Can We Save the American Dream?

A Dynamic General Equilibrium Analysis of the Effects of School Financing and Rent Subsidies on Local Opportunities

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Abstract

Neighborhoods in the US differ substantially in the educational and economic opportunities that they offer to children who grow up in them. We develop and estimate a structural spatial equilibrium model of residential and education choice to study the effects of school financing policies on education outcomes, intergenerational mobility, and welfare—at the local and aggregate level. Our model generates persistent effects of children's neighborhoods on adult outcomes through local labor market access and local human capital formation. Local school funding is an important component of the latter. We estimate the model using a range of US Census datasets by fitting model predictions to regional data of the actual US geography. We use the estimated model to study the effects of several counterfactual policy interventions, such as equalizing school funding across all students, guaranteeing a minimum level of school funding to all students, or providing rent subsidies to low-income parents who live in selected neighborhoods. We find that general equilibrium responses in local prices and local skill compositions significantly dampen the partial equilibrium effects of policies. In particular, we find that an equalization of school funding across all students has positive but only moderate effects on education outcomes and intergenerational mobility in general equilibrium.

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1 Introduction

Neighborhoods in the US differ substantially in the educational and economic opportunities that they offer to children who grow up in them. This observation has been used to argue that we can increase social mobility and equality by moving disadvantaged families to locations that produce better outcomes. Alternatively, it has been suggested that education policies should target specific locations to reduce opportunity gaps across neighborhoods and socio-economic backgrounds. One example of such a policy is to shift the responsibility of public school funding from local to federal sources, in order to reduce differences in resources across locations. However, the success of such policies depends crucially on the underlying mechanisms that make certain locations better, and whether or not these local factors change in response to a policy.

There are two broad determinants of children's economic and educational outcomes, both of which can differ across locations: human capital formation and labor market access. The quality of local human capital formation directly matters for education outcomes and can depend on a variety of local factors such as school funding, instruction and teacher quality, peer effects, the provision of information, role models, community networks or social capital. Labor market access is local because it is costly to move, so that workers are more likely to stay in or near the location in which they grow up. This fact matters for children's long-run outcomes in two ways. First, it determines the wages to which workers have access as adults. Second, returns to education are determined by local skill premia, which can further impact education choices. Both of these local channels—human capital formation and labor market access—can depend on a location's demographic composition and local factor prices. A key challenge in assessing the effects of policies is to accurately predict how households will adjust their residential and education choices. This determines the demographic composition of locations and further influences local rents, wages, returns to education, and local education environments.

In this paper, we develop and estimate a structural spatial equilibrium model of residential and education choice, which captures these interactions and generates persistent effects of childhood locations on adult outcomes by incorporating these two key mechanisms. Labor market access is local due to moving costs between labor markets and differences in local production technologies. Each labor market consists of several neighborhoods, which differ in local education environments, housing supply and residential amenities. Education environments differ in local school funding and other local characteristics, which can differentially affect children from different family backgrounds. Agents live for two periods: childhood and adulthood. During childhood they acquire education, which determines their skill level

as adults. After finishing their education, children become adults and learn whether or not they will have children themselves. Next, they choose the neighborhood where they want to work and raise their own children (in case they have any). Parents are altruistic and their residential and education choices are inherently dynamic, due to the accumulation and intergenerational transmission of human capital, so that the model has a dynastic structure.

While the general framework can be applied to many research questions, we focus in this paper on the distribution of school funding as a potentially important mechanism for explaining the opportunity gap across neighborhoods and socio-economic backgrounds. School funding in the United States relies heavily on local property taxes. Such local funding generates unequal opportunities, as richer communities live in more expensive neighborhoods with a higher property tax base, so provide more resources and thus better schools for their children. In the last decades, many states implemented school financing reforms to reduce differences in local school funding.[1] However, differences still persist and vary widely across states, causing the distribution of school funding to remain at the forefront of academic and public policy debates. The geographic dimension of school funding is very salient since families have to live in a specific school district in order to have access to its public schools. This fact highlights the importance of analyzing the effects of school financing policies in a spatial framework, which can account for regional heterogeneity and interactions between households' residential and educational choices, local prices, and local education environments. We use our estimated model to illustrate the importance of these mechanisms and to study the effects of a budget-neutral school financing reform, where the federal government raises all funds and distributes them equally among all students.

To estimate our model, we rely on a range of US Census datasets. To identify workers' preferences for different regional characteristics, and so the determinants of their moving decisions, we use a two-step estimator, which is similar to methods developed in the empirical industrial organization literature (i.e. Berry et al. [2004]).[2] Our approach consists of a first step that uses data on residential choices to estimate the mean utility that each demographic group attributes to each neighborhood. The second step identifies how a group's mean utility of living in a location depends on the preference weights that it places on different regional characteristics. We use exogenous variation in real wages to identify how workers trade off local wages and rents against other local attributes. To separately identify local amenities and the weight that parents place on local child opportunities, we exploit the location choices of non-parents. More specifically, holding local wages and rents constant, residential choices

[1] Many of these reforms were mandated by state supreme courts after lawsuits were filed against state governments to contest the legality of these large differences in per-student school funding across locations.

[2] Relevant applications of this method include Bayer et al. [2007], Artuç and McLaren [2015], Caliendo et al. [2018] and Diamond [2016].

of non-parents identify local amenities, as non-parents do not value local education. We then use these amenity estimates to identify parental altruism from the extent to which parents sort more into locations with better opportunities for children, after accounting for local prices and amenities.

To estimate local characteristics, we rely on methods developed by the Quantitative Spatial Economics literature,[3] which allows us to capture rich heterogeneity in local features. The approach recovers unobserved local characteristics as structural residuals by fitting model predictions to observed outcomes of each location in the United States. We use this procedure to infer amenities, as mentioned above, as well as housing supply, local productivity, and a residual component of local human capital production.

In particular, we model the quality of local education environments through local school funding, as well as a residual component that captures all other factors relevant to local human capital formation. We allow local school funding to respond to changes in local prices by modeling the reliance of local school funding on local property taxes. We infer the residual component of local human capital production by fitting model predictions to data on local education outcomes, after accounting for observed local school funding and estimated returns to education. We refer to this residual as local exogenous education costs. In counterfactuals, we assume that these local education costs are constant and do not respond to changes in the local skill composition.[4]

We use the estimated model to study the effects of counterfactual policy interventions. In particular, we consider different school funding reforms and targeted rent subsidies. First, we analyze whether these policies can reduce differences in education outcomes and opportunities across children with low- and high-skilled parents. Secondly, we evaluate whether policies can reduce differences across locations by documenting the effects of policies on the cross-sectional dispersion of relevant outcomes.

We first consider a reform that equalizes school funding across all students, which increases average school funding for low skill families and reduces it for high skill families. First, we fix families' locations, as well as local wages and rents, to evaluate the direct effects of school funding changes on education outcomes. In this partial equilibrium (PE) case, we find that the college-educated share increases by 2.8 pp. among children from low skill families, while it decreases by 0.2 pp. among children from high skill families. In general equilibrium (GE), where we allow for responses in local prices and local skill compositions,

[3] A review of the approach is provided by Redding and Rossi-Hansberg [2017]. Other references are discussed in the literature review below.

[4] In future work, we can relax this by modeling additional channels that endogenously affect local education quality. One example is peer effects, which depend on the local skill mix.

gains are much smaller (1 pp. increase) for low skill families, while effects remain the same for high skill families. The differences in GE are due to changes in both average returns to education and average education costs.[5] Average returns to education decrease after the policy, due to an increase in aggregate skill supply, which depresses the average skill premium. Local education costs are held constant by definition. However, we find that low skill families on average live in locations with higher education costs after the reform, so that average education costs increase for their children. The opposite is true for children from high skill families, for which average education costs decline after the reform. This explains why education outcomes are lower in GE for low skill families, while they remain unchanged for high skill families. The difference between PE and GE results emphasizes the importance of accounting for responses in local prices and households' locations when analyzing the long-run effects of education policies.

Furthermore, we find that the reform increases the cross-sectional dispersion of education outcomes and child opportunities across locations. This is due to the fact that local school funding is only weakly (0.1) correlated with local education outcomes in the baseline, so that the (budget-neutral) equalization of school funding also takes resources away from locations with initially low education outcomes. In addition, we find that equalizing school funding increases the cross-sectional dispersion of skill premia, and hence, returns to education. We consider two other school funding reforms that respectively increase school funding in locations where school funding is low or where initial education outcomes are low prior to the reform. Both of these targeted reforms reduce the cross-sectional dispersion of education outcomes. However, the reforms have smaller effects on education outcomes among children from low-skilled families, despite an increase in aggregate school funding expenditure.

Last, we consider a policy that provides rent subsidies to low-skilled parents, who live in locations where education outcomes are high prior to the reform. This policy increases the college-educated share among children from low-skilled families, because more low-skilled parents move to locations with good education environments (and low education costs) to take advantage of the rent subsidy. The fact that only low-skilled parents are eligible for the rent subsidy increases the welfare of low-skilled parents, which reduces returns to education (measured in utility), as it becomes relatively more attractive to remain low-skilled. The reduction in returns to education decreases college attainment rates among children from high skill families.

The remainder of the paper proceeds as follows. Section 2 describes how our paper relates to the literature. Section 3 presents our model. Section 4 explains the data and how we calibrate

[5]Recall that local education costs refer to the residual component, which captures all local factors that matter for the quality of local education environments besides school funding.

certain parameters outside the model. Section 5 discusses our estimation technique. Section 6 presents our estimation results. Section 7 discusses policy counterfactuals and Section 8 concludes.

2 Related Literature

This paper relates to several strands in the literature, starting with a theoretical literature that focuses on the relation between inequality, local human capital formation, and local school financing, which dates back to Benabou [1993, 1996] and Fernandez and Rogerson [1996, 1998]. Fernandez and Rogerson [1998] study the effects of school finance reforms on income inequality and intergenerational mobility in a dynamic general equilibrium model. Fernandez and Rogerson [1996] develop a multi-community model to study the effects of policies on public education, income distribution, and welfare across communities. Our paper adds to this literature by developing a quantitative spatial framework that we can estimate and use for policy counterfactuals.

Next, our paper relates to the empirical literature on childhood exposure effects. Altonji and Mansfield [2018] find evidence for substantial treatment effects of better schools and neighborhoods for children's education and earning outcomes. Chetty and Hendren [2018] use administrative data on tax records and estimate substantial causal effects of growing up in different counties in the United States on children's long-run outcomes. Our paper contributes to this literature by developing a structural framework that we can estimate to study policy counterfactuals. Furthermore, our quantitative model allows us to study different mechanisms and to evaluate policy counterfactuals, while accounting for resorting of households across locations, which affects local wages and rents.

Given our application, our paper also relates to a large empirical literature on school financing. Two recent examples are Biasi [2018] and Jackson et al. [2016], who use instrumental variable strategies to estimate the causal effects of school funding on children's long-run education outcomes. We add to this literature by developing a structural model that can account for resorting and general equilibrium effects. More generally, our paper relates to a large literature which studies skill formation and optimal education policies, including Abbott et al. [2018], Cunha et al. [2010], Daruich [2018], and many others. Our framework adds to this literature by modeling location-specific human capital production, so that choosing the neighborhood where parents raise their children becomes an important way of investing in their children's human capital. This framework allows us to study how education policies differentially affect education outcomes and child opportunities in specific locations and at

the aggregate level.

Our paper relates to a third literature that—broadly speaking—studies the determinants and effects of location choices of heterogeneous agents, focusing on different applications that emphasize either inequality, segregation, school choice, or local labor market outcomes. Papers that emphasize the divergence of human capital levels across cities include Berry and Glaeser [2005], Diamond [2016], and Moretti [2013], all of whom emphasize how different location choices between high and low skill workers can affect local labor markets, rents, and amenities. A literature that specifically focuses on the link between location choices and education environments includes Bayer et al. [2007], Nechyba [2006], and Fogli and Guerrieri [2018]. Bayer et al. [2007] estimate households' preferences for living in areas with better schools or with neighbors of better socio-economic characteristics using a discrete choice model and boundary discontinuity design. Most related to this paper is Fogli and Guerrieri [2018], who develop an overlapping generations model with two neighborhoods that differ in education spillovers and rents, where parents choose one of the two neighborhoods to raise their children in, and invest in their children's human capital. The authors use the calibrated model to study the effects of a skill premium shock on inequality and segregation in the short and long run. Our model emphasizes differences in local labor market access as an additional local determinant of children's educational and economic outcomes. In addition, our paper adds to this literature by developing a spatial framework that we can estimate and use to analyze the effects of place-based policies on a range of outcomes at the local and aggregate level. To do so, our model incorporates local human capital production and local labor market access, as well as moving costs, housing markets, and rich heterogeneity in unobserved regional characteristics. All of these ingredients are important for households' location and education choices, which further affect equilibrium wages, rents, and the quality of local education environments. Consequently, we determine all of these equilibrium outcomes simultaneously in our model.

To take our framework to the data, we utilize methods from the Quantitative Spatial Economics literature. References include Ahlfeldt et al. [2015] and Allen and Arkolakis [2014], in addition to Bilal and Rossi-Hansberg [2018], Caliendo et al. [2018], Desmet et al. [2018], and Allen and Donaldson [2018] for dynamic settings. Redding and Rossi-Hansberg [2017] provide a review of the approach. Our paper extends this literature by incorporating education choices, which depend on parental background and childhood location, and which determine the dynamic evolution of workers' skill levels across generations. It is essential to study local human capital formation, moving costs, and local labor market access in a unified dynamic framework to fully analyze the effects of education policies, because these channels interact with each other and are simultaneously determined in equilibrium.

3 Theory

We now present the spatial equilibrium model. First, we describe the economy and geography structure. Then, we summarize the timing of the dynamic model and solve families' decision problem. We then describe market clearing and conclude by defining the recursive equilibrium.

3.1 Economy and Geography

Worker Characteristics: Agents live for two periods: childhood and adulthood. Families choose children's education which determines children's skills once they become adults and workers. Workers skills are $e \in \{l, h\}$, where l denotes low and h high skills. Workers may or may not have children $k \in \{0, 1\}$, which is exogenously determined by the probability $\Pr(k|e)$ that can vary across workers' education e.[6] To ensure that total population is constant, we assume that each parent has $1/\Pr(k|e)$ children. To simplify notation, we refer to the respective households as *parents* ($k = 1$) and *non-parents* ($k = 0$) or as *families with and without children*. Hence, families can be classified into four *demographic groups* that differ by skills and the presence of children, which we denote by $ek \in \{l0, h0, l1, h1\}$.

Preferences: Families have Cobb-Douglas preferences over housing units H and a homogeneous consumption good C. The utility is equal to:

$$U = \log\left[\left(\frac{H}{\alpha^{ek}}\right)^{\alpha^{ek}}\left(\frac{C}{1-\alpha^{ek}}\right)^{1-\alpha^{ek}}\right], \tag{1}$$

where α^{ek} is the housing expenditure share, which can differ across groups. This captures, for example, that families with children may demand larger houses. In addition, parents are altruistic and place a weight β on the utility of their children, so that the model is dynastic and each time period represents one generation.

Geography: We consider a geography with multiple local labor markets, indexed by $m \in \mathbb{M}$ for $\mathbb{M} = \{1, ...M\}$. Each labor market consists of several neighborhoods, indexed by $n \in \mathbb{N}_m$. The set of all neighborhoods is $\mathbb{N} = \bigcup_{m=1}^{M} \mathbb{N}_m$.

[6] Our analysis focuses on the family level, but we abstract from modeling the process of meeting a partner and forming a household. Implicitly this assumes that each person meets a partner with the same education level. Then, these young families learn whether or not they will have children.

Production Technology in Labor Market m: The consumption good C is produced by perfectly competitive firms in each labor market m. Local production technologies are assumed to be CES over low and high skill labor, which is locally supplied by residents in each labor market L_m^e, $e \in \{l, h\}$:

$$G(L_m^l, L_m^h) = \mathcal{Z}_m \left[\mathcal{S}_m^l \left(L_m^l \right)^\rho + \mathcal{S}_m^h \left(L_m^h \right)^\rho \right]^{\frac{1}{\rho}}, \tag{2}$$

where ρ determines the elasticity of substitution. Total factor productivity $\mathcal{Z}_m$ and skill intensity $\mathcal{S}_m^e$ differ across labor markets and $\mathcal{S}_m^h + \mathcal{S}_m^l = 1$.

Moving Costs across Labor Markets: Labor markets are separated by bilateral moving costs $\mathcal{C}_{mm'}^{ek}$, which are measured in utils and can vary across demographic groups. We normalize the cost of staying in the childhood location m to zero without loss of generality, so that $\mathcal{C}_{mm}^{ek} = 0$. We assume that there is perfect mobility across neighborhoods within labor markets.[7]

Human Capital Production in Neighborhood n: Education environments differs across neighborhoods. In particular, we model the local quality of education as a utility cost $\mathcal{D}_n^{ee'}$ that families with parental skills e who live in neighborhood n have to pay in order to obtain skills e'. Since education is a binary choice between low and high skills, we can normalize the cost of remaining low-skilled to zero without loss of generality, so that $\mathcal{D}_n^{el} = 0$. The local cost of becoming high-skilled $\mathcal{D}_n^{eh}$ for a child with parents of skills e depends on local school funding per-student f_n and a local exogenous component $\mathcal{K}_n^{eh}$, which can differ by parental background e and captures all other features of a neighborhood that matter for education.[8] The cost $\mathcal{D}_n^{eh}$ is given by:

$$\mathcal{D}_n^{eh} = -\gamma^e \log(f_n) + \mathcal{K}_n^{eh}, \tag{3}$$

where γ^e captures the causal effect of per-student school funding on the total education cost, which can differ by parental background e.

Residential Amenities in Neighborhood n: Neighborhoods differ in residential amenities $\mathcal{A}_n^{ek}$ that capture local characteristics that make a neighborhood a more or less desirable

[7] We impose this assumption for empirical reasons, because we only observe moving flows across labor markets in the data. The model could easily incorporate moving costs within labor markets.

[8] Local factors that can be captured by $\mathcal{K}_n^{ee'}$ include, for example, information, role models, culture, peer effects, social norms, community networks, and social capital.

place to live. We allow amenities to differ across family types ek, as they may value certain local characteristics differentially. Local amenities $\mathcal{A}_n^{ek}$ enter additively into families' utility function over housing H and consumption C (described in Equation 1).

Housing Supply in Neighborhood n: We assume that housing is inelastically supplied in each neighborhood and is denoted by $\mathcal{H}_n$. Equilibrium rents per housing unit are determined by rental market clearing in each neighborhood n and are denoted by r_n.

Taxation and School Funding Allocation Rules: School funding is paid through taxes, which are raised at the federal, state, and local level. All tax revenues in our model are used for school funding. We do not model other features of the tax system or public goods provision. We index the federal government by g, and states by $s \in \mathbb{S}$. Local governments operate at the neighborhood level, indexed by n.[9] State governments s impose proportional tax rates $\tau_s^{\boldsymbol{w}}$ on wage income, which can vary across states. The federal government g imposes another proportional tax rate $\tau_g^{\boldsymbol{w}}$ on wage income, after allowing for deductibility of state taxes. Local governments n impose proportional tax rates $\tau_n^{\boldsymbol{r}}$ on rent payments, which can vary across neighborhoods. Hence, total rent paid by tenants per housing unit is $r_n = (1+\tau_n^{\boldsymbol{r}})r_n^*$, which consists of market rent r_n^* and tax rate $\tau_n^{\boldsymbol{r}}$. School Funding allocation rules determine how federal and state governments distribute their tax revenues to different neighborhoods. We denote these allocation rules by $\delta_n^{\boldsymbol{s}}, \delta_n^{\boldsymbol{g}}$.

Aggregate Rent Rebates: We assume that aggregate rent payments (excluding taxes) are reimbursed to all families proportional to their wage income.[10] It follows that every household receives a rebate from aggregate rent payments equal to Rw_m^e, where w_m^e are wages of a worker with skill e in labor market m and R is the ratio of the economy's total rent payments (excluding taxes) to total wage income.

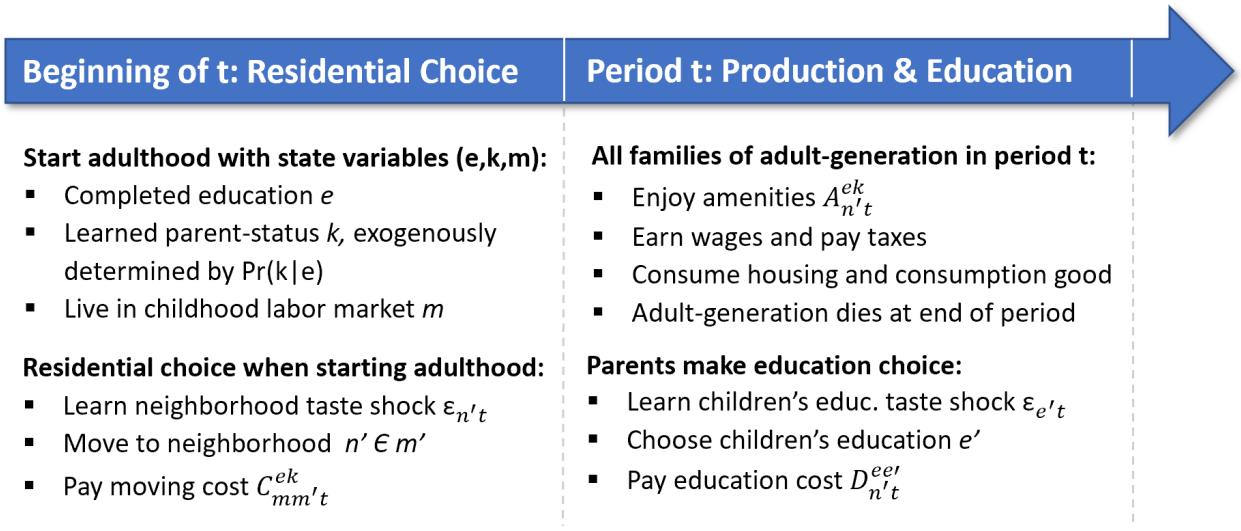
Timing and Decisions: Families make two key dynamic decisions. Young families first choose the neighborhood where they want to live as adults. Then they choose their children's education.[11] We assume that young families receive additive idiosyncratic taste shocks $\epsilon_{n'}$

[9] Consequently, a neighborhood n is fully characterized by its affiliation to a labor market m and a state s, so that $n \in \mathbb{N}_{ms}$. Labor markets can cross state boundaries, so we denote all neighborhoods in a labor market by $\mathbb{N}_m = \bigcup_{s=1}^{S} \mathbb{N}_{ms}$, and all neighborhoods in a state by $\mathbb{N}_s = \bigcup_{m=1}^{M} \mathbb{N}_{ms}$. Finally, all neighborhoods in the whole country are denoted by $\mathbb{N} = \bigcup_{m=1;s=1}^{M;S} \mathbb{N}_{ms}$.

[10] One way to think about this is to assume that all households invest an amount proportional to their wage income into the national real estate portfolio.

[11] Recall that having children is exogenously determined by probability $\Pr(k|e)$ and is not a choice variable.

