanged in targeted locations because a small decrease in returns to education is offset by a small increase in per-student school funding in these locations, as shown in column 5 of Table 3. Returns to education decrease, because the policy increases the supply of college-educated workers, which lowers the average education wage premium. Average per-student school funding increases in subsidized locations, despite a reduction in local rental prices, because the housing expansion increases the available tax base. Quantitatively, the increase in the tax base is large enough to accommodate the additional inflow of children into targeted neighborhoods, so that average per-student funding increases in targeted locations.

The policy improves intergenerational mobility, because education outcomes increase more for children from low-education than from high-education parents. Three channels explain this result: First, children from low-education parents have a higher marginal benefit from an extra dollar of school funding; second, low-education parents spend a larger fraction of their income on housing, so they respond more to decreasing rental prices in targeted neighborhoods; and third, the policy specifically targets neighborhoods with the best education outcomes for children from low-education parents.

Summary. Our analysis shows that the effectiveness of policies to restore equality of opportunity across locations and parental backgrounds can be mitigated in equilibrium by responses in local wages, rents, and residential sorting. Our findings further indicate the presence of an equity-efficiency trade-off, as policies that reduce differences in college education rates across locations can create a mismatch between the local supply and demand of educated workers, which can lower aggregate output. Among the considered policies, equalizing school funding is most effective at reducing differences in education outcomes across locations and parental backgrounds, but the reform decreases aggregate output. The policies that we consider to expand access to neighborhoods with good education outcomes strike a different balance in the equity-efficiency trade-off: they have positive but smaller effects on intergenerational mobility, but they raise aggregate output by increasing the share of workers in productive locations. Policies' overall effects on equity and efficiency are reflected in the welfare measures implied by our model.

3.3 Effects on Welfare.

We now discuss the effects of each policy on two welfare measures: child opportunity values by parental background and compensating wage differentials.

Child Opportunity Values. Child opportunity values measure children's expected utility at the beginning of their life, before knowing their idiosyncratic education taste shocks. We average child opportunity values across locations for each parental background.

The school-funding equalization increases the average child opportunity value by 2.9% for children from non-college-educated parents and by 0.8% for children from college-educated parents (cf. Table 4). The average opportunity value increases also for children from college-educated parents–despite a decrease in their education outcomes–because children's expected future utility places a positive weight on the welfare of all education and parent types, and because welfare increases for non-college-educated adults.

The subsidy increases the average child opportunity value by 1% for children from non-college-educated parents and decreases it by 0.2% for children from college-educated parents. Children from college-educated parents are likely to become college-educated themselves, so that their average child opportunity value decreases, because the tax-funded subsidy decreases the adult utility of all demographic groups expect for low-education parents, who are eligible for the subsidy. Children from non-college-educated parents are relatively more likely to be non-college-educated and to be eligible for the subsidy as adults, so their average child opportunity value increases.

The housing expansion improves the average child opportunity value for children from low- and high-education parents because both groups experience an increase in their probability of becoming college-educated and because average wages increase for college- and non-college-educated workers.[19]

[19] Since we compare steady states, any one-off cost of building more housing is sunk and irrelevant for welfare calculations. However, our analysis abstracts from the flow-cost of maintaining housing due to depreciation. Lopez and Yoshida (2022) estimate the annual depreciation rate of newly constructed multifamily homes to be about 1.5%.

TABLE 4: WELFARE MEASURES – CHANGES RELATIVE TO BASELINE

	Equalization	Subsidy	Housing Expansion
PANEL A: Δ CHILD OPPORTUNITY VALUES (IN %)			
Children Non-College Parents	2.9	1.0	4.3
Children College Parents	0.8	-0.2	3.2
PANEL B: COMPENSATING WAGE DIFFERENTIAL (IN %)			
Average of All Groups	0.5	-0.2	3.6

Notes: Panel A of this table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents. Panel B reports the compensating wage differential which measures the average percentage change in workers' baseline wages that is required to make them indifferent between the baseline and the counterfactual steady state.

Compensating Wage Differential. To measure aggregate welfare across all workers, we compute the compensating wage variation necessary to make the average worker indifferent between an economy with and without each policy reform.[20]

The housing expansion has the largest welfare gains, as we would have to pay workers an additional 3.6% of their baseline income to make them, on average, indifferent between the baseline and counterfactual steady state. Welfare gains are large because the housing expansion increases the aggregate college-education rate and aggregate output and offers more families access to attractive and high-opportunity neighborhoods. The school-funding equalization increases welfare by an equivalent of 0.5% of baseline income despite a decrease in aggregate output because more families have access to well-funded schools after the reform.[21] In contrast, the subsidy decreases average welfare by 0.2% of baseline steady-state income because the tax-funded subsidy lowers the welfare of all workers that are not eligible for the subsidy.

Appendix D shows the presented results are robust to using different data samples and different parameter values.

3.4 Model Extensions: Peer Effects and Elastic Housing Supply

We consider two separate model extensions: peer effects in education and elastic housing supply. We then implement our three policy counterfactuals in each model extension. For each extension, we re-calibrate all parameters that are affected by the model extension, solve for a new baseline steady state, and then compare this baseline to the counterfactual steady state of each policy counterfactual. We now briefly describe the model extensions

[20] This calculation holds prices, tax rates, and all parameters constant at the levels of the baseline steady state.

[21] In a stylized model, Fernandez and Rogerson (1998) find equalizing school funding across locations would lead to a welfare increase of 3.2% of steady-state income. In their model, all locations have the same production technology, so their analysis abstracts from changes in the allocation of educated workers across labor markets, which lower welfare effects in our context.

and how the results of our policy counterfactuals change in the extended versions. We replicate the tables shown above for each model extension in the Online Appendix.

Peer Effects in Education. An extensive literature studies the effects of peers on children's education outcomes, emphasizing that the presence of highly skilled and educated children or families in a classroom, school, or neighborhood can have positive spillovers on education outcomes of other children (cf. Benabou, 1993; Benabou, 1996; Durlauf, 1996b; Agostinelli, 2018; Carrell, Hoekstra, and Kuka, 2018; etc.). To include peer effects in education in our model, we add the local college share among adults as an additional determinant of the local education index (cf. equation 2).

The extension requires an elasticity of children's local college-education rates to the local college share among adults. There is no consensus in the literature on the strength of such neighborhood-level peer effects, since most studies focus on peer effects in classrooms. We therefore consider a bounding exercise in which we consider respectively low, medium, and high levels of peer-effect parameters, which we allow to differ by parental background. We choose the range of peer effects so that a 10 pp increase in the local college share among adults leads to a causal increase in children's local college-education rate between 1 and 4.5 pp. Appendix C.1 describes the chosen values in more detail.

The results for our three policy counterfactuals in the extended model versions are qualitatively and quantitatively similar to the baseline model. Peer effects introduce a direct spillover from local college shares among workers to children's local college-education rates, which amplifies effects in either direction.

For the school-funding equalization, this amplification leads to a larger increase in the aggregate college-education rate, but also to a larger decrease in aggregate output. Output declines more because peer effects amplify effects at the local level, so education outcomes and the supply of college-educated workers decrease even more in highly productive and skill-intensive labor markets.

The additional increase in the aggregate education rate in the model with peer effects is driven by better outcomes for children from high-education parents, which now sort even more into neighborhoods with higher shares of college-educated workers. Children from low-education parents shift on average toward neighborhoods with lower shares of college-educated workers after the reform, which lowers their spillovers from peers and therefore their education outcomes. The aggregate amplification effect and the increase in segregation offset each other for children from low-education parents, whereas both mechanisms benefit children from high-education parents.

The subsidy program provides incentives to low-education parents to move into subsidized neighborhoods, which increases the share of low-education families in these locations. With peer effects, this sorting reduces spillovers from local college shares and reduces the effects of the subsidy on children's education outcomes. In the scenario with "high" peer effects, this mechanism is so strong that the aggregate college-education rate even decreases for children from low-education parents due to the subsidy, which stands in clear contrast to the main objective of the policy.

The housing-supply expansion has similar effects with and without peer effects because expanding housing supply does not meaningfully change the educational composition of a neighborhood, only its total size.

Elastic Housing Supply. In this model extension, we allow each neighborhood's housing supply to respond elastically to increases in housing demand. We calibrate local housing-supply elasticities for each county following Diamond (2016) and Saiz (2010) which we describe in more detail in Appendix C.2.

The interpretation of our counterfactual results and the economic mechanisms behind the effects of each policy remain as in our baseline model. Quantitatively, the school-funding equalization and targeted subsidy have larger effects on college outcomes when housing supply is elastic. The reason is that housing supply now increases in locations where the demand for housing increases–either due to an increase in local school funding or due to the subsidy. The endogenous housing-supply response then mitigates the rent increase associated with higher housing demand, which benefits particularly low-education families who are more sensitive to rents.

The housing-supply expansion policy is instead less effective at raising college education for children from both parental background when housing supply is elastic. A given amount of housing-supply expansion now translates into a smaller net increase in local housing supply, because decreasing rents lead to an endogenous decrease in housing supply that counteracts the original policy. The policy is therefore less effective at providing access to "good" neighborhoods when housing supply is elastic.

