From Kindergarten to College: The Impact of Education Policies over the Lifecycle*

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Abstract

Across all education levels, recent policies aim to diversify the socioeconomic composition of student bodies. We study the interactions among these integration policies and their effects on intergenerational mobility. We develop a heterogeneous-agent where households sort into public schools through residential location and into college via a competitive admissions process. Empirically, we causally establish a key model mechanism in which increased college competition affects parental investment in children and sorting across school zones. At the public school level, we examine a rezoning policy that increases the proportion of low-income students at the highest-quality school. For college, we examine an income-based affirmative action policy. Public school integration weakens the link between residential location and school quality, increasing intergenerational mobility by 2.2%. The college policy, by contrast, decreases intergenerational mobility by 2.3%. When the high-quality college reserves seats for low-income students, college admissions become more competitive, which increases income sorting at the public school level.

JEL Codes: I2, R23

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1 Introduction

In the United States, at each stage of childhood and young adult development, individuals face different educational opportunities depending on their family's socioeconomic status (SES). There is substantial income segregation across public schools (Owens et al., 2016), and significant test score gaps between students of varying SES (Hanushek et al., 2019). In addition, recent work on colleges and economic mobility highlights a stark relationship between family income and the quality of college attended (Chetty et al., 2020).

In light of these inequities, there has been a growing emphasis on policies designed to diversify the socioeconomic composition of student bodies. We refer to these policies as "integration policies." For elementary and high schools, integration policies involve re-sorting students across schools.[1] At the college level, the previous U.S. federal administration advised colleges to consider applicants' family income and high school background during the admissions process. Interest in income-based integration policies has also risen in part due to the recent U.S. Supreme Court ban on race-based affirmative action (Levine and Reber, 2023).

While the effects of integration policies have been studied in isolation (Agostinelli et al., 2024; Brotherhood et al., 2023; Chyn and Daruich, 2022; Hendricks et al., 2024), the interactions among these policies across stages of human capital development are not well understood. Moreover, integration policies are often implemented independently by different policymakers, and individuals may be exposed to multiple treatments over their lifecycle. This paper studies the lifecycle interactions of integration policies and asks how they affect intergenerational mobility and inequality.

To do so, we begin with a standard lifecycle heterogeneous-agent model of incomplete markets and augment it with intergenerational motives in the style of Becker and Tomes

[1] See *Appendix A* for a discussion of institutional details and examples.

(1979) and multi-period dynamic human capital accumulation à la Ben-Porath (1967). Crucial to our research question, the model includes the key phases of education over the lifecycle: elementary school, secondary school, and college.

The model begins when children graduate from secondary school and become independent adults differing in ability, human capital, and wealth, with the latter two endogenously determined. The agent then decides whether to apply to college, and, contingent on acceptance, which college to attend. Our model has two public colleges, which differ in terms of peer effects (average ability), tuition, and per-pupil expenditures. The high-quality college, which represents the state flagship college, has a fixed supply of seats with an endogenous admissions cutoff score based on the human capital and ability of its applicants.

After attending college, agents work and make consumption-savings and human capital investment decisions. Each adult exogenously gives birth to one child. Parents choose a school zone to live in, which determines the quality of the K-12 school. There are two school zones, each with a fixed housing supply and house prices determined in equilibrium. School quality is determined through peer effects, measured by the average ability of peers in that school. At each education stage, the quality of education influences the level and growth rate of human capital. The parent also chooses how much to invest in their child's human capital, and the size of inter-vivos transfers to leave.

In the model, integration policies allocate seats at higher-quality institutions for individuals from lower-income families. These policies interact over the lifecycle by affecting the competition for seats. For example, a college integration policy will create a quota for low-income students at the high-quality college, making it more difficult for non-targeted students to get in. The change in competition can then affect human capital investment decisions of parents at earlier stages in the lifecycle. In particular, parents can change their time investment or school zone sorting choices. This adjustment is a crucial mechanism in our model that drives the interaction of integration policies across life-cycle stages.

Quantifying our structural model comes with a key challenge. In order to make credible predictions on the interaction of integration policies, the model needs to match the sensitivity of parental human capital investments (through time spent and school zone choice) to changes in competition at future schooling levels in the data. Indeed, if parental investments are not sensitive to competition changes, then integration policies are unlikely to interact across time periods. As there are no estimates of these elasticities in the literature, we turn to a novel empirical strategy to estimate them. These elasticities will then serve as key moments that our model will match during the calibration.

Estimating these elasticities via ordinary least squares is not feasible due to unobservable shocks that may jointly affect competition and human capital investment. We exploit a 2006 change in U.S. visa policy for Chinese international students which exogenously increased enrollment of these students at top public universities and tightened admissions for domestic students. We show that parents in states more exposed to this enrollment shock increased their time investment in children, and that demand for high-quality K-12 schools increased, consistent with our model mechanism.

In particular, we build a shift-share instrument in which the shares are the pre-2006 ratios of foreign students at top universities by state and the shift is aggregate fluctuations in the number of Chinese students in the United States. Our high-quality elementary school is mapped to the top 20% of schools in the United States, and the top quality college is defined to be high selective public (also known as flagship) colleges, which enroll only 13% of all college students. Our measure of human capital investment is time invested in children, and our measure of sorting into high-quality schools is the ratio of house prices between the high- and low-quality school zones. We follow recent work on shift-share identification (Goldsmith-Pinkham et al., 2020) and validate our instrument by recasting it in a difference-in-differences framework. We find that on average, a 10 percentage point decrease in admissions rates at top-state colleges increases time investment by 0.2 hours per day. In addition, the median house value ratio between low and high-quality school zones rises by 0.22.

Recovering these elasticities also allows us to estimate our production function for child human capital. We model the production of child human capital as a constant elasticity of substitution (CES) function over parental time investment and K-12 school quality. Given our model structure featuring dynamic child investment and differentiated K-12 school quality choices, together with a competitive college sector, we are able to run a similar experiment in the model to recover the two CES parameters. In particular, we exogenously change college competition in the model and choose these CES parameters so that the elasticities of parental time investment and school zone house price ratios match our causal estimates from the data.

The remainder of the model is disciplined by matching cross-sectional moments on parental income sorting across schools, time investment across schools, earnings growth by college quality, and the effects of school quality on human capital. In addition, our model matches the income Gini coefficient, the intergenerational elasticity of earnings, and the transfers-to-net-worth ratio. To assess whether our model generates reasonable predictions concerning the importance of neighborhoods and colleges for future earnings, we externally validate our model against estimates from the literature (Chetty et al. (2016) and Hoekstra (2009)).

We use our structural model to run several integration policies which have been considered or implemented by policymakers. First, we simulate an income-based affirmative action policy where the high-quality college implements a quota for low-income students. At the elementary and secondary school level, we study school integration policies that involve rezoning of students across schools. For each policy, we run two versions. First, the policy is anticipated but in partial equilibrium, leaving house prices and the college admission score fixed. Next, we solve for the general equilibrium, allowing house prices and the college admission score to adjust. These policies are studied in isolation and in concert with one another.

We now highlight the key takeaways from our analysis. An integration policy at the elementary school or the secondary school level has positive effects on mobility: the intergenerational elasticity of income (IGE) decreases by 1.1% in the former case and 1.7% in the latter case.[2] Intergenerational mobility improves because a rezoning policy reduces the expected school quality in the expensive school zone, leading to a drop in the house price. Lower-income families can move in, increasing the human capital of their children. Even though elementary and secondary school rezoning policies move the same number of students, the effects of the policy at the secondary school level are starker. The price of the high-quality school zone declines by approximately 3% when rezoning is during secondary school, but only by 1% when at elementary school. The difference arises from the model timing: under an elementary rezoning policy, the high-quality school zone is more valuable as it still guarantees access to the high-quality secondary school. Parents can thus insure against a bad elementary school shock by increasing time investment during secondary school.