Figure 1: **Dynamic Timeline**



over neighborhoods n', and children receive idiosyncratic taste shocks $\epsilon_{e'}$ over education levels e'. These idiosyncratic preference shocks allow accounting for the fact that individuals with similar observable characteristics make different residential or education choices in the data. To facilitate the solution of these discrete choice problems, we impose the following assumption:

Assumption 1. Idiosyncratic taste shocks over neighborhoods $\epsilon_{n'}$ and education levels $\epsilon_{e'}$ are i.i.d. across choices and over time and distributed Type-I Extreme Value with zero mean: $\Pr(\epsilon \leq x) = \exp\left(-\exp(-x - \bar{\gamma})\right)$.[12]

The adult-generation of period t experiences the following timeline, illustrated in Figure 1:

1. Young families start their adulthood-period t after they have completed education e, learned exogenously whether or not they will have children k, and (still) live in childhood labor market m. Consequently, their state variables are (e, k, m).

2. At the beginning of period t, young families learn their neighborhood taste shocks $\epsilon_{n't}$ and choose the neighborhood $n' \in m'$ to which they move and where they live as adults.

3. During their adulthood in neighborhood n', families enjoy local amenities $\mathcal{A}^{ek}_{n't}$, earn wages $w^{e}_{m't}$, pay taxes, and spend their disposable income on consumption goods C_t and housing H_t.

[12]The term $\bar{\gamma}$ is the Euler-Mascheroni constant which ensures that the distribution has zero mean. Assumption 1 is common in the discrete choice literature as it facilitates the solution of discrete choice problems. See Aguirregabiria and Mira [2010] for a discussion.

4. In addition, parents learn their children's education taste shock $\epsilon_{e't}$ and choose their children's education level e'. To obtain skills e', families pay the (utility) cost $D_{n't}^{ee'}$ that depends on their neighborhood n' and parents' skills e.

5. At the end of period t, the adult-generation dies. Children become young adults and finish their education e', learn whether or not they have children k', and (still) live in their childhood labor market m'.

6. This new generation of young families then starts their adulthood period $t+1$ with state variables (e', k', m') and the sequence is repeated.

3.2 Family Decision Problem

We now describe families' static consumption choice, as well as their dynamic education and moving decisions, taking local competitive equilibrium wages w_{mt}^e and rents r_{nt} as given.

Static Choice between Housing and Consumption Goods

In each period t, families of demographic group ek who live in neighborhood n choose housing units H_t and consumption goods C_t by solving:

$$\max_{C_t, H_t} \left\{ \log \left[\exp(\mathcal{A}_{nt}^{ek}) \left(\frac{H_t}{\alpha^{ek}} \right)^{\alpha^{ek}} \left(\frac{C_t}{1-\alpha^{ek}} \right)^{1-\alpha^{ek}} \right] \right\},$$

subject to the budget constraint:

$$Y_{nt}^e = r_{nt} H_t + C_t,$$

where α^{ek} denotes the housing expenditure share of group ek, r_{nt} are rents per housing unit in neighborhood n, and the consumption good is chosen as numeraire. Y_{nt}^e is disposable income, which is determined by gross wages w_{mt}^e, federal and state income tax rates $\tau_{gt}^{\boldsymbol{w}}, \tau_{st}^{\boldsymbol{w}}$, and rent rebates $R_t w_{mt}^e$:[13]

$$Y_{nt}^e = (1-\tau_{gt}^{\boldsymbol{w}})(1-\tau_{st}^{\boldsymbol{w}}) w_{mt}^e + R_t w_{mt}^e. \tag{4}$$

Utility maximization gives the following indirect utility for demographic groups ek in neighborhood n:

[13] Disposable income varies at the neighborhood n level as labor markets can extend across state boundaries. Hence, workers in the same labor market m who earn gross wage income w_m^e can be taxed by different states, so that their disposable income can differ.

$$U_t(e,k,n) = \mathcal{A}_{nt}^{ek} + \log(Y_{nt}^{e}) - \alpha^{ek}\log(r_{nt}),$$

where $\mathcal{A}_{nt}^{ek}$ are residential amenities, Y_{nt}^{e} disposable income and r_{nt} rental rates.

Dynamic Decision Problem

As shown in the timeline of Figure 1, young families start their adulthood-period t after they completed education e, know whether they have children k, and still live in labor market m where they were raised. Education e, family-type k and childhood labor market m are state variables as they directly influence families' choices and utility payoffs in the following period(s). Childhood labor markets m affect future choices and utility due to the existence of bilateral moving costs $\mathcal{C}_{mm't}^{ek}$.

The average value of all young families with state variables (e,k,m) can be expressed as:

$$V_t(e,k,m) = \mathbb{E}_{\epsilon} \underset{n' \in \mathbb{N}}{max} \left\{ U_t(e,k,n') - \mathcal{C}_{mm't}^{ek} + \sigma_N \epsilon_{n't} + 1_{k=1}\beta O_t(e,n') \right\}, \tag{5}$$

where σ_N measures the dispersion of idiosyncratic neighborhood taste shocks $\epsilon_{n't}$. In Equation 5 we take the expectation over these shocks to describe the average value for all families with state variables (e,k,m).

When families choose a neighborhood n', they consider the indirect utility that they receive in each destination $U_t(e,k,n')$. In addition, they consider the bilateral moving costs $\mathcal{C}_{mm't}^{ek}$, which is measured in utils and which families have to pay when moving from (childhood) labor market m to destination m'.[14] Furthermore, altruistic parents value the expected utility that each destination n' offers to their children, which we denote by $O_t(e,n')$ and which we will determine shortly. $1_{k=1}$ is an indicator function that is one for parents and zero for non-parents. Parental altruism makes the model dynamic because parents value their children's future utility. Decisions of non-parents are static.

Children's expected utility depends on their parents' skills e and the neighborhood n' where they grow up and is equal to:

$$O_t(e,n') = \mathbb{E}_{\epsilon} \underset{e'}{max} \left[-\mathcal{D}_{n't}^{ee'} + \sigma_E \epsilon_{e't} + \sum_{k'} \Pr{}_t(k'|e') V_{t+1}(e',k',m') \right], \tag{6}$$

where σ_E measures the dispersion of children's idiosyncratic education taste shocks $\epsilon_{e't}$. In Equation 6 we take the expectation over idiosyncratic shocks. Throughout the rest of

[14] This cost captures monetary and psychic implications of moving away from home, which can include a disutility from being far away from family, friends, social networks, or other local bonds.

the paper, we refer to $O_t(e, n')$ as *local Child Opportunities* as it represents the *average* utility that a neighborhood offers to all children from the same family background, before idiosyncratic shocks are observed. Parents choose the neighborhood where they want to raise their children based on these *Child Opportunities* $O_t(e, n')$ as they learn children's education taste shocks $\epsilon_{e't}$ only after moving—but before choosing their children's education.

When choosing children's education e', parents trade-off local costs against local returns to education. Local costs of obtaining education e' $\mathcal{D}^{ee'}_{n't}$ depend on neighborhoods n' and parental skills e and are measured in utils.[15] Local returns to education depend on the continuation values $V_{t+1}(e', k', m')$ that location m' offers to young adults with each education level e'.

Assumption 1 states that taste shocks over neighborhoods and education $\epsilon_{n't}, \epsilon_{e't}$ are Extreme Value distributed, which allows us to express the average values defined in Equations 5 and 6 in closed form where expectations are taken over the max operators. In addition, we can aggregate idiosyncratic choices into the shares of each group that make a given decision. This makes the model very tractable and allows us to take key model predictions to the data.

We solve the problem backwards by first solving for education, and then neighborhood choices.

Child Opportunities and Education Choices

Under Assumption 1, we can express the Opportunities (i.e. average utility) for children with parents of skills e who grow up in neighborhood n' (Equation 6) as

$$O_t(e, n') = \sigma_E \log \left(\sum_{e'} \exp \left[-\frac{1}{\sigma_E} \mathcal{D}^{ee'}_{n't} + \frac{1}{\sigma_E} Q_{t+1}(e', m') \right] \right), \tag{7}$$

where we define $Q_{t+1}(e, m)$ as the expected continuation value of young families before they know whether they will have children or not, i.e. $Q_{t+1}(e, m) \equiv \sum_k \Pr_t(k|e) V_{t+1}(e, k, m)$.

We can further express the share of children from families with skill level e who grow up in neighborhood n', and who choose education e' as:

$$\Pr_t(e'|e, n') = \frac{\exp \left[-\frac{1}{\sigma_E} \mathcal{D}^{ee'}_{n't} + \frac{1}{\sigma_E} Q_{t+1}(e', m') \right]}{\sum_{e''} \exp \left[-\frac{1}{\sigma_E} \mathcal{D}^{ee''}_{n't} + \frac{1}{\sigma_E} Q_{t+1}(e'', m') \right]}. \tag{8}$$

[15] All choices depend on the *total* local education cost $\mathcal{D}^{ee'}_{n't}$, so that it is not necessary here to specify how this cost depends on local school funding $f_{n'}$ and the exogenous component $\mathcal{K}^{ee'}_{n'}$.

Equations 7 and 8 show that both local Child Opportunities and education choices depend on local education costs $\mathcal{D}_{n't}^{ee'}$ and local returns to education, where the latter is given by the continuation values for each skill type $Q_{t+1}(e', m')$. Both of these channels generate persistent effects of childhood neighborhoods on children's long-run outcomes.

Recall that we normalize the cost of remaining low-skilled to zero without loss of generality, i.e. $\mathcal{D}_{nt}^{el} = 0$. Hence, we can express the local odds of becoming high-skilled as:

$$\frac{\Pr_t(h|e,n)}{1-\Pr_t(h|e,n)} = \exp\left[-\frac{1}{\sigma_E}\mathcal{D}_{nt}^{eh} + \frac{1}{\sigma_E^e}\left(Q_{t+1}(h,m) - Q_{t+1}(l,m)\right)\right], \tag{9}$$

where we simply divided the share of children that become high- and low-skilled in Equation 8. Equation 9 shows that a neighborhood (all else equal) produces more high skill adults if it has lower *costs* of becoming high-skilled $\mathcal{D}_{nt}^{eh}$. Recall that this cost depends on per-student school funding f_{nt} and exogenous education costs $\mathcal{K}_{nt}^{eh}$ in the following way: $\mathcal{D}_{nt}^{eh} = -\gamma^e \log(f_{nt}) + \mathcal{K}_{nt}^{eh}$. It follows that the share of children that becomes high-skilled in a neighborhood increases in school funding f_{nt}, but decreases in the exogenous cost $\mathcal{K}_{nt}^{eh}$.

Equation 9 further shows that a neighborhood (all else equal) produces more high skill adults if it has higher *returns* to education $Q_{t+1}(h,m) - Q_{t+1}(l,m)$, which are defined as the difference between average continuation values for high and low skill young families. These returns are measured in utils and vary across childhood labor markets m. Consequently, childhood labor markets have persistent effects on adult outcomes through two channels: first, they affect education decisions due to differences in returns; second, they affect wages of workers conditional on their skill level.[16]

Equation 9 furthermore shows that $1/\sigma_E$ can be interpreted as the elasticity of education with respect to local characteristics. If the dispersion in idiosyncratic education taste shocks σ_E is large, then education choices are primarily driven by idiosyncratic reasons and respond less to local differences in costs of or returns to education. This would imply a small education elasticity $1/\sigma_E$. The dispersion σ_E is a key parameter that we estimate.

[16]The importance of this channel depends on the presence and magnitude of moving cost. To build intuition for this, consider the following example of two children. Anna grows up in the center of region A, which includes several labor markets with high skill premia. Bob grows up in the center of region B, which consists of several labor markets with low skill premia. Due to bilateral moving costs, which increase in distance from the childhood labor market, Anna knows that she has a high probability of spending her adulthood in a labor market with a high skill premium (i.e. in region A). The opposite is true for Bob. It follows that Anna has larger expected returns to education and she is therefore more willing to incur the costs of becoming high-skilled than Bob.

Family Value Functions and Residential Choices

We use Assumption 1 once more, this time to express the expected value that childhood labor market m offers to young families with education e and children k (Equation 5) as:

$$V_t(e,k,m) = \sigma_N \log \sum_{n' \in \mathbb{N}} \exp\left[\frac{1}{\sigma_N} U_t(e,k,n') - \frac{1}{\sigma_N} \mathcal{C}^{ek}_{mm't} + 1_{k=1} \frac{\beta}{\sigma_N} O_t(e,n')\right], \tag{10}$$

where $O_t(e,n)$ denotes local Child Opportunities derived in Equation 7. Equation 10 shows that the value of being in childhood labor market m depends on the utility levels (i.e. flow utilities $U_t(e,k,n')$ and Child Opportunities $O_t(e,n')$) offered by all possible destinations n'. These utility values are reduced by the bilateral moving cost $\mathcal{C}^{ek}_{mm't}$ between childhood labor market m and each destination m'.

Under Assumption 1, we can furthermore express the share of young families with skill level e and children k that move from childhood labor market m to neighborhood n' as:

$$\Pr{}_t(n'|e,k,m) = \frac{\exp\left[\frac{1}{\sigma_N} U_t(e,k,n') - \frac{1}{\sigma_N} \mathcal{C}^{ek}_{mm't} + 1_{k=1} \frac{\beta}{\sigma_N} O_t(e,n')\right]}{\sum_{n'' \in \mathbb{N}} \exp\left[\frac{1}{\sigma_N} U_t(e,k,n'') - \frac{1}{\sigma_N} \mathcal{C}^{ek}_{mm''t} + 1_{k=1} \frac{\beta}{\sigma_N} O_t(e,n'')\right]}. \tag{11}$$

Equation 11 shows that a neighborhood attracts more migrants from a particular demographic group if it offers them higher flow utility $U_t(e,k,n)$ and Child Opportunities $O_t(e,n)$, net of moving costs $\mathcal{C}^{ek}_{mm't}$.

We can also see in Equation 11 that $1/\sigma_N$ can be interpreted as the elasticity of migration with respect to local characteristics. If the dispersion in idiosyncratic neighborhood taste shocks σ_N is large, then moving choices are primarily driven by idiosyncratic factors and respond less to local differences in wages, rents, amenities, or Child Opportunities. This would imply a small migration elasticity $1/\sigma_N$. The dispersion σ_N is a key parameter that we estimate.

Law of Motion

Equations 8 and 11 characterize education and moving choices. These are key equilibrium conditions as they determine how the distribution of population evolves across neighborhoods, skill-levels, and family types over generations. Together with exogenous fertility transitions $\Pr_t(k|e)$, the dynamic evolution of the adult population (i.e. workers) is given by

the following law of motion:

$$L_t(e', k', n') = \sum_{m \in \mathbb{M}} \Pr{}_t(n'|e', k', m) \Pr{}_{t-1}(k'|e') \sum_e \sum_{n \in \mathbb{N}_m} \Pr{}_{t-1}(e'|e, n) \frac{L_{t-1}(e,1,n)}{\Pr_{t-1}(k|e)} \quad (12)$$

which nicely illustrates the timing of our model. We briefly summarize it here:

1. Parents from generation $t-1$ are characterized by skills e and neighborhood n, in which they live as adults and raise their children $L_{t-1}(e, 1, n)$.[17] To hold total population constant, each of these parents has $1/\Pr_{t-1}(k|e) > 1$ children.

2. A share $\Pr_{t-1}(e'|e, n)$ of children chooses education e'. Summing over neighborhoods n in m and across parental backgrounds e gives the total number of children that attain skill level e' in each childhood labor market m.

3. At the end of $t-1$, the adult-generation dies. Children become young families and a share $\Pr_{t-1}(1|e')$ of them has own children, which is exogenously determined.

4. This marks the start of a new period t. Young adults of the new generation have education e', children k', and (still) live in their childhood labor markets m.

5. After learning their neighborhood taste shocks, a share $\Pr_t(n'|e', k', m)$ of these young families moves to neighborhood n' where they spend their adulthood during period t.

6. To derive the population distribution across neighborhoods, skills, and family types for the adult-generation of period t $L_t(e', k', n')$, we sum across origin labor markets m for each demographic group $e'k'$.

3.3 Market Clearing

Housing Market

Recall that housing supply in each neighborhood is inelastically supplied and denoted by $\mathcal{H}_{nt}$. Given Cobb Douglas preferences, all families spend a constant share α^{ek} of their income on housing. Consequently, housing demand equals supply in each neighborhood when:

$$\mathcal{H}_{nt} = \frac{1}{r_{nt}} \sum_e \sum_k \alpha^{ek} Y^e_{nt} L_t(e, k, n), \quad (13)$$

[17] Non-parents of this generation are not relevant for the dynamic evolution of the economy as their dynasties terminate at the end of $t-1$.

where r_{nt} is total rent per housing unit, Y^e_{nt} is disposable income, and $L_t(e,k,n)$ is the measure of families with demographics ek that live in neighborhood n. Equilibrium condition 13 ensures that housing markets clear at the neighborhood level in each period t.

Labor Market

Firms' labor demand is determined by profit maximization. Given CES production technology (as defined in Equation 2) and wages w^e_{mt}, the first-order conditions of firms with respect to high or low skill labor L^e_m is equal to:[18]

$$w^e_{mt} = \mathcal{S}^e_{mt} \left(L^e_{mt}\right)^{\rho-1} \mathcal{Z}_{mt} \left[\mathcal{S}^h_{mt} \left(L^h_{mt}\right)^{\rho} + \mathcal{S}^l_{mt} \left(L^l_{mt}\right)^{\rho}\right]^{\frac{1}{\rho}-1}. \tag{14}$$

Equation 14 shows that (all else equal) equilibrium wages increase in local total factor productivity $\mathcal{Z}_{mt}$, and wages of high-skilled workers increase in local skill intensity $\mathcal{S}^h_{mt}$.

Labor is locally and inelastically supplied by residents of each labor market, so that local labor supply $L_t(e,m)$ is determined by the law of motion (Equation 12) and by families' residential and education choices.[19] Each labor market m clears in each period t at equilibrium wages w^e_{mt}, which ensure that local labor supply (Equation 12) equals local labor demand (14). Equation 14 shows that an increase in local supply of high skill workers $L_t(h,m)$ (all else equal) decreases high skill wages w^h_{mt} and increases low skill wages w^l_{mt} in the location, so that the local skill premium decreases. Equilibrium wages and skill premia can differ across labor markets.

3.4 Recursive Equilibrium

To take stock, let us first summarize all exogenous parameters of the model before defining the equilibrium. Locations exogenously differ in productivity, skill intensity, bilateral moving costs, residential amenities, housing supply, and the exogenous component of education costs. Throughout the rest of our paper, we refer to these exogenous, time-varying, and location-dependent parameters as regional *fundamentals*, which we denote by:

$\Theta_t \equiv \left(\mathcal{Z}_{mt}, \mathcal{S}^e_{mt}, \mathcal{C}^{ek}_{mm't}, \mathcal{A}^{ek}_{nt}, \mathcal{H}_{nt}, \mathcal{K}^{ee'}_{nt}\right)$. In addition, neighborhoods are differentially affected by time-varying tax and school funding policies of the federal, state, and local government, which we denote by: $\mathit{\Gamma}_t \equiv \left(\tau^{\boldsymbol{w}}_{gt}, \tau^{\boldsymbol{w}}_{st}, \tau^{\boldsymbol{r}}_{nt}, \delta^{\boldsymbol{g}}_{nt}, \delta^{\boldsymbol{s}}_{nt}\right)$.[20] Finally, model parameters are denoted by:

[18] As firms take labor supply as given, we facilitate notation by using: $L^e_{mt} \equiv L_t(e,m)$.

[19] Residential and education choices (and therefore local labor supply) respond to local wages, but also to a variety of other local factors, including education environments, rents, and residential amenities.

[20] These policies are exogenous, and they endogenously determine local school funding and education outcomes in the model.

$\Upsilon = \left(\alpha^{ek}, \beta, \sigma_E, \sigma_N, \gamma^e, \rho, \Pr(k|e)\right)$.[21] We denote the full set of exogenous parameters, which includes regional fundamentals, policies, and time-invariant parameters by: $\bar{\Theta}_t = (\Theta_t, \Gamma_t, \Upsilon)$. The state of the economy is characterized in each period by the distribution of population $L_t(e, k, n)$ across neighborhoods $n \in \mathbb{N}$, skills $e \in \{l, h\}$, and family types $k \in \{0, 1\}$. We define the full equilibrium of our model in two stages following Caliendo et al. [2018]. We begin by defining the *temporary equilibrium* that is given by equilibrium wages and rents, which ensure that labor and housing markets clear conditional on (exogenous) parameters $\bar{\Theta}_t$ *and* conditional on the (endogenous) population distribution across demographic groups and neighborhoods $L_t(e, k, n)$. We then proceed to define the full recursive, competitive equilibrium of the dynamic model where the population (i.e. worker) distribution is endogenous.

Definition 1. Temporary Equilibrium. Conditional on exogenous parameters $\bar{\Theta}_t$ and the distribution of population $L_t(e, k, n)$, the temporary equilibrium is a vector of factor prices $\{w^e_{mt}, r_{nt}\}$ that satisfy market clearing conditions in Equations 14 and 13. To emphasize the dependence of prices on $\bar{\Theta}_t$ and $L_t(e, k, n)$, we denote the factor prices of the temporary equilibrium by $w^e_{mt}\left(\bar{\Theta}_t, L_t(e, k, n)\right)$ and $r_{nt}\left(\bar{\Theta}_t, L_t(e, k, n)\right)$.

We now define the recursive competitive equilibrium.

Definition 2. Recursive Competitive Equilibrium. Given a path of exogenous parameters $\left\{\bar{\Theta}_t\right\}_{t=0}^{\infty}$ and an initial distribution of households across neighborhoods, skills, and parent types $L_0(e, k, n)$, a recursive competitive equilibrium is given by the paths of: (i) families' residential and education choices $\{\Pr_t(n'|e, k, m), \Pr_t(e'|e, n)\}_{t=0}^{\infty}$, (ii) value functions of each demographic group ek in each labor market $\{V_t(e, k, m)\}_t^{\infty}$, (iii) the distribution of population across neighborhoods, skills, and family types $\{L_t(e, k, n)\}_{t=0}^{\infty}$, and (iv) factor prices $\{w^e_{mt}, r_{nt}\}_{t=0}^{\infty}$, such that:

1. Residential and educational choices maximize families' utility and correspond to the optimal choices that we derived in Equations 8 and 11.

2. Value functions are consistent with Equation 10.

3. The distribution of population across neighborhoods, skills, and family types is consistent with the law of motion given in Equation 12 and with families' residential and education choices.

4. Factor prices are given by temporary equilibria, as defined above.

[21] These parameters are housing expenditure shares α^{ek}, altruism β, dispersion of neighborhood and education taste shocks σ_E,σ_N, effects of school funding on education outcomes γ^e, the elasticity of substitution between low- and high-skilled workers ρ, and fertility probabilities $\Pr(k|e)$.

4 Data and Calibrated Parameters

4.1 Data and Summary Statistics

For our quantitative exercise, we interpret Commuting Zones (CZ) as labor markets m and counties as neighborhoods n (and we use these terms interchangeably throughout the rest of the paper). There are 741 CZs in the United States, which are defined to capture areas that represent integrated, but separate local labor markets,[22] and which cover the whole area of the United States (contrary to MSA). There are approximately 3,000 counties in the United States.[23] Individuals whose highest degree is high-school graduation or less are considered low-skilled. All others are considered high-skilled. Households in which a child under 18 is *currently* present are considered "parents". This definition is chosen as we expect that only those households value local education environments at that moment of time.[24]

The quantitative analysis of our model requires six key sets of data: Mobility across and residential choices within CZs, educational choices of high- and low-skilled families by county, school funding by county, rents by county, and wages by skill and CZ. We now briefly present the sources and summary statistics for these data moments. More information is available in Appendix B.