CONCLUSION

Our paper offers a quantitative spatial equilibrium model in which education decisions in each location respond to the local costs and returns to education that are determined in equilibrium. In our quantitative application, we evaluate the effectiveness of three policies that are commonly proposed to reduce differences in education outcomes across US counties and parental backgrounds. We show quantitatively that the effects of these policies are mitigated in general equilibrium by responses in local wages, rents, and residential sorting. These equilibrium responses have feedback effects on local education outcomes because they change the local returns and costs of education. In addition, we find that policies that redistribute education resources away from skill-intensive labor markets can create a mismatch between the local supply and demand for educated workers, which can reduce aggregate output.

Our quantitative application is specific to the US economy, to which we calibrate our model. Many of the results depend on the empirical relationships in the data. Future applications could use our framework to study education policies in other countries. The framework is also well-suited for studying whether industrial policies are more effective when targeting either the demand or the supply side of educated workers. An additional avenue for future work is to analyze optimal education policy in our framework.

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Appendix

This Appendix presents more information about the model estimation and model extensions, provides brief results for a model "validation" exercise, and discusses a set of robustness checks.

A. Quantification Appendix

This appendix provides more information on the model estimation.

A.1 Inferring Regional Characteristics as Structural Residuals

This section shows how we recover location-specific parameters, which include labor markets' total factor productivity and factor-specific productivity shifters, and neighborhoods' housing supply. Neighborhood amenities are recovered to match the residential choices of non-parents as described in the main part of the paper. To quantify local education environments and the tax-funded school-funding system, we need to recover additional location-specific parameters, which include neighborhoods' education productivity, tax rates from the federal, state, and neighborhood governments, and allocation rules that determine how federal and state governments distribute their tax revenues across neighborhoods. We now describe how we recover these parameters.

Production Technology. We use the first-order conditions of the representative firm in each labor market to recover the location-specific productivity parameters. The ratio of the first-order conditions is given by:

$$\frac{\mathcal{S}_m^h}{\mathcal{S}_m^l} = \frac{\mathcal{S}_m^h}{1-\mathcal{S}_m^h} = \frac{w_m^h}{w_m^l}\left(\frac{L_m^l}{L_m^h}\right)^{\frac{1}{\rho}},$$

where we can infer factor-specific productivity shifters, $\mathcal{S}_m^e$, to match observed data on the wages and the supply of low- and high-education workers–conditional on our estimate of the elasticity of substitution between these workers types ρ that we describe in section 2.2 of the main paper. We then use these estimates to recover local TFP, $\mathcal{Z}_m$, by rearranging the first-order conditions, so that

$$\mathcal{Z}_m = \frac{w_m^e}{\mathcal{S}_m^e\left(L_m^e\right)^{-\frac{1}{\rho}} \times \left(\mathcal{S}_m^l\left(L_m^l\right)^{\frac{\rho-1}{\rho}} + \mathcal{S}_m^h\left(L_m^h\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}-1}}.$$

Housing Supply. We infer housing supply $\mathcal{H}_n$ for each neighborhood from the housing market clearing equation, which is given by:

$$\mathcal{H}_n = r_n^{-1} \sum_{e,p} \alpha^{ep} L_n^{ep} Y_n^e,$$

where all objects on the right-hand side are known from the data or previous estimates. Disposable income, Y_n^e, is constructed from data on wage income net of our calibrated tax rates, which are described below.

Amenity Level for Low- and High-Education Workers. We infer amenities for each education type a_n^e from agents' residential choices (cf. section 2.2 of main paper). This procedure identifies amenities up to a constant of normalization for each education type and does not identify any level difference in amenities between low- and high-education workers.

Returns to education measure the utility premium of high- relative to low-education adults in each location. The *level* of returns to education in all locations therefore depends on the level difference in amenities between low- and high-education workers. Any level change in returns to education gets absorbed into a compensating level change in education productivity, $\mathcal{Q}_n^e$ (cf. equation A.1 below), so that any chosen level generates observationally equivalent results in all endogenous variables, including agents' educational and residential choices. We therefore choose a relative amenity level between low- and high-education adults that generates a plausible relationship in our model between the aggregate college wage premium–which affects the level of education returns–and the costs of education.[22]

In particular, we choose the relative amenity level between education groups, so that the aggregate college wage premium is zero in a counterfactual steady state of our model in which we set the cost of obtaining college education to zero.

To identify the relative amenity-level shifter, we target this moment via a simulated method of moments. To do so, we set the education indices in all neighborhoods to zero, that is, $\mathcal{E}_n^e = 0 \forall n$, and compute the steady state of the model. We then iterate on a guess of the amenity-level shifter until the average college wage premium is zero in the steady state of our model.

Education Productivity. To infer local education productivity, we rearrange the education choice probabilities from equation (11) as follows:

$$\mathcal{Q}_n^e = \bar{V}(h,m) - \bar{V}(l,m) + \gamma^e \log f_n - \sigma_E \log \frac{\pi_n^{eh}}{\pi_n^{el}}. \tag{A.1}$$

[22]The amenity-level shifter does not affect the results of our counterfactual analysis; however, it affects the respective *percentage* changes in education returns that we report in Table 3 of the main paper, because percent changes are a function of the respective baseline levels. The direction of these changes is independent of the amenity-level shifter.

We then solve for the value-function, $\bar{V}(e, m)$, once by value function iteration while conditioning on our estimates of amenities and other parameter estimates, and on observed data of local college-education rates. All other terms of equation A.1 are known from the data or previous estimates, so that we can recover local education productivity to match the observed data on children's education outcomes by parental background in each neighborhood.

Mapping Per-Student School-Funding Levels to the Data. In the model, we want to match *per-student* school funding in each neighborhood to the observed levels in the data. We therefore re-scale the funding amounts observed in the data by the ratio between the model-implied and the observed number of students in each neighborhood. In the model, the total number of students in each neighborhood is equal to $C_n = \sum_e L_n^{e1}/\phi^{e1}$, where ϕ^{e1} is the probability that an adult of education e has children and where we assume each parent has $1/\phi^{e1}$ children to ensure total population remains constant. Our model perfectly matches local population stocks of parents, L_n^{e1}; however, our assumption that the fertility rate is constant across locations and restrictions on the age range of our sample imply the model-implied number of students is not equal to the number of students in each neighborhood in the data. We therefore adjust the school-funding amounts in the data accordingly before calibrating the tax rates and school-funding allocation rules. We set the aggregate amount of nationwide school funding to 6% of aggregate wage income, which matches the share of the nationwide labor income allocated to education expenditure in the US.

Tax Rates. To calibrate federal and state income tax rates, t_f^w and t_s^w, and neighborhood rent tax rates, t_n^r, we assume each government balances its budget and uses the entire tax revenue to cover the observed school-funding amounts. We can then recover tax rates from each government's budget constraint to match observed data on school-funding amounts for given data on the respective tax bases (that is, local wage and rent incomes). Each state government funds schools only within its borders, so that the budget constraint of state government s is equal to:

$$\sum_{n \in \mathbb{N}_s} F_n^s = t_s^w \sum_{n \in \mathbb{N}_s} \sum_e w_m^e L_m^e, \tag{A.2}$$

where F_n^s is total school funding from state s to neighborhood n, and $\mathbb{N}_s$ indicates the set of all neighborhoods in state s. We observe school-funding amounts F_n^s, wage rates w_m^e, and labor stocks L_m^e in the data as described in section 2.1 and in the Online Appendix. We can therefore use the budget constraint of each state government to infer each state's income tax rate that is required to raise the total school-funding amount. We proceed in a similar manner for the federal government, for which the budget constraint is equal to:

$$\sum_{n\in\mathbb{N}} F_n^f = t_f^w \sum_{n\in\mathbb{N}} \sum_e (1-t_s^w) w_m^e L_n^e, \tag{A.3}$$

which incorporates the state tax deduction of the US tax system.

We next calibrate the tax rates that neighborhoods impose on rental income, which are given by $r_n = (1+t_n^r)r_n^*$, where r_n^* is the rental rate net of taxes. For each neighborhood government, the budget constraint is therefore equal to:

$$F_n^n = t_n^r r_n^* \mathcal{H}_n = \frac{t_n^r}{1+t_n^r} r_n \mathcal{H}_n, \tag{A.4}$$

where we observe the total amount of local school funding raised and spent in each neighborhood, F_n^n. We can construct total rent expenditure in each neighborhood using data on rental rates and calibrated housing supply in each neighborhood. With these data, we recover each neighborhood's tax rate on rental income from equation A.4.

Dividends from National Real Estate Portfolio. We assume all after-tax rental payments are sent to a national real estate portfolio that pays them out to workers in proportion to their wage income, which follows Caliendo et al. (2019). As a result, we can write the disposable after-tax income of a worker with education e in neighborhood n as:

$$Y_n^e = (1-t_f^w)(1-t_s^w) w_m^e + D w_m^e, \tag{A.5}$$

where D reflects the payments workers receive from the national housing portfolio. To solve for the proportion D, we can then rearrange the budget constraint of the local government as

$$\begin{aligned} D &= \frac{\sum_{n\in\mathbb{N}} r_n^* \mathcal{H}_n}{\sum_{m\in\mathbb{M}} \sum_e w_m^e L_m^e} = \frac{\sum_{n\in\mathbb{N}} r_n \mathcal{H}_n - \sum_{n\in\mathbb{N}} F_n^n}{\sum_{m\in\mathbb{M}} \sum_e w_m^e L_m^e} \\ &= \frac{\sum_{n\in\mathbb{N}} \sum_e \sum_p L_n^{ep} \alpha^{ep} w_m^e (1-t_f^w)(1-t_s^w) - \sum_{n\in\mathbb{N}} F_n^n}{\sum_{n\in\mathbb{N}} \sum_e \sum_p L_n^{ep} (1-\alpha^{ep}) w_m^e}, \end{aligned} \tag{A.6}$$

where the second line uses the housing market clearing condition. All objects on the right-hand side are known from the data or previous estimates, so we can now compute D and the local disposable income Y_n^e in the data.