We find that an integration policy at the college level has a negative effect on income mobility, with the IGE increasing by 2.3%. Since the high-quality college has a fixed supply of seats, a quota for students from low-income families raises the admissions score required to get into the high-quality college by 11.5%. The rise in college competition then affects human capital development during the public school stage. A higher admissions score drives up the price of the high-quality school zone by 1.8%. Parents know being admitted into the good college is more difficult, so their valuation of a good K–12 school increases. The negative effects of the income-affirmative action policy are driven by the general equilibrium responses of the school zone price, which drives low-income children out of the high-quality school zone. They then no longer have sufficient human capital to attend the high-quality college.

A result that follows from above is the importance of understanding how policies interact. For instance, an integration policy at both the elementary and secondary school

[2] The intergenerational elasticity of income is the coefficient from a regression of logged child income on the logged income of their parent. A higher (lower) coefficient indicates lower (higher) intergenerational mobility.

reduces the IGE by 2.2%. However, if those policies are implemented in conjunction with a college integration policy, the IGE declines by just 1.1%. While the public school integration policy creates more equality across the two school zones, the college policy counteracts this by driving up the value of the good school zone. Our work highlights the importance of policy coordination. Currently, colleges, school districts, and other forms of government are independently implementing integration policies.

The remainder of our paper is organized as follows. In the next section, we provide a literature review and discuss our contribution. *Section 2* lays out our quantitative framework, and *Section 3* provides causal evidence for our main model mechanisms. In *Section 4*, we describe our calibration strategy. The results of our policy analysis are presented in *Section 5*. *Section 6* concludes.

1.1 Related Literature

Our work is most closely related in research question to two papers that also study the timing of human capital policy interventions. Krueger et al. (2024) investigate whether it is more effective to increase funding toward public schools or towards college. Lee and Seshadri (2019) study the effectiveness of policies to increase child investment at different points in the lifecycle. Our paper studies the timing of integration policies, which specifically aim to change the student body composition.

As mentioned in the introduction, previous works have studied individual integration policies. Brotherhood et al. (2023) build a structural model with overlapping generations and investment in child human capital to investigate the effects of recent income-based affirmative action policies at universities in Brazil. Hendricks et al. (2024) study how these policies would affect welfare in the United States. Their structural model features heterogeneous agents that face not only financial frictions when it comes to college decisions but also information frictions. They find that such policies improve economic opportunity and have few negative consequences for aggregate earnings. Gu and Zhang (2026) study how expanding college seats affects intergenerational mobility in China. We also model college decisions, but incorporate them into a framework with public schooling as well.

At the public school level, Chyn and Daruich (2022) analyze the effects of place-based policies in the form of housing vouchers and neighborhood wage subsidies. In addition, Agostinelli et al. (2024) build a rich urban model of school zones to evaluate the effects of housing vouchers on access to quality education. While our model lacks their fine spatial heterogeneity, we instead incorporate a dynamic lifecycle model that captures policy interaction across time while still including sufficient spatial features to answer our research question.

Our structural model brings together elements on sorting, human capital development, and intergenerational mobility. The sorting features are built off of several seminal works that studied the link between neighborhood residence and school financing (Durlauf et al., 1993; Benabou, 1996; Durlauf, 1996; Fernandez and Rogerson, 1998). More recently, work by Aliprantis and Carroll (2018), Gregory et al. (2022), Fogli et al. (2025), and Zheng and Graham (2022) study neighborhood spillovers in dynamic lifecycle models. Our work is also related to the literature on child development (Cunha et al., 2010; Del Boca et al., 2014; Caucutt et al., 2020) and to works studying the macroeconomic and intergenerational implications of child development policies (Daruich, 2018; Caucutt and Lochner, 2020).

2 Model

Time is discrete and has an infinite horizon. The economy is populated by a continuum of 11 overlapping generations with a uniform demographic structure. Agents are altruistic towards their children (Becker and Tomes, 1979), and dynasties are infinitely lived. One model period represents six biological years and is denoted by j. Throughout, "hat" variables denote the next generation (i.e., the current generation's child), and "prime" variables denote the next period in an agent's lifecycle. We occasionally use subscript j notation when "prime" notation would otherwise be unclear. *Figure 1* summarizes an agent's lifecycle.

A child is born in period $\hat{j} = 0$ with ability $\hat{a}$, stochastically inherited from their parent. For periods $\hat{j} = 0$ to $\hat{j} = 2$, children live with their parent and do not make independent decisions. The parent makes preschool $\hat{Q}_P$, school zone $\hat{Q}_S \in \{\hat{Q}_S^l, \hat{Q}_S^h\}$, and human capital investment $\hat{n}_j$ decisions for the child.

At the beginning of period $j = 3$ (biological age 18), the child becomes independent from their parent. In addition to ability a, the initial states for this adult include an endogenous level of human capital h and inter-vivos transfers b. Upon independence, the agent chooses whether to attend college and which quality of college to attend, $Q_C \in \{Q_C^l, Q_C^h\}$. If an agent attends college, they have access to government-sponsored student loans. Otherwise, an agent may save but not borrow.

As an adult, agents are endowed with one unit of time, which is divided between market work and human capital accumulation. Human capital determines labor market earnings and is subject to uninsurable idiosyncratic risk. For the remainder of the agent's lifecycle, they supply labor, accumulate human capital (with and without children in the household), and solve a consumption-savings problem. At age $j = 11$, exogenous retirement/death is imposed. Only steady states are considered, and so time scripts are omitted throughout.

We assume that the period utility is valued by the CRRA function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$. During periods $j = 6$ to $j = 8$ when the child is present in the household, period utility is maximized by solving a Pareto problem over child and parent consumption,

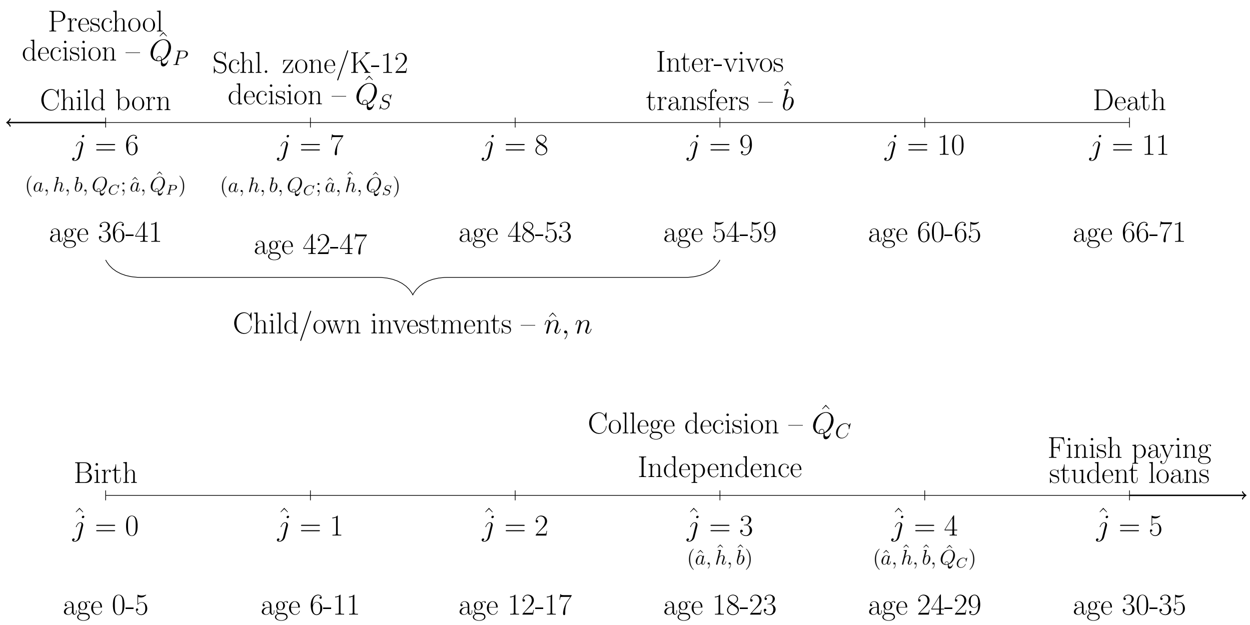
$$U(\tilde{c}_j) = \max \Big\{ u(c_j) + \theta u(\hat{c}_{j-6}) \Big\}$$

where $\tilde{c}_j$ is aggregate household consumption of parent and child, and θ represents altruistic motives of parents towards children. Given the CRRA form of period utility, we have:

$$U(\tilde{c}_j) = \xi u(\tilde{c}_j)$$

with $\xi \equiv (1 + \theta^{1/\gamma})^\gamma$ being interpreted as an adult consumption-equivalence.