Mobility across Commuting Zones. We construct moving flows across commuting zones (CZs) for each demographic group $L(m'|e,k,m)$ using individual-level data on education, presence of children, and the Public Use Microdata Area (PUMA) of residence for the current year and five years ago.[25] PUMAs are mapped to CZs with geographic crosswalks. Data for 1990 and 2000 is obtained from the 5 percent samples of the decennial US Census and from the American Community Survey in 2006-10. All are accessed from the Integrated Public Use Microdata Series (IPUMS). We restrict the sample to ages 25 to 45 to capture the fact that families move only once in our model, after finishing education and before joining the labor market.[26]

[22] For this purpose, CZs are clusters of counties that are characterized by strong commuting ties within, and weak commuting ties across their boundaries. This matches our model assumption that local labor markets are separated by moving costs.

[23] In extensions, we plan to use school districts as neighborhoods, as this geographic unit best represents local education environments. However, a key variable (the causal effects of neighborhoods on children's education outcomes) is only available at the county-level, so that we would need to predict this variable at the school-district level.

[24] Even if families had a child in the past, we treat them as "family without children (non-parents)" if the child no longer lives in the household.

[25] For more details on the data construction, see Appendix B.1

[26] This excludes moves that are motivated by different considerations, e.g. moves after retirement.

Table 1: **Summary Statistics**

VARIABLES	(1) Obs.	(2) Mean	(3) Std. Dev.	(4) p10	(5) p90
Panel A. Moving Probability					
Share of Young Adults Moving across CZ (5yrs)					
Low-Skill Non-Parent	741	41.5%	21.4%	19.8%	77.6%
High-Skill Non-Parent	741	42.1%	20.1%	22.8%	76.1%
Low-Skill Parent	741	30.8%	23.3%	9.6%	71.9%
High-Skill Parent	741	30.5%	22.0%	11.8%	69.2%
Panel B. Educational Outcomes					
Probability that Child Attends College					
Low-Income Parents	2,935	55.5%	8.8%	44.7%	66.6%
High-Income Parents	2,935	84.1%	4.1%	79.1%	88.7%
Causal Effect of County (20 yrs, perc. pts)					
Low-Income Parents	2,384	0.02	14.66	-14.68	13.59
High-Income Parents	2,384	-0.03	18.15	-10.54	9.73
Panel C. Per-student School Funding					
Per Student School Funding	2,359	12,122	3,280	9,232	17,218
Share of Local School Funding from					
Federal Government	2,359	12.0%	4.7%	5.8%	17.8%
State Government	2,359	44.0%	13.6%	26.3%	61.7%
Local Government	2,359	44.0%	15.3%	23.8%	65.7%
Panel D. Local factor prices					
Rental rates in counties	2,359	1	0.30	0.63	1.47
Wages in commuting zones					
Low-Skill Worker	2,371	0.71	0.07	0.63	0.79
High-Skill Worker	2,371	1.28	0.19	1.05	1.56
Skill Premia in CZ	2,371	58.6%	6.9%	50.3%	66.9%

Notes: All summary statistics are weighted by the total population in the respective geographic unit. The share of movers is weighted by the origin-population of the respective demographic group; hence means of moving shares represent the total share of movers in the demographic group.

Panel A of Table 1 reports population-weighted summary statistics on the share of young adults that moved across CZs during the last 5 years. We find that families without children are more mobile (42 percent move) than families with children (30 percent move).

Residential Choices within Commuting Zones. Residential choices are measured by the population stock of each demographic group ek in each county n $L(e,k,n)$. These are obtained from special tabulations of census data provided by the National Center for Education Statistics (NCES) which include information on population stocks by education and presence of children at the school district level. To analyze differences in residential choices across demographic groups, we measure Segregation between high- and low-skilled families across counties, for which we use the Information Index (see Appendix B.1 for more information). We compute the Segregation Index separately for families with and without children, which shows that skill segregation is 10 percent higher among families with children. In addition, the Index is additively decomposable across nested geographic layers, so that we can decompose overall Skill Segregation into the shares of variation that are explained across and within CZs. The decomposition shows that a large share of Segregation is explained *within* CZs: 46 percent for parents and 38 percent for non-parents. The decomposition indicates that residential choices of parents are driven more by county characteristic (e.g. rents, residential amenities, and local education environments), and less by CZ characteristics (e.g. wages) compared to non-parents.

Educational Outcomes. Data on local education outcomes are obtained from Chetty and Hendren [2018]. The authors' estimate the causal effects of growing up in a county on children's probability of going to college, relative to the average county. These effects are available for families with income at the 25th and 75th percentile of the national income distribution, which we use as proxies for high- and low-skilled families. Since causal county effects are estimated relative to the average county, we adjust them by the average college-going rates of children from high- and low-income families. This allows us to match the aggregate level of college enrollment, while preserving the cross-sectional variation of the causal estimates. The re-scaled estimates then correspond to the model predictions of local education choices $\Pr(e'|e,n)$.[27]

Panel B of Table 1 reports summary statistics of the college-going probability across coun-

[27]In the model, children only differ by parental education, childhood neighborhood and idiosyncratic education taste shocks. We assume that taste shocks are only realized *after* families make their moving decision, so that families cannot sort into certain regions based on these shocks. It follows that all differences in education outcomes across neighborhoods $\Pr(e'|e,n)$ (conditional on parental background) are causal to location n. Therefore, we use the causal county estimates to map our model predictions to the data.

ties.[28] On average, 56 percent of children from low-income families go to college, compared to 84 percent of children from high-income families. The causal effects of spending the whole childhood (20 years) in a county, relative to the average county, is zero on average (by definition) and the standard deviation is 15 (18) percentage points (pp.) for children from low- (high-) income families. Spending the whole childhood in a county at the 10th percentile, instead of the average county, decreases the probability of going to college by 15 (11) pp. for children from low- (high-) income families. Growing up in a county at the 90th percentile, instead of the average county, increases this probability by 14 (10) pp. for children from low- (high-) income families.

Local School Funding. Data on school funding that each school district receives from federal, state, and local sources are obtained from the Finance Survey (F-33) in 1990, 2000, and 2010. Information on the number of students in each school district is available in the Common Core of Data (CCD) files. Both datasets are provided by the National Center for Education Statistics (NCES). We use these datasets to compute per-student school funding in each county, which allows us to calibrate tax rates and school funding allocation rules.

Panel C of Table 1 provides population-weighted summary statistics of per-student school funding and the share of school funding that counties receive from each level of government. Annual per-student school funding averages $12,122 with a standard deviation of $3,280 across counties. This ranges from $9,232 for the county at the 10th percentile to $17,218 for the county at the 90th percentile. The share of school funding that counties receive from the federal government averages 12 percent with a standard deviation of 5 percent. The share received from state and local governments both average 44 percent with a standard deviation of 14 (15) percent.

Local Rents. We estimate rental rates per quality-adjusted housing unit in each county from Hedonic Price Regressions which control for possible differences in housing quality and housing characteristics across counties. Using block-group data, we regress log median rent on several housing characteristics and county fixed effects. We obtain the data from the US Census, accessed through the National Historical Geographic Information System (NHGIS). More details are provided in Appendix B.1.

Panel D of Table 1 shows summary statistics of rents, which we normalize to have a mean of one. The standard deviation is 0.3. Rent in the county at the 90th percentile is 47 percent above the average, while the 10th percentile is 2/3 of the average.

[28] This probability is measured with data from permanent residents in each county.

Local Wages by Skill. Wages of high- and low-skilled workers in each CZ are estimated by Mincer regressions. Using individual-level data, we regress log wages on the interaction between education and CZ fixed effects while controlling for demographic characteristics of workers. We obtain the data from the US Census, accessed through IPUMS. More details are provided in Appendix B.1.

Panel D of Table 1 reports population-weighted summary statistics of high- and low-skilled wages across CZs. Wages across all workers are normalized to have population-weighted mean of one. Wages of low-skilled workers average 0.7 with a standard deviation of 0.07. Wages of high-skilled workers average 1.28 with a standard deviation of 0.19. Using this wage data, we compute the skill premium in each CZ. The average skill premium is 59 percent with a standard deviation of 7 percent. The skill premium is 50 (67) percent in the CZ at the 10th (90th) percentile.

4.2 Calibrated Parameters

We now explain the calibration of several model parameters. The results for all calibrated parameters are provided in Table 2.

Elasticity of Substitution. Following the literature, we set the elasticity of substitution across high- and low-skilled workers in the CES production function to 1.5, which corresponds to $\rho = 1/3$.[29]

Probability of having Children. The probability of having children for each skill type $\Pr(k|e)$ is calibrated to the share of parents in each skill group that is observed in the data, i.e: $\Pr(k|e) = L(e,1)/L(e)$. In the 2010 sample of our data, the share of households where a child is present is 35 percent among high-skilled, and 26 percent among low-skilled.

Housing Expenditure. Housing expenditure shares α^{ek} are calibrated to expenditure data from the 2011 Consumer Expenditure Survey (CEX). The CEX provides individual-level information on education, presence of children in the household, expenditure on housing (variable sheltcq) and total expenditure (variable totexpcq). We use these data to compute average housing expenditure shares for each demographic group. We find that low-skilled

[29] A large literature estimated this parameter and most results fall in the range between 1.4 and 1.6. Ciccone and Peri [2005] find estimates of 1.5 using US micro-data, and instrumenting for cross-city variation in relative skill supply with compulsory schooling laws. They use completed high-school graduation as the cutoff between low and high skill workers. Katz and Murphy [1992] estimate the elasticity to be 1.41, Heckman et al. [1998] finds an estimate of 1.44. Autor et al. [1998] provides a review of this literature.

families spend 34 percent on housing if they do not have children, and 38 percent if they do. High-skilled families spend 33 percent on housing if they do not have children, and 36 percent if they do.

Tax Rates and Reimbursement from Rental Income. Federal and state governments impose taxes $\tau_g^{\boldsymbol{w}}, \tau_s^{\boldsymbol{w}}$ on income and local governments impose taxes $\tau_n^{\boldsymbol{r}}$ on rent payments. We assume that all tax revenues are used to fund schools[30] and each level of government balances its budget. We calibrate local tax rates using governments' budget constraints, along with data on school funding, wages, and rents. More information is provided in Appendix C.1.

Panel B of Table 2 reports (population-weighted) summary statistics of the calibrated tax rates that raise revenue for school funding. The federal income tax rate is 0.6 percent. State income tax rates average 2.3 percent with a standard variation of 0.6 percent. Local (county) tax rates on rent average 5 percent with a standard deviation of 2.4 percent. Variation in local tax rates is large because counties differ in the extent to which they rely on local, state, or federal governments to finance their schools.

School Funding Allocation Rules. Local governments use their entire tax revenue locally. We calibrate allocation rules for federal and state governments $\delta_n^{\boldsymbol{s}}, \delta_n^{\boldsymbol{g}}$ non-parametrically to approximate the current distribution of per-student school funding. This allows us to capture some of the heterogeneity and complexity of existing allocation rules without explicitly modeling them. Particularly, $\delta_n^{\boldsymbol{s}}$ is the *relative* funding that a student in county n receives compared to the state's average per-student funding. It follows that school funding in each county is endogenously determined by the number of students, tax revenues at the federal, state and local level, and funding allocation rules.[31]

Effects of School Funding on Education Outcomes. Recall that education choices for children who grow up in neighborhood n with parents of skills e are given by:

$$\frac{\Pr(h|e,n)}{1-\Pr(h|e,n)} = \exp\left[-\frac{1}{\sigma_E}\mathcal{K}_n^{eh} + \frac{\gamma^e}{\sigma_E}\log(f_n) + \frac{1}{\sigma_E}\left(Q(h,m) - Q(l,m)\right)\right],$$

where $\mathcal{K}_n^{eh}$ are exogenous local education costs, and γ^e/σ_E measures the causal effect of per-student school funding on the (log) odds of becoming high-skilled. We identify γ^e from

[30] In counterfactuals, we study the effects of school financing reforms. Therefore, we focus only on tax revenues that are used for school funding. It is not our objective to capture all features of the tax system or public goods provision because these are assumed to remain constant in our counterfactuals.

[31] In an extension it would be possible to estimate allocation rules that allow federal and state funding to endogenously respond to counties' characteristics or demographic composition.

Table 2: Parameters Calibrated or Inferred from Literature

	(1)	(2)	(3)	(4)	(5)
Panel A: Parameters					
VARIABLES	Low skill Non-Parent	High-skill Non-Parent	Low-skill Parent	High-skill Parent	
Housing Exp. Share α^{ek}	0.336	0.334	0.383	0.364	
Fertility Probability $\Pr(k\|e)$	0.74	0.65	0.26	0.35	
Effect of School Funding γ^e	n/a	n/a	2.41	2.22	
Rent Rebates R	0.476				
Elasticity of Substitution ρ	0.33				
Panel B: Tax Policies and School Funding Allocation Rules					
	Obs.	Mean	Std. Dev.	p10	p90
Federal Tax Rate on Inc. $\tau_g^{\boldsymbol{w}}$	1	0.6%			
State Tax Rates on Inc. $\tau_s^{\boldsymbol{w}}$	49	2.3%	0.6%	1.5%	3.3%
Local Tax Rates on Rent $\tau_n^{\boldsymbol{r}}$	2,358	5.0%	2.4%	2.4%	7.8%

Jackson et al. [2016], who estimate the causal effects of school funding on adulthood outcomes by using court-mandated reforms to construct plausibly exogenous variation in school funding. The authors kindly provided us estimates of the effects of school funding on children's probability to attend (and graduate from) college, which were separately estimated for children from high- and low-skilled families.[32] We map the 2SLS estimates of the linear probability model to our model structure by noting that:

$$\gamma^{e,2SLS} = \frac{\Delta \Pr(h|e,n)}{\Delta \log(f_n)}|_m.$$

The IV-regressions control for school district fixed effects, so that the estimates $\gamma^{e,2SLS}$ do not include effects that are due to changes in the returns to education, i.e. $\partial Q(e,m)/\partial f_n$. To compute the equivalent measure from the logit form in our model, we take the derivative of education outcomes (Equation 9) with respect to per-student school funding while holding returns to education constant. This gives:

$$\frac{\partial P(h|e,n)}{\partial \log(f_n)}|_m = \frac{\gamma^e}{\sigma_E} \Pr(h|e,n) \left(1 - \Pr(h|e,n)\right).$$

[32]The original paper Jackson et al. [2016] provides results for similar model specifications, however, not for this exact model specification that directly maps to the structural parameters of our model. We are very grateful for the time and effort that the authors, and in particular Rucker Johnson, invested to provide us with these additional results.

Equating marginal effects gives the following map between both parameters:

$$\gamma^{e,2SLS} = \frac{\gamma^e}{\sigma_E} \Pr(h|e,n) \left(1 - \Pr(h|e,n)\right), \tag{15}$$

which allows us to solve for γ^e/σ_E as $\Pr(h|e,n)$ is the population-weighted average of the college-going probability across all counties.

Jackson et al. [2016] find that a 10 percent increase in childhood school funding increases the probability of attending (graduating from) college by 7 (4.6) percentage points (pp.) for children with low-skilled parents. For children with high-skilled parents, the probability of attending college is not significantly affected, and the probability of graduating from college increases by 3.2 pp. Averaging these values, we set $\gamma^{l,2SLS} = 0.58$ and $\gamma^{h,2SLS} = 0.29$. So, Equation 15 implies that $\gamma^l/\sigma_E = 2.42$ for low skill and $\gamma^h/\sigma_E = 2.23$ for high skill families. With these calibrated parameters in hand, we now proceed to describe the estimation of the remaining model parameters, summarized in Table 3.

5 Estimation

The key model parameters that we need to estimate are parental altruism β and the dispersion of idiosyncratic taste shocks over neighborhoods and education σ_N, σ_E. To estimate these parameters, we use a two-step estimator that relies on methods from the empirical industrial organization literature (i.e. Berry et al. [2004]) which have been extended and used in Artuç and McLaren [2015] and Diamond [2016].

The first step identifies the terms listed in Panel A of Table 3. We estimate moving costs and the mean utility that each demographic group attaches respectively to CZs and counties from data on residential choices. These results further allow us to construct estimates of value functions. We estimate the model to the transition because the data shows that the economy is *not* in steady state.[33]

The second step of the estimator decomposes the mean county utility of each demographic group into the weights that groups place on local rents, wages, and Child Opportunities. These weights correspond to the parameters listed in Panel B of Table 3. Identifying these parameters is challenging because county-utility also depends on unobserved amenities, which

[33] Using data from 1990, 2000, and 2010, we see that counties' population size and skill mix change over time. Specifically, we observe positive net moving flows across CZs and educational deepening, (i.e. more children go to college compared to their parents' generation) which is not compatible with the definition of steady state.

Table 3: **Parameters to Estimate**

Name	Symbol	Description of Estimation
Panel A: Auxiliary Terms and Model Objects *(estimated in Step 1 and used in Step 2 of estimation)*		
Moving Cost	$c_{mm'}^{ek} \equiv \mathcal{C}_{mm'}^{ek}/\sigma_N$	Parametrized and estimated from moving flows across commuting zones (CZs).
CZ-utility	$u_m^{ek} \equiv \mathcal{U}_m^{ek}/\sigma_N$	Estimated from moving flows across CZs.
County-utility	$\chi_n^{ek} \equiv \mathcal{X}_n^{ek}/\sigma_N$	Estimated from CZ-utility and residential choices within CZs.
Value Function	$v(e,k,m) \equiv V(e,k,m)/\sigma_N$	Estimated from CZ-utility and moving costs.
Panel B: Model Parameters *(estimated in Step 2 of estimation)*		
Dispersion of county taste shock	σ_N	Identified from relationship btw. county-utility and real income using Bartik instruments.
Dispersion of education taste shock	σ_E	Identified from the extent to which parents sort more into neighborhoods with better Child Opportunities than non-parents.
Altruism	β	same as σ_E
Panel C: Regional fundamentals *(inferred as structural residual after estimation)*		
Productivity & skill intensity	$\mathcal{Z}_m, \mathcal{S}_m^e$	Inferred from labor market equilibrium condition and data on local wages and labor supply of high and low skill workers.
Housing supply	$\mathcal{H}_n$	Inferred from rental market equilibrium condition and data on local rents and housing expenditure.
Residential amenities	$a_n^{ek} \equiv \mathcal{A}_n^{ek}/\sigma_N$	Inferred from data on residential choices of non-parents, after accounting for local wages and rents.
Exogenous component of education cost		Inferred from data on education choices, after accounting for local school funding and (estimated) local returns to education.

are correlated with the remaining local characteristics. We explain below how we address this identification challenge.

We then use the estimated parameters to compute structural residuals that exactly fit key model predictions to regional data. We interpret these structural residuals as regional characteristics. Specifically we use this approach to infer local productivity, skill intensity, housing supply, local amenities and exogenous education costs (i.e. all parameters listed in Panel C of Table 3). This method was developed in the Quantitative Spatial Economics literature (see Redding and Rossi-Hansberg [2017] for a review) and allows capturing rich heterogeneity in regional characteristics.

Normalization: To facilitate the description of the estimation, we normalize utility by the dispersion of neighborhood taste shocks σ_N. This normalizes model objects and regional fundamentals that are measured in utils. We use small-caps to denote normalized terms, as defined in Table 3.[34] Normalized indirect utility is now given by:

$$u_t(e,k,n) = a_{nt}^{ek} + \frac{1}{\sigma_N} I_{nt}^{ek},$$

where I_n^{ek} is real income which is defined as $I_{nt}^{ek} = \log(Y_{nt}^e) - \alpha^{ek} \log(r_{nt})$. Recall that Y_n^e is disposable income, r_n is total rent per housing unit, and α^{ek} are housing expenditure shares that we previously calibrated.

Normalized value functions of young families with demographics ek in labor market m before moving (Equation 10) can be written as:

$$v_t(e,k,m) = \log \sum_{n' \in \mathbb{N}} \exp \left[a_{n't}^{ek} + \frac{1}{\sigma_N} I_{n't}^{ek} - c_{mm't}^{ek} + 1_{k=1} \beta o_t(e,n') \right], \tag{16}$$

where we again use small-caps to denote normalized Child Opportunities: $o(e,n) \equiv O(e,n)/\sigma_N$.

5.1 Step 1: Mean Utility of Locations

The objective of the first step is to estimate mean utility levels for each demographic group in each county. We estimate these utility levels from observed residential choices, which relies on a revealed preference approach and does not require us to impose any restrictions on families' expectations.[35] Given our nested geography structure, we first estimate mean CZ-

[34] The normalization further shows that idiosyncratic shocks weaken the link between regional characteristics and moving decisions.

[35] If families make moving choices based on naive (or mistaken) expectations, then the estimation would infer utility levels based on these expectations.

utility and moving costs using observed moving flows across CZs.[36] Due to perfect mobility within CZs, we can then compute county-utilities by using the estimates of CZ-utility and observed residential choices across counties within each CZ. In addition, we can use the results to construct estimates of value functions. This identifies all terms listed in Panel A of Table 3 and we now describe the estimation.

Definition of County and CZ-Utility. Mean county-utility $\varkappa_{nt}^{ek}$ is defined over local characteristics that are identically valued by all families in each demographic group, which are residential amenities, real income, and Child Opportunities, so that:

$$\varkappa_{nt}^{ek} \equiv a_{nt}^{ek} + \frac{1}{\sigma_N} I_{nt}^{ek} + 1_{k=1} \beta o_t(e,n). \tag{17}$$

Estimating $\varkappa_{nt}^{ek}$ is a key objective, so that we can consequently use Equation 17 to identify the model parameters. To obtain estimates of county-utilities $\varkappa_{nt}^{ek}$, we first estimate CZ-utility which is defined as:

$$u_{mt}^{ek} \equiv \log \left(\sum_{n \in \mathbb{N}_m} \exp(\varkappa_{nt}^{ek}) \right). \tag{18}$$

We can show with some algebra (see Appendix C.2) that group's mean county-utility $\varkappa_{nt}^{ek}$ can be expressed as a function of CZ-utility u_{mt}^{ek} and the share of the group's CZ population that lives in county n:

$$\exp(\varkappa_{nt}^{ek}) = \frac{L_t(e,k,n)}{L_t(e,k,m)} \times \exp(u_{mt}^{ek}). \tag{19}$$

This Equation shows that groups' relative county-utilities *within* a CZ are directly inferred from groups' population in each county. This result holds because there are no moving costs within CZs. Population stocks in each county $L_t(e,k,n)$ are observed in the data and we now discuss the estimation of CZ-utility u_{mt}^{ek}.