School-Funding Allocation Rules. Neighborhood governments use their entire tax revenue to fund local education. Federal and state governments distribute their tax revenues across neighborhoods according to specific school-funding allocation rules, δ_f^n and δ_s^n. We choose these allocation rules to match observed data on the relative amount of per-student school funding that each neighborhood receives from the federal (or its associated state) government compared with the average neighborhood.

A.2 Estimating the Dispersion of Location Taste Shocks

This section describes the instrumental variable strategy used to identify the dispersion of location preference shocks, σ_N.[23]

The dispersion of location preference shocks, σ_N, measures the extent to which workers' location choices depend on idiosyncratic factors as opposed to commonly-valued neighborhood characteristics such as rents, wages, amenities, and–in our model–child opportunity values. A common strategy of estimating the parameter is to derive a model-implied equation that links agents' location choices to these local characteristics, where the inverse of σ_N pre-multiplies the commonly-valued neighborhood characteristics. That is, a higher dispersion value reduces the effect of these characteristics on agents' location choices. A key challenge to estimating σ_N is that local amenities are unobservable and correlate with other local characteristics. To proceed, we first restrict our sample to *non-parents* who value neighborhood amenities, wages, and rents but do not value future continuation values. Importantly, location choices of non-parents are static decisions, and the only unobservable local characteristics are amenities, which allows us to follow instrumental variable strategies from the literature.

We first describe how we derive an estimating equation from our model that links non-parents' residential choices to neighborhood characteristics. We then describe our instrumental variable strategy, which builds on Diamond (2016) and uses Bartik-like local labor demand shocks, local housing-supply elasticities, and their interactions as instruments for changes in local real income. To implement this estimation strategy, we construct data moments of agents' location choices, local wages, rents, and the instruments using the 1980, 1990, 2000, and 2010 cross sections of data.

Model-Implied Estimating Equation. To derive the estimating equation from our model, we modify the expression of cross-CZ moving flows from equation (12) to express moving flows from each origin CZ m to each destination neighborhood n' in the following way:

$$\text{(A.7)} \qquad \frac{L_{mn'}^{e0}}{\bar{L}_m^{e0}} = \frac{\exp\left(a_{n'}^{e0} + \frac{1}{\sigma_N}\log I_{n'}^{e0} - c_{mm'}^{e0}\right)}{\sum_{n''}\exp\left(a_{n''}^{e0} + \frac{1}{\sigma_N}\log I_{n''}^{e0} - c_{mm''}^{e0}\right)},$$

where a_n^{ep} are normalized amenities, $c_{mm'}^{ep}$ are normalized moving costs, and I_n^{ep} =

[23]Our results are comparable to estimates from the literature. We choose a mean value between our estimates and the literature in our baseline calibration and present robustness checks around this value in Appendix D.

$Y_n^{ep}/r_n^{\alpha^{ep}}$ is disposable real income adjusted for local rents. We evaluate the objects in equation (A.7) for non-parents, setting the superscript $p = 0$.

Taking the log of this equation and rearranging yields the following estimating equation:

$$\text{(A.8)} \qquad \log \frac{L_{mn'}^{e0}}{\bar{L}_m^{e0}} + c_{mm'}^{e0} = a_{n'}^{e0} + \frac{1}{\sigma_N} \log I_{n'}^{e0} - \delta_{m'}^{e0},$$

where δ_m^{e0} is the origin fixed effect of CZ m, which absorbs the log of the denominator of equation (A.7).

The left-hand side of the equation captures location choices adjusted for moving costs across CZs. We construct the object on the left-hand side using the moving-cost estimates from the gravity estimation (cf. section 2.2 of the main paper) together with data on cross-CZ moving flows and county-level population stocks of low- and high-education non-parents, by noting

$$\text{(A.9)} \qquad \frac{L_{mn'}^{e0}}{\bar{L}_m^{e0}} = \frac{L_{mm'}^{e0}}{\bar{L}_m^{e0}} \times \frac{L_{n'}^{e0}}{L_{m'}^{e0}}.$$

Instrumental Variable Strategy. To estimate equation (A.8), unobserved amenities are left in the residual, which can bias the regression estimates if local amenities correlate with local wages and rents. We therefore follow Diamond (2016) and estimate equation (A.8) in differences across the 1990, 2000, and 2010 cross sections of the data, and we use Bartik-like local labor demand shocks, local housing supply elasticities, and their interactions as instruments for local changes in real income. These instruments need to be orthogonal to changes in unobserved amenities which are in the residual of the regression.

Bartik Labor Demand Shocks. To compute Bartik-like labor demand shocks, we compute national wage trends for each industry between 1980 and each consecutive decade (1990, 2000, 2010). To identify local labor demand shocks in each CZ, we weigh each industry's national wage trend by the CZ's employment share in this industry in 1980. CZs are differentially exposed to national changes in industry-level wages because CZs differ in the initial share of their workers who are employed in each industry. National trends in industry-level wages are plausibly exogenous to changes in local amenities, as required by the instrument's exclusion restriction. To avoid any connection between a CZ's Bartik shock and changes in this CZ's local amenities, we compute national changes in industry wages by excluding the respective CZ from the nationwide sample. We compute these local labor demand shocks separately for workers with and without college-education.

Local Housing-Supply Elasticity. Local housing-supply elasticities provide additional variation for changes in locations' real income by affecting the extent to which local housing supply can respond to exogenous labor demand shocks. We proxy local housing-supply elasticities with the Wharton index of land-use regulation constructed by Gyourko, Saiz, and Summers (2008). The Wharton index provides zoning indicators for more than 2,000 small geographical units. We use a geographical crosswalk to map these data to the county level, which provide us with a measure of zoning regulations for more than 1,000 counties. We find substantial variation in zoning restrictions not only across MSAs but also across counties within MSAs.

Estimation Results. With these instruments at hand, we estimate equation (A.8) in differences between the 1990, 2000, and 2010 cross sections of the data. We use a two-stage least squares regression estimator and find values for the inverse of σ_N between 4 and 7.5 depending on the time sample and the initial period used to construct the Bartik instrument. These estimates are comparable to the literature. For our baseline calibration, we therefore choose $\sigma_N = 1/4 = 0.25$. In Appendix D, we show the counterfactual results are robust to setting $\sigma_N = 1/7$.

A.3 Estimating Parents' Valuation of Local Child Opportunity Values

This section provides further robustness for our estimates of parents' altruism parameter, β, and the dispersion in children's education taste shocks, σ_E. In the main paper, we identify these parameters from parents' valuation of neighborhoods' education outcomes and continuation values by estimating the following equation:

$$u_n^{e1} - \frac{1}{\sigma_N} I_n^{e1} = \theta a_n^e + \beta \left[\bar{v}(l,m) - \frac{\sigma_E}{\sigma_N} \log \pi_n^{el} \right], \tag{A.10}$$

where the term in brackets expresses child opportunity values $o(e,n)$ as a function of the local continuation value of low-education young adults and of the local probability of choosing low-education. We estimate the equation by OLS and include the amenity estimates obtained from the residential choices of non-parents as a regressor. This procedure eliminates the typical omitted variable bias that arises when unobserved amenities enter the residual of the regression. This strategy relies on the identifying assumption that parents and non-parents value the same neighborhood amenities up to a different average valuation θ, as stated in Assumption 3. The fit of the regression is very high with an R-squared of 0.97, which aligns with the assumption.

To provide further robustness, we re-estimate the equation while controlling for a list of observable proxies for neighborhood amenities, and we allow parents and non-parents to value these amenities differently. For observable amenities, we include the log of the violent crime rates per 100,000 inhabitants at the county level, the log of property crime rates per 100,000 inhabitants at the county level, the log of median air quality at the MSA level, a dummy for moderate temperature, and the log of total public expenditure on parks and recreation. In addition, we include dummies for the distance to the city center,

TABLE A.1: ESTIMATING PARENT-SPECIFIC PARAMETERS

PANEL A: REGRESSION SPECIFICATIONS			
	Baseline	Small Sample	Added Controls
Amenities	0.897***	0.873***	0.901***
	(0.003)	(0.007)	(0.008)
Continuation value low-education	0.233***	0.257***	0.194***
	(0.009)	(0.017)	(0.017)
Prob low-education	-0.296***	-0.316***	-0.272***
	(0.018)	(0.035)	(0.036)
Observations	4,760	1,198	1,198
R-squared	0.967	0.971	0.975
PANEL B: IMPLIED PARAMETER ESTIMATES			
Parent amenity valuation θ	0.897	0.873	0.901
Parent altruism β	0.233	0.257	0.194
Dispersion education taste shock σ_E	0.318	0.307	0.351
Dispersion location taste shock σ_N	0.250	0.250	0.250

Notes: All regressions use data from the 2010 cross section and restrict the sample to ages between 35 and 44 years. We pool observations for low- and high-education workers and include education fixed effects. Column (1) of the table reports our baseline estimates. Column (2) repeats the baseline regression in the reduced sample of counties for which we can estimate the next specification with additional controls. Column (3) estimates the regression with additional controls for observable amenities. Panel B reports the estimated parameter values. All regressions condition on the estimate of $\sigma_N = 0.25$. Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the closest lake, and the coastline. Table A.1 shows the estimates of our model parameters (θ, β, and σ_E) change little with the inclusion of these additional controls. All regressions pool observations for low- and high-education workers and include education-fixed effects. Column (1) of the table reports our baseline estimates without controlling for observable amenities. Column (2) shows the same regression in the smaller sample of counties for which the selected control variables are available. Column (3) shows the estimates while controlling for the list of observable amenities. Our parameter estimates for θ, β, and σ_E–shown at the bottom of the table–change little in all three specifications.