Figure 1: **Lifecycle Timeline**



2.1 Human Capital Development

2.1.1 Child Human Capital Production

The functional forms we use for child human capital production are similar to those of Lee and Seshadri (2019). At the beginning of period $j = 6$, each agent exogenously gives birth to one child, which begins its lifecycle in period $\hat{j} = 0$. Children differ by an initial ability $\hat{a}$, transmitted stochastically from the parent by some transition function $\mathcal{A}(a, \hat{a})$. The parent has complete information with respect to their child's ability, which remains a fixed state for the lifecycle. From $\hat{j} = 0$ to $\hat{j} = 2$ the human capital of the child develops according to,

$$\hat{h}_{j+1} = \hat{a}\Big(\lambda_j \hat{n}_j^{\omega_j} + (1 - \lambda_j)\hat{Q}_j^{\omega_j}\Big)^{1/\omega_j}\hat{h}_j + \hat{h}_j, \text{ where } \hat{h}_0 = 1 \tag{1}$$

where $\hat{h}_{j+1}$ is the human capital stock in the next period, and $\hat{h}_j$ is current human capital. $\hat{Q}_j$ is school quality, and $\hat{n}_j$ is the time investment adults make in their child. The choice to model only time investments is consistent with previous work in the literature (Chyn and

Daruich, 2022) and the fact that spending on education goods is a very small share of overall expenditure.[3] The parameters λ_j and ω_j capture the relative weights and complementarity between school quality and parental time investments. Throughout, we refer to equation (1) as $g(\hat{h}, \hat{a}, \hat{n}, \hat{Q}_j)$.

Preschool – The parent begins period $j = 6$ by making a preschool enrollment decision. There is a single private preschool that has some exogenous quality $Q_0 = Q_P$ and cost t_P. Preschool quality affects how the child develops human capital during their first period. If the parent decides not to enroll the child in preschool, they must spend at least $\hat{n}_0 = n_P$ of their time endowment investing in the child's human capital. The quality of no preschool is normalized to zero.

Elementary and Secondary School – At $j = 7$, the parent chooses a school zone $\hat{Q}_S \in \{\hat{Q}^l_S, \hat{Q}^h_S\}$. The school zone determines the school a child is sent to.[4] In order to live in a school zone, parents must rent one unit of housing at the equilibrium price P_S.[5] Without loss of generality, we assume that $P_{S^h} > P_{S^l}$ and normalize P_{S^l}. Housing is supplied inelastically with measure $\mathcal{N}$ in school zone Q^h_S and $1-\mathcal{N}$ in Q^l_S. The assumption of fixed housing supply is important to the model results; *Figure B.2* in *Appendix B* shows that the number of seats enrolled at top public schools as a share of overall students has been fairly stable over time.

The quality of elementary and secondary schools in each school zone S is given by,

$$Q_S = \bar{a}_S^{\alpha_S} \tag{2}$$

The term $\bar{a}_S$ is average ability of children living in school zone Q_S and captures peer effects.

[3] The 2017 Consumer Expenditure Survey from the Bureau of Labor Statistics reported a share of spending on education goods of only 2.5%.

[4] This is in line with the main school assignment method in the United States.

[5] We assume that agents only have the option to rent housing and that housing is owned by absentee landlords.

We choose to model peer effects in this way in line with Burke and Sass (2013) who provide empirical evidence that student test scores respond to the average peer ability of their classroom.[6,7]

Previous literature modeling school quality has included expenditure per student accruing from property tax revenue. However, property taxes are collected at the district level whereas our interest is school quality across school zones within the same district. The reason is that integration policies at the elementary and secondary school level primarily focus on within-district re-sorting of students. The other funding source that could vary with school zone socioeconomic status is funds from parent-teacher associations. However, work from Brown et al. (2017) shows that these funds account for less than one percent of nationwide education spending for the U.S.

Integration policies at the school zone level take on the following form. When a parent lives in a school zone $\in \{\hat{Q}_S^l, \hat{Q}_S^h\}$, with some probability, their child will be sent to the other school instead. This is a simple way to model the variety of policies that seek to break the link between residential location and school assignment. In particular, it is an accurate representation of a redrawing or redistricting of K-12 boundaries.

2.1.2 Adult Human Capital Production

Following Cunha et al. (2010), Del Boca et al. (2014), and Lee and Seshadri (2019), at the beginning of the working phase of an agent's lifecycle, a constant anchor ζ transforms children's human capital (proxied by test scores) into adult human capital (measured by labor earnings). The adult human capital production function is,

$$h' = \epsilon_m' \Big(a \cdot (1 + Q_C) \cdot (nh)^\eta + (1 - \delta) h \Big) \tag{3}$$

[6]Burke and Sass (2013) model peer ability using individual student fixed effects. They find nonlinear effects where the effect of average peer ability depends on individual ability.

[7]In the baseline model, we do not allow agents to change schools between ages $\hat{j} = 1$ and $\hat{j} = 2$, and so Q_S is fixed across both ages.

where $n \in [0,1]$ is time spent accumulating human capital, $\delta \in [0,1]$ is period depreciation of human capital, ϵ'_m is a market luck shock, and $\eta \in (0,1)$ is the elasticity of human capital production with respect to investment. The market luck shock is drawn from an i.i.d. log-normal distribution with mean and variance μ_m and σ_m^2, respectively. Throughout, we will use $h' = f(h, a, Q_C, n, \epsilon'_m)$ to denote equation (3). An agent's pre-tax labor market earnings in period j are then given by $e_j = wh_j(1 - n_j)$, where w is an exogenously given wage rate.

The non-standard addition to this Ben-Porath (1967) production function is Q_C, which represents college quality. Q_C is normalized to zero for agents who do not attend college. Chetty et al. (2020) find that (controlling for observable characteristics) earnings levels and growth rates vary significantly across college qualities. Motivated by this finding, we model college quality as some factor that alters the growth of human capital over the agent's life-cycle. This is a similar modeling to Leukhina et al. (2021) and Brotherhood et al. (2023).

College – Agents begin making their own decisions at the beginning of period $j = 3$ (biological age 19). Initial heterogeneity is with respect to ability a, human capital h, and parental inter-vivo transfers b.

Upon becoming independent, agents must first decide whether or not to apply to college. There are two colleges in the economy, $Q_C \in \{Q_C^l, Q_C^h\}$. Each college charges an exogenous tuition schedule $r_C(Q_C, b, a)$. There is a measure $\mathcal{C}$ of spots available at Q_C^h, and no constraint on the number of spots offered at Q_C^l. The assumption on the fixed supply of seats at top colleges is in line with previous work (Blair and Smetters, 2021) and our own empirical evidence (see *Figure B.1* in *Appendix B*).

The selective college observes a noisy signal of an agent's admission score z and sets the highest possible value of $\bar{z}$ to fill available spots. Following Brotherhood et al. (2023), admission scores are formed by combining innate ability and human capital,

$$z = \ln(ah^{\nu}) + \sigma_z \epsilon_z, \tag{4}$$

where ϵ_z is i.i.d standard normal and $\sigma_z$governs noisiness of the admissions process. ν is the elasticity of admissions scores with respect to human capital. The probability that an agent with human capital h, and ability a, is admitted to college is given by,

$$p(z) = 1 - \Phi\Big(\frac{\bar{z} - z}{\sigma_z}\Big) \tag{5}$$

where $\Phi(\cdot)$ is the cumulative distribution function for the standard normal distribution.

Given the admission cutoff and tuition price, college quality is determined by,

$$Q_C = (\bar{r}_C)^{\alpha_C}(\bar{a}_C)^{1-\alpha_C} \tag{6}$$

where the term $\bar{a}_C$ is average ability of the student body. $\bar{r}_C$ is average expenditures per-student generated from tuition revenues. The elasticity of school quality with respect to expenditures per pupil is given by α_C.