Estimation of CZ-Utility and Moving Costs. Moving flows of young adults across CZs, denoted by $L_t(m'|e,k,m)$, are derived from the law of motion in Equation 12 and can be expressed as:

[36] CZ-utility and moving costs are simultaneously estimated, because moving costs can weaken the link between moving choices and the overall attractiveness of a location by making it less likely that families move to the most desirable location.

$$L_t(m'|e,k,m) = \frac{\exp(u^{ek}_{m't} - c^{ek}_{mm't})}{\sum_{m'' \in \mathbb{M}} \exp(u^{ek}_{m''t} - c^{ek}_{mm''t})} \tilde{L}_t(e,k,m), \tag{20}$$

where $\tilde{L}_t(e,k,m)$ is the origin-population, i.e. young families with given demographics ek who still live in their childhood labor market m right before moving.[37] The share of families that moves from m to m' depends on CZ-utility levels and moving costs.[38]

For the estimation, we now parameterize moving costs across CZs as:

$$c^{ek}_{mm't} = \lambda^{ek}_t X_{mm'},$$

where λ^{ek} is a vector of group-specific coefficients. $X_{mm'}$ is a vector of characteristics that describe CZ pairs, for which we use distance, distance squared, and dummies that indicate whether the move changes states, divisions, or the urban or coast-status of CZs, so that $X_{mm'} = \left\{dist_{mm'}, dist^2_{mm'}, D^{st}_{mm'}, D^{div}_{mm'}, D^{urb}_{mm'}, D^{coast}_{mm'}\right\}$.

We can now rewrite Equation 20 as a function of the parameterized moving cost, destination and origin fixed effects in the following way:

$$L_t(m'|e,k,m) = \exp\left\{dest^{ek}_{m't} - \lambda^{ek}_t X_{mm'} + orig^{ek}_{mt}\right\} + \epsilon_{mm'}. \tag{21}$$

Destination fixed effects $dest^{ek}_{m'}$ correspond to CZ-utilities $u^{ek}_{m'}$, which capture the attractiveness or the pull-factor of each destination. Origin fixed effects $orig^{ek}_m$ capture all remaining terms of Equation 20, which include the origin-population $\tilde{L}(e,k,m)$ and all terms in the denominator that characterize families' outside option of moving from childhood CZ m to any other destination m''.

We estimate Equation 21 by Pseudo Poisson Maximum Likelihood (PPML) using data on moving flows across CZs $L_t(m'|e,k,m)$ and bilateral CZ characteristics $X_{mm'}$.[39] A key advantage of the PPML estimation is that it estimates migration flows in levels and not logs, so that it can rationalize zero observed migration flows between some locations. This is important for many studies of migration and also for our context since we observe only a subset of all movers and many observed flows are zero.[40] Equation 21 is estimated separately

[37] The law of motion (Equation 12) shows how $\tilde{L}^{ek}_{mt}$ is determined from the previous parent generation: $\tilde{L}^{e'k'}_{mt} \equiv \Pr_{t-1}(k'|e') \sum_e \sum_{n \in \mathbb{N}_m} \Pr_{t-1}(e'|e,n) \frac{L^{e1}_{nt-1}}{\Pr_{t-1}(k|e)}$. Moving flows are the last component of the law of motion.

[38] Moving probabilities were derived in Equation 11.

[39] For more details on the data see Section 4.1 and Appendix B.

[40] The advantages of PPML are discussed in more detail by Silva and Tenreyro [2006]. PPML estimation

for each demographic group. The estimation simultaneously identifies groups' CZ-utilities ($dest^{ek}_{m't} = u^{ek}_{m't}$) and parametrized moving costs $\left(c^{ek}_{mm't} = \lambda^{ek}_t X_{mm'}\right)$ up to a constant of normalization. We normalize the cost of staying to zero without loss of generality. This allows us to construct estimates of county-utility χ^{ek}_{nt} using Equation 19.

Construction of Value Function. We can further use the estimates to construct normalized value functions of young families before moving by re-writing Equation 16 as:

$$v_t(e,k,m) = \log \sum_{m' \in \mathbb{M}} \exp\left(u^{ek}_{m't} - c^{ek}_{mm't}\right). \tag{22}$$

This Equation shows that the average value of being in CZ m before moving depends on the utility offered by *all* possible destinations $u^{ek}_{m't}$; however, the utility of destinations is reduced by the bilateral moving cost between m and m' $c^{ek}_{mm'}$.

5.2 Step 2: Estimation of Model Parameters

In the second step, we treat estimated county-utilities $\hat{\chi}^{ek}_n$ as data and estimate model parameters by decomposing groups' mean county-utility into the weights that groups' place on different local characteristics.

The altruism parameter β is the weight that parents place on local child opportunities $o_t(e,n)$, which are a function of local continuation values $v_{t+1}(e,k,m)$. We therefore now need to make assumptions on families' expectations about future values. We assume that parents are naive and expect local values to remain the same in their children's generation, i.e. we impose $v_{t+1}(e,k,m) = v_t(e,k,m)$.[41] Given the assumption of naive expectations, we omit time-subscripts as we describe the remainder of the estimation.

For convenience, we repeat the definition of county-utility here:

$$\chi^{ek}_n = a^{ek}_n + \frac{1}{\sigma_N} I^{ek}_n + 1_{k=1}\beta o(e,n),$$

where estimates of county-utilities $\hat{\chi}^{ek}_n$ and real income I^{ek}_n are known,[42] but residential

has also been used in several relevant papers including Artuç and McLaren [2015] and Bryan and Morten [2018].

[41] In future extension, we can assume that families have perfect foresight and correctly predict future values in all locations. To do so, we can estimate value functions $v_t(e,k,m)$ in consecutive decades as data is available for 1990, 2000, and 2010. Under perfect foresight, parents in $t = 2000$ would expect future values to be equal to the values that we estimate from the observed 2010 data, i.e. $v_{2010}(e,k,m)$.

[42] Real income is constructed from data on local rents, wages, and calibrated tax rates and housing expenditure shares.

amenities a_n^{ek} are unobserved.

We first use families without children to identify the dispersion of idiosyncratic taste shocks over neighborhoods σ_N. Then we use families with children to estimate parental altruism β and the dispersion of idiosyncratic education taste shocks σ_E.

Families without Children Identify Dispersion in Neighborhood Taste Shock. For families without children, altruism is zero and county-utility is given by:

$$\chi_n^{e0} = a_n^{e0} + \frac{1}{\sigma_N} I_n^{e0}. \tag{23}$$

Identifying σ_N is challenging because local amenities a_n^{ek} are unobserved and correlated with real income. We therefore need variation in real income that is uncorrelated with unobserved local amenities. To do so, we use two instrumental variable approaches that have been used to solve similar identification problems in the literature. We first use lagged wages as instruments following Artuç and McLaren [2015] and Caliendo et al. [2018]. Alternatively, Equation 23 can be estimated in differences to exploit exogenous variation in *changes* of real income that is unrelated to *changes* in unobserved amenities. Following Diamond [2016], we use Bartik [1991]-like local labor demand shocks interacted with local housing supply elasticities as such instruments. Bartik labor demand shocks rely on the insight that national changes in productivity of certain industries affect locations differentially, depending on the location's initial industrial composition. We construct local labor demand shocks for low and high skill workers by interacting local industry employment with national changes in industry wages for low and high skill workers. These labor demand shocks are used as instruments for changes in local wages w_m^e that are unrelated to changes in unobserved local amenities. Positive local labor demand shocks increase wages and attract additional workers into the labor market. This increases local rents; however, to an extent that depends on the local housing supply elasticities. Hence, the interaction between Bartik labor demand shocks and housing supply elasticities provides variation in changes of local wages and local rents that are uncorrelated with changes in local amenities. To proxy variation in housing supply elasticities across counties, we use data on land-use regulations that is documented for many municipalities in Gyourko et al. [2008] and Saiz [2010]. Using these instruments, we can identify σ_N by estimating Equation 23 in levels and differences by GMM.

We then use the estimate of $\hat{\sigma}_N$ and Equation 23 to infer local amenities as structural residuals in each county in the following way:

$$\hat{a}_n^{e0} = \hat{\chi}_n^{e0} - \frac{1}{\hat{\sigma}_N} I_n^{e0}. \tag{24}$$

These inferred amenities $\hat{a}_n^{e0}$ ensure that the model perfectly fits the estimated county-utilities of non-parents after accounting for their preferences for local real income I_n^{e0}.

Families with Children Identify Altruism and Dispersion in Education Taste Shock. We now use these results and the county-utility estimates of parents to identify parent-specific parameters, which include altruism β and the dispersion of education taste shocks σ_E.

To do so, we first express local Child Opportunities as a function of observables terms:

$$o(e,n) = q(l,m) - \frac{\sigma_E}{\sigma_N} \log\left(\Pr(l|e,n)\right), \tag{25}$$

which is derived in Appendix C.3.[43] $\Pr(l|e,n)$ is the local share of children from families with skill level e that remains low-skilled, which is observed in the data. $q(l,m)$ is the expected value for low-skilled young adults in labor market m before they know whether or not they will have children (recall the definition $q(l,m) \equiv \sum_k \Pr(k|l)v(l,k,m)$). We can construct estimates of $\hat{q}(l,m)$ using known fertility probabilities and our estimates of $\hat{v}(l,k,m)$ (see Equation 22 in first estimation step).

In addition, we need to impose the following identification restriction:

Assumption 2. *Residential amenities differ between skill groups, but not between parents and non-parents, so that* $a_n^{ek} = a_n^e$.

Parents can place a different weight on amenities, which we denote by θ^{e1}. Using Assumption 2 and the expression of Child Opportunities from Equation 25, we can derive the following estimating Equation from parents' county-utilities:

$$\hat{\chi}_n^{e1} - \frac{1}{\hat{\sigma}_N} I_n^{e1} = \quad \theta^{e1}\hat{a}_n^e + \quad \beta\hat{q}(l,m) - \beta\frac{\sigma_E}{\sigma_N}\log(\Pr(l|e,n)), \tag{26}$$

where all variables are known from data or previous estimates. Estimating this Equation by OLS identifies the model parameters θ^{e1}, β and σ_E as regression coefficients on amenities, continuation values, and education outcomes.

Intuitively, Assumption 2 allows us to use residential choices and county-utilities of non-parents to identify the general attractiveness (i.e. unobserved amenities) of locations that is

[43] For this derivation, we normalize costs of remaining low-skilled to zero ($\mathcal{D}_n^{el} = 0$), which is without loss of generality.

independent of local Child Opportunities. Then we use differences in county-utilities between parents and non-parents to identify parent-specific parameters. Altruism is identified from the extent to which parents value locations with better Child Opportunities more than non-parents, after adjusting for differences in preferences between parents and non-parents. Assumption 2 is crucial for this identification. Without restrictions on amenities $\mathcal{A}_n^{ek}$, *all* differences in residential choices or county-utilities between parents and non-parents could simply be explained by differences in parent-specific amenities. Suppose, for example, that altruism is erroneously assumed to be zero. As true altruism is positive, parents will sort more than non-parents into places with better Child Opportunities. To rationalize this sorting behavior, together with the imposed absence of altruism, the model simply infers that locations with better Child Opportunities have higher *parent*-specific amenities $\mathcal{A}_n^{e1}$, i.e. the model would predict a positive correlation between local Child Opportunities and amenity differences between parents and non-parents: $corr\left(O(e,n)\ ,\ \mathcal{A}_n^{e1} - \mathcal{A}_n^{e0}\right) > 0$. This illustrates that differences in residential choices between parents and non-parents can only identify parent-specific preferences with additional restrictions on amenities.

5.3 Regional fundamentals

We now infer latent regional characteristics as structural residuals by fitting key model predictions to data moments in each location. We infer total factor productivity, skill intensity, housing supply and exogenous education costs. Amenities were already inferred and used in Section 5.2.

Production Technology Given CES production technologies, firms' first order conditions (Equation 14) predict that relative wages between low and high skill workers w_m^e depend on the relative skill supply L_m^e and relative skill intensity $\mathcal{S}_m^e$. It follows that skill intensities $\mathcal{S}_m^e$ can be inferred from:

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

where we set $\rho = 1/3$ and recall that $S_m^h + S_m^l = 1$.

Productivity $\mathcal{Z}_m$ is inferred by fitting firm's first order conditions to data on local output, wage levels, and labor supply, so that:

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

Housing Supply. We infer housing supply $\mathcal{H}_n$ from local housing market clearing (Equation 32) using data on housing expenditure and rental rates, so that:

$$\mathcal{H}_n = \frac{1}{r_n} \sum_e \sum_k \alpha^{ek} Y_n^e L_n^{ek}.$$

Exogenous Education Costs. Local education choices depend on local school funding f_n, returns to education $Q(h,m) - Q(l,m)$, and exogenous education costs $\mathcal{K}_n^{eh}$.[44] Hence, education costs are inferred as structural residuals that fit this Equation to the data, so that:

$$\mathcal{K}_n^{eh} = Q(h,m) - Q(l,m) + \gamma^e \log(f_n) - \sigma_E \log\left(\frac{\Pr(h|e,n)}{1-\Pr(h|e,n)}\right). \tag{27}$$

Education Costs and Amenity Levels across Skill Groups. We show in Appendix C.4 that amenities a_n^e and exogenous education cost $\mathcal{K}_n^{eh}$ are jointly identified up to constant of normalization within each (parental) skill group. It is therefore without loss of generality to normalize amenity levels a_n^e within each skill group. Any such normalization generates observationally equivalent outcomes (in residential and education choices) because levels of estimated value functions $V(e,k,m)$ and exogenous education costs $\mathcal{K}_n^{eh}$ re-adjust to each normalization. More information on this result and the identification of amenities and education costs is provided in Appendix C.4.

6 Estimation Results

Parameters. Table 4 shows the GMM results that identify the dispersion in neighborhood taste shocks σ_N from the relation between non-parental county-utility and exogenous variation in real incomes. Panel A estimates Equation 23 in levels using lagged wages as instruments for real income, while Panel B estimates Equation 23 in differences using Bartik shocks, along with their interaction with land-use regulations as instruments for changes in real income. Panel B has a smaller sample as measures of land-use regulation (obtained from

[44] This is derived in Equation 9. Recall that we normalize the total cost of remaining low-skilled to zero without loss of generality, $\mathcal{D}_n^{el} = 0$.

Table 4: **GMM Results using Non-Parental County-Utilities**

	(1) 2000	(2) 2010	(3) all years
Panel A: Lagged wage as IV			
Dep. var.: County-Utility Non-Parents (level)			
Real income	7.312***	12.81***	10.09***
	(0.729)	(1.115)	(0.860)
Observations	2,793	2,795	5,588
Panel B: Bartik × housing regulation as IV			
Dep. var.: County-Utility Non-Parents (difference)			
Δ Real income	15.67***	0.0140	12.04***
	(3.562)	(1.509)	(3.179)
Observations	1,111	1,131	2,242

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Notes: We restrict the sample to exclude outliers at the 1st percentile of estimated CZ-utilities, which contains mostly small CZs for which moving data is sparse. Regressions which pool data across decades include time fixed effects.

Gyourko et al. [2008]) are only available for a subset of counties. We estimate the IV regressions separately for each decade and then pooled across decades, where the latter includes time fixed effects. Across different model specifications and samples, estimates for $1/\sigma_N$ vary between 7.3 and 15.5. We use $1/\sigma_N = 12$ as our preferred estimate. This is aligned with recent estimates from the literature, such as Allen and Donaldson [2018].

Table 5 shows the estimation results of Equation 26, where we regress parental county-utility adjusted for their valuation of real income $\hat{\chi}_n^{e1} - \frac{1}{\hat{\sigma}_N} I_n^{e1}$ on local amenities $\hat{a}_n^e$, continuation values for low-skilled workers $\hat{q}(l, m)$, and the probability of remaining low-skilled $\Pr(l|e, n)$. The sample is pooled across education backgrounds and results are presented separately for each decade and then pooled across decades.[45] The results of the pooled sample (column (4) of Table 5) are our preferred estimates. We find that parents place a smaller weight on amenities ($\theta^{e1} = 0.84$) compared to non-parents, for whom the weight is normalized to one. In the pooled sample, altruism β and the dispersion of education taste shocks σ_E are both equal to 0.11.

Table 5 furthermore shows that the R^2 values are large across all samples, which indicates that the model is able to fit parents' county-utility well despite Assumption 2, which restricts

[45] We include education and time fixed effects in regressions with pooled samples.

Table 5: **OLS Results for Parent-Specific Parameters**

	(1) 1990	(2) 2000	(3) 2010	(4) all years
Panel A: Regression coefficients pooling education backgrounds				
Dependent var.: County-Utility Parents (net of real income)				
Amenity a_n^e	0.887***	0.763***	0.872***	0.835***
	(0.005)	(0.007)	(0.006)	(0.004)
Value of Low-Skilled $q(l,m)$	0.054***	0.186***	0.289***	0.113***
	(0.005)	(0.016)	(0.019)	(0.006)
Prob Remaining Low-Skilled	-0.101***	-0.200***	-0.157***	-0.154***
$Pr(l\|e,n)$	(0.016)	(0.024)	(0.020)	(0.012)
Observations	4240	4278	4280	12798
R-squared	0.959	0.909	0.953	0.941
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				
Panel B: Implied Model Parameters				
Parent Pref. for Amenities	0.887	0.763	0.872	0.835
Altruism	0.054	0.186	0.289	0.113
Disp. Educ. Taste Shock	0.154	0.090	0.045	0.114
Disp. County Taste Shock	0.083	0.083	0.083	0.083

Notes: We restrict the sample to exclude outliers at the 1st percentile of estimated CZ-utilities, which contains mostly small CZs for which moving data is sparse.

amenities to be the same for parents and non-parents. In Appendix D.1, we provide more details about the model fit for parents. In addition, we show there that our inferred amenities are correlated with observable characteristics that have been used in the literature to proxy local amenities.

Transitional Dynamics and Changes in Regional Fundamentals. To evaluate policy counterfactuals in our model, we have to make assumptions on the evolution of regional fundamentals. Data shows that the economy is in transition over the last decades because observed endogenous outcomes, such as local wages, rents, education and residential choices change over time. These aggregate dynamics can be driven by ongoing changes in regional fundamentals or they can represent transitional dynamics, which are slow adjustments of endogenous variables in response to past shocks to fundamentals.[46] We use data from 1990,

[46]Convergence of education levels and local populations toward a new steady state can take a long time, due to frictions in mobility and human capital accumulation.

2000 and 2010 to evaluate both of these explanations. We find that regional fundamentals are strongly correlated across these decades (see Appendix C.5). We therefore conclude that transitional dynamics (and not changes in fundamentals) seem to be the main driver of observed changes in endogenous outcomes. Given this finding, we hold fundamentals constant at levels implied by the 2010 data when we evaluate policy counterfactuals.

7 Decomposition and Policy Counterfactuals

We now use the estimated model to study the effects of counterfactual policy interventions, in particular school funding reforms and rent subsidies. We evaluate the long run effects of policies by comparing the steady states of a baseline and counterfactual economy. To solve for the baseline steady state, we fix regional fundamentals $\{\Theta_{2010}\}$[47] and school financing policies $\{\Gamma_{2010}\}$[48] at values that we infer from the 2010 data. For the policy counterfactuals, we again fix regional fundamentals $\{\Theta_{2010}\}$ and we implement the respective policy of interest by changing taxes and the allocation of school funding or by introducing rent subsidies.[49]

We evaluate the effects of these policies on education outcomes, child opportunities and welfare. In particular, we study whether the policies can reduce differences in opportunities and education outcomes between children from low and high skill families. In addition, we document the effects of policies on the cross-sectional dispersion of relevant outcomes to examine whether the policies can reduce the opportunity gap across locations.

7.1 Baseline Steady State and Decomposition

Baseline Steady State. Recall that education choices differ across locations due to differences in local returns to education $Q(h,m)-Q(l,m)$ and local education costs $\mathcal{D}_n^{eh}$, where the latter can be decomposed into local per-student school funding f_n and local exogenous education costs $\mathcal{K}_n^{eh}$ (as shown in Equation (9)). In the baseline steady state, we find that

[47] These include productivities, skill intensities, moving costs, residential amenities, housing supply, and exogenous education costs: $\Theta_t \equiv \left(\mathcal{Z}_{mt}, \mathcal{S}_{mt}^{e}, \mathcal{C}_{mm't}^{ek}, \mathcal{A}_{nt}^{ek}, \mathcal{H}_{nt}, \mathcal{K}_{nt}^{ee'}\right)$.

[48] These include federal, state, and local tax rates, and the shares of per-student school funding that federal and state governments allocate to each neighborhood $\Gamma_t \equiv \left(\tau_{\boldsymbol{gt}}^{\boldsymbol{w}}, \tau_{st}^{\boldsymbol{w}}, \tau_{nt}^{\boldsymbol{r}}, \delta_{nt}^{\boldsymbol{g}}, \delta_{nt}^{\boldsymbol{s}}\right)$.

[49] Given a set of regional fundamentals and government policies $\bar{\Theta}$, the stationary equilibrium is defined by a time-invariant, ergodic distribution of population (i.e. workers) across neighborhoods, skills, and family types $L(e,k,n)$ that is consistent with the law of motion in Equation (12), and with utility-maximizing residential and education choices that satisfy Equations (8) and (11). Young adults can still move across neighborhoods and skill levels change across generations of the same dynasty. However, these changes balance in the stationary equilibrium so that the aggregate adult population of each demographic group remains constant in each neighborhood, i.e. the distribution of workers $L(e,k,n)$ is time-invariant.

local education outcomes are strongly and negatively correlated with exogenous education costs (-0.67). However, education outcomes are only weakly correlated with local returns to education (0.06) and local school funding (0.1). To explain these weak correlations, the model infers that exogenous education costs are positively correlated with returns to education (0.4) and school funding (0.46).[50] Recall that wages and therefore returns to education are endogenously determined by local labor market clearing. Hence, the positive correlation between education costs and returns to education can be explained by the fact that high local education costs limit local skill supply, which directly leads to higher skill premia and higher returns to education. The positive correlation between exogenous education costs and school funding suggests that a part of school funding is already targeted towards places with high education frictions. This indicates that the current school funding system already seems to have some redistributive (or equalizing) elements.

Decomposition. To study the importance of these channels in driving the cross-sectional dispersion of education outcomes, we first equalize returns to education $Q(h,m) - Q(l,m)$ and then total education costs $\mathcal{D}_{nt}^{eh}$ across all locations. To measure the cross-sectional dispersion we use the ratio between the 90th and 10th percentile (population-weighted), which we denote by P90-P10.

To equalize returns to education we set moving costs to zero, so that all children have equal access to all labor markets. Surprisingly, this experiment *increases* the P90-P10 ratio of the probability of going to college from 2.2 to 2.9 for low skill families and from 1.38 to 1.6 for high skill families. This increase is driven by the fact that more families live in locations with very low and very high exogenous education costs $\mathcal{K}_n^{eh}$ after the elimination of moving costs, which increases the (population-weighted) dispersion in exogenous education costs.

We then equalize total education costs by setting it to the mean value. This experiment *decreases* the P90-P10 ratio of college attainment from 2.2 to 1.3 for low skill families and from 1.38 to 1.09 for high skill families. The reduction is large because the equalization of education costs also substantially decreases the variation in returns to education.[51] To understand this additional effect, recall that education costs are positively correlated with returns to education (and skill premia) in the baseline. The equalization of costs therefore decreases education costs in locations where returns are *initially high*. This reduction in education costs increases education and local skill supply, which depresses local high skill

[50] Recall that exogenous education costs are inferred as structural residuals that perfectly fit the model to data on local education outcomes, returns and school funding. If a location has low education outcomes despite high school funding and high returns to education, the residual approach therefore infers that other education costs $\mathcal{K}_n^{eh}$ must be high in this location, which prevent children from going to college.