B. MODEL VALIDATION

In this section, we first show the extent to which observable proxies of amenities correlate with the model-implied amenities that we recover as structural residuals. Second, we show correlations of endogenous variables between the data and the baseline steady state of our model.

B.1 Correlation between Observable Amenities and Model-Implied Structural Residuals

In this section, we show the extent to which observable proxies of amenities correlate with the model-implied amenities that we recover as structural residuals to match residential choices of non-parents, as explained in the main paper. We obtain data on observable amenity proxies from Diamond (2016) and Lee and Lin (2018). When possible, we extend their datasets to the 2010 cross section and to the more disaggregated county level using the original data sources referenced in these papers. We obtain data on average temperatures and distances from city centers, lakes, and shorelines from Lee and Lin (2018), which we map to the county level. The number of establishments at the county level comes from the County Business Patterns. We obtain information on government expenditure on parks and recreational activities from the county-area files of the Census of Governments. Property and violent crime rates are obtained from Diamond (2016) at the MSA level and expressed per 100,000 inhabitants. Table B.1 regresses our model-implied amenity estimates on these amenity proxies. The unit of observation is the county, and we estimate the regression separately for the model-implied amenities that we recover for low- and high-education individuals. We find a strong association with an R-squared around 0.75 for amenities from both education types.

B.2 Correlation of Endogenous Variables in Data and Baseline Steady State

We estimate most of the structural parameters and regional fundamentals by taking model-implied estimating equations to the data, which does not require us to solve for the model's steady state or to assume the data are in steady state. To evaluate our policy counterfactuals, we then first solve for the baseline steady state conditional on our estimates of all structural parameters, regional fundamentals, and policy parameters. In our policy analysis, we compare the baseline and counterfactual steady states.

Table B.2 shows the correlation between selected variables in the data and the baseline steady state, focusing on variables that are endogenous model outcomes which adjust when solving for the baseline steady state. For each variable, we compute the correlation between its distribution across locations that we observe in the data and the one that is implied by the steady state of our model. We find strong correlations for all relevant endogenous variables. Panel A shows the model outcomes that vary across counties: population stocks by education level and parent status, college-education rates for children from low- and high-education parents, rents, and per-student school funding. For each of these variables, the correlation between the cross-county distribution in the data and in the baseline steady state is very high with correlation coefficients between 0.91 and 0.99. Panel B shows the distribution of wages across CZs is highly correlated between the data and the baseline steady-state with a correlation coefficient of 0.93 for wages from low-education workers and 0.99 for wages from high-education workers. These results imply a strong association between the data and the baseline steady state, which is reassuring for the relevance of our policy counterfactuals.

C. MODEL EXTENSIONS: PEER EFFECTS AND HOUSING SUPPLY

This Appendix provides more details about how we calibrate additional parameters that are associated with the two separate model extensions that we consider in this paper. The first model extension introduces peer effects in education. The second model extension allows for elastic local housing supply.

C.1 Peer Effects in Education

In this extension, we add the local share of college-educated adults as an additional determinant to the parameterization of the education index. The education index for children from parents with education e who grow up in location n is then equal to:

$$\mathcal{E}_n^e = \mathcal{K}_n^e + \gamma^e \log\left(f_n\right) + \zeta^e \log \frac{L_n^h}{L_n}, \tag{C.1}$$

where L_n^h / L_n is the share of college-educated adults in neighborhood n, ζ^e measures the effects of these peer effects on local education outcomes, and $\mathcal{K}_n^e$ captures all residual factors that matter for local education indices after accounting for local school-funding and local peer effects.

The literature has no clear consensus on the strength of peer effects ζ^e, and most studies focus on peer effects in classrooms rather than at the neighborhood level. Agostinelli (2018) finds, for example, large peer effects in classrooms that are stronger for children from disadvantaged backgrounds. Instead, Carrell et al. (2018) find exposure to disruptive peers to have large negative effects on children's future income.

Identifying the strength of peer effects is outside the scope of our paper. Instead, we choose a range of peer-effect parameters ζ^e, which generate a low, medium, and high elasticity of children's local education outcomes to local college shares among adults. To derive these elasticities in the extended model, we take the first-order condition of the educational choice probability with respect to the local college share, which gives the following equation:

$$\frac{d\pi_n^{eh}}{d\log\frac{L_n^h}{L_n}} = \frac{\zeta^e}{\sigma_E}\pi_n^{eh}(1-\pi_n^{eh}),$$

which is a partial-equilibrium response, because we hold school funding and education returns constant. We then choose the peer-effect parameters ζ^e so that a 10 pp increase in the local college share among adults leads to a x pp increase in children's local college-education rate. As values for x, we consider a low-, medium-, and high-peer-effect scenario for which we respectively set $x = 1, 2, 3$ for children from high-education parents and $x = 1.5, 3, 4.5$ for children from low-education parents. In each scenario, we assume a larger impact of peer effects on children from low-education parents following evidence from Agostinelli (2018). These estimates present plausible bounds on the strength of peer effects in the economy. Rearranging the equation above gives the following expression:

$$\frac{\zeta^e}{\sigma_E} = \frac{d\pi_n^{eh}}{\left[\log \frac{L_n^h}{L_n} + 0.1 - \log \frac{L_n^h}{L_n}\right] \times \pi_n^{eh}(1-\pi_n^{eh})},$$

which allows us to solve for the peer-effect parameter ζ^e by setting $d\pi_n^{eh} = x/100$ for each of the values of x mentioned above and by using data on local college shares among adults and local college-education rates among children. We take the population-weighted average across neighborhoods. This procedure yields a value of ζ^e respectively for children from low- and high-education parents and for each of the low-, medium-, and high-peer-effect scenarios.

C.2 Elastic Housing Supply

The second model extension allows for elastic housing supply in each neighborhood, which we model in the following way:

$$\mathcal{H}_n = \bar{H}_n r_n^{\xi_n}, \tag{C.2}$$

where $\bar{H}_n$ captures an exogenous component of housing supply and ξ_n measures the extent to which housing supply responds to local housing demand, that is, to local rents. This definition is a common reduced-form representation of a housing sector that combines land and the final good to produce housing services. With this formulation, we express the housing-supply elasticity–which we allow to differ across neighborhoods–as

$$\frac{d\log \mathcal{H}_n}{d\log r_n} = \xi_n.$$

We set the housing-supply elasticity in each neighborhood to the MSA-level estimates from Diamond (2016) by using a crosswalk to map counties to MSAs. For counties that lie outside of MSAs, we set the housing-supply elasticity to the highest value observed in each state. We then use these estimates of ξ_n to infer the "fixed" component of local housing supply, $\bar{H}_n$, from equation (C.2). In this step, we further use data on local rents and our estimates of the total housing stock $\mathcal{H}_n$ in each neighborhood. The inference of this total housing stock is explained in Appendix A and does not depend on the housing-supply elasticities.

D. Robustness of Counterfactual Results

To test the robustness of our results, we evaluate the same policy counterfactuals as in the main paper for a set of different samples and parameter values. For each robustness check, we re-estimate all structural parameters and all regional characteristics affected by the considered changes.

First, we re-estimate the model in the sample of all working-age individuals, that is, individuals between the ages of 25 and 64. In the baseline calibration, we restrict the sample to individuals between the ages of 35 and 50, because adults in this age group are plausibly "old enough" to have finished their education and to have children–if they will have any–but "young enough" to still have school-age children who live in their household. Re-estimating the model and redoing our counterfactual exercises with the extended age sample does not change the main results or their conclusions.

Second, we re-estimate the model with a sample that includes all US CZs. In the baseline calibration, we exclude CZs for which we have to drop any given county due to data availability. In this specification, we drop the counties with missing data moments but retain the complete set of CZs. Re-estimating the model and the policy counterfactuals with the full sample of CZs does not change the main counterfactual results or their interpretation.

Third, we provide robustness around the chosen value for the dispersion of location taste shocks. In the baseline calibration, we set this parameter equal to $\sigma_N = 1/4$, in line with the literature and our IV estimates. Re-estimating the model and the counterfactual exercise with a value of $\sigma_N = 1/7$ does not change the main counterfactual results or their interpretation.

To summarize, we find for all considered robustness checks and the model extensions that our counterfactual results, their interpretation, and the underlying mechanisms are qualitatively unchanged and quantitatively similar.

The Online Appendix replicates the main tables of our paper for each robustness check and model extension.