Expenditures per student is given by the exogenous tuition schedule,

$$\bar{r}_C = \frac{1}{n_C}\sum_{k=1}^{n_C}\{t(Q_C) - \rho(b_k, Q_C) - s(a_k) + f\} \tag{7}$$

where $t(Q_C)$ is the sticker tuition price for each college quality, $g(Q_C, b)$ is all needs-based (non-repayable) financial aid by an agent's wealth level and quality of college, $s(a)$ is a merit-based scholarship based on the agent's ability, and f is a fixed cost of attending college. n_C is the number of students attending college of quality Q_C.

If an agent decides to attend college, they are given a government-sponsored student loan of size $D(Q_C, b) = \min\{t(Q_C) - g(Q_C, b), \bar{D}\}$. While not all university attendees take on full student loans, we make this assumption in order to simplify computations, as in Matsuda and Mazur (2022). The modeling of student loans is designed to represent the current U.S. income-contingent college loan plan.

The interest rate on student loans is given by $\bar{r} = r + \iota$, where ι is the premium paid on student loans above the market rate. Interest does not begin to accrue until after college, and repayments are made for two periods beginning in $j = 4$. Repayments depend on the loan size and an agent's current income level. No repayments are made for individuals with income below some threshold $\hat{y}$. Agents with income above $\hat{y}$ make repayments proportional to a factor χ of their income. Proportional repayments are made up to the level $\bar{L}(D)$, at which point they make fixed repayments of size $\bar{L}(D)$. Fixed repayments are given by

$$\bar{L}(D) = \begin{cases} D\left(\bar{r}\frac{(1+\bar{r})^2}{(1+\bar{r})^2-1}\right) & \text{if } 4 \leq j \leq 5 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

and hence the loan repayment schedule is given by,

$$\bar{L}(D, y) = \begin{cases} \min\{\chi \cdot \max\{0, y - \hat{y}\}, \bar{L}(D)\} & \text{if } 4 \leq j \leq 5 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Fixed repayments are such that their present value over two periods equals the present value of student debt, inclusive of interest. If the student loan is not fully repaid within the two periods, it is assumed that the remainder is paid by the government. The repayment length of twelve years is in line with the standard 10-year federal student loan term.

In the case of a college integration policy, students from households with below-median income are granted an admissions advantage at Q_C^h. Specifically, these students receive additional points added to their admission scores, effectively raising their likelihood of securing a place. This bonus-point mechanism is formally equivalent to a reserved-seat quota system, in which a designated share of spots at the selective institution is set aside for low-income applicants, with a larger bonus corresponding to a greater proportion of reserved seats (Brotherhood et al., 2023).

2.2 Recursive Decision Problems

All discrete school and college decisions made by agents in the model are subject to preference shocks. These shocks are distributed according to the Type I Extreme Value distribution.

2.2.1 Independence from Parent, $j = 3$

Agents become independent at the beginning of period $j = 3$ (biological age 19). The states are, ability level a, human capital h, and inter-vivos transfers b. The first decision is whether or not to apply to college,

$$\max\left\{V^{not\ apply}(j = 3, a, b, h), V^{apply}(j = 3, a, b, h)\right\} \tag{10}$$

If the agent does not apply to college they immediately enter the workforce. This problem is given by equation (12). Contingent on being admitted, the agent chooses, consumption c, assets b', and college quality $Q_C \in \{Q_C^l, Q_C^h\}$ to solve,

$$\begin{aligned} V^{admitted}(j = 3, a, b, h) = \max_{c,b',Q_C} &\left\{u(c) + \beta\mathbb{E}_{\epsilon_m}\left[V(j = 4, Q_C, a, b', h'\right]\right\} \\ \text{subject to,}& \\ & c + b' + \bar{r}_C = b + D(Q_C, b) \\ & Q_C \in \{Q_C^l, Q_C^h\} \\ & h' = f(h, a, Q_C, 1, \epsilon_m') \\ & b' \geq 0 \end{aligned} \tag{11}$$

An agent who attends college is assumed to have chosen $n = 1$, which implies they cannot work while in college. They enter period $j = 4$ with the human capital level resulting from setting $n = 1$ in equation (3).

Notice that agents use the loan amount $D(Q_C, b)$ and initial wealth b to pay for college expenses while in college. This is an important assumption since agents do not have access to private borrowing. Needing to immediately pay for college in full prevents agents from attending college to gain access to borrowing and smooth consumption over their lifecycle. An agent who applied to college but is not admitted decides between attending the low-quality college Q_C^l or immediately entering the workforce.

2.2.2 Pre-child Working, $j = 3, 4, 5$

The problem of an agent who decides not to attend (or apply to) college, or an agent who has attended college but has not yet given birth to a child, is given by the standard consumption–saving problem with endogenous human capital accumulation. The agent chooses consumption c, human capital investment n, and savings b' to solve,

$$
\begin{aligned}
V(j, Q_C, a, b, h) = \max_{c,n,b'} & \Big\{ u(c) + \beta \mathbb{E}_{\epsilon_m} \big[V(j+1, Q_C, a, b', h') \big] \Big\} \\
\text{subject to,} & \\
& c + b' + L(D, y) = y(e, b) + b \\
& e = wh(1-n) \\
& h' = f(h, a, Q_C, n, \epsilon_m') \\
& n \in [0, 1] \\
& b' \geq 0
\end{aligned}
\tag{12}
$$

Where, $L(D, y) = 0$ if the agent did not attend college. $y(e, b)$ is after-tax income. That is, defining $y = e + rb$ and for some arbitrary tax function $\tau(y)$, after tax income is given by,

$$
y(e, b) = \big(1 - \tau(y)\big) y \tag{13}
$$

For brevity we are suppressing an explicit formulation of the period $j = 5$ problem where agents will form expectations over the ability of their child to be born in the following period.

2.2.3 Child in Household

At $j = 6$ a child is born into each household. Then, at $j = 8$, the child graduates secondary school and receives independence from the parent.

Preschool, $j = 6$ – A parent with own states (Q_C, a, b, h) and child of ability $\hat{a}$ first makes the preschool enrollment decision,

$$\max\left\{\underbrace{V(j=6,Q_C,a,b,h;\hat{a},0)}_{\text{No Preschool}},\underbrace{V(j=6,Q_C,a,b,h;\hat{a},\hat{Q}_P)}_{\text{Preschool}}\right\} \tag{14}$$

The agent then chooses consumption c, own human capital investment n, savings b', and child human capital investment $\hat{n}$ which solves,[8]

$$\begin{aligned} V(j=6,Q_C,a,b,h;\hat{a},\hat{Q}_P) = \max_{c,n,b',\hat{n}} & \left\{U(\tilde{c}) + \beta\mathbb{E}_{\epsilon_m}\left[V(j+1,Q_C,a,b',h';\hat{a},\hat{h}',\hat{Q}_S)\right]\right\} \\ \text{subject to,} & \\ & c + b' + \mathbb{1}\{\hat{Q}_P \neq 0\}t_P = y(e,b) + b \\ & e = wh(1-n-\hat{n}) \\ & h' = f(h,a,Q_C,n,\epsilon_m') \\ & \hat{h}' = g_0(\hat{a},\hat{n},\hat{Q}_P) \\ & n \in [0,1], \quad \hat{n} \in [0,1-n] \\ & b' \geq 0 \end{aligned} \tag{15}$$

Elementary and Secondary School, $j = 7, 8$ – At the beginning of $j = 7$ $(\hat{j} = 1)$ the agent chooses a school zone $\{Q_S^l, Q_S^h\}$, which determines the elementary and secondary school quality of the child, by solving,

[8] For simplicity of exposition, there is a constraint omitted that $\hat{n} \geq n$ when $\hat{Q}_P = 0$.

$$\max\left\{V(j, Q_C, a, b, h; \hat{a}, \hat{h}, \hat{Q}_S^l), V(j, Q_C, a, b, h; \hat{a}, \hat{h}, \hat{Q}_S^h)\right\} \tag{16}$$