[51] The P90-P10 ratio of returns decreases from 1.35 to 1.1.

wages and skill premia. Local returns to education therefore decrease in locations that started with high returns to education in the baseline. The opposite is true for locations that started with low returns so that the cross-sectional dispersion of returns to education decreases. This decomposition illustrates that the properties of the baseline steady state, as well as interactions between different channels and geographic linkages, are important to understand the effects of counterfactuals.

Keeping the discussed properties of the baseline steady state in mind, we now study the effects of school funding reforms.

7.2 Equal School Funding

First we consider a school funding reform, where the federal government raises all school funding through federal taxation and allocates it equally across all students. The reform is budget neutral, state and local taxes are set to zero, and we set the federal tax rate to ensure that the government balances its budget. In Section 7.2.1, we discuss how the reform affects education outcomes, child opportunity and welfare of children from low and high skill families. In Section 7.2.2 we focus on the effects on specific regions and the cross-sectional dispersion of outcomes.

7.2.1 Equal Funding and Opportunity Gaps Between Children from High and Low Skill Families

Effects of Equal School Funding on Education Outcomes. Table 6 documents the effects of equalizing school funding on education outcomes for children from low and high skill families. Column 1 documents population-weighted averages of education outcomes in the baseline steady state.[52] We find that average college attainment is 67 percent, which is equal to 45 percent for children from low skill families and 78 percent for children from high skill families. The equalization of school funding increases average per-student funding by 1.9 percent for children from low skill families and decreases it by 0.9 percent for children from high skill families. This implies that low skill families lived on average in counties with less resources before the reform, because we assume that school funding is equally available to all students in a given county.[53]

[52]The economy converges to this baseline steady state if we hold regional fundamentals and school funding policies constant.

[53]Aggregating school funding to the county level can underestimate initial differences in school funding. In future work, we therefore intend to extend our analysis to the school-district level. This extension is trivial from a computational and theoretical standpoint. However, the causal effects of neighborhoods on children's probability of going to college (Chetty and Hendren [2018]) is not available at the school-district level, so

Table 6: **Effects of Equal Funding on Education Outcomes**

	(1) *Level* **Baseline Steady State**	(2) *Equal Funding: Changes from Baseline* **Partial Equilibrium**	(3) **General Equilibrium**
Probability of College Education			
All Children	66.79	0.80 pp.	0.25 pp.
Children with Low Skill Parents	44.58	2.84 pp.	0.92 pp.
Children with High Skill Parents	77.83	-0.22 pp.	-0.21 pp.

Notes: This table shows the effects of equalizing school funding on education outcomes for children from low and high skill families. Column 1 shows college enrollment rates in the baseline; columns 2 and 3 represent changes from the baseline. Column 2 documents the direct effects of school funding, as prices and location choices are fixed. This corresponds to the short-run partial equilibrium. Column 3 shows the effects in general equilibrium, where we allow for changes in local prices and skill compositions. The reform increases per-student school funding by 2% for children from low skill families and decreases it by 1% for children from high skill families.

Column 2 of Table 6 shows the short run effects of the policy on the first cohort, for which prices and families' locations are fixed.[54] These effects are exclusively driven by changes in local school funding, as other mechanisms are held constant, and we refer to this experiment as Partial Equilibrium (PE). We find that the share of children that obtains college education increases by 0.8 percentage points (pp.) on average, which consists of an increase of 2.8 pp. among low skill families and a decrease of 0.2 pp. among high skill families.

Column 3 of Table 6 documents the long run general equilibrium (GE) effects, where we allow for responses in rents, wages, and families' education and moving choices. In GE, we find that college education increases by only 0.25 pp. on average. The increase in college education is now much smaller for low skill families (1 pp. compared to 2.8 pp. in PE), while the effects remain the same for high skill families.

Mechanisms. We now investigate the mechanisms that mitigate the effects on education outcomes in GE. Local education choices are driven by school funding, returns to education, and exogenous education cost. The policy directly determines school funding changes, which are the same in PE and GE by definition.[55] Therefore, changes in returns to education

that we would need to make additional assumptions to estimate our model.

[54]This is equivalent to announcing the policy after families moved, but before they choose their children's education. In addition, we assume that continuation values remain the same as rents and wages are constant.

[55]Funding increases on average by 2 percent for low skill families and decreases by 1 percent for high skill families.

$Q(h,m) - Q(l,m)$ or exogenous education costs $\mathcal{K}_n^{eh}$ have to explain the difference between the PE and GE results. We document these changes in Table 7.

By definition, returns to education and exogenous education costs do not change in PE, as families' locations and prices are fixed. In GE aggregate skill supply increases, which reduces the average skill premium by 1.3 percent and returns to education by 1.35 percent (as shown in Column 2 of Table 7).

In addition, average exogenous education costs increase in GE by 0.7 percent for children from low skill families, but decrease by 1.13 percent for children from high skill families. Recall that exogenous education costs are constant in each location; however, the proportion of families that lives in locations with low or high costs can change in response to policies, which affects the average education cost to which children are exposed. Further recall that school funding is positively correlated (0.46) with exogenous education costs in the baseline (as discussed in Section 7.1). This implies that the equalization of school funding *decreases funding* in locations where *exogenous education costs are high*. These changes in school funding have two effects on the local skill mix in these high-education-cost locations. First, it affects local skill production because lower school funding reduces local education outcomes. As moving is costly, this implies that more low-skilled and less high-skilled families live in these locations after the reform. Secondly, it affects net migration of different skill groups due to changes in wages. Specifically, the reduction in local skill supply increases high-skilled wages and depresses low-skilled wages in high-education-cost locations. These wage changes attract more high-skilled workers, so that net in-migration of high skill families increases into the (high-education-cost) locations, while it decreases for low skill families. Overall, changes in local skill production dominate migration effects, so that more low-skilled families live in high-education-cost places after the reform, which increases average education costs for their children. The opposite holds for high skill families, so that average education costs decreases for their children.

To summarize, we find that the increase in the college attainment rate is mitigated in GE for children from low skill families due to a decrease in average returns to education *and* a shift of low skill families towards locations, where exogenous education costs are higher. For high skill families, effects are the same in PE and GE, because lower returns to education are offset by a reduction in average exogenous education costs.

To further disentangle the role of rent and wage changes in driving the GE effects, we now document how our results change when we hold each of these prices constant, while allowing for all other GE effects. These experiments are documented in columns 3 and 4 of Table 7.

Column 3 shows that effects on education outcomes with constant rents are larger than

Table 7: **Effects of Equal Funding on Education Outcomes: Mechanisms**

	(1) Partial Equilibrium	(2) General Equilibrium	(3) GE Fixed Rents	(4) GE Fixed Wages
Probability of College Education				
All Children	0.80 pp.	0.25 pp.	0.39 pp.	0.68 pp.
Children of low skill parents	2.84 pp.	0.92 pp.	1.06 pp.	-0.19 pp.
Children of high skill parents	-0.22 pp.	-0.21 pp.	-0.13 pp.	0.77 pp.
Return to College Education				
Children of low skill parents	0 %	-1.35 %	-2.10 %	0.24 %
Children of high skill parents	0 %	-1.36 %	-2.17 %	-0.08 %
Skill Premium	0 %	-1.29 %	-2.32 %	0.10 %
Exogenous Education Cost				
Children of low skill parents	0 %	0.71 %	-1.35 %	6.99 %
Children of high skill parents	0 %	-1.13 %	-2.80 %	-2.30 %

Notes: All numbers in this table represent *changes* from the baseline steady state. Determinants of local education choices—returns to education and education costs—are presented in the row dimension. We document how the reform affects these mechanisms and education outcomes in several exercises: First, we consider PE, where local prices and families' locations are fixed (column 1). In full GE, we allow for responses in local prices and local skill compositions (column 2). Last, we consider restricted versions of GE, where we first hold rents (column 3) and then wages (column 4) constant, while allowing for responses in the other price and local skill compositions.

in full GE (column 2). This is true despite an even larger decline in average returns to education, because average exogenous education costs now also decline for children from low skill families and even more for children from high skill families. In full GE, rents increase in low-education-cost locations after the reform, as these locations receive on average more school funding and produce more high skill workers. Holding local rents constant therefore makes low-education-cost places relatively more attractive for both skill groups, so that more families live in them, which decreases children's average education costs. Lower average education costs dominate the additional decline in returns to education, so that college education is higher than in full GE.

Column 4 shows that aggregate education increases by 0.68 pp. when holding wages constant, which is similar to the PE results. However, effects on intergenerational mobility are very different in this experiment, as college education increases for high skill families by 0.77 pp., but declines for low skill families by 0.2 pp. As wages are constant, we find only small changes in average returns to education.[56] However, changes in average education costs are large, with a 2.3 percent decrease for children from high skill families and 7 percent increase for children from low skill families. Recall that in full GE, high-education-cost locations receive less school funding after the reform, so that these locations produce less high-skilled workers, which reduces local skill supply. This decreases low skill wages and increases high skill wages. These wage changes attract high skill workers to move into these high-education-cost locations, while more low skill workers move out. Now that we hold wages constant, more low skill parents stay in these high-education-cost locations, so that average education costs increase much more for their children (by 7 percent). Overall, the school funding equalization with constant wages decreases college education among children from low skill families due to the large increase in exogenous education costs, despite the increase in average school funding. For children from high skill families, average education costs decrease, so that their college attainment increases due to the reform.

The discussion of mechanisms emphasizes that interactions between local factor prices and households' education and residential choices are important to evaluate the long-run effects of school financing reforms on education outcomes. This highlights the advantages of our spatial framework, which accounts for these interactions and predicts how the skill composition, and so the exposure of children to specific locations, changes in response to policies. In Appendix D.2 we furthermore test the sensitivity of our results on education outcomes to key parameter estimates.[57]

[56]The population-weighted average of the skill premium increases by 0.1 percent due to changes in population weights.

[57]Specifically, we show how the effects on college education change if we separately vary one of our three key parameters: altruism β and either the dispersion of neighborhood or education taste shocks σ_N, σ_E.

Table 8: **Effects of Equal Funding on Child Opportunities and Welfare**

	(1) Baseline Steady State	(2) Change under Equal Funding
Expected Income		
Children with Low Skill Parents	0.94	0.60%
Children with High Skill Parents	1.12	-0.43%
Child Opportunity (i.e. expected utility)		
Veil of Ignorance	0.58	1.52%
Low Skill Parents	0.50	1.92%
High Skill Parents	0.62	1.30%
Welfare of Young Families		
Low Skill Non-Parents	0.39	1.30%
High Skill Non-Parents	1.01	-0.18%
Low Skill Parents	0.40	1.46%
High Skill Parents	1.01	-0.23%

Notes: This table documents the effects of equalizing school funding on children's expected income, Child Opportunities, and welfare—each for different demographic groups. We compute population-weighted averages of these outcomes over all locations. Column 1 documents the outcomes in levels in the baseline. Column 2 shows percent changes from the baseline. We compute expected income for children from each parental background in each childhood location by taking the expectation over children's future skill levels, parent status, and moving decisions. Child Opportunities are expected utility levels of children before education outcomes are known. Welfare is expressed for young adults who finished their education, learned their parent status, but still live in the labor markets where they grew up.

Effects of Equal School Funding on Child Opportunities and Welfare. Table 8 documents the long-run effects of equalizing school funding on expected income and expected utility for children from low and high skill families, as well as welfare measures for young adults.

We compute expected income for children from each parental background in each childhood county by taking the expectation over children's future skill levels, parent status, and moving decisions. We find that expected income increases by 0.6 percent for children from low skill families and decreases by 0.4 percent for children from high skill families.

In addition, we find that Child Opportunities increase for all children. Child Opportunities are defined as the expected utility of children before education choices (and idiosyncratic education taste shocks) are known. First, we consider Child Opportunities under the veil of ignorance, where we take the expectation over children's utility across the skill levels and locations of potential parents. We find that this welfare measure increases by 1.52 percent.

Table 9: **Opportunity Gap across Locations**

Ratio 90th to 10th Percentile	(1) Baseline	(2) Equal Funding GE
Probability of College Education		
Children with low skill parents	2.2	2.49
Children with high skill parents	1.38	1.45
Child Opportunity (i.e. expected utility)		
Children with low skill parents	1.3	1.37
Children with high skill parents	1.36	1.44

Notes: This table documents the cross-sectional dispersion of key outcomes before (column 1) and after (column 2) the reform. Column 3 computes the percent changes in the dispersion measures. Specifically, we compute the ratio of key outcomes between counties at the 90th and 10th percentile (P90-P10 ratio). We find that the cross-sectional dispersion of education outcomes and Child Opportunities both increase after the reform. This fact further holds for children from both low and high skill families.

In addition, Child Opportunities increase by 1.9 percent for children from low skill families and by 1.3 percent for children from high skill families. For children from low skill families, this increase is due to both a higher average probability of going to college and higher average wages for low skill adults. Expected utility also increases for children from high skill parents in spite of a lower average probability of going to college, because wages and expected utility levels are higher for children who remain low-skilled. In addition, children from high skill families face lower average education costs after the reform (as shown in Table 7).

Last, we document the effects of the reform on average welfare for young adults, who finished their education, learned whether they have children, but still live in the labor markets where they grew up. This welfare measure increases for low skill families by 1.3 percent if they do not have children and by 1.5 percent if they do. For high skill families, welfare decreases by 0.2 percent if they do not have children and by 0.23 percent if they do.

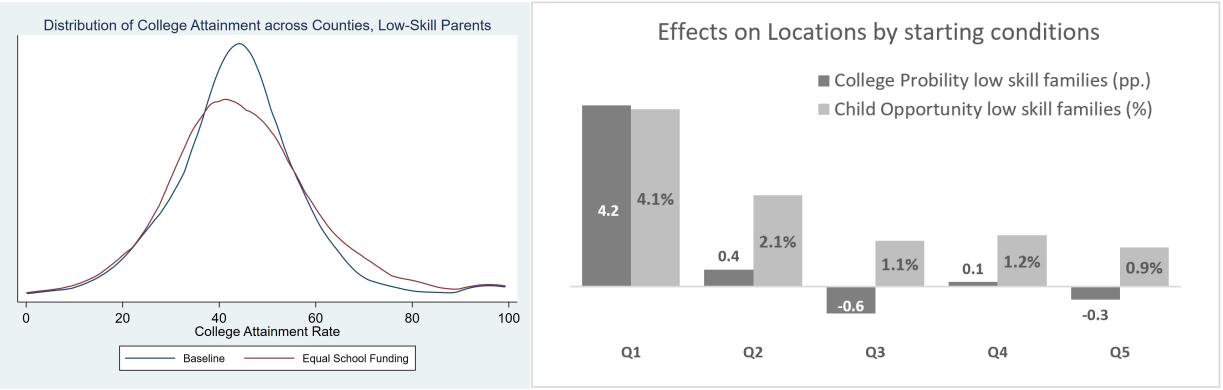
Overall, we conclude from this Section that an equalization of school funding moderately reduces the gap in education outcomes, expected income, and opportunities between children from low and high skill families. Our results further show that the effects are smaller in GE than in PE, which highlights the importance of accounting for GE effects.

7.2.2 Equal School Funding and the Opportunity Gap Across Locations

We now turn to the second key question: can an equalization of school funding reduce the opportunity and achievement gap across locations?

As above we use the P90-P10 ratio to measure the cross-sectional dispersion of outcomes.

Figure 2: **Equal Funding: Cross-Sectional Dispersion and Effects on Specific Locations**



Notes: Both graphs in this figure focus on children from low skill families. The left graph of this figure plots the density of college enrollments rates in the baseline steady state and after the equalization of school funding across all students. The right graph of this figure shows how the reform affects college education and Child Opportunities in locations with different starting conditions. To do so, we group counties into quintiles based on their college attainment rates prior to the reform. The first quintile (Q1) corresponds to the lowest initial education outcomes. We find that college education and Child Opportunities improve most in those counties that had low education outcomes prior to the reform. Recall that Child Opportunities are defined as the expected utility of children before they know their education outcomes. Therefore, Child Opportunities can increase in counties despite a lower probability of going to college, since low skill wages increase after the reform, which raises the expected utility of children who remain low-skilled.

Table 9 shows that the equalization of school funding *increases* the P90-P10 ratio of the probability of going to college from 2.2 to 2.5 for low skill families and from 1.38 to 1.45 for high skill families. The left graph of Figure 2 plots the densities of college attainment rates among children from low skill families—in the baseline and after the reform. The density shows that the mass increases at lower and higher college attainment rates, so that the overall dispersion increases after the reform. By definition, the reform eliminates the cross-sectional dispersion of school funding; however, the dispersion of returns to education and of total education costs increase after the reform. Recall that education outcomes and school funding are only weakly correlated in the baseline (0.1). Equalizing school funding is therefore not enough to compensate the other effects, so that the cross-sectional dispersion of education outcomes increases.

The cross-sectional variation in returns to education increases due to the following mechanism. Prior to the reform, local school funding is positively correlated with returns to education (0.2). Equalizing school funding consequently increases funding in locations where returns to education (and skill premia) *are initially low*. Higher funding increases local college attainment and local skill supply, which further depresses skill premia in the locations that already started with lower skill premia prior to the reform. Consequently, the P90-P10

ratio increases from 1.37 to 1.49 for skill premia and from 1.35 to 1.4 for returns to education. In addition, recall that total education cost $\mathcal{D}_{nt}^{eh}$ consists of school funding f_n and exogenous education costs $\mathcal{K}_{nt}^{eh}$. Further recall that exogenous education costs and school funding are positively correlated in the baseline (0.46). Equalizing school funding consequently *decreases* funding in locations where exogenous education costs are high. This change increases total education costs in locations that already started with higher education costs prior to the reform, which increases the cross-sectional variation in total education costs.

Table 9 further shows that the cross-sectional dispersion of Child Opportunities[58] increases, which is due to higher variation in education outcomes and wages.

Effect on locations with different starting conditions. So far we discussed changes in the cross-sectional dispersion of outcomes. However, this provides only limited information about the effects of the reform on specific regions. We therefore now examine how the reform affects locations that started with different education outcomes prior to the reform. To do so, we group counties into five quintiles based on their initial college attainment rates in the baseline (where Q1 corresponds to lowest education). We then document the effects of the equalization of school funding on college education and Child Opportunities in each of these quintiles. We see in the right graph of Figure 2 that effects are largest for counties in Q1, for which the probability of going to college increases by 4.2 percentage points (pp.) and Child Opportunities increase by 4.1 percent on average. Effects on college education are much smaller or even negative in counties, which initially had better education outcomes. Child Opportunities increase in all quintiles, but more in counties which have low education outcomes prior to the reform. Specifically, Child Opportunities increase by 4 percent in Q1, by 2 percent in Q2, and by approximately 1 percent in counties of higher quintiles. Child Opportunities are defined as the expected utility of children before they make their education choice. Child Opportunities therefore depend on expected college attainment and the continuation values for low and high skill adults. Welfare of low skill adults increases under the policy so that Child Opportunities increase in all quintiles even if average college attainment decreases.[59] Overall, the right graph of Figure 2 shows that an equalization of school funding would disproportionately benefit those locations which have the lowest education outcomes prior to the reform. Nevertheless, the cross-sectional dispersion of education outcomes increases after the reform (as discussed above), because

[58]Recall that Child Opportunities are defined as the expected utility of children before they learn their education taste shocks and before they choose their education.

[59]Higher welfare for low skill adults (i.e. less inequality) can therefore be interpreted as an insurance mechanism, because it offers a higher continuation value to children who receive low education taste shocks and remain low-skilled.

Table 10: **Effects of Target School Funding Reforms on Education**

Changes from Baseline; pop-weighted averages	(1) *Minimum f_n* **PE**	(2) *Minimum f_n* **GE**	(3) *Incr. f_n if educ. low* **PE**	(4) *Incr. f_n if educ. low* **GE**
Share of Children in College	1.23	0.26	0.81	0.17
Low-skill Parents (pp)	1.80	0.40	1.16	0.25
High-skill Parents (pp)	0.95	0.06	0.64	0.05
Funding p.st., low-skill fam. (%)	2.6	2.9	2.3	2.4
Funding p.st., high-skill fam. (%)	2.1	2.1	1.8	1.8

Notes: This table shows the effects of targeted school funding reforms on college enrollment among children from low and high skill families. All numbers represent changes from the population-weighted averages in the baseline steady state (documented in Column 1 of Table 6). Columns 1 and 2 show the effects of a school funding reform that guarantees a minimum level of per-student school funding to all students. Columns 3 and 4 focus on a reform that increases school funding by 10 percent in locations where education outcomes lie in the lowest quartile prior to the reform. For both reforms, we first show the results in partial (PE) and then general equilibrium (GE), which is defined in the same way as in Table 6.

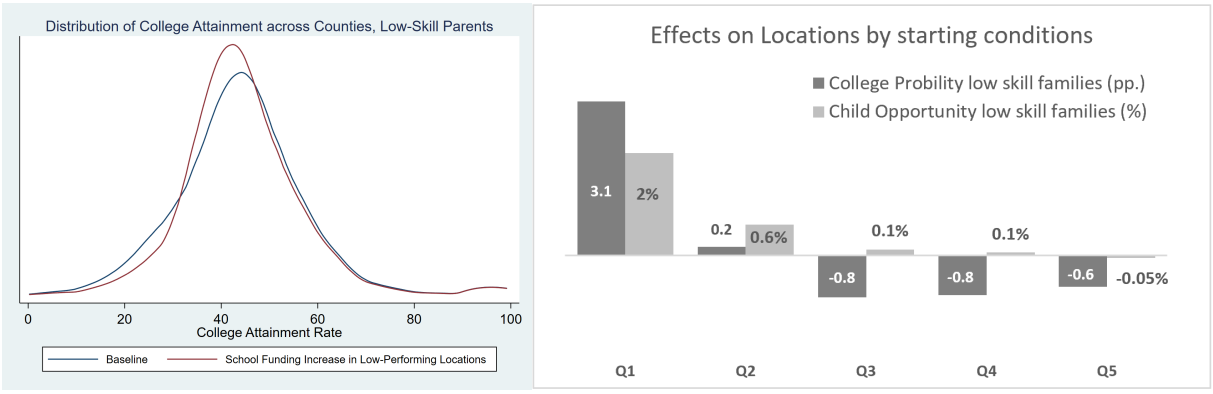
the lowest performing counties before and after the reform are not the same ones.

7.3 Targeted School Funding

In this Section we briefly discuss the effects of two alternative school funding reforms that target specific locations. The first reform guarantees a minimum level of school funding to all students. All other tax and school funding policies remain the same, but the federal government now provides additional resources to locations where per-student funding lies below the guaranteed level. For the minimum funding level, we choose the 25th percentile of per-student school funding in the baseline. In the second reform, the federal government increases school funding by 10 percent in all locations where education outcomes were particularly low (bottom quartile) prior to the reform. Table 10 shows that both reforms increase per-student school funding for low and high skill families, but the increase is higher for children from low-skilled families. Similarly, college attainment increases among children from low- and high-skilled families, but effects are larger for children from low-skilled families. Effects are again mitigated in GE, which is mostly driven by a decrease in average returns to education.