TABLE B.1: CORRELATION OF OBSERVABLE AMENITIES AND MODEL-IMPLIED STRUCTURAL RESIDUALS

	Low-Education	High-Education
Moderate Temperature	0.0193	-0.0449**
	(0.0177)	(0.0220)
Distance City Dummy1	-0.110***	-0.172***
	(0.0169)	(0.0210)
Distance City Dummy2	-0.154***	-0.263***
	(0.0226)	(0.0281)
Distance Lake Dummy1	-0.0202	-0.0308
	(0.0161)	(0.0200)
Distance Lake Dummy2	-0.0130	-0.0175
	(0.0196)	(0.0244)
Distance Shore Dummy1	0.0143	0.00489
	(0.0185)	(0.0229)
Distance Shore Dummy1	-0.00892	-0.0185
	(0.0224)	(0.0278)
Property Crime Rate (ln)	0.325***	0.335***
	(0.0305)	(0.0379)
Violent Crime Rate (ln)	-0.0660***	-0.122***
	(0.0212)	(0.0263)
Park Expenditure (ln)	0.000329	0.000520
	(0.00447)	(0.00556)
Number of Establishments (ln)	0.160***	0.180***
	(0.00727)	(0.00904)
Observations	473	473
R-squared	0.748	0.742

Notes: All regressions are for the year 2010. Moderate temperature is a dummy that is equal to 1 if the minimum temperature during January lies between -5 and 15 degrees and the maximum temperature during July lies between 15 and 32 degrees. Distances from the city center, lakes, or shores enter each as three dummy variables indicating whether a distance lies in the bottom quartile (D1), the second or third quartile (D2), or the top quartile (D3) of distances observed in the sample. The omitted category is the shortest-distance dummy (D1). Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE B.2: CORRELATION OF ENDOGENOUS VARIABLES IN DATA AND BASELINE STEADY STATE

Variable	Correlation Coefficient
PANEL A: CORRELATION ACROSS COUNTIES	
Population non-college-educated non-parents	0.99
Population non-college-educated parents	0.95
Population college-educated non-parents	0.98
Population college-educated parents	0.98
College rates for children from low-education parents	0.92
College rates for children from high-education parents	0.93
Rental rates	0.91
Per-student school funding	0.97
PANEL B: CORRELATION ACROSS COMMUTING ZONE	
Wages for non-college-educated workers	0.93
Wages for college-educated workers	0.99

Notes: This table shows the correlation between selected variables in the data and in the baseline steady state. Panel A shows variables which vary across counties. Panel B shows variables that vary across commuting zones. The selected variables are endogenous outcomes of the model, which adjust when solving for the baseline steady state.

ONLINE APPENDIX MATERIAL FOR
THE GEOGRAPHY OF OPPORTUNITY:
EDUCATION, WORK, AND INTERGENERATIONAL MOBILITY ACROSS US COUNTIES

BY FABIAN ECKERT AND TATJANA KLEINEBERG

April 2024

FOR ONLINE PUBLICATION

A. Details on Data Sources and Processing

In this section, we present additional information on our data sources and data construction, and we provide summary statistics.

A.1 Data Sources

Population Stocks in Each County by Education Level and Parent Status. We obtain data on local population stocks by education and parent status from the Education Demographic and Geographic Estimates (EDGE) provided by the National Center for Education Statistics (NCES). The NCES provides special tabulations of census data, which are available at https://nces.ed.gov/programs/edge/. For 1990, 2000, and 2010, we obtain information on the number of individuals by education level and "presence of children" for each school district. In 2010, the data are further disaggregated into age groups. The data allows us to distinguish between households whose children are enrolled in public versus private schools. We use a crosswalk to aggregate the data from school districts to the county level.

Children's Education Outcomes by Childhood County and Parental Background. We obtain data on education outcomes by childhood county and by parental background from the replication files of Chetty and Hendren (2018b). For each childhood county in the US, the data provide children's college-education rates for families at the 25th and 75th percentiles of the national income distribution. We use families' income percentile as proxies for low- and high-education levels.

School Funding by County. We obtain school-funding data at the school-district level from the NCES. The annual Finance Survey (F-33) provides information on each school district's number of students and funding amounts from federal, state, and local sources. We use a crosswalk to aggregate the data from school districts to the county level.

Rental Rates by County. To estimate rental rates in each county, we obtain data from the National Historical Geographic Information System (NHGIS), which provides specific tabulations of US census data at a granular spatial disaggregation. We use information on median rent and mean housing characteristics at the block-group level. The US has more than 200,000 block groups, so that each county contains multiple block groups. We use these data to estimate hedonic price regressions, following Eeckhout, Pinheiro, and Schmidheiny (2014). The unit of observation in the regression are block groups. We regress each block group's median rent on the mean or median of several housing characteristics and include county fixed effects as follows:

$$\log\left(rent_j\right) = \log\left(year_j\right) + rooms_j + unit_j + T_n + \epsilon_j, \tag{OA.1}$$

where j indexes each block group, r_j is median gross rent in each block group, $year_j$ is the median year of construction, $rooms_j$ is the median number of rooms, and $unit_j$ is a dummy that indicates the most common type of structure in each block group. The county fixed effects, T_n, then measure rental rates for each county n, which are adjusted for differences in housing size and quality. We estimate the hedonic price regressions separately for the 1990, 2000, and 2010 cross sections, and we weigh each block group by its number of renters.

Wages of College- and Non-College-Educated Workers. To construct wages for college- and non-college-educated workers at the CZ level, we use micro data from the US Decennial Census and American Community Survey (ACS). We obtain the data from Integrated Public Use Microdata Series (IPUMS) (see Ruggles, Genadek, Goeken, Grover, and Sobek, 2017). These data sources provide information about respondents' wage income and their current Public Use Microdata Area (PUMA) of residence. We restrict the sample to individuals between 25 and 60 years who work full time, which we define as working at least 43 weeks per year and at least 35 hours per week. We exclude self-employed and individuals with missing wages, weeks, or hours. To compute hourly wages, we follow the same data cleaning procedure as Autor and Dorn (2013) and divide the reported annual wage income by weeks worked and by usual weekly hours. We adjust for top-coded wages by multiplying them by a factor of 1.5, and we restrict hourly wages to not exceed this value divided by 50 weeks times 35 hours. We set hourly wages below the first percentile to the value of the first percentile. We use a crosswalk to map PUMAs to CZs. We then average hourly wages for college- and non-college-educated workers to the CZ level.

Housing Expenditure Shares. Housing expenditure shares α^{ep} are calibrated to expenditure data from the 2010 Consumer Expenditure Survey (CEX) provided by the Bureau of Labor Statistics (BLS). The CEX *fmli111x* provides information on individuals' education, presence of children in the household, expenditure on housing (variable *sheltcq*), and total expenditure (variable *totexpcq*). We restrict our sample to families with and without children (*fam_types* 1-4) who earn a minimum weekly income of 150 USD. We use these data to compute average housing expenditure shares by education level and parent status.

Moving Flows by Education Level and Parent Status across CZs. We construct moving flows across CZs by education type and parent status using individual-level data from the decennial census in 1990 and 2000 and the American Community Survey (ACS) in 2006-2010. We obtain the data from the Integrated Public Use Microdata Series (IPUMS) (see Ruggles et al., 2017). The data sources provide information on respondents' current and past Public Use Microdata Area (PUMA) of residence. We use a crosswalk to map PUMAs to CZs. The 1990 and 2000 censuses report respondents' PUMAs of residence five years ago and the 2006-2010 ACS report residence one year ago. The model assumes individuals make moving decisions once in their lifetime, after finishing their education and before joining the labor market. To capture such moves in the data, we restrict the sample to adults between the ages of 35 and 60 years. Because lifetime migration rates are not observed at the commuting-zone level in the data, we assume five-year moving flows in this age range come close to capturing lifetime moving rates. Because we only observe one-year moving flows in 2010, we adjust these moving flows by simulating them forward for five years. To do so, we start with the accounting identity:

$$L_{m',t} = \mathbf{B}_{mm',t,t-1} L_{m,t-1}, \tag{OA.2}$$

where $L_{m,t-1}$ is the population in origin m before moving and $L_{m,t}$ is the population in destination m' after moving. The term $\mathbf{B}_{mm',t,t-1}$ denotes the one-year moving matrix, that is, the population share that moves from origin m to destination m' between the years $t-1$ and t. These objects are observed in the data. We simulate the one-year moving matrix forward five times to construct five-year moving flows as

$$L_{m',t} = \mathbf{B}_{mm',t,t-5} L_{m,t-5} \approx \left(\mathbf{B}_{mm',t,t-1}\right)^5 L_{m,t-5}. \tag{OA.3}$$

We use this procedure separately for each education level and parent status.

Characteristics of CZ Pairs. We parameterize moving costs as a function of observable characteristics that vary across CZ pairs. We obtain these CZ-pair characteristics from the 1990 and 2000 US census and the 2006-2010 ACS. For each CZ pair, we calculate the distance between CZs in ArcGIS using shapefiles from the census TIGER files. In addition, we compute dummies that are equal to 1 if two CZs lie in different states, different divisions, or have different urban/rural status. We classify a CZ as urban if part of its area overlaps with a metropolitan statistical area (MSA).

A.2 Summary Statistics of Relevant Data Moments

We provide summary statistics of relevant data moments in Table OA.1 using data from 2006-2010. For each variable, we report the population-weighted mean, standard deviation, and the 10th and 90th percentiles.