The agent now chooses consumption c, own human capital investment n, savings b', and child human capital investment $\hat{n}$, which solve,

$$\begin{aligned} V(j, Q_C, a, b, h; \hat{a}, \hat{h}, \hat{Q}_S) = \max_{c,n,b',\hat{n}} & \left\{U(\tilde{c}) + \beta\mathbb{E}_{\epsilon_m}\left[V(j+1, Q_C, a, b', h'; \hat{a}, \hat{h}, \hat{Q}_S)\right]\right\} \\ \text{subject to,} & \\ & c + b' + P_S = y(e, b) + b \\ & e = wh(1 - n - \hat{n}) \\ & h' = f(h, a, Q_C, n, \epsilon_m') \\ & \hat{h}' = g(\hat{h}, \hat{a}, \hat{n}, \hat{Q}_S) \\ & n \in [0, 1], \quad \hat{n} \in [0, 1 - n] \\ & b' \geq 0 \end{aligned} \tag{17}$$

Child Independence, $j = 9$ – At the beginning of period $j = 9$ ($\hat{j} = 3$) the agent's child becomes independent. The agent now chooses consumption c, human capital investment n, savings b', and an inter-vivos transfer $\hat{b}$, in order to solve,

$$\begin{aligned} V(j = 9, Q_C, a, b, h; \hat{a}, \hat{h}) = \max_{c,n,b',\hat{b}} & \Big\{u(c) + \beta\mathbb{E}_{\epsilon_m}\left[V(j = 10, Q_C, a, b', h')\right] \\ & + \theta\mathbb{E}_{\epsilon_m,\epsilon_z}\left[\max\left\{V^{not\ apply}(\hat{j} = 3, \hat{a}, \hat{b}, \hat{h}), V^{apply}(\hat{j} = 3, \hat{a}, \hat{b}, \hat{h})\right\}\right]\Big\} \\ \text{subject to,} & \\ & c + b' + \hat{b} = y(e, b) + b \\ & e = wh(1 - n) \\ & h' = f(h, a, Q_C, n, \epsilon_m') \\ & n \in [0, 1], \quad b', \hat{b} \geq 0 \end{aligned} \tag{18}$$

The intergenerational transfer, $\hat{b}$ is subject to a non-negativity constraint, meaning that parents cannot borrow against their child's future income. Parents make the transfer before any uncertainty faced by the child at the start of period $\hat{j} = 3$ is realized.

2.2.4 Post-child Working, $j = 10, 11$

During periods $j = 10$ and $j = 11$ the individual's problem solved is identical to the problem defined by equation (12) with the exception of no term $L(y, D)$, as student loans are no longer being repaid. The terminal condition is given by $V(j = 12, Q_C, a, b, h) = 0$.

2.3 Government

Government revenues consist of tax proceeds and student loan repayments. The government levies taxes on labor earnings and returns to household savings using the tax function $\tau(y)$. Government expenditures consist of student loan disbursements and expenditures on college. We assume that some government consumption G ensures a balanced budget in each period. Government consumption provides no utility to the household.[9]

2.4 Equilibrium

Let $\mathbf{x}_j$ denote the state space of an adult in period j, $\mathbf{X} = [\mathbf{x}_3, ..., \mathbf{x}_{11}]$ the aggregate state space, and $\Lambda(\mathbf{X})$ its distribution.

A stationary recursive competitive equilibrium is a set of value and policy functions, house prices $\{P^l_S, P^h_S\}$, college admissions score cutoff $\bar{z}$, and distribution $\Lambda(\mathbf{X})$, such that, *(i)* households optimize, *(ii)* housing markets clear and school qualities are consistent, *(iii)* admissions markets clear and college qualities are consistent, and *(iv)* the distribution over the state space is stationary.

[9] We discuss this assumption in more detail when performing the main counterfactual in *Section 5*.

2.4.1 Equilibrium Selection

Given the presence of peer effects, multiple equilibria may arise in this model. At the college level, we follow Epple et al. (2017) and Hendricks et al. (2021) and consider what are referred to as "hierarchical adherence" equilibria, which require that college quality follows tuition cost rankings $t(Q_C)$. Computationally, we find that a unique equilibrium exists in the relevant parameter region. At the K–12 level, we again follow the literature (Aliprantis and Carroll, 2018; Fogli et al., 2025; Zheng and Graham, 2022) and focus on the empirically relevant equilibrium where both school zones have positive populations.

2.5 Sources of Inefficiency

In this section we briefly discuss the four main sources of market inefficiency in our model. First, markets are incomplete. It is a standard result that borrowing constraints prevent agents who suffer adverse income shocks from smoothing consumption over their lifecycle. Additionally, borrowing constraints have implications for models featuring school zone and college decisions. Agents would otherwise make different optimal decisions with respect to education choices without the presence of financial constraints. That is, agents may choose lower-quality education when experiencing negative earnings shocks. Borrowing constraints also affect the optimal time investments a parent may choose to make in their child.

Second, parents may not borrow against their child's future income. This means that consumption cannot be smoothed across generations. In the context of our model, children cannot use their own (higher) later-life earnings to compensate their parents for preschool, elementary school, or time investments. This causes parents to under-invest in their children.

Third, noisy college admission scores interact with borrowing constraints. From the policy functions for problems (15) and (17), parental time investment in children is an increasing function of parental income. Therefore, for two college applicants with identical admissions scores but different income levels, it must be that the lower-income student has higher ability. This has two effects: (1) these students' future income will differ, and (2) their effect on college quality will differ. Both imply that the college admission process is inefficient.

Fourth, externalities exist at both the school zone and college level in our model. Individuals do not internalize the impact they have on elementary or college education quality. This arises in our model due to the presence of peer effects.

3 Causal Evidence for Model Mechanisms

With a structural model in hand, the next step is establishing a key model mechanism in the data. The mechanism is how parental human capital investments respond to changes in competition for college spots. The strength of this mechanism is crucial to our research question: if parental investments are not sensitive to competition, then integration policies are unlikely to interact across time periods. Recall that integration policies make high-quality schools more competitive to those who are not targeted.

Quantifying this model mechanism consists of estimating two elasticities: the elasticity of parental time investment to college competitiveness, and the elasticity of demand for good school zones to college competitiveness.

These elasticities then allow us to estimate the child human capital production function, equation (1). Our calibration strategy involves performing a similar shift to college competitiveness in the model and comparing the model-generated moments to these two elasticities. This identifies the elasticity and productivity parameters ω_1 and λ_1 in equation (1). *Section 4* discusses the details of our calibration procedure.

3.1 Relationship of Interest

Broadly, we are interested in estimating the following relationship,

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t} + \epsilon_{i,t} \tag{19}$$

where $y_{i,t}$ is human capital investment (either in residential location choice or time investment form) and $x_{i,t}$ is the admissions rate of the college of interest for parent i.

Our model has two measures of human capital investment: time investment and school zone choice. We calculate time investment in children using the 2003-2019 waves of the American Time Use Survey (ATUS). The ATUS asks a subset of respondents from the Current Population Survey about their time use during a day. In our model, adults have children at $j = 6$, when they are 36, so in the ATUS we keep adults aged 36-50 with at least one child under 18 in the household. Following Chyn and Daruich (2022) and Moschini (2023), we sum all time that a parent spends doing an activity that involves a child.

In the model, parents can also invest in their child's human capital by purchasing a house in the high-quality school zone. We infer demand for school zones by constructing valuations of school zone qualities in the data through house price data from the American Community Survey (ACS). To determine which schools are of high quality we use test score data from the Stanford Education Data Archive (SEDA). The SEDA provides average standardized test scores over the period 2009-2019 for each school. To map the schools in the data to our model, we rank schools within district according to their average test score and group them into enrollment-weighted quintiles. The top quintile maps to school Q_S^h in the model, and the bottom four quintiles map to school Q_S^l.

Our model captures valuation of school quality through P_S^h, the price of housing in Q_S^h relative to Q_S^l. In the data, there is no information on real estate prices at the school zone level. Instead, we collect median house prices at the census tract level from the ACS 5-year estimates and create a crosswalk from census tracts to school zones using the School Attendance Boundary Survey (SABS). Our crosswalk computes a school zone house price index by taking weighted averages of census tract house prices, based on the area of intersection they have with the school zone. The moment of interest is the average house price in the top quintile of schools relative to the bottom four quintiles. We note that our measures of time investment are more accurate than our house price ratios as the latter are over a five-year time window and interpolated through geographic crosswalks.