In addition, we again examine the effects of the targeted school funding reforms on specific regions. Effects of both reforms go in the same direction and only differ slightly in magnitude, so that we focus here on the reform that increases school funding in locations where education

Figure 3: **Targeted Funding: Cross-Sectional Dispersion and Effects on Specific Locations**



Notes: This figure shows the same outcomes as figure 2; however, this figure focuses on a reform that increases school funding in locations where education outcomes are low in the baseline steady state. The left graph of this figure plots the density of college enrollments rates among children from low skill families in the baseline steady state and after the reform. The right graph shows the effects on college education and Child Opportunities for locations with different education levels prior to the reform.

is low prior to the reform. The left graph of Figure 3 shows that the cross-sectional dispersion of education outcomes decreases after the reform for children from low skill families. In particular, we find that the P90-P10 ratio decreases from 2.2 to 1.9. The reduction in variation is mostly driven by improvements in locations with lower outcomes, because the reform specifically targets locations which have low education outcomes prior to the reform.

In the right graph of Figure 3, we document again the effects of the reform on locations that start with either low or high education outcomes prior to the reform (see Section 7.2.2 for more details on the construction of the graph). We find that education outcomes and child opportunities increase most in counties which have the lowest outcomes prior to the reform (Q1). College attainment decreases in higher quintiles; however, Child Opportunities increase in most counties.

We can now compare the targeted reforms to the equalization of school funding. First, we note that the equalization of school funding is budget-neutral, while targeted reforms increase school funding by approximately 2 percent.[60] In addition, we find that targeted reforms have smaller effects on education outcomes and intergenerational mobility. However, the cross-sectional dispersion of education outcomes and Child Opportunities decreases under the targeted reforms, while it increases under the equalization of school funding. Hence, targeted reforms can reduce the achievement and opportunity gap across locations, while the equalization of school funding is more effective in reducing the achievement and opportunity

[60]The additional expenditure corresponds to 0.1 percent of aggregate wage income in the economy.

gap across socio-economic backgrounds.

7.4 Rent Subsidies

Targeted rent subsidies is another policy that can increase social mobility by providing incentives to disadvantaged families to move to locations that provide better opportunities for their children. A well-known study of such a policy is the Moving to Opportunity (MTO) experiment, which offered housing vouchers to randomly selected families if they moved from high-poverty housing projects to lower-poverty neighborhoods. Previous research (e.g. Katz et al. [2001]) found that these moves had no significant effects on earnings and employment rates of adults. A recent study by Chetty et al. [2016] analyzes MTO's effects on children's long-term outcomes and the authors find that moving to a lower-poverty neighborhood increases college attendance and earnings of children who moved at young ages.[61] The MTO experiment offered vouchers only to a small number of families, so that the experiment did not generate any general equilibrium effects. However, implementing rent subsidies as an economy-wide and permanent policy would change the skill composition of neighborhoods and labor markets, which would furthermore affect local rents and local wages. We therefore use our model to study the long-run effects of rent subsidy policies, which allows us to account for general equilibrium effects and interactions between market outcomes and families' education and residential choices.

Specifically, we consider a policy that reimburses 20 percent of total rent expenditure to low-skilled parents conditional on living in locations where education outcomes are high (top quartile) prior to the reform. Table 11 documents the long-run (general equilibrium) effects of this policy on education outcomes, welfare and Child Opportunities. We see that college attainment increases by 1.7 percentage points (pp) among children from low skill families and decreases by 0.75 pp. among children from high skill families. To take advantage of the rent subsidy, more low skill parents move to locations with good education environments and low exogenous education costs, which decreases average exogenous education costs for their children by 8 percent. High skill parents are not eligible for the subsidy, so that education costs for their children remain the same. Returns to education decrease by 1.4 percent, because average welfare of low-skilled parents increases by 6 percent, while it decreases for all other demographic groups by 0.3 percent.[62] Welfare increases for low skill parents

[61] Both of these findings are consistent with our model predictions. In the MTO experiment, most families moved between close-by neighborhoods so that they usually stayed in the same commuting zone. Our model therefore predicts that earnings of adults should not change. However, children's education choices and therefore their future income can change if children are exposed to different neighborhoods and therefore different education environments.

[62] Recall that returns to education are measured in utility and defined as the difference between expected

Table 11: **Effects of Targeted Rent Subsidies for Low-Skill Parents**

Changes from Baseline; pop-weighted averages

Share of Children going to College, all	0.1 pp.
Low-skill Parents	1.7 pp.
High-skill Parents	-0.74 pp.
Exog. Educ. Cost, low-skill Parents	-7.9 %
Return to College Education	-1.4 %
Welfare; low-skill Parents (bef. moving)	5.7 %
Welfare; all other Groups	-0.3 %
Child Opportunity, low-skill Parents	1.9 %
Child Opportunity, high-skill Parents	0.0 %

Notes: This figure shows the long-run (general equilibrium) effects of a rent subsidy that reimburses 20 percent of total rent payments to low-skilled parents who lives in locations where education outcomes were high (top quartile) prior to the reform. All numbers represent changes from population-weighted averages of the baseline steady state.

precisely because they are eligible to receive the rent subsidy. Welfare decreases for all other groups due to a small reduction in high skill wages (the average skill premium decreases by -0.2 percent) and a small increase in rents, which is driven by higher housing demand due to the subsidy. Overall, the rent subsidy itself is the most important driver in reducing returns to education, because eligibility is restricted to low-skilled parents, which makes it more attractive to remain low-skilled. Table 11 further shows that Child Opportunities increase by 2 percent for children from low skill families, which is due to the higher probability of going to college and higher welfare for the share of children that become low-skilled parents. Child Opportunities for high-skilled families remain unchanged, because lower college attainment rates are offset by higher welfare for the share of children that become low-skilled parents.[63] The rent subsidy requires total expenditure equal to 0.3 percent of aggregate wage income. In comparison, the equalization of school funding was budget-neutral and targeted school funding reforms increased expenditure by 0.1 percent of aggregate wage income.

welfare of high and low skill adults.

[63]We find that the cross-sectional dispersion of education outcomes increases by 2 percent for low-skilled families and is not affected for high-skilled families.

8 Conclusion

We develop a structural spatial equilibrium model of residential and educational choice that generates persistent effects of childhood locations through local education environments, local labor market access and moving costs. The model incorporates rich heterogeneity in regional characteristics, such as residential amenities and local housing markets, which are essential to predicting responses in residential choices accurately. We estimate the model to a range of US census datasets, and infer latent regional characteristics as structural residuals by fitting model predictions to the data of actual US regions.

Using our estimated model, we find that the three school funding reforms, that we consider, have positive but moderate effects on education outcomes, intergenerational education mobility and child opportunities. We find that a partial equilibrium analysis substantially overestimates the effects on education outcomes, as effects are mitigated in general equilibrium, when we allow for responses in local prices and local skill composition. In addition, we find that an equalization of school funding increases the cross-sectional dispersion of college attainment rates across locations, while targeted school funding reforms reduce the cross-sectional dispersion. Last, we consider a policy that provides rent subsidies to low skill parents who live in locations with good education outcomes. College attainment rates increase under this policy for children from low-skilled families but decrease for children from high-skilled families. The decrease is driven by the fact that only low-skilled parents are eligible for the rent subsidy, which increases the welfare of low-skilled parents and therefore makes it relatively more attractive to remain low-skilled, thus reducing returns to education (measured in utility).

Overall, the results of the three policies show that local rents and wages, as well as families' education and residential choices, interact with each other and change in response to policies. Therefore, it is important to evaluate the long-run effects of policies in the unified spatial framework, where all of these outcomes are simultaneously determined in equilibrium.

There are several extensions to our framework that we started to implement and that we want to work on in the future. In Appendix E we discuss a model extension which incorporates skill spillovers in local human capital formation, so that changes in the local college share directly affect the quality of local education environments. Appendix E also provides preliminary results for the extended model. Another interesting extension for future work is to include agglomeration effects in local production technologies, which allows local productivity to respond to changes in the local skill mix.

In addition, our unified framework that includes local human capital production, local labor markets, and costly migration can be used in future work to study a variety of other research

questions. Our framework could, for example, shed new light on the channels that contribute to the persistence of poverty in rural areas in developing countries, where well-being and productivity gaps are particularly large. The unified framework can also be used to compare the effectiveness of place-based policies that can either target local skill-supply (for example, by improving local education or by attracting skilled workers to specific regions) or local skill-demand (for example, by subsidizing companies and job creation in specific regions).

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A Notation Glossary

A.1 Demographic Characteristics and Geography

Demographics	*(superscripts)*
Education: Low- or high-skilled	$e \in \{l, h\}$
Children or no Children	$k \in \{0, 1\}$
Core Geography	*(subscripts)*
Labor markets	$m \in \mathbb{M}$ where $\mathbb{M} = \{1, ..., M\}$
Neighborhoods	$n \in \mathbb{N}$
Governments for Tax and School Funding	*(subscripts)*
Federal Government	g
State Governments	$s \in \mathbb{S}$ where $\mathbb{S} = \{1, ..., S\}$
Neighborhood Governments	$n \in \mathbb{N}$
Sets of Neighborhoods	
Set of Neighborhoods in Labor Market m and State s	$\mathbb{N}_{ms}$
Set of Neighborhoods in Labor Market m	$\mathbb{N}_m = \bigcup_{s=1}^{S} \mathbb{N}_{ms}$
Set of Neighborhoods in State s	$\mathbb{N}_s = \bigcup_{m=1}^{M} \mathbb{N}_{ms}$
Set of all Neighborhoods	$\mathbb{N} = \bigcup_{m=1;s=1}^{M;S} \mathbb{N}_{ms}$

A.2 Parameters and Model Objects

Description	**Symbol**	**Norm. by σ_N**	**Estimated**
Regional and Time-Varying Fundamentals	*(curly font)*	*(small-caps)*	*(hat)*
Moving Costs	$\mathcal{C}_{mm'}^{ek}$	$\mathfrak{c}_{mm'}^{ek}$	$\hat{\mathfrak{c}}_{mm'}^{ek}$
Total Educ. Cost (incl. Effect of Funding)	$\mathcal{D}_n^{ee'}$		
Exogenous Component of Education Cost	$\mathcal{K}_n^{ee'}$	$\mathfrak{k}_n^{ee'}$	$\hat{\mathfrak{k}}_n^{ee'}$
Residential Amenities	$\mathcal{A}_n^{ek}$	$\mathfrak{a}_n^{ek}$	$\hat{\mathfrak{a}}_n^{ek}$
Housing Supply	$\mathcal{H}_n$		$\hat{\mathcal{H}}_n$
Productivity	$\mathcal{Z}_m$		$\hat{\mathcal{Z}}_m$
Skill Intensity	$\mathcal{S}_m^e$		$\hat{\mathcal{S}}_m^e$
Regional Utility Levels	*(curly font)*	*(small-caps)*	*(hat)*
Commuting Zone Utility		$\mathfrak{u}_m^{ek}$	$\hat{\mathfrak{u}}_m^{ek}$
County Utility		$\mathfrak{x}_n^{ek}$	$\hat{\mathfrak{x}}_n^{ek}$

Structural Parameters	*(Greek letters)*		*(hat)*
Housing Expenditure Share	α^{ek}		$\hat{\alpha}^{ek}$ etc
Altruism Parameter	β		
Weight placed on Residential Amenities	θ^{e1}		
Effect of School Funding on College Prob.	γ^{e}		
Dispersion of Neighborhood Taste Shock	σ_N		
Dispersion of Education Taste Shock	σ_E		
Elasticity of Substitution btw Skill Types	ρ		
Probability of Fertility	$\Pr(k'\|e)$		

Policy Parameters	*(Greek letters)*
Federal Tax Rate on Wage Income	$\tau_g^{\boldsymbol{w}}$
State Tax Rates on Wage Income	$\tau_s^{\boldsymbol{w}}$ for $s \in \mathbb{S}$
Local Tax Rates on Rent Payments	$\tau_n^{\boldsymbol{r}}$ for $n \in \mathbb{N}$
School Funding Allocation from Federal Gov. and States to Neighborhood n	$\delta_n^{\boldsymbol{g}}, \delta_n^{\boldsymbol{s}}$ for $n \in \mathbb{N}$

Endogenous Objects	*(Latin letters)*	*(small-caps)*	*(hat)*
Population Distribution across Skills, Family Types, and Neighborhoods	$L(e,k,n)$		
Population Distribution before Moving	$\tilde{L}(e,k,m)$		
Probability that Child in n with parents of Skill e obtains skill e' grew up in n with parents of skill e	$\Pr(e'\|e,n)$		
Probability of Type ek to move from m to n'	$\Pr(n'\|e,k,m)$		
Value Function	$V(e,k,m)$	$v(e,k,m)$	$\hat{v}(e,k,m)$
Exp. Value Funct. before knowing Fertility	$Q(e,m)$	$q(e,m)$	$\hat{q}(e,m)$
Child Opportunity for Families of Skill e in n	$O(e,n)$	$o(e,n)$	$\hat{o}(e,n)$
Indirect Utility Function	$U(e,k,n)$	$u(e,k,n)$	
Wage Income	w_m^e		
Total Rent per Housing Unit (incl. tax)	r_n		
Market Rent per Housing Unit (excl. tax)	r_n^*		
Disposable Income	Y_n^e		
Real Disposable Income	I_n^{ek}		
School Funding in n; received from federal, (own) state, or (own) local gov.	$F_n^{\boldsymbol{g}}, F_n^{\boldsymbol{s}}, F_n^{\boldsymbol{n}}$ for $n \in \mathbb{N}$		

School Funding per Student in n (total)	f_n for $n \in \mathbb{N}$
Rebate of Aggregate Rent Payments	R

Other Notation

Consumption Good	C
Housing Unit (quality-adjusted)	H
Neighborhood and Education Taste Shock	$\epsilon_{n'}, \epsilon_{e'}$
Moving Cost Parametrization	$\lambda^{ek} X_{mm'}$

B Data Appendix

Table B.1: **Data Sources and Descriptions**

Variable	Source	Sample	Description
Moving flows across commuting zones by skill and family type	US Census 1990, 2000, ACS 2006-10 Obtained through Integrated Public Use Microdata Series (IPUMS).	Individuals aged 25-45. Variable used is Public-Use-Micro-Area (PUMA) of residence today and 5 (1) year ago.	PUMA's are mapped to commuting zones using crosswalks obtained from the website of Peter McHenry at *wmpeople.wm.edu/site/page/pmchenry*. Low skills are defined as high-school graduation or less. All other education levels are considered high skills. Parental status is defined by presence of child in the household. Adjustments to 1 year flows are discussed in the next Section.
Commuting zone characteristics	US Census 1990, 2000, ACS 2006-10	All PUMAs are linked to commuting zones.	We observe the state and division of each commuting zone. CZ are classified as coastal if they are part of division 1 or 9. They are classified as urban if they overlap with a metropolitan area (MSA).
Distance between commuting zones	ArcGIS shapefiles from census TIGER files	1990	Distance between centroids of commuting zones is calculated in arcGIS with the use of Census shapefiles.

Neighborhood stocks of households by skill and family type	US Census 1990, 2000, ACS 2006-10 Special tabulations from National Center for Education Statistics (NCES).	Age groups 25-45 and 25-65.	Population stocks for ages above 25 are available by education at the school district level. Stocks are available for "total population" and "parents of all children." This allows us to compute the relevant groups of parents and non-parents by education. Population stocks are aggregated to county level.
Local high- and low-skilled wages	US Census 1990, 2000, ACS 2006-10 Obtained through IPUMS.	Full-time employed, aged 25 to 55, working 36-60 hours per week and at least 48 weeks per year.	Wages of high- and low-skilled workers in each commuting zone are estimated by Mincer regressions which control for possible differences in the composition of workers across commuting zones. The regressions are discussed in more detail in the next Section. Skills are defined as above.
Local Housing Rent	US Census 1990, 2000, ACS 2006-10 Obtained through National Historical Geographic Information System (NHGIS).	All rented housing units.	Rental rates per quality-adjusted housing unit are estimated from Hedonic Prices Regressions which control for possible differences in housing quality and housing characteristics across counties. The regressions are estimated from blockgroup data. The regression and results are presented in the next section.

Local College-going Probabilities	Chetty and Hendren [2018]	Children that grow up in each county with parents from the 25th and 75th percentile of the national income distribution.	Chetty and Hendren [2018] use quasi-experimental evidence from movers to estimate the causal effect of neighborhoods on children's probability to go to college. See Chetty and Hendren [2018] for more information on the estimation. Causal county effects are estimated relative to the average county. To construct the total local probability to go to college, we therefore adjust the causal estimates to match the national probability that children from high- and low-income families go to college.
Local School Funding	F33 Survey and Common Core of Data Files (CCD) in 1990, 2000, 2010 from NCES.	Data is available on school district level, which we aggregate to the county level.	We use data on total revenues that by each school district receives respectively from the federal, state, and local government. In addition, we use data on total number of students per district.
Housing Expenditure	Public use microdata (PUMD) from CEX provided by BLS. First quarter 2011, data file fmli111x.	Families with- and without children (fam_types 1-4), with weekly income above $150	We compute average housing expenditure shares for each demographic group using data on: individuals' education, presence of child under 18, expenditure on housing (variable sheltcq), utilities (utilcq), and total expenditure (variable totexpcq).

B.1 Data construction

Adjustment of Moving Flows

Equation 21 uses moving flow data to estimate moving costs and destination and origin fixed effects. In the model moving flows represent moves of young adults under the assumption that agents only move once in their lifetime. However, in the census data, we only observe

Table B.3: **Moving Cost and Fixed Effect with Simulated and Real Moving Flows**

	(1) **Mean**	(2) **Var**	(3) **p10**	(4) **p90**	(5) **p90-p10**
Panel A: Moving Costs					
1yr flow data (acs)	-7.55	0.34	-8.15	-6.64	1.50
5 yr flow data (census)	-6.14	0.29	-6.71	-5.28	1.43
5 yr flows simulated (acs)	-5.86	0.31	-6.45	-4.99	1.46
Panel B: Destination Fixed Effects					
1yr flow data (acs)	-0.14	0.25	-0.94	0.40	1.34
5 yr flow data (census)	-0.20	0.28	-1.04	0.43	1.47
5 yr flows simulated (acs)	-0.16	0.29	-1.04	0.42	1.46

short-run moving flows. The decennial census in 1990 and 2000 asks respondents about their "PUMA of residence 5 years ago" and the and the American Community Service (ACS) in 2010 asks about "PUMA of residence 1 year ago". To construct moving flows that capture migration between childhood and adulthood commuting zones, we restrict the sample to young adults between 25 and 45. We assume that 5 year flows in this age range represent the moving flows which are relevant in our model. These 5 year moving flows for each education and family type can be directly constructed in the census data. However, for the 2010 data we only observe 1 year moving flows. Hence, in this year we use 1 year moving flows to simulate 5 year moving flows. First we estimate the 1-year $m \times m$ transition matrix which is equal to:

$$L^{ek}_{2010,m'} = \boldsymbol{B}^{ek}_{2010-2009,mm'} \times L^{ek}_{2009,m}$$

We then simulate 5 year flows by iterating the 2010 population stock backwards to compute simulated 5 year moving flows:

$$L^{ek}_{2010,m'} = (\boldsymbol{B}^{ek}_{2010-2009,mm'})^5 \times L^{ek}_{2005,m}$$

Hence, this provides us with 5 year moving flows for each cross-section in 1990, 2000, and 2010.

We can verify the validity of our simulation approach using ACS and decennial census data which overlap in 2000. Specifically, we compare results on 5-year moving flows (obtained from the 2000 census) and from 5-year moving flows that were simulated from 1-year flows (obtained from the 2010 ACS). To have a larger sample size, this comparison is implemented

using moving data across states and pooling all family and education types. We then estimate Equation 21 using the real and simulated 5 year moving flows. The estimated moving costs and destination fixed effects are shown in in Table B.3. We see that 1 year moving flows predict higher moving costs and destination fixed effects with a smaller variance compared to 5 year moving flows. Comparing results from the simulated and real 5 year moving flows shows that both imply similar levels of moving costs and similar dispersion of destination fixed effects. Hence, both, simulated and real 5 year moving flows predict smaller moving costs and smaller variance in destination fixed effects compared to the results from 1 year moving flows. These findings confirm the validity of the simulation strategy that we use to construct 5 year moving flows in the 2010 data.

Mincer Wage Regressions

Finally, we use data on local factor prices to estimate households' preferences for different regional characteristics.

To compute wages for each skill type in each commuting zone, we use the individual-level data from the census and ACS (described above). This dataset has rich information on demographics such as worker's weekly pre-tax wage, education category, sex, race, age, and their commuting zone of residence.[64] To adjust for composition effects on the commuting zone level, we estimate the following Mincer regressions by regressing weekly wages on a rich set of individual controls:

$$\log(w_i) = D_{i,male} + D_{i,black} + a_1 exp_i + a_2 exp_i^2 + a_3 exp_i^3 + a_4 exp_i^4 + D_{i,e} \times D_{i,m} + \epsilon_i$$

where i denotes each individual, w_i is weekly, gross wage income, D_{male} is a dummy for male, D_{black} a dummy for black, exp is a polynomial on experience and $D_e \times D_m$ are fixed effects for each education category interacted with labor markets. We restrict the sample to workers between 25 and 55 years who work full time, i.e. who work at least 48 weeks per year and on average between 36 and 60 hours per week.

The interaction between education and commuting zone fixed effects then estimates wage rates for each education type and each commuting zone. Hence, we compute: $\log(w_m^e) = D_e \times D_m$ where $e = \{l, h\}$.

Table B.4: **Hedonic Price Regressions for Rented Housing**

Dep. var.: Median Gross Rent (log)	(1)	(2)	(3)
Number of Rooms:			
2	0.190***	0.382***	0.371***
	(0.012)	(0.013)	(0.023)
3	0.278***	0.487***	0.504***
	(0.011)	(0.012)	(0.022)
4	0.356***	0.545***	0.534***
	(0.011)	(0.012)	(0.022)
5	0.468***	0.641***	0.602***
	(0.011)	(0.012)	(0.022)
6	0.578***	0.738***	0.694***
	(0.011)	(0.012)	(0.022)
7	0.664***	0.821***	0.763***
	(0.012)	(0.013)	(0.022)
8	0.756***	0.908***	0.833***
	(0.014)	(0.014)	(0.023)
9+	0.815***	1.029***	0.895***
	(0.024)	(0.021)	(0.026)
Unit Type:			
1-family house, attached	-0.038***	-0.024***	-0.032***
	(0.003)	(0.004)	(0.004)
2-family building	-0.009***	-0.004	-0.056***
	(0.003)	(0.003)	(0.003)
3-family building	-0.020***	-0.029***	-0.088***
	(0.002)	(0.002)	(0.003)
5-family building	-0.047***	-0.043***	-0.114***
	(0.002)	(0.002)	(0.002)
10-family building	-0.016***	-0.014***	-0.102***
	(0.002)	(0.003)	(0.002)
20-family building	-0.037***	-0.046***	-0.129***
	(0.002)	(0.003)	(0.003)
50-family building	-0.079***	-0.056***	-0.150***
	(0.002)	(0.002)	(0.003)
Median Construction Yr (log)	10.483***	10.649***	9.168***
	(0.102)	(0.100)	(0.093)
Observations	211,977	201,714	186,250
R-squared	0.565	0.527	0.529

Standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

Notes: Numbers of rooms enter as a categorical variable and the omitted category is 1-room apartments. Types of housing units also enter as a categorical variable and the omitted category is detached one-family homes. Construction Year is a continuous variable. The unit of observation are block-groups. Explanatory variables are median number of rooms, the mode of unit types, and the median construction year in each block group.