Panel A shows summary statistics for rental prices and school funding. School funding per student varies substantially across counties: funding in the county at the 10th percentile is 26% lower than the average and it is 40% higher than the average in the county at the 90th percentile. The standard deviation is 29%.

On average, 12% of school funding is provided by the federal government, and 44% respectively from state and local governments. Substantial variation exists across counties in the composition of funding. The federal share of funding constitutes 6% of total

TABLE OA.1: Summary Statistics

Variable	Mean	p10	p90	sd
Panel A: Summary Statistics across Counties				
Rental rates (normalized)	1.00	0.63	1.48	0.31
School funding per student (normalized)	1.00	0.74	1.40	0.29
School funding from federal government (in %)	12%	6%	18%	5%
School funding from state government (in %)	44%	27%	61%	13%
School funding from local government (in %)	44%	23%	66%	15%
Panel B: Summary Statistics across CZs				
Wages for non-college-educuated workers (normalized)	0.72	0.63	0.82	0.07
Wages for college-educuated workers (normalized)	1.25	0.97	1.61	0.22
College wage premium (in %)	52%	37%	67%	12%
Panel C: Percent of Stayers across CZs				
Stayers non-college-educated non-parents	81%	68%	89%	8%
Stayers non-college-educated parents	88%	77%	94%	6%
Stayers college-educated non-parents	82%	71%	89%	7%
Stayers college-educated parents	88%	79%	93%	6%

Notes: This table provides summary statistics of relevant data moments using data from the 2006-2010 cross section. For each variable, we report the population-weighted mean, standard deviation, and the 10th and 90th percentiles.

funding in the county at the 10th percentile and 18% in the county at the 90th percentile. The corresponding numbers for the state share of funding are 27% and 61% and for local funding, 23% and 66%. This finding shows local funding is very important on average, and in particular for certain counties.

Rents vary substantially across counties: in the county at the 10th percentile, they are 37% below average, and in the county at the 90th percentile, they are 48% above average.

Panel B shows summary statistics for wages and college wage premia, which vary across CZs. The population-weighted mean of wages from college and non-college-educated workers is normalized to 1. The average wage of non-college-educated workers is 0.72 with a standard deviation of 0.07. The average wage of college-educated workers is 1.25 with a standard deviation of 0.22. The average skill premium is 52%, which has a standard deviation of 12%.

Panel C shows the percent of stayers by education level and parent status. On average, 88% of parents stay in the same CZ in our sample. For non-parents, this number is lower, with rates around 82%. The share of stayers varies across CZs with a standard deviation of 6% for parents and around 8% for non-parents.

Table OA.2 reports Theil's H-index to measure segregation between college- and non-college-educated individuals. We compute the index separately for parents and non-

TABLE OA.2: Segregation between College- and Non-College-Educated Workers (H-Index)

	Parents	Non-Parents
Total segregation across counties	0.037	0.037
Segregation across CZs	0.018	0.023
Segregation within CZs (pop-weighted mean)	0.020	0.015
Percent of total segregation explained within vs. across CZs	51%	38%

Notes: This table shows Theil's H-Index to measure segregation between college and non-college-educated individuals, separately for parents and non-parents. The table reports total segregation by college-education across all counties and segregation across all CZs. The third row shows segregation across counties within each CZ, for which the table reports the population-weighted mean across all CZs. The H-index is additively decomposable across nested geographies. The last row shows the percent of total segregation that is explained by segregation across neighborhoods within CZs (as opposed to segregation across CZs).

parents to document how residential choices differ by parent status. The H-index is a Multigroup Entropy Index where a value of 0 implies no segregation and 1 implies perfect segregation. The Index is additively decomposable across nested geographies. Table OA.2 shows parents and non-parents are equally segregated by college-education across all counties. However, segregation across CZs is larger for non-parents, whereas segregation across neighborhoods within CZs is larger for parents. Hence, the share of total segregation that is explained by segregation across neighborhoods *within* CZs is 51% for parents and only 38% for non-parents. These findings are consistent with the idea that parents sort more across neighborhoods within labor markets because they value neighborhoods' education opportunities. Non-parents have higher moving probabilities across labor markets (as shown above), which can result in stronger sorting across CZs as they take advantage of better labor market opportunities specific to their education level.

B. DERIVATIONS FOR ESTIMATION

In this section, we present two derivations referenced in the estimation section of the main paper.

B.1 Derivation of County-Utility

In this section, we derive equation (14), which expresses county-utility u_n^{ep} as a function of county population stocks L_n^{ep} and average CZ-utility u_m^{ep} in the following way:

$$\exp\left(u_n^{ep}\right) = \frac{L_n^{ep}}{L_m^{ep}} \exp\left(u_m^{ep}\right). \tag{OA.1}$$

To derive this expression, we start from the share of young adults who choose to move from their childhood labor market m to a destination labor market m', which is given by:

$$L_{m'}^{ep} = \sum_{m \in \mathbb{M}} \sum_{n' \in \mathbb{N}_{m'}} \lambda_{mm'}^{ep} \tilde{L}_m^{ep} = \sum_{m \in \mathbb{M}} \frac{\exp\left(u_{m'}^{ep} - c_{mm'}^{ep}\right)}{\sum_{m'' \in \mathbb{M}} \exp\left(u_{m''}^{ep} - c_{mm''}^{ep}\right)} \tilde{L}_m^{ep}, \tag{OA.2}$$

where $\tilde{L}_m^{ep}$ are young adults who finished their education e, learned their parent status p, and still live in their childhood location m. Rearranging this equation gives:

$$\exp\left(u_{m'}^{ep}\right) = L_{m'}^{ep} / \left[\sum_{m \in \mathbb{M}} \frac{\exp\left(-c_{mm'}^{ep} + \log \tilde{L}_m^{ep}\right)}{\sum_{m'' \in \mathbb{M}} \exp\left(u_{m''}^{ep} - c_{mm''}^{ep}\right)} \right]. \tag{OA.3}$$

We further express the population stock in each destination n' by summing moving inflows across all origin labor markets in the following way:

$$L_{n'}^{ep} = \sum_{m \in \mathbb{M}} \lambda_{mn'}^{ep} \tilde{L}_m^{ep} = \sum_{m \in \mathbb{M}} \frac{\exp\left(u_{n'}^{ep} - c_{mm'}^{ep}\right)}{\sum_{n'' \in \mathbb{N}} \exp\left(u_{n''}^{ep} - c_{mm''}^{ep}\right)} \tilde{L}_m^{ep}.$$

With some algebra and rearranging, the equation gives the desired expression that links county utility to county population stocks and CZ-utilities as follows:

$$\begin{aligned} \exp\left(u_{n'}^{ep}\right) &= \frac{L_{n'}^{ep}}{L_{m'}^{ep}} L_{m'}^{ep} / \left[\sum_{m \in \mathbb{M}} \frac{\exp\left(-c_{mm'}^{ep} + \log \tilde{L}_m^{ep}\right)}{\sum_{n'' \in \mathbb{N}} \exp\left(u_{n''}^{ep} - c_{mm''}^{ep}\right)} \right] \\ &= \frac{L_{n'}^{ep}}{L_{m'}^{ep}} \exp\left(u_{m'}^{ep}\right), \end{aligned}$$

where the last row uses the expression for CZ-utilities from equation (OA.3).

B.2 Derivation of Child Opportunity Values

We show that child opportunity values for children with parents of education e in neighborhood n, $O_t(e,n)$, can be expressed as:

$$O_t(e,n) = \bar{V}_{t+1}(l,m) - \sigma_E \log \pi_n^{el}, \tag{OA.4}$$

where π_n^{el} is the share of children who choose low-education and $\bar{V}_{t+1}(l,m)$ is the continuation value of low-education young adults who still live in their childhood location and who have not yet learned their parent status or their future location taste shocks. We suppress time subscripts in the derivation. We start from the standard expressions for child opportunity values and education choices:

$$O(e,n) = \sigma_E \log \left(\sum_{e'} \exp \left[\frac{1}{\sigma_E} \bar{V}(e',m) + \frac{1}{\sigma_E} 1_{e'=h} \mathcal{E}_n^e \right] \right) \tag{OA.5}$$

and

$$\pi_n^{ee'} = \frac{\exp\left[\frac{1}{\sigma_E}\bar{V}(e',m) + \frac{1}{\sigma_E}1_{e'=h}\mathcal{E}_n^e\right]}{\sum_{e''}\exp\left[\frac{1}{\sigma_E}\bar{V}(e'',m) + \frac{1}{\sigma_E}1_{e''=h}\mathcal{E}_n^e\right]} = \frac{\exp\left[\frac{1}{\sigma_E}\bar{V}(e',m) + \frac{1}{\sigma_E}1_{e'=h}\mathcal{E}_n^e\right]}{\exp\left[\frac{1}{\sigma_E}O(e,n)\right]}, \tag{OA.6}$$

where we substitute equation (OA.5) into the denominator of the education-choice equation. We then evaluate the education choice for choosing low-education setting $e' = l$, which gives:

$$\pi_n^{el} = \frac{\exp\left[\frac{1}{\sigma_E}\bar{V}(l,m)\right]}{\exp\left[\frac{1}{\sigma_E}O(e,n)\right]}, \tag{OA.7}$$

which uses the fact that we normalize the education index to zero when choosing low-education. The education index can therefore be interpreted as capturing the *relative* cost of choosing high- versus low-education. Rearranging equation (OA.7) gives the desired expression for child opportunity values.