Constructing a measure of competition, we focus on top public colleges, which we map to Q_C^h in the model. For a household i, in state s, in year t, we assume that they consider a summary statistic of admissions rates, $\bar{m}_{s,t}$, which is constructed by taking a weighted average of admissions rates at year t at the top public colleges by state,

$$\bar{m}_{s,t} = \sum_k \gamma_{s,k} \hat{m}_{k,t} \tag{20}$$

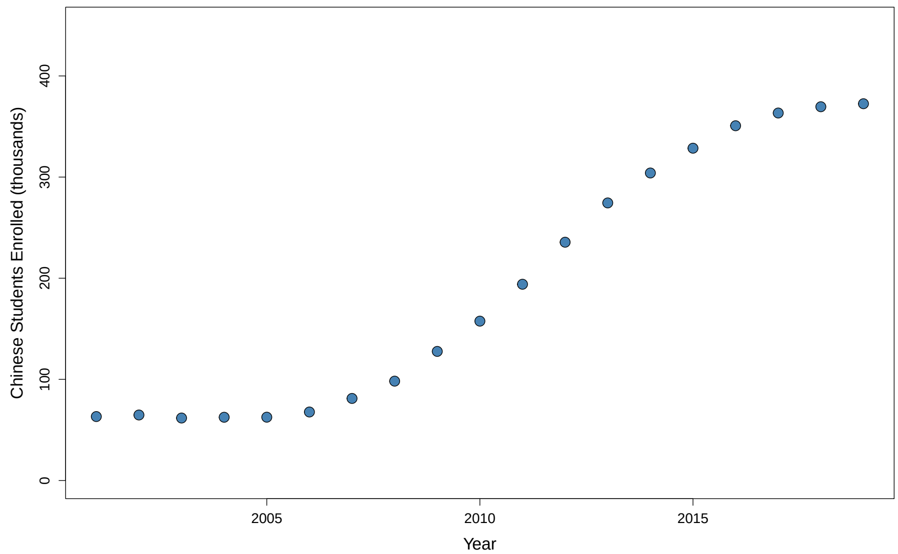
where $\hat{m}_{k,t}$ is the average admissions rate at top public colleges in state k at time t. $\gamma_{s,k}$ is the share of post-secondary students residing in state s who enroll in a post-secondary institution in state k during some fixed initial year. Since most individuals attend an institution in their state of residence, when. The weighting takes into account that most individuals attend an institution in their own state of residence (so when $k = s$, $\gamma_{s,k}$ is close to one). The weights also capture geographic proximity of universities to state of residence. It is unlikely that a shock to admissions rates at colleges in Maine will affect parental investment behavior in Utah, but it is likely to affect parental investment decisions in New Hampshire.

The weighted admissions rate $\bar{m}_{s,t}$ defined, our OLS relationship of interest is given by,

$$y_{ist} = \beta \bar{m}_{s,t} + \epsilon_{ist} \tag{21}$$

where again, y_{ist} is a measure of parental time investment in child human capital, or the ratio of house prices across neighborhood qualities.

Figure 2: **Number of Chinese Students in the United States**



Notes: This figure plots the number of international students (in thousands) from China, studying in the United States. Data is taken from Open Doors Institute.

Estimating the equation (21) via OLS comes with an endogeneity issue. There is an omitted variable issue as economic shocks, such as rises in the skill premium, could affect both the admissions rate and parental human capital investment decisions. We turn to an instrumental variable (IV) strategy that exploits exogenous variation in college admission rates coming from inflows of international students.

3.2 Identification Strategy

Our strategy exploits a large increase in the demand for American universities from Chinese students in the mid-2000s. In 2006, the United States eased the student visa application process for international students from China. The new policy allowed Chinese students to hold a visa that was valid for a year instead of the previous six months. It also allowed for multiple entries.[10] *Figure 2* shows that the number of Chinese students enrolled at post-secondary institutions in the U.S. increased sharply after 2006.

The growth in Chinese students primarily affected public post-secondary institutions.

[10]See https://2001-2009.state.gov/r/pa/prs/ps/2005/47974.htm.

These institutions used the revenue generated from international students as a buffer against decreases in government funding (Bound et al., 2020). From 2007 to 2012, international student enrollment at the undergraduate level increased by 133% at public research universities but only by 61% at private research universities (Bound et al., 2020).[11] Furthermore, the influx of international students did not affect enrollment at non-research colleges, in line with evidence that Chinese students were drawn to top-quality schools.[12] Importantly, Shen (2016) finds that the increase in international students displaced domestic students at top research universities.

We build a shift-share instrument (Shen, 2016; Shih, 2017) that predicts how inflows of international students affect colleges based on their initial shares of foreign student enrollment.[13] First, we collect the identities of the top public colleges in the United States. These colleges include the top flagship state school in each state and any public colleges ranked in the top sixty by US News in 2025.[14,15] The colleges are listed in *Table G.4* in the *Appendix C*. We then use the Integrated Postsecondary Education Data System from the National Center for Education Statistics for information on full-time undergraduate student enrollment, state of residence, admissions rates, and foreign student enrollment.

To form the instrument shares ζ_k, for each state k, we calculate the lagged initial share of foreign undergraduate students enrolled in each top public institution in the year 2000. We then compute the average share across all top institutions in the state, weighted by total enrollment in 2000.[16] The shifts of the instrument are the percent change in national Chinese student enrollment. The instrument for admissions rates is then,

[11] Michigan State saw an eightfold increase in Chinese students from 2007 to 2015 (Wall Street Journal, 2015). At Purdue University, Chinese student enrollment increased by 228% between 2007 and 2008, and during the same period there was a 400% increase at Ohio State (NBC News).

[12] See https://edition.cnn.com/2012/11/25/world/asia/china-ivy-league-admission

[13] The origins this instrument are Bartik (1991) and Card (2001).

[14] See https://www.usnews.com/best-colleges/rankings/national-universities/top-public?_sort=rank&_sortDirection=asc

[15] These colleges enrolled around 300,000 undergraduate students in 2006.

[16] Ideally we would use the share of Chinese students, but we do not see enrollment by sending nation in the IPEDS data.

$$z_{s,t} = \sum_k \gamma_{s,k} \zeta_k \% Chinese_t \tag{22}$$

where $\%Chinese_t$ is from Open Doors Institute.

The final two-state least squares (2SLS) estimating equation for time investment is,

$$hours_{ist} = \beta \bar{m}_{s,t-1} + X_{ist} + \nu_{st} + \lambda_s + \delta_t + \epsilon_{ist} \tag{23}$$

where $hours_{ist}$ is hours invested by person i in state s in year t, $\bar{m}_{s,t-1}$ is the weighted average admission rate in state s at $t-1$ across top-state colleges in state s, X_{ist} are household characteristics, ν_{st} are state controls in 2000 interacted with year fixed effects, λ_s are state fixed effects, and δ_t are year fixed effects. Then $\bar{m}_{s,t-1}$ is instrumented with $z_{s,t-1}$ from equation (22).

The 2SLS estimating equation for sorting is,

$$median\ house\ ratio_{dst} = \beta \bar{m}_{s,t-1} + X_{dt} + \nu_{st} + \lambda_s + \delta_t + \epsilon_{dst} \tag{24}$$

where $median\ house\ ratio_{dst}$ is the ratio of median house prices in the top quintile of school zones in district d versus the bottom four quintiles in district d. X_{dt} are district controls from the 2005–2009 ACS interacted with year fixed effects, ν_{st} are state controls in 2000 interacted with year fixed effects, λ_s are state fixed effects, and δ_t are year fixed effects. $\bar{m}_{s,t-1}$ is instrumented with $z_{s,t-1}$.

3.3 Instrument Validity

The identification assumption is that the initial shares of foreign students across top public colleges only affect changes in child human capital investment through changes in college admission rates. There has been recent work on how to assess validity of shift-share instruments (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). We follow the approach of

Goldsmith-Pinkham et al. (2020), where identification relies on exogeneity of the shares.