Hedonic Rental Price Regressions

To compute rental rates on the school district level, we obtain data on median rents and on housing characteristics from the National Historical Geographic Information System (NHGIS). However, rents on school-district level is not directly comparable since housing size and quality can substantially differ across school districts. We therefore need to estimate rental rates for a homogeneous, quality-adjusted housing unit in each school district to ensure that the rates are comparable. We do this by estimating the following hedonic price regression which regress median rent on a range of housing characteristics and school district fixed effects:

$$\log(rent_i) = rooms_i + \log(year_i) + unit_i + D_n + \epsilon_i$$

Since microdata of these variables is not available on school district level for the entire US, we instead estimate the regression with data on the block group level. Hence, i denotes a block group, r_i is median gross rent of the block group, $rooms_i$ the median number of rooms, $year_i$ is the median year of construction, and $unit_i$ the most common type of structure in the block group (i.e. one-, two-family house, condo, etc.). D_n are school district fixed effects which estimate differences in rental rates across school districts after controlling for differences in housing size and quality across districts. Hence, the fixed effects represent local prices for a homogeneous and quality-adjusted housing unit in each school district and we compute: $\log(r_n) = D_n$. Table B.4 provides the coefficients from the hedonic price regression.

Segregation Measure: Entropy / Information Index

We use the Entropy / Information Index to measure segregation between both skill groups. The Entropy measure for a given geography (e.g. for labor markets m) is expressed as:

$$E_m = -p_m ln(p_m) - (1 - p_m) ln(1 - p_m).$$

This measure is maximized at $p_m = 0.5$ where p_m is the fraction of a group in region m. The Entropy Index measures segregation across smaller units (e.g. labor markets denoted by m) within a larger unit (e.g. the whole United States denoted by g) by taking the difference between the Entropy measures of the respective units. Hence, segregation between labor markets m in the US g, denoted by Seg_{gm} is:

[64] where we again use a geographic crosswalk to map PUMAs to commuting zones.

$$Seg_{gm} = \frac{1}{L_g E_g} \sum_{m \in \mathbb{M}} L_m \left(E_g - E_m \right) = 1 - \sum_{m \in \mathbb{M}} \left(\frac{L_m E_m}{L_g E_g} \right). \tag{28}$$

where L_m is population in m. Segregation between neighborhoods n in each labor market m is defined in the analogous way and denoted by Seg_{mn}.

The Segregation Index varies between 0 (when all smaller units have the same composition as the larger unit) and 1 (when each area contains only one group). Segregation between neighborhoods n in the whole country g can be additively decomposed into variation between and within labor markets in the following way:

$$Seg_{gn} = Seg_{gm} + \sum_{m \in \mathbb{M}} \frac{N_m E_m}{N_g E_g} Seg_{mn}.$$

C Estimation Appendix

In this Appendix, we first explain the calibration of tax rates and the amount that is rebated to households from aggregate rent payments. Next, we derive the expression of county-utilities stated in Equation 19. We then derive the expression of Child Opportunities as stated in Equation 25. Finally, we show that amenities can be normalized within each skill group without loss of generality and that amenity differences are jointly identified with education costs as explained in Section 5.3. We further explain how we infer amenities and education costs for our quantitative exercise.

C.1 Calibration of tax rates and rent rebates

In this Section, we explain how federal, state, and local government $\tau_g^{\boldsymbol{w}}, \tau_s^{\boldsymbol{w}}, \tau_n^{\boldsymbol{r}}$ are calibrated. Recall that we assume that all tax revenues are used to fund schools and each level of government balances its budget. We calibrate tax rates using governments' budget constraints, along with data on school funding, wages and rents.

States impose a proportional tax rate $\tau_s^{\boldsymbol{w}}$ on wage income, so that their budget constraint is:

$$\sum_{n \in \mathbb{N}_s} F_n^{\boldsymbol{s}} = \tau_s^{\boldsymbol{w}} \sum_{n \in \mathbb{N}_s} \sum_e w_m^e L_n^e, \tag{29}$$

where $F_n^{\boldsymbol{s}}$ denotes total school funding that a neighborhood n receives from its state government.[65] Each state funds only schools within its borders, so the state that provides funding

[65] As the distribution of population is taken as exogenous by governments, we simply the notation by using:

is determined by neighborhood $n \in \mathbb{N}_s$. The federal government imposes a proportional tax rate $\tau_g^{\boldsymbol{w}}$ on wage income and allows for deductibility of state taxes, so that the Federal budget constraint is:

$$\sum_{n \in \mathbb{N}} F_n^{\boldsymbol{g}} = \tau_g^{\boldsymbol{w}} \sum_{n \in \mathbb{N}} \sum_e (1 - \tau_s^{\boldsymbol{w}}) w_m^e L_n^e, \tag{30}$$

where $F_n^{\boldsymbol{g}}$ denotes total federal school funding to neighborhood n. These budget constraints identify federal and state tax rates, as we observe data on wages, population by skill type, and school funding that each neighborhood receives from the federal and state government. We model local real estate taxes as proportional tax rates $\tau_n^{\boldsymbol{r}}$ that local governments impose on total market rents $r_n^* \mathcal{H}_n$. Hence the budget constraint of local governments is:

$$F_n^{\boldsymbol{n}} = \tau_n^{\boldsymbol{r}} r_n^* H_n = \frac{\tau_n^{\boldsymbol{r}}}{1 + \tau_n^{\boldsymbol{r}}} r_n \mathcal{H}_n, \tag{31}$$

where $F_n^{\boldsymbol{n}}$ is school funding that is raised (and spent) in neighborhood n, which we observe in the data. To compute total rental expenditure in each neighborhood n, we use the fact that households spend a constant share α^{ek} on housing which gives:

$$r_n \mathcal{H}_n = \sum_e \sum_k \alpha^{ek} Y_n^e L_n^{ek}. \tag{32}$$

Housing expenditure shares α^{ek} are calibrated above and population stocks L_n^{ek} are observed in the data. Recall that disposable income Y_n^e is equal to:

$$Y_n^e = (1 - \tau_{\boldsymbol{g}}^{\boldsymbol{w}})(1 - \tau_s^{\boldsymbol{w}}) w_m^e + w_m^e R,$$

where R determines the amount that is reimbursed to households from aggregate rental income. R equals total rent payments (excluding taxes) divided by total wage income of the economy, so that:

$$R = \frac{\sum_{n \in \mathbb{N}} r_n^* \mathcal{H}_n}{\sum_{m \in \mathbb{M}} \sum_e w_m^e L_m^e} = \frac{\sum_{n \in \mathbb{N}} r_n \mathcal{H}_n - \sum_{n \in \mathbb{N}} F_n^{\boldsymbol{n}}}{\sum_{m \in \mathbb{M}} \sum_e w_m^e L_m^e}. \tag{33}$$

Substituting Equation 32 into 33 and rearranging them allows us to solve for R as a function of observables in the following way:

$L_n^{ek} \equiv L(e, k, n)$.

$$R = \frac{\sum_{n\in\mathbb{N}}\sum_{e}\sum_{k} L_n^{ek}\alpha^{ek}w_m^e(1-\tau_{\boldsymbol{g}}^{\boldsymbol{w}})(1-\tau_s^{\boldsymbol{w}}) - \sum_{n\in\mathbb{N}} F_n^{\boldsymbol{n}}}{\sum_{n\in\mathbb{N}}\sum_{e}\sum_{k} L_n^{ek}(1-\alpha^{ek})w_m^e}.$$

We use these calibrated parameters, together with data on wages and population stocks of each demographic group, to construct disposable income and total rent payments in each neighborhood (using Equation 32). Together with data on local school funding $F_n^{\boldsymbol{n}}$, we then use Equation 31 to solve for real estate tax rates in each neighborhood $\tau_n^{\boldsymbol{r}}$.

C.2 County-Utility as Function of Population Stocks and CZ-utility

Here we show that county-utilities χ_n^{ek} can be expressed as a function of county population and CZ-utility u_m^{ek} in the following way (c. Equation 19):

$$\exp(\chi_{n'}^{ek}) = \frac{L(e,k,n')}{L(e,k,m')} \times \exp(u_{m'}^{ek}).$$

First, we show that CZ-utility (u_m^{ek}) can be written in a recursive form. To do so, we first use the law of motion (Equation 12) to express the population distribution across (destination) CZ m' as:[66]

$$L(e,k,m') = \sum_{m\in\mathbb{M}}\sum_{n'\in\mathbb{N}_{m'}} \Pr(n'|e,k,m)\tilde{L}(e,k,m) = \sum_{m\in\mathbb{M}} \frac{\exp\left[u_{m'}^{ek} - c_{mm'}^{ek})\right]}{\sum_{m''\in\mathbb{M}}\exp(u_{m''}^{ek} - c_{mm''}^{ek})}\tilde{L}(e,k,m),$$

where we used the definition of moving probabilities $\Pr(n'|e,k,m)$ from Equation 11. Rearranging gives:

$$\exp(u_{m'}^{ek}) = L(e,k,m') / \left[\sum_{m\in\mathbb{M}} \frac{\exp\left(-c_{mm'}^{ek}) + \log(\tilde{L}(e,k,m))\right)}{\sum_{m''\in\mathbb{M}}\exp(u_{m''}^{ek} - c_{mm''}^{ek}))}\right]. \tag{34}$$

Now, we use the law of motion (Equation 12) again to express the distribution of families across (destination) counties n' as:

[66] Alternatively, this expression can be derived by summing Equation 20, which characterizes cross-commuting-zone moving flows, across origins m. Recall that $\tilde{L}_{mt}^{ek}$ is the (young) population of generation t after their skills and family-types have been determined, but before moving. Hence these families are captured in the labor markets m in which they grew up.

$$L(e,k,n') \;=\; \sum_m \Pr(n'|e,k,m)\tilde{L}(e,k,m) = \sum_{m\in\mathbb{M}} \frac{\exp\left(\varkappa_{n'}^{ek} - \mathfrak{c}_{mm'}^{ek}\right)}{\sum_{n''\in\mathbb{N}}\exp\left(\varkappa_{n''}^{ek} - \mathfrak{c}_{mm''}^{ek}\right)}\tilde{L}(e,k,m).$$

Pulling out the county-utility in destination n', dividing and multiplying by $L_{m'}^{ek}$, and rearranging gives the desired expression:

$$\begin{aligned}
\exp(\varkappa_{n'}^{ek}) &= \frac{L(e,k,n')}{L(e,k,m')} \times L_{m'}^{ek} / \left[\sum_{m\in\mathbb{M}} \frac{\exp\left(-\mathfrak{c}_{mm'}^{ek} + \log\left(\tilde{L}(e,k,m)\right)\right)}{\sum_{n''\in\mathbb{N}}\exp\left(\varkappa_{n''}^{ek} - \mathfrak{c}_{mm''}^{ek}\right)}\right] \\
\exp(\varkappa_{n'}^{ek}) &= \frac{L(e,k,n')}{L(e,k,m')} \times \exp(\mathfrak{u}_{m'}^{ek}).
\end{aligned}$$

C.3 Child Opportunities as Function of Continuation Value and Education Outcomes

We now show that local Child Opportunities $O(e,n)$ can be expressed as a function of local continuation values of low-skilled families $Q_{t+1}(l,m)$ and the local probability of remaining low-skilled $\Pr(l|e,n)$ in the following way (as proposed in Equation 25):

$$O_t(e,n) = Q_{t+1}(l,m) - \sigma_E \log(\Pr{}_t(l|e,n)).$$

Recall that average Opportunities for children with parents of skill level e that grow up in neighborhood n is equal to:

$$O_t(e,n) = \sigma_E \log\left(\sum_{e'} \exp(\frac{1}{\sigma_E}Q_{t+1}(e',m) - \frac{1}{\sigma_E}\mathcal{D}_{nt}^{ee'})\right), \tag{35}$$

as derived in Equation 7.

Further recall from Equation 8 that the share of children from families with skill level e, who grew up in neighborhood n', and who acquire education e' is given by:

$$\Pr{}_t(e'|e,n) = \frac{\exp(\frac{1}{\sigma_E}Q_{t+1}(e',m) - \frac{1}{\sigma_E}\mathcal{D}_{nt}^{ee'})}{\sum_{e''}\exp(\frac{1}{\sigma_E}Q_{t+1}(e'',m) - \frac{1}{\sigma_E}\mathcal{D}_{nt}^{ee''})} = \frac{\exp(\frac{1}{\sigma_E}Q_{t+1}(e',m) - \frac{1}{\sigma_E}\mathcal{D}_{nt}^{ee'})}{\exp(\frac{1}{\sigma_E}O_t(e,n))},$$

where we use Equation 35 in the last term to rewrite the denominator as a function of Child Opportunities $O_t(e,n)$ and the dispersion of the education taste shock σ_E. Recalling that the

cost of remaining low-skilled is normalized to zero without loss of generality (i.e. $\mathcal{D}_n^{el} = 0$), allows expressing the probability of remaining low-skilled $e' = l$ in the following way:

$$\Pr{}_t(l|e,n) = \frac{\exp\left(\frac{1}{\sigma_E} Q_{t+1}(l,m)\right)}{\exp\left(\frac{1}{\sigma_E} O_t(e,n)\right)}.$$

Rearranging this Equation gives the desired expression.

C.4 Residential Amenities and Education Costs

In this Section, we show that amenities a_n^e and education cost $\mathcal{K}_n^{eh}$ are only identified up to constant of normalization within each skill type, as mentioned in Section 5.3. We show that any normalization of amenities within each skill type generates observationally equivalent outcomes (in residential and education choices), because any normalization re-adjusts the levels of value functions $v(e,k,m)$ and education costs $\mathcal{K}_n^{eh}$. It is therefore without loss of generality to normalize residential amenities a_n^e within each skill group.

Intuition of the Results. To build intuition for this result, let us recall how these parameters are estimated, and how they affect residential and education choices. Amenities a_n^e are inferred from county-utilities of non-parents (Equation 24). County-utilities themselves are estimated separately for each demographic group from the group's observed residential choices. County-utilities are therefore only identified up to a constant of normalization within each group, since each group's moving choices are invariant to an additive in- or decrease of utility in *all* counties. Consequently, moving choices identify *relative* utility differences across counties within each skill group, but they do not identify total utility levels or differences in county-utility *across* demographic groups.

To illustrate this, let us first consider non-parents. When moving, their skills as adults have already been determined, so that they move to the county where relative utility is highest for their specific skill and family type $e0$ given amenities and real income a_n^e, I_n^{e0}. It follows that moving choices of non-parents identify cross-county amenity differences *within* each skill type, but they cannot discipline amenity differences *across* skill types, (i.e. $a_n^h - a_n^l$).

In addition to amenities and real income, parents further value Child Opportunities $o(e,n)$. When parents move, their skills as adults have also been determined, however, their children's future skills are not yet known and respond to local characteristics. Therefore, parents evaluate counties based on the flow utility for their skill type $e1$ *and* based on the continuation values offer to their children. Continuation values depend on the entire distribution of

amenities across both skill levels and all counties $\{a_n^e\}_{e,n}$, as children's future skills and the county to which they move as adults are not yet determined. Hence, amenities of both skill levels affect parents' moving choices (and county-utilities). However, we can show that differences in local amenities between skill types $a_n^h - a_n^l$ have the same effects on parents' moving and education choices as level changes in the local education cost $\mathcal{K}_n^{ee'}$. A larger difference between high and low skill specific amenities $a_n^h - a_n^l$ increases the return to becoming high-skilled $Q(h,m) - Q(l,m)$, while lower education cost $\mathcal{K}_n^{eh}$ make it less costly to become high-skilled. We can therefore change both terms in a way that leaves local education outcomes unchanged.

It follows that education costs $\mathcal{K}_n^{eh}$ and relative amenity levels between skill types $a_n^h - a_n^l$ are only *jointly*, but not separately identified. In particular, we show that the model can fit observed residential and education choices for *any* normalization of amenities within each skill level when value functions $V(e,k,m)$ and education costs $\mathcal{K}_n^{eh}$ are adjusted accordingly. Therefore it is without loss of generality to normalize amenities within each skill level. Conditional on this normalization, education costs $\mathcal{K}_n^{eh}$ are identified.

Formal Derivation of the Result. First (1), we show that residential choices of non-parents identify amenities only up to a constant of normalization within each skill type. Second (2), we show that residential choices of parents identify amenities only up to a normalization with each skill type *conditional* on average local education choices. Third (3), we show that education choices identify the level of amenities across skill groups only *jointly* with education costs. We can therefore show that amenities can be normalized without loss of generality, which then identifies value function and education cost levels.

We denote normalized amenities of each skill type as $\tilde{a}_n^e = b^e + a_n^e$. Analogously, we denote other model objects, that are functions of re-normalized amenities as: $\tilde{v}(e,k,m)$, $\tilde{\mathcal{K}}_n^{eh}$, $\tilde{\Pr}(n'|e,k,m)$, and $\tilde{\Pr}(e'|e,n)$. We will characterize these terms in the derivation. In particular, we want to show that residential and education choices are observationally equivalent under any normalization, such that: $\tilde{\Pr}(n'|e,k,m) = \Pr(n'|e,k,m)$ and $\tilde{\Pr}(e'|e,n) = \Pr(e'|e,n)$.

(1) Residential choices of non-parents under normalized amenities $\tilde{a}_n^e$ are given by:

$$\tilde{\Pr}(n'|e,0,m) \;= \frac{\exp\left[b^e + a^e_{n'} + \frac{1}{\sigma_N} I^{e0}_{n'} - c^{e0}_{mm'}\right]}{\sum_{n'' \in \mathbb{N}} \exp\left[b^e + a^e_{n''} + \frac{1}{\sigma_N} I^{ek}_{n''} - c^{e0}_{mm''}\right]} \;= \Pr(n'|e,0,m),$$

where we see that the normalization factor b^e cancels from the denominator and numerator. Hence, residential choices of non-parents are invariant to the normalization.

(2) Parents residential choices further include dynamic terms, and are given by:[67]

$$\Pr(n'|e,1,m) \quad = \frac{\exp\left[a^e_{n'} + \frac{1}{\sigma_N} I^{e1}_{n'} - c^{e1}_{mm'} + \beta q(l,m') - \frac{\beta\sigma_E}{\sigma_N}\log(\Pr(l|e,n')\right]}{\sum_{n''\in\mathbb{N}} \exp\left[a^e_{n''} + \frac{1}{\sigma_N} I^{e1}_{n''} - c^{e1}_{mm''} + \beta q(l,m'') - \frac{\beta\sigma_E}{\sigma_N}\log(\Pr(l|e,n'')\right]} \quad ,$$

where we used Equation 25 to express Child Opportunities. For parents, normalizing amenities within each skill type affects the flow utility and continuation values. Hence we first examine how the normalization affects continuation values, which are given by (c. Equation 16):[68]

$$v(e,k,m) = \log \sum_{n'\in\mathbb{N}} \exp\left[a^e_{n'} + \frac{1}{\sigma_N} I^{ek}_{n'} - c^{ek}_{mm'} + 1_{k=1}\beta \sum_{k'} \Pr(k'|l) v(l,k',m') - 1_{k=1}\frac{\beta\sigma_E}{\sigma_N}\log\left(\Pr(l|e,n')\right)\right].$$

We now guess and verify that normalizing amenities by b^e shifts value functions by an additive constant X^{ek}, so that $\tilde{v}(e,k,m) = X^{ek} + v(e,k,m)$. For non-parents, this is trivial to show since amenities only enter through the current flow utility so that:

$$\tilde{v}(e,0,m) = X^e + v(e,0,m) \quad = \quad \log \sum_{n'\in\mathbb{N}} \exp\left[b^e + a^e_{n'} + \frac{1}{\sigma_N} I^{e0}_{n'} - c^{e0}_{mm'}\right],$$

where we see that our guess holds if $X^{e0} = b^e$. For parents, the normalization of amenities affects flow utility and continuation values so that:

$$\begin{aligned}
\tilde{v}(e,1,m) &= \log \sum_{n'\in\mathbb{N}} \exp\left[b^e + a^e_{n'} + \frac{1}{\sigma^{e1}_N} I^{e1}_{n'} - c^{e1}_{mm'} + \beta \sum_{k'} \Pr(k'|l)\left[X^{lk'} + v(l,k',m')\right] - \frac{\beta\sigma_E}{\sigma_N}\log\Pr(l|e,n')\right] \\
&= \log \sum_{n'\in\mathbb{N}} \exp\left[b^e + a^e_{n'} + \frac{1}{\sigma^{e1}_N} I^{e1}_{n'} - c^{e1}_{mm'} + \beta \sum_{k'} \Pr(k'|l)\left[X^{lk'} + v(l,k',m')\right] - \frac{\beta\sigma_E}{\sigma_N}\log\Pr(l|e,n')\right] \\
&= b^e + \beta \sum_{k'} \Pr(k'|l) X^{lk'} + v(e,1,m),
\end{aligned}$$

where we apply the guess $\tilde{v}(e,k,m) = X^{ek} + v(e,k,m)$ on both sides of the Equation. We show that our guess holds and that we can solve for X^{e1} using:

[67] We omit time subscripts as we assumed that households have naive expectations.

[68] We again use Equation 25 to express Child Opportunities.

$$
\begin{aligned}
X^{e1} &= b^e + \beta \sum_{k'} \Pr(k'|l) X^{lk'} \\
&= b^e + \beta \left(\Pr(0|l) b^l + \Pr(1|l) X^{l1} \right),
\end{aligned}
$$

where we used the solution of non-parents ($X^{l0} = b^l$) in the second row. Hence, value functions for low skill parents are adjusted by:

$$
X^{l1} = \frac{b^l \left(1 + \beta \Pr(0|l)\right)}{1 - \beta \Pr(1|l)},
$$

and for high skill parents by:

$$
X^{h1} = b^h + \frac{\beta b^l \left(1 + \Pr(0|l)\right)}{1 - \beta}.
$$

Having shown that the normalization of amenities shifts value functions by X^{ek}, we can now show that residential choices of parents are invariant to the normalization. Residential choices of parents under re-normalized amenities $\tilde{a}^e_n = b^e + a^e_n$ are given by:

$$
\begin{aligned}
\tilde{\Pr}(n'|e,1,m) =& \frac{\exp\left[b^e + a^e_{n'} + \frac{1}{\sigma_N} I^{e1}_{n'} - c^{e1}_{mm'} + \beta \sum_{k'} \Pr(k'|l) \left[X^{lk'} + v(l,k',m')\right] - \frac{\beta \sigma_E}{\sigma_N} \log(\Pr(l|e,n')\right]}{\sum_{n'' \in \mathbb{N}} \exp\left[b^e + a^e_{n''} + \frac{1}{\sigma_N} I^{e1}_{n''} - c^{e1}_{mm''} + \beta \sum_{k'} \Pr(k'|l) \left[X^{lk'} + \bar{v}(l,k',m'')\right] - \frac{\beta \sigma_E}{\sigma_N} \log(\Pr(l|e,n'')\right]} \\
=& \frac{\exp\left(b^e + \beta \sum_{k'} \Pr(k'|l) X^{lk'}\right)}{\exp\left(b^e + \beta \sum_{k'} \Pr(k'|l) X^{lk'}\right)} \times \Pr(n'|e,1,m) \\
=& \Pr(n'|e,1,m),
\end{aligned}
$$

where we see that normalization terms cancels in the numerator and denominator. Hence, we have shown that residential choices of parents and non-parents are invariant to normalizing amenities within each skill level, when we condition on local education outcomes. However, education outcomes themselves respond to amenity differences across skill groups, which we discuss now.