C. Additional Tables: Counterfactual Results for Model Extensions and Robustness Checks

C.1 Counterfactual Results for Model Extensions

In this section, we replicate the tables from the counterfactual section of the main paper (cf. Tables 2, 3, and 4) for each model extension and for each robustness check that we consider. Overall, we implement four model extension scenarios: low, medium, and high peer effects and elastic housing supply. We then consider the following three robustness checks: First, we use a larger age sample by including all working-age individuals, that is, individuals between the ages of 25 and 64. Second, we use a larger sample of CZs. Last, we test the sensitivity of our results when setting the dispersion of the location taste shocks to $\sigma_N = 1/7$ (instead of the baseline value of $\sigma_N = 1/4$). See Appendix C and D for more information about the calibration of each model extension and for more information about the robustness checks.

For each extension and robustness check, we first present the effects of the three policies on education and wages across labor markets (cf. Table 2 of the main paper). We then show effects on intergenerational mobility (cf. Table 3 of the main paper). Last, we show

TABLE OA.1: EFFECTS ON COLLEGE SHARES AND WAGES ACROSS CZS - LOW PEER EFFECTS

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	1.4	-5.2	-0.9	-9.8	0.7	0.1
College-Share Workers	1.4	-8.3	-0.9	-8.3	0.7	-0.2
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	0.7	-31.2	-1.2	-10.5	0.7	2
College Wage	-0.8	9.7	0.8	2.2	0.6	0.6
College Wage Premium	-7.3	42.8	6.1	6	-0.5	-0.3
Output	-0.5	0	0	0	0.7	0

Notes: The table considers the model extension with low peer effects. The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

effects on welfare (cf. Table 4 of the main paper).

TABLE OA.2: EFFECTS ON COLLEGE SHARES AND WAGES ACROSS CZS - MEDIUM PEER EFFECTS

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	1.3	-6.6	-0.8	-9.1	0.6	0.1
College-Share Workers	1.3	-8.8	-0.8	-7.2	0.6	-0.3
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	0.8	-31.5	-1.3	-11.2	0.7	2.1
College Wage	-1	11.2	0.9	2.5	0.6	0.6
College Wage Premium	-9.2	47.6	7.3	6.3	-0.6	-0.4
Output	-0.6	0	0.1	0	0.7	0

Notes: The table considers the model extension with medium peer effects. The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

TABLE OA.3: EFFECTS ON COLLEGE SHARES AND WAGES ACROSS CZS - HIGH PEER EFFECTS

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	1.6	4.4	-0.9	-10.3	0.6	0.5
College-Share Workers	1.6	-6.6	-0.9	-7.2	0.6	0.1
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	1.2	-30.9	-1.4	-10.2	0.7	2.2
College Wage	-1.3	12.7	0.8	2.2	0.5	0.8
College Wage Premium	-15.8	54.3	9.7	5.5	-1	0.1
Output	-0.8	0	0	0	0.6	0

Notes: The table considers the model extension with high peer effects. The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

TABLE OA.4: EFFECTS ON COLLEGE SHARES AND WAGES ACROSS CZS - ELASTIC HOUSING SUPPLY

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	1.2	-8.2	0.1	-8.4	0.3	0.3
College-Share Workers	1.2	-8	0.1	-7.2	0.3	0.2
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	0.6	-32.2	-0.4	-8.3	0.4	1.7
College Wage	-1.6	6.7	1.2	2.8	0.4	0.6
College Wage Premium	-8.8	33.5	4.9	5	-0.2	-0.4
Output	-0.9	0	0.8	0	0.4	0

Notes: The table considers the model extension with elastic housing supply. The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

TABLE OA.5: EFFECTS ON COLLEGE SHARES AND WAGES ACROSS CZS - EXTENDED AGE

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	1	-9.4	-0.6	-7.8	0.7	0.1
College-Share Workers	1	-9.1	-0.6	-6.4	0.7	-0.2
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	0.5	-28.1	-0.9	-7.8	0.6	1.7
College Wage	-0.6	9.5	0.7	1.8	0.5	0.4
College Wage Premium	-5.5	42.3	4.5	5.8	-0.3	-0.5
Output	-0.4	0	0.1	0	0.7	0

Notes: The table uses the extended age sample, including all individuals between ages 25 and 64. The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

TABLE OA.6: EFFECTS ON COLLEGE SHARES AND WAGES ACROSS CZS - ALL CZ SAMPLE

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	1	-8	-0.5	-7.2	0.7	0.8
College-Share Workers	1	-7.5	-0.5	-6	0.7	0.5
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	0.5	-24.9	-1	-9	0.7	2.6
College Wage	-0.7	8.7	0.7	2.2	0.5	0.9
College Wage Premium	-5.6	36.9	4.5	5.6	-0.7	-0.2
Output	-0.3	0	0.1	0	0.7	0

Notes: The table uses the extended CZ sample, including all CZ even if some counties are excluded due to missing data. The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

TABLE OA.7: EFFECTS ON COLLEGE SHARES & WAGES ACROSS CZS - SENSITIVITY TO σ_N

	Equalization		Subsidy		Housing Expansion	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE SHARES (IN %)						
College-Rate Children	0.9	-10.9	-0.7	-10.3	0.7	0.5
College-Share Workers	0.9	-8.2	-0.7	-7.8	0.7	0.1
PANEL B: Δ WAGES AND OUTPUT (IN %)						
Non-College Wage	0.4	-25.7	-1.1	-11.1	0.7	2.2
College Wage	-0.6	7.5	0.8	2.8	0.6	0.9
College Wage Premium	-4.2	30.8	4.8	7.6	-0.4	-0.3
Output	-0.3	0	0.1	0	0.8	0

Notes: This table provides sensitivity to setting the dispersion parameter of location preference shocks to $\sigma_N = 1/7$ (instead of the baseline calibration of $\sigma_N = 1/4$). The table shows percentage changes in the mean and standard deviation between the counterfactual and baseline steady state for the following variables in each CZ: The college education rate among children, the college share among adult workers, wages of college- and non-college-educated workers, the college wage premium, and aggregate output. The columns indicate each of the three counterfactuals that we consider: the equalization of school funding, the subsidy, and the housing-supply expansion.

TABLE OA.8: EFFECTS ON INTERGENERATIONAL MOBILITY – LOW PEER EFFECTS

	Equalization		Subsidy		Housing Expansion	
	Direct	GE	Targeted GE	All GE	Targeted GE	All GE
Parental Edu.	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE-SHARE CHILDREN (IN P.P.)						
No College	4.05	1.5	-2.63	0.05	-0.05	0.5
College	0.16	0.01	-1.76	-0.64	-0.09	0.14
PANEL B: Δ SCHOOL FUNDING (IN %)						
No College	2.46	2.46	-1.26	0.62	0.33	1.12
College	-1.42	-1.42	-1.14	0.1	0.35	1.16
PANEL C: Δ RETURNS TO EDUCATION (IN %)						
No College	0	-2.57	-2.38	-0.95	-0.48	-0.19
College	0	-3.81	-2.38	-1.3	-0.47	-0.21

Notes: This table presents effects of each policy on intergenerational mobility in a model extension with low peer effects. All numbers in the table represent changes in population-weighted averages between the baseline and counterfactual steady states. Panel A documents percentage point changes in college-education rates for children from low- and high-education parents. Panel B shows percent changes in per-student school funding. Panel C shows changes in returns to education that measure the utility premium between college-educated and non-college-educated workers. Column (1) reports direct effects for the school-funding equalization where we implement only changes in school funding but hold everything else constant. Columns (3) and (5) show changes in full general equilibrium but conditioning only on the sample of neighborhoods that we target in the subsidy and housing-supply expansion. Columns (2), (4), and (6) show changes in full general equilibrium across all neighborhoods.

TABLE OA.9: EFFECTS ON INTERGENERATIONAL MOBILITY – MEDIUM PEER EFFECTS

	Equalization		Subsidy		Housing Expansion	
	Direct	GE	Targeted GE	All GE	Targeted GE	All GE
Parental Edu.	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE-SHARE CHILDREN (IN P.P.)						
No College	4.02	1.42	-2.78	0.06	-0.08	0.47
College	0.15	-0.04	-2.07	-0.58	-0.1	0.12
PANEL B: Δ SCHOOL FUNDING (IN %)						
No College	2.35	2.35	-1.11	0.61	0.33	1.1
College	-1.42	-1.42	-1.02	0.15	0.35	1.13
PANEL C: Δ RETURNS TO EDUCATION (IN %)						
No College	0	-3.34	-1.8	-0.7	-0.55	-0.24
College	0	-4.41	-1.86	-1.01	-0.55	-0.27

Notes: This table presents effects of each policy on intergenerational mobility in a model extension with medium peer effects. All numbers in the table represent changes in population-weighted averages between the baseline and counterfactual steady states. Panel A documents percentage point changes in college-education rates for children from low- and high-education parents. Panel B shows percent changes in per-student school funding. Panel C shows changes in returns to education that measure the utility premium between college-educated and non-college-educated workers. Column (1) reports direct effects for the school-funding equalization where we implement only changes in school funding but hold everything else constant. Columns (3) and (5) show changes in full general equilibrium but conditioning only on the sample of neighborhoods that we target in the subsidy and housing-supply expansion. Columns (2), (4), and (6) show changes in full general equilibrium across all neighborhoods.