To start, Goldsmith-Pinkham et al. (2020) argue for demonstrating that the shares are not correlated with other economic variables. In *Table G.5* in *Section C* of the Appendix we compute the correlation between the average share of foreign students in 2000 and demographic indicators at the state level. Our demographics are population levels, racial composition, unemployment rate, and median household income. All correlations are below 0.3 in absolute value, suggesting that the initial share of foreign students is exogenous to other state-level economic forces.

Second, in the setting where the shares are exogenous Goldsmith-Pinkham et al. (2020) show that the shift-share can be recast into a difference-in-difference framework. We consider two groups of states: treated ones, who have an above-average share of foreign students in 2000 and control ones, who had below-average foreign students shares in 2000. We can then test the validity of the instrument by assessing parallel trends prior to the policy change.

To start, *Figure 3* shows the trends in weighted average admission rates at top state schools for states that had an above-median share of foreign students in 2000 (dashed line) and those states with a below-average share (solid line). We see that the admission rates are trending similarly in the early 2000s, and then post-2006 there is a noticeable drop in admission rates in states with a high share of foreign students. This figure highlights the variation that the instrument exploits and also that admission growth rates did not differ in treated and control states prior to the policy change.

As an additional test, we also show that there were no pre-trends in parental time investment in children across treated and control states leading up to the Chinese student visa change. *Figure 4* plots the difference in average time investment across treated and control states. The coefficient in 2006 is normalized to zero. The figure shows that there is no pre-trend in time investment prior to 2006 and that after, there is higher investment in children in treated states.[17]

[17]We cannot do the same figure for house prices as our data starts in 2005 so we only have pre-policy year.

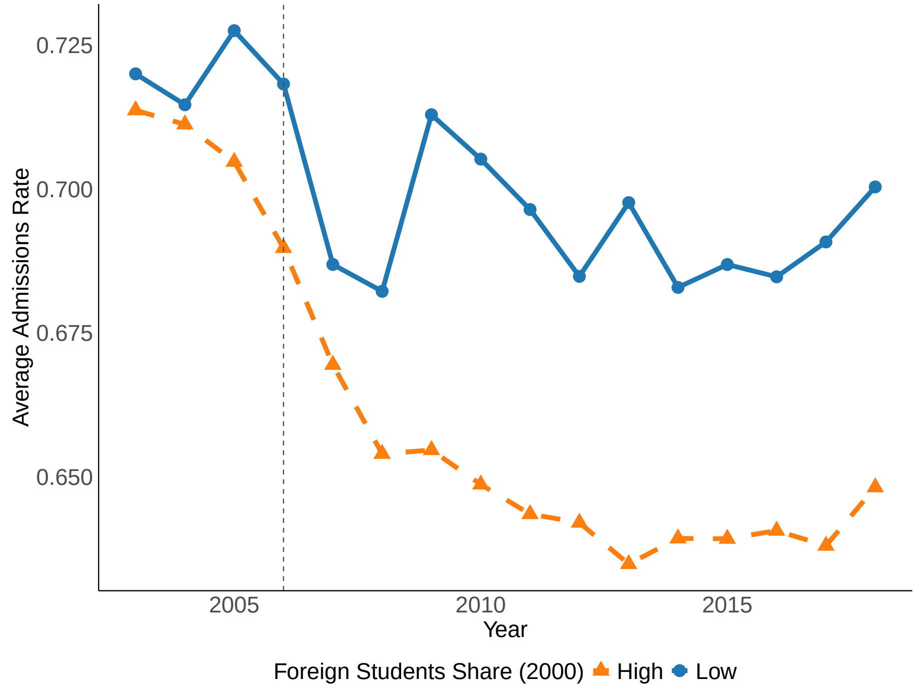
Another possible concern is if schools with larger initial shares of foreign students used the extra funding they received from the influx of Chinese students to increase the quality of their flagship schools through higher expenditure. Another channel could be that these schools experienced improvements in their peer effects from the increase in Chinese students. In both of these cases, the identification assumption would be violated, as parents would increase investment because of improving college quality and not because of lower admission rates. To address these concerns, we include controls for the initial (2005 year) expenditure per pupil and average SAT scores at the state level. These initial 2005 values are then interacted with year fixed effects. Having initial values interacted with year fixed effects mitigates the concern that the influx of Chinese students could also cause changes in SAT scores and per pupil expenditure- which is why we do not use time varying controls (Goldsmith-Pinkham et al., 2020). To alleviate any concerns about state-specific shocks that may correlate with parental time investment, in a robustness check we include state-specific time trends.

3.4 Estimation Results

Table 1 presents our time investment estimates. Column (1) reports the OLS estimate of -0.3. Column (2) shows that the OLS estimate is attenuated toward zero relative to the 2SLS estimate, which is -1.78. In Column (3), we add household demographics from the ATUS, in Column (4), state-level controls from 2000 interacted with year fixed effects, and in Column (5) state linear time trends. Our preferred estimate in Column (5) is -1.99, indicating that, on average, a 10 percentage point decrease in admissions rates at top-state colleges increases time investment by 0.199 hours per day.

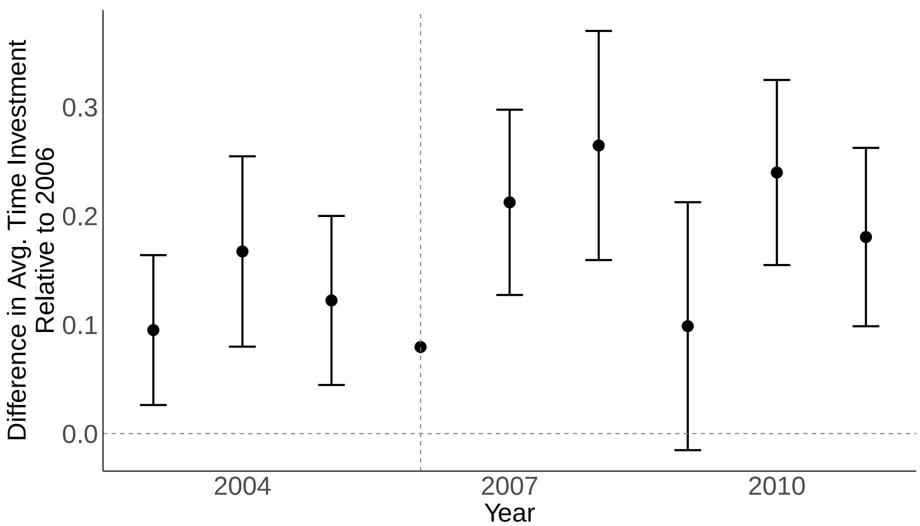
Table 2 presents our sorting estimates. The OLS estimate is 0.093. Column (2) shows the 2SLS estimate with year and district fixed effects. Column (3) includes district-level controls, while Column (4) also includes state-level controls. Our preferred estimate is -2.157. A 10 percentage point decrease in the admissions rate increases the median house value ratio by 0.22.

Figure 3: **First Stage – Admission Rates by High-Low Foreign Students**



Notes: This figure plots average admission rates at top public colleges across states that had a share of foreign students in 2000 above and below average. Data is from the Integrated Postsecondary Education Data System (IPEDS).

Figure 4: **Parallel Trends: Time Investment**



Notes: This figure plots the difference in average parental time investment between states with above- and below-average foreign student shares in 2000, relative to 2006. Data is from the American Time Use Survey (ATUS).