(3) We now show that education choices identify amenity levels across skill groups only *jointly* with education costs. Recall that education outcomes are given by:

$$
\sigma_E \log\left(\frac{\Pr(h|e,n)}{\Pr(l|e,n)}\right) = Q(h,m) - Q(l,m) - \mathcal{K}^{eh}_n + \gamma^e \log(f_n),
$$

where we normalize costs of remaining low-skilled to zero without loss of generality. Education choices identify education costs $\mathcal{K}_n^{eh}$ as a structural residual *conditional* on knowing school funding and the returns to education. The latter is given by differences in value functions between high and low skill adults, which depend on amenity differences across skill types as $Q(e,m) = \sum_{k'} \Pr(k'|e)V(e,k',m)$.

Hence, education choices under normalized amenities $\tilde{a}_n^e$ can be expressed as:

$$\begin{aligned}
\sigma_E \log\left(\frac{\tilde{\Pr}(h|e,n)}{\tilde{\Pr}(l|e,n)}\right) =& \tilde{Q}(h,m) - \tilde{Q}(l,m) - \tilde{\mathcal{K}}_n^{eh} + \gamma^e \log(f_n) \\
=& \sum_{k'} \Pr(k'|h) X^{hk'} - \sum_{k'} \Pr(k'|l) X^{lk'} + Q(h,m) - Q(l,m) - \tilde{\mathcal{K}}_n^{eh} + \gamma^e \log(f_n) \\
=& Q(h,m) - Q(l,m) - \mathcal{K}_n^{eh} + \gamma^e \log(f_n) \\
=& \sigma_E \log\left(\frac{\Pr(h|e,n)}{\Pr(l|e,n)}\right),
\end{aligned}$$

where we have shown that the same education probabilities $\Pr(e'|e,n)$ can be generated under any normalization of amenities if education costs $\tilde{\mathcal{K}}_n^{eh}$, that are inferred as structural residual, are adjusted in the following way:

$$\tilde{\mathcal{K}}_n^{eh} = \mathcal{K}_n^{eh} + \sum_{k'} \Pr(k'|h) X^{hk'} - \sum_{k'} \Pr(k'|l) X^{lk'},$$

where X^{ek} is derived above and depends on the specific normalization of amenities. This shows that the same education outcomes can be generated under any normalization of amenities, as the model adjusts local cost of becoming high-skilled (relative to remaining low-skilled) to fit observed education outcomes under given amenity levels. Hence, if a normalization increases returns to education (i.e. $\sum_{k'} \Pr(k'|h) X^{hk'} - \sum_{k'} \Pr(k'|l) X^{lk'} > 0$), then education costs $\tilde{\mathcal{K}}_n^{eh}$ are increased by the same amount to offset the effect, thus fitting observed education choices to model predictions. This shows that levels of education costs and amenity differences across skill groups are jointly, but not separately identified. Hence, normalizing amenities by one constant within each skill group is without loss of generality since value functions and education costs adjust to generate observationally-equivalent outcomes (in residential and education choices).

Identifying Amenities and Education Costs: Building on these results, we now explain how we infer amenities and education costs in our estimation. First, we infer amenities $\tilde{a}_n^e$ as a structural residual from non-parents' county-utilities using Equation 24. We then normalize

amenities to have mean zero across all neighborhoods within each skill group, which we denote as $a_n^e = b^{e0} + \tilde{a}_n^e$. Second, we solve for value functions $v(e, k, m)$ that are consistent with the normalization of amenities by value function iteration using Equation 16. Third, we infer education costs $\mathcal{K}_n^{eh}$ given normalized amenities a_n^e and corresponding value functions $v(e, k, m)$.

C.5 Transitional Dynamics and Persistence in Regional Fundamentals

As described in Section 6, we have to make assumptions about the evolution of regional fundamentals to evaluate policy counterfactuals. We therefore test whether observed changes in endogenous variables over the last decades are driven primarily by continuing changes in fundamentals or by transitional dynamics. To do this, we leverage data from 1990, 2000, and 2010 to infer regional fundamentals for each of these decades. We then compute correlations of each fundamental over time, which are documented in Table C.1. We find that total productivity and skill intensity of commuting zones are very persistent with correlations between 0.82 and 0.95 across consecutive decades. Housing supply in each county is also strongly correlated, with correlations of 0.98 across consecutive decades. The correlation between counties' low skill specific residential amenities is 0.3 between 1990 and 2000 and 0.8 between 2000 and 2010. High skill specific residential amenities are more persistent with a correlation of 0.86 and 0.88 across consecutive decades.[69] The persistence of moving costs (not reported in the table) is very high with correlations of 0.99 across decades for each demographic group. Education costs are assumed to be the same across the three decades.[70] Overall, we conclude that there is a strong persistence in all regional fundamentals between 1990 and 2010. We therefore conclude that transitional dynamics (and not changes in fundamentals) drive the observed changes in endogenous outcomes over the last decades. Given this finding, we hold fundamentals constant at levels implied by the 2010 data when we evaluate policy counterfactuals.

[69] Amenities are inferred from moving flows and population stocks of each demographic group so that their link to the data is less direct than it is the case for productivity, skill intensity, and housing supply.

[70] This is because we infer education costs from estimates of causal neighborhood effects on the probability to go to college (Chetty and Hendren [2018]). These estimates are only available once and they use data from cohorts born between 1980 and 1988, so that the childhood of these cohorts covers the decades 1990, 2000, and 2010.

Table C.1: **Persistence of Regional Fundamentals over Time**

Regional Fundamental	Corr(90,00)	Corr(00,10)	Corr(90,10)
Total Productivity $\hat{\mathcal{Z}}_m$	.91	.82	.81
Skill Intensity $\hat{\mathcal{S}}^e_m$	.93	.95	.88
Housing Supply $\hat{\mathcal{H}}_n$	.98	.98	.96
Low-Skill-Specific Amenities $\hat{a}^l_n$	.3	.8	.46
High-Skill-Specific Amenities $\hat{a}^h_n$	.86	.88	.82

D Model Fit and Sensitivity of Results

D.1 Model Fit and Residential Amenities

Correlation between Model Amenities and Observable Characteristics Table D.1 shows how amenities inferred from our model correlated with observable regional characteristics that have been used in the literature to proxy amenities (Diamond [2016] and Lee and Lin [2018]). We use available datasets from both of these papers and extend the datasets when necessary to more years or to a more disaggregated geographic level. The R^2 of the regression varies across samples between 0.34 and 0.53, indicating that observable characteristics can explain a substantial share of the amenities inferred in our model.

Model fit under assumption that amenities vary across skills but not parent-status

Here we analyze how well our model fits the data under the Assumption 2 that amenities vary only across skills, but not across parent types. In our estimation approach, we used non-parental county utilities to infer residential amenities of non-parents and parents. Hence, we now assess how well our model fits parental county utilities under this restriction. A first indication is given by the regression results in Table 5, where we regress parental county utilities adjusted for real income on amenities, and child opportunity values. These regressions have a high R^2 indicating that the model fits parents county utility values well. In addition, we now compute structural residuals that would perfectly fit parents' county utilities. Without Assumption 2, we could have interpreted these as "parent-specific amenities". In Figure D.2 we regress these "parent-specific amenities" on the amenities used in our model. Both values are very correlated across all years and for both skill types, which confirms that the restriction imposed on amenities is aligned with the data.

Table D.1: **Correlation between Model Amenities and Observable Characteristics**

Dep. var.: Amenity by Skill and Year	(1) Low Skill 1990	(2) High Skill 1990	(3) Low Skill 2000	(4) High Skill 2000	(5) Low Skill 2010	(6) High Skill 2010
Moderate temperature	2.109***	2.110***	-0.519	0.900**	0.0349	-0.0836
	(0.537)	(0.448)	(0.343)	(0.357)	(0.315)	(0.357)
Nb. estab. / stores	0.00054***	0.00068***	0.00042***	0.0006***	0.0005***	0.00056***
	(8.34e-05)	(6.95e-05)	(4.82e-05)	(5.02e-05)	(3.86e-05)	(4.38e-05)
Median Air Quality	0.342***	0.119*	-0.0516	-0.0298	-0.109***	-0.0611
	(0.0861)	(0.0718)	(0.0365)	(0.0380)	(0.0338)	(0.0383)
Spending on parks/rec.	0.254**	0.289***	-0.0643**	0.0328	0.0296	0.0742**
	(0.122)	(0.102)	(0.0308)	(0.0321)	(0.0289)	(0.0328)
Distance to city center	-13.35***	-17.95***	-10.58***	-13.19***	-9.418***	-12.05***
	(1.620)	(1.351)	(1.091)	(1.135)	(1.016)	(1.153)
Distance to lake	-5.532***	-6.696***	-4.982***	-6.409***	-2.995***	-5.456***
	(1.492)	(1.244)	(1.017)	(1.059)	(0.952)	(1.080)
Distance to shore	-2.810***	-6.262***	-1.008	-5.060***	-0.234	-2.780***
	(1.052)	(0.877)	(0.724)	(0.754)	(0.677)	(0.768)
Property Crime Rate	-0.387***	0.0127	0.347***	0.0942**	0.152***	0.124***
	(0.117)	(0.0975)	(0.0359)	(0.0373)	(0.0335)	(0.0380)
Violent Crime Rate	0.127*	-0.201***	-0.0996***	-0.175***	-0.0647**	-0.160***
	(0.0710)	(0.0592)	(0.0295)	(0.0308)	(0.0276)	(0.0313)
Observations	799	799	793	793	797	797
R-squared	0.339	0.478	0.521	0.526	0.465	0.469

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table D.2: **Correlation of Amenities across Parent Type**

Dep. var.: Residual that fits parents' county-utility	(1) Low Skill 1990	(2) High Skill 1990	(3) Low Skill 2000	(4) High Skill 2000	(5) Low Skill 2010	(6) High Skill 2010
Model Amenity	1.021***	1.074***	1.137***	1.047***	1.154***	1.028***
	(0.00583)	(0.00675)	(0.00943)	(0.00851)	(0.00916)	(0.00951)
Observations	2,773	2,773	2,793	2,777	2,795	2,795
R-squared	0.917	0.901	0.839	0.845	0.850	0.807

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

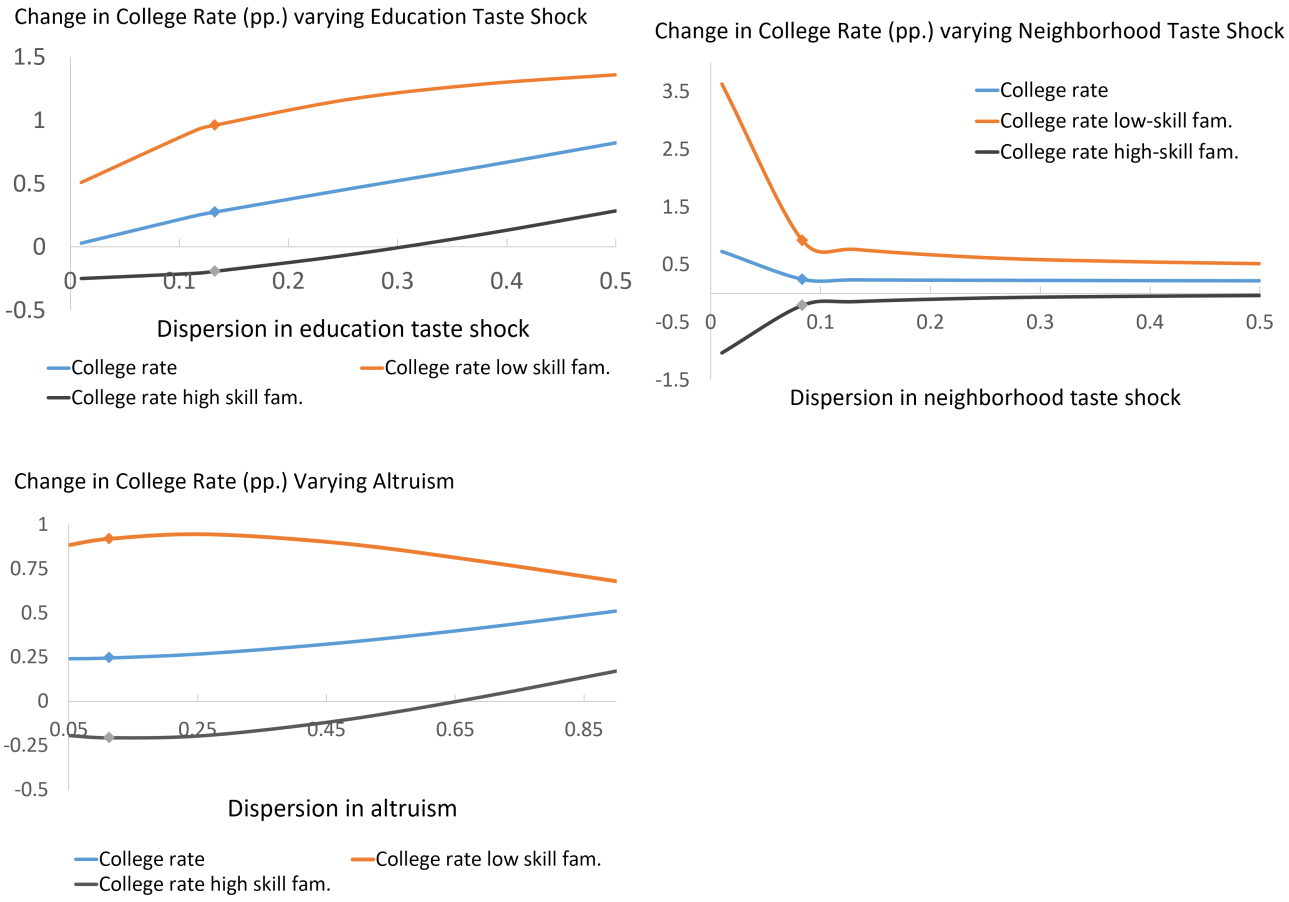
D.2 Sensitivity of Results to Changes in Parameters

Three key parameters in our model are altruism β, and the dispersion of idiosyncratic taste shocks over neighborhoods and education σ_N, σ_E. In our baseline estimation, we find: $\beta = 0.11, \sigma_E = 0.114, \sigma_N = 0.08$. To test the sensitivity of our results to these parameters, we re-estimate our policy counterfactual by varying one of the three parameters across a range of values. Figure 4 shows the effects of equalizing school funding on skill acquisition under different parameter values. For each parameter combination, we first recover the regional fundamentals that are implied by the selected parameter combination. We first solve for the benchmark steady state to which the economy converges when regional fundamentals and current calibrated tax and school funding policies are held constant. We then solve for the steady state under equalized school funding and compute the changes which are plotted in this figure. As we recompute in each case the steady states of the benchmark and the counterfactual economy, the absolute benchmark values also differ in each scenario. However, in Figure 4 we only report changes that occur under the school funding reform. We focus on skill acquisition as a key outcome of interest. Each figure shows the percentage point change in the share of children that become high skill—in the aggregate economy and separately for low and high skill families. The highlighted marker in each figure corresponds to the results obtained with our baseline estimates, which are: $\beta = 0.11, \sigma_E = 0.114, \sigma_N = 0.08$.

The left upper graph shows changes in skill acquisition when varying the dispersion in the education taste shock σ_E between values of 0.01 and 0.5, while the other two parameters are fixed at the baseline estimates. We see that skill acquisition increases more in response to the policy for larger values in the dispersion of education taste shocks. Across the considered range of values, the increase in the share of children from low skill families that become high-skilled varies from 0.5 pp. to 1.36 pp. For aggregate skill acquisition effects range from close to none to 0.64 pp. For high skill families, effects range from a decease of 0.25 pp. to an increase of 0.29 pp.

The right upper graph varies the dispersion in neighborhood taste shocks σ_N between values of 0.05 and 0.5, while holding the other two parameters fixed at our baseline estimates. We see that policy effects are much larger for a small dispersion in neighborhood taste shocks. For $\sigma_N = 0.01$, the equalization of school funding increases the share of children from low skill families by 3.6 pp. and decreases the share by 1 pp. for children from low skill families. For $\sigma_N = 0.13$, skill acquisition increases by only 0.76 pp. for low skill families and decreases by 0.14 pp. for high skill families. Changes become even smaller as σ_N further increases. At $\sigma_N = 0.5$, skill acquisition increases by 0.5 pp. for low skill families and decreases by 0.03 for high skill families, with an overall increase of 0.22 pp. in aggregate skill acquisition.

Figure 4: **Sensitivity of Results to Parameter Estimates**



Notes: This figure shows the effects of equalizing school funding on skill acquisition under different parameter values. For each parameter combination, we first recover the regional fundamentals that are implied by the modified parameters. We first solve for the benchmark steady state to which the economy converges when regional fundamentals and current calibrated tax and school funding policies are held constant. We then solve for the steady state under equalized school funding and compute the changes which are plotted in this figure. In this figure, we focus on skill acquisition as a key outcome of interest. Each figure shows the percentage point change in the share of children that become high skill—in the aggregate economy and separately for low and high skill families. The highlighted marker in each figure corresponds to the results obtained with our baseline estimates, which are: $\beta = 0.11, \sigma_E = 0.114, \sigma_N = 0.08$. The left upper graph shows changes in skill acquisition by fixing $\beta = 0.11$ and $\sigma_N = 0.08$ while varying the dispersion in the education taste shock σ_E between values of 0.05 and 0.5. The right upper graph varies the dispersion in neighborhood taste shocks σ_N between values of 0.05 and 0.5, while holding the other two parameters fixed at our baseline estimates. Finally, the left bottom graph values altruism β between 0.05 and 0.9, while again holding the other two parameters fixed at our baseline estimates.

The bottom graph varies altruism β between 0.05 and 0.9, while again holding the other two parameters fixed at our baseline estimates. We find that an equalizing of school funding leads to a decrease in skill acquisition among high skill families for low values of altruism, however, effects become positive for altruism values above 0.65. For children from low skill families effects are always positive and they increase varies between 0.94 pp. and 0.68 pp. Effects first increase slightly in altruism and then decrease again for altruism values above 0.4.

E Extension: Skill Spillovers in Education [In Progress]

In this Section, we extend the model to incorporate local skill spillovers that affect the quality of education environments. Specifically, we now assume that the total cost of going to college $\mathcal{D}_n^{eh}$ in each neighborhood depends on local school funding f_n, the local share of college-educated adults $\bar{e}_n$, and a residual component, which we again interpret as exogenous education costs and which we now denote by $\tilde{\mathcal{K}}_n^{eh}$. Hence, $\mathcal{D}_n^{eh}$ is given by:

$$\mathcal{D}_n^{eh} = -\mu^e \log(\bar{e_n}) - \gamma^e \log(f_n) + \tilde{\mathcal{K}}_n^{eh},$$

where μ^e and γ^e respectively represent the causal effects of the local skill share $\bar{e}_n$ and local school funding f_n on the local education quality. Recall that we identified γ^e by matching the causal effects of school funding on college attainment rates, which were estimated by Jackson et al. [2016]. However, there is no consensus in the literature about the strength of local skill spillovers on education outcomes, so that it is not clear how we can identify the parameter μ^e. Most papers in the literature study peer effects in the classroom, which can differ from the broader skill spillovers at the neighborhood level that we capture in our model. Agostinelli [2018] finds large estimates of peer effects, which are strongest for children from disadvantaged backgrounds. Fogli and Guerrieri [2018] estimate the strength of local skill spillovers by targeting the moment that children's adulthood income increases by 10 percent if average income (and average skills) increase by one standard deviation in their childhood location. On the other hand, Carrell et al. [2018] find that exposure to disruptive peers has particularly large negative effects on children's future income.

Despite the identification challenges, we provide illustrative results where we set $\mu^e/\sigma_E = \{2; 1.5\}$. Under this parametrization, an increase in the local share of college-educated adults from 67 to 77 percent would (all else equal) increase college enrollments by 5.5 percentage points (pp.) among children from low-skilled families and by 4 pp. among children from

Table E.1: **Skill Spillovers: New Baseline and Effects of Equal School Funding**

Changes from averages (pop.-weighted)	(1) Baseline vs. Spillover Steady State	(2) Spillover: Equal Funding vs. Steady State
Share of Children to College	1.17	0.26
Low-Skill Parents (pp)	2.55	1.02
High-Skill Parents (pp)	-0.05	-0.21
Child Opportunity (exp. utility)		
Low-Skill Parents	6.3%	2.1%
High-Skill Parents	4.3%	1.4%
Welfare of Young Families		
Low-Skill Non-Parents	5.8%	1.4%
High-Skill Non-Parents	-1.0%	-0.2%
Low-Skill Parents	6.5%	1.6%
High-Skill Parents	-0.7%	-0.2%

Notes: This table shows how education outcomes, child opportunities and welfare change in the extended model which incorporates local skill spillovers. Column (1) documents how outcomes change in the new Spillover Steady State compared to the Baseline Steady State. Column (2) documents the effects of an equalization of school funding in the extended model.

high skill families.[71]

Conditional on knowing μ^e, the extension is very easy to implement because the numerical solution of the model already keeps track of the skill share in each neighborhood. Due to the sequential structure of the estimation strategy, we do not need to re-estimate the whole model. However, we need to infer a new residual measure that we interpret as exogenous education costs and that we denote by $\tilde{\mathcal{K}}_n^{eh}$. As before, we then fix regional fundamentals $\{\Theta_{2010}\}$ and school financing policies $\{\Gamma_{2010}\}$ at the values estimated in the 2010 data and solve for the long-run steady state with local skill spillovers.

Column (1) of Table E.1 documents how outcomes change in the new steady state with spillovers compared to the baseline steady state. We find that aggregate college attainment is 1.2 percentage points (pp) higher with the skill spillover, which is driven by a 2.55 pp. increase in the college-educated share of children from low-skilled families. Higher skill supply also decreases the skill premium and increases welfare of low skill adults. These results should be considered illustrative as they depend on the value that we choose for the causal effect of

[71] Effects of skill spillovers on education outcomes depend on the initial level as well as the increase in the local college share due to the logit form of education choices. This can be seen in the following Equation: $\log\left(\frac{\Pr_t(h|e,n)}{1-\Pr_t(h|e,n)}\right) = \frac{\mu^e}{\sigma_E}\log(\bar{e_n}) + \frac{\gamma^e}{\sigma_E}\log(f_n) - \frac{1}{\sigma_E}\tilde{\mathcal{K}}_n^{eh} + \frac{1}{\sigma_E^e}\left(Q_{t+1}(h,m) - Q_{t+1}(l,m)\right)$.

local college shares on education outcomes (μ^e/σ_E). Following the results from Agostinelli [2018], we assume that the causal effect is larger for children from low-skilled families, which explains that college attainment is higher among low-skilled families in the steady state of the extended model.

In addition, we can use the extended model to study the effects of equalizing school funding in the model with spillovers. Column (2) of Table E.1 documents changes in the steady state with spillovers and equalized funding compared to the steady state with spillovers. We find that the equalization of school funding has very similar effects in the baseline model and extended model (compare to Section 7.2.1).