TABLE OA.10: EFFECTS ON INTERGENERATIONAL MOBILITY – HIGH PEER EFFECTS

	Equalization		Subsidy		Housing Expansion	
	Direct	GE	Targeted GE	All GE	Targeted GE	All GE
Parental Edu.	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE-SHARE CHILDREN (IN P.P.)						
No College	4.03	1.43	-4.47	-0.05	-0.09	0.42
College	0.05	0.19	-3.54	-0.52	-0.09	0.12
PANEL B: Δ SCHOOL FUNDING (IN %)						
No College	2.44	2.44	-1.05	0.41	0.4	0.95
College	-1.32	-1.32	-0.64	0.16	0.4	1
PANEL C: Δ RETURNS TO EDUCATION (IN %)						
No College	0	-4.16	-1.03	-0.13	-0.74	-0.39
College	0	-6.49	-0.75	-0.39	-0.72	-0.4

Notes: This table presents effects of each policy on intergenerational mobility in a model extension with high peer effects. All numbers in the table represent changes in population-weighted averages between the baseline and counterfactual steady states. Panel A documents percentage point changes in college-education rates for children from low- and high-education parents. Panel B shows percent changes in per-student school funding. Panel C shows changes in returns to education that measure the utility premium between college-educated and non-college-educated workers. Column (1) reports direct effects for the school-funding equalization where we implement only changes in school funding but hold everything else constant. Columns (3) and (5) show changes in full general equilibrium but conditioning only on the sample of neighborhoods that we target in the subsidy and housing-supply expansion. Columns (2), (4), and (6) show changes in full general equilibrium across all neighborhoods.

TABLE OA.11: EFFECTS ON INTERGENERATIONAL MOBILITY – EXTENDED AGE SAMPLE

	Equalization		Subsidy		Housing Expansion	
	Direct	GE	Targeted GE	All GE	Targeted GE	All GE
Parental Edu.	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE-SHARE CHILDREN (IN P.P.)						
No College	3.75	1.31	-2.26	0.23	-0.11	0.48
College	0.16	-0.18	-1.27	-0.51	-0.13	0.11
PANEL B: Δ SCHOOL FUNDING (IN %)						
No College	2.19	2.19	-1.91	0.51	0.3	1.04
College	-1.39	-1.39	-1.76	0.23	0.31	1.03
PANEL C: Δ RETURNS TO EDUCATION (IN %)						
No College	0	-2.42	-1.96	-0.88	-0.5	-0.23
College	0	-3.04	-1.87	-1.17	-0.51	-0.24

Notes: This table presents effects of each policy on intergenerational mobility in an extended age sample, including all individuals between ages 25 and 64 years. All numbers in the table represent changes in population-weighted averages between the baseline and counterfactual steady states. Panel A documents percentage point changes in college-education rates for children from low- and high-education parents. Panel B shows percent changes in per-student school funding. Panel C shows changes in returns to education that measure the utility premium between college-educated and non-college-educated workers. Column (1) reports direct effects for the school-funding equalization where we implement only changes in school funding but hold everything else constant. Columns (3) and (5) show changes in full general equilibrium but conditioning only on the sample of neighborhoods that we target in the subsidy and housing-supply expansion. Columns (2), (4), and (6) show changes in full general equilibrium across all neighborhoods.

TABLE OA.12: EFFECTS ON INTERGENERATIONAL MOBILITY – ALL CZ SAMPLE

	Equalization		Subsidy		Housing Expansion	
	Direct	GE	Targeted GE	All GE	Targeted GE	All GE
Parental Edu.	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE-SHARE CHILDREN (IN P.P.)						
No College	3.85	1.3	-2.28	0.25	-0.08	0.47
College	0.22	-0.22	-1.27	-0.52	-0.13	0.14
PANEL B: Δ SCHOOL FUNDING (IN %)						
No College	2.1	2.1	-1.66	0.55	0.44	1.11
College	-1.38	-1.38	-1.32	0.29	0.46	1.13
PANEL C: Δ RETURNS TO EDUCATION (IN %)						
No College	0	-2.58	-2.18	-0.79	-0.58	-0.24
College	0	-2.99	-2.04	-1.11	-0.56	-0.23

Notes: This table presents effects of each policy on intergenerational mobility in an extended CZ sample, including all CZs even if some counties are missing due to data availability. All numbers in the table represent changes in population-weighted averages between the baseline and counterfactual steady states. Panel A documents percentage point changes in college-education rates for children from low- and high-education parents. Panel B shows percent changes in per-student school funding. Panel C shows changes in returns to education that measure the utility premium between college-educated and non-college-educated workers. Column (1) reports direct effects for the school-funding equalization where we implement only changes in school funding but hold everything else constant. Columns (3) and (5) show changes in full general equilibrium but conditioning only on the sample of neighborhoods that we target in the subsidy and housing-supply expansion. Columns (2), (4), and (6) show changes in full general equilibrium across all neighborhoods.

TABLE OA.13: EFFECTS ON INTERGENERATIONAL MOBILITY – SENSITIVITY TO σ_N

	Equalization		Subsidy		Housing Expansion	
	Direct	GE	Targeted GE	All GE	Targeted GE	All GE
Parental Edu.	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Δ COLLEGE-SHARE CHILDREN (IN P.P.)						
No College	4.11	1.36	-3.59	0.32	-0.12	0.51
College	0.2	-0.36	-1.83	-0.71	-0.18	0.12
PANEL B: Δ SCHOOL FUNDING (IN %)						
No College	2.23	2.23	-4.07	0.33	0.51	1.35
College	-1.52	-1.52	-2.64	0.55	0.51	1.37
PANEL C: Δ RETURNS TO EDUCATION (IN %)						
No College	0	-2.48	-1.87	-0.95	-0.58	-0.33
College	0	-2.55	-1.89	-1.2	-0.57	-0.35

Notes: This table presents effects of each policy on intergenerational mobility when setting the dispersion parameter of location preference shocks to $\sigma_N = 1/7$ (instead of the baseline calibration of $\sigma_N = 1/4$). All numbers in the table represent changes in population-weighted averages between the baseline and counterfactual steady states. Panel A documents percentage point changes in college-education rates for children from low- and high-education parents. Panel B shows percent changes in per-student school funding. Panel C shows changes in returns to education that measure the utility premium between college-educated and non-college-educated workers. Column (1) reports direct effects for the school-funding equalization where we implement only changes in school funding but hold everything else constant. Columns (3) and (5) show changes in full general equilibrium but conditioning only on the sample of neighborhoods that we target in the subsidy and housing-supply expansion. Columns (2), (4), and (6) show changes in full general equilibrium across all neighborhoods.

TABLE OA.14: WELFARE MEASURES – LOW PEER EFFECTS

	Equalization	Subsidy	Housing Expansion
Children Non-College Parents	3.1	0.93	4.26
Children College Parents	1.07	-0.31	3.16

Notes: This table presents welfare effects for a model extension scenario with low peer effects. This table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents.

TABLE OA.15: WELFARE MEASURES – MEDIUM PEER EFFECTS

	Equalization	Subsidy	Housing Expansion
Children Non-College Parents	3.12	0.7	4.16
Children College Parents	1.16	-0.41	3.09

Notes: This table presents welfare effects for a model extension scenario with medium peer effects. This table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents.

TABLE OA.16: WELFARE MEASURES – HIGH PEER EFFECTS

	Equalization	Subsidy	Housing Expansion
Children Non-College Parents	3.48	0.09	3.19
Children College Parents	1.99	-0.69	2.39

Notes: This table presents welfare effects for a model extension scenario with high peer effects. This table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents.

TABLE OA.17: WELFARE MEASURES – ELASTIC HOUSING SUPPLY

	Equalization	Subsidy	Housing Expansion
Children Non-College Parents	3.1	1.15	0.81
Children College Parents	1.2	0.05	0.62

Notes: This table presents welfare effects for a model extension with elastic housing supply. This table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents.

TABLE OA.18: WELFARE MEASURES – EXTENDED AGE SAMPLE

	Equalization	Subsidy	Housing Expansion
Children Non-College Parents	2.59	1.1	4.41
Children College Parents	0.52	-0.12	3.28

Notes: This table presents welfare effects using an extended age sample which includes all workers from age 25 to 64. This table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents.

TABLE OA.19: WELFARE MEASURES – EXTENDED CZ SAMPLE

	Equalization	Subsidy	Housing Expansion
Children Non-College Parents	2.57	0.78	3.66
Children College Parents	0.59	-0.17	2.82

Notes: This table presents welfare effects using an extended CZ sample which includes all CZs even if some counties are missing due to data availability. This table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents.

TABLE OA.20: WELFARE MEASURES – SENSITIVITY TO σ_N

	Equalization	Subsidy	Housing Expansion
Children Non-College Parents	2.97	1.04	5.69
Children College Parents	0.67	-0.4	4.22

Notes: This table presents welfare effects when setting the dispersion parameter of location preference shocks to $\sigma_N = 1/7$ (instead of the baseline calibration of $\sigma_N = 1/4$). This table presents percentage changes in the population-weighted average of child opportunity values (that is, children's expected utility at birth) between the baseline and counterfactual steady states, separately for children from college- and non-college-educated parents.