Table 1: **Effect of College Admission Rates on Time Investment**

	Dependent variable, Time Investment				
	(1)	(2)	(3)	(4)	(5)
Admissions Rate	-0.299^{***}	-1.782^{*}	-1.703^{*}	-1.696^{*}	-1.992^{*}
	(0.0869)	(0.782)	(0.743)	(0.698)	(0.801)
Method	OLS	2SLS	2SLS	2SLS	2SLS
Observations	83,195	83,195	83,195	83,195	83,195
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Individual Controls	No	No	Yes	Yes	Yes
State Controls	No	No	No	Yes	Yes
State Linear Time Trends	No	No	No	No	Yes
R^2	0.004	-0.003	0.082	0.083	0.084

Notes: This table presents OLS and 2SLS results for Equation (23). Column (1) is the OLS equation. Columns (2)–(5) are 2SLS where the admissions rate is instrumented by Equation (22). Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: **Effect of College Admission Rates on School Zone Housing Values**

	Dependent variable, Price in Q_S^h			
	(1)	(2)	(3)	(4)
Admissions Rate	0.093***	−0.794***	−1.600***	−2.157***
	(0.016)	(0.124)	(0.184)	(0.386)
Method	OLS	2SLS	2SLS	2SLS
Observations	27,664	27,664	19,296	19,296
District Controls	No	No	Yes	Yes
State Controls x Year FE	No	No	No	Yes
R^2	0.954	0.948	0.934	0.927

Notes: This table presents OLS and 2SLS results for Equation (24). Column (1) is the OLS equation. Columns (2)–(4) are 2SLS where the admissions rate is instrumented by Equation (22). *p<0.1; **p<0.05; ***p<0.01. Data from Stanford Education Data Archive, IPEDS, and American Community Survey.

4 Calibration

In this section, we describe our internal and external identification strategies. Externally calibrated parameters are taken directly from the data or literature. Internally calibrated parameters are determined using the simulated method of moments (SMM). While SMM estimates all internal parameters jointly, we discuss which moments are most affected by each parameter.

All monetary values are reported as a fraction of real mean household income from the 2015 American Community Survey (ACS). *Table 3* lists the parameters estimated internally. In *Appendix G Table G.3* summarizes the parameters set externally. Additional details or adult and child human capital production are reported in *Appendix D*.

4.1 Preferences

A time period in the model is six years. The annual discount factor is given by $\beta = {}^{1}/_{1.02}$, where the average risk-free rate in 2019 is 0.02. The wage rate w is normalized to 1.0. The relative risk aversion γ is set to 1.0, which implies $u(c) = \ln(c)$.

The altruism parameter, θ, is internally calibrated to match an aggregate share of transfers to net worth of 1.26 from the Survey of Consumer Finances (Feiveson and Sabelhaus, 2018). A higher value of θ increases the weight of a child's continuation value in its parent's value function and thus increases the incentive for parents to transfer wealth to their child.

4.2 Adult Human Capital

4.2.1 Ability Transmission

We assume that the transmission of ability across generations, given by the function $\mathcal{A}(a, \hat{a})$, is a first-order autoregressive process (AR(1)),

$$\ln(\hat{a}_i) = \rho_a \ln(a_i) + \epsilon_i^a \tag{25}$$

where $\hat{a}_i$ and a_i denote the ability of child and parent in family i, ρ_a determines the persistence of ability across generations, and $\epsilon_i^a \sim N(0, \sigma_a^2)$. ρ_a and σ_a^2 are calibrated internally. ρ_a and σ_a affect the intergenerational elasticity of income of 0.34 (Chetty et al., 2014) and the Gini coefficient of income inequality (OECD, 2024), respectively. In the model, the intergenerational elasticity of income is the slope coefficient from a regression of the log of child income (age $j = 5$) on the log of parental income (age $j = 8$). The Gini is taken for adults at ages $j = 4$-11.

4.2.2 Colleges

Qualities – We must map our two college qualities in the model to the many colleges in the data. As in the empirical section, we focus only on public colleges. We use information from two sources: the College Mobility Report Card from Opportunity Insights (Chetty et al., 2020) and the 2016 Undergraduates Survey from the National Post-Secondary Student Aid Study (NPSAS). In both sources, there is a variable that describes the selectivity of each college. In Chetty et al. (2020), we group public colleges with the "Tier" variable valued at "Highly selective public" and "Other elite schools (public and private)" into Q_C^h, and the remaining 4- and 2-year colleges as Q_C^l.[18] In the NPSAS, we group the public colleges labeled as "Very Selective" into Q_C^h. From both sources, our Q_C^h college is composed of

[18] We do not include institutions that provide less than 2-year degrees.

roughly thirteen percent of all college students in a public post-secondary institution.

Using IPEDS, we find that the enrollment per state high school population for these public colleges has been largely steady over the past decade, supporting our assumption that Q_C^h has fixed supply.

College quality in the model is a function of the average ability of the student body and per-pupil expenditure. The parameter governing this function is the elasticity of school quality with respect to per-pupil expenditure, α_C. α_C moves the difference in earnings growth and earnings level for those who attend the high-quality versus the low-quality college. This moment is calculated in the data by taking the ratio of earnings for those who went to a certain college quality and are aged 30-35 versus those who are 24-29 (Chetty et al., 2020).[19]

Admissions – Q_C^h college enrolls thirteen percent of all college-going students. Having Q_C^h represent highly selective public colleges aligns with our finding in the data that the number of enrolled students relative to in-state high school graduates has largely been constant over time for these institutions. In equilibrium, we solve for $\bar{z}$ so that college markets clear for Q_C^h. To represent the many "open-admissions" colleges, we do not set a capacity constraint at the low-quality college Q_C^l. However, we do match the total share of agents in college in 2016 at 0.45.

Admissions are governed by two additional parameters which we internally calibrate: ν, the elasticity of admission scores with respect to human capital, and σ_z, the noisiness of the admission score. As in Brotherhood et al. (2023), ν moves the percentage of low-income people (calculated from Chetty et al., 2020) in the high-quality college. σ_z also affects sorting, and together with ν, we target the parental income distribution across each college type.

Preference Shocks – In the model, preference shocks across college attendance and type of college affect the sorting into the post-secondary school options. We discipline the preference

[19]Note that Chetty et al., 2020 measure earnings at the same point in time, so wage growth is obtained from separate cohorts.

shocks using the share of individuals from different income quintiles in each college type (Chetty et al., 2020).

4.3 Child Human Capital Development

We use the Panel Study of Income Dynamics (PSID), a longitudinal dataset tracking families since 1968, to discipline child human capital production. Our sample of interest consists of children who participated in the 1997, 2002, 2007, 2014, and 2019 Child Development Supplement (CDS) studies. The CDS gathered information on child care arrangements, schools attended, child cognitive skills, and parental time investment in children. The study complements information in the main PSID study on parental income and hours worked. We follow Lee and Seshadri (2019) in cleaning and preparing the PSID sample. Furthermore, we restrict our sample to those with school identifiers. In all, we end up with 3,202 child-year observations. See *Appendix C* for details and sample summary statistics.

4.3.1 Time Investment

The CDS contains twenty-four-hour time diaries that track child activities. Additionally, these diaries collect information on whether a parent was actively participating during the activity ("active investment") or if they were simply present ("passive investment").[20] We focus on active hours invested per week, in addition to the opportunity cost of these hours, using hourly parental wages (Lee and Seshadri, 2019).

4.3.2 Human Capital

The CDS assesses child cognitive skills through Letter-Word questions. There are fifty-seven questions, which increase in difficulty and are each given a score of zero or one. We follow the methodology in Lee and Seshadri (2019) and adjust raw scores by difficulty to ensure

[20] This activity classification follows Del Boca et al. (2014) and Lee and Seshadri (2019).

that they are comparable over time. We normalize scores to a scale of 100, and we call these adjusted scores human capital in our model.

4.3.3 Elementary School

Qualities – The restricted version of the PSID allows us to identify the school attended by the child through the National Center for Education Statistics school identifier. Next, we merge in information on school quality. We use the only comparable metric of school test scores nationwide from the Stanford Education Data Archive (SEDA). This metric is constructed using the National Assessment of Educational Progress (NAEP), a nationwide standardized exam, to correct for different testing standards across states. School-level data are available as an average across 2009 to 2019.[21] To map the schools in the data to our model, we rank schools according to their average test scores and group them into the top quintile (which we map to school Q_S^h in the model) and the bottom four quintiles (which represent school Q_S^l). In the model equilibrium, we solve for the neighborhood price, P_S, which ensures that housing markets clear.

Several parameters at the elementary school level are internally calibrated. ζ is the anchor of child human capital to adult human capital (earnings). As ζ increases, child human capital becomes more valuable, and the incentive for parents to invest in child human capital increases. Hence, ζ targets average parental time investment rates.

The two parameters in the CES child human capital function, λ_1 and ω_1, control the relative importance and sustainability of K-12 quality versus parental time investment in child human capital formation.[22] We discipline these two parameters using our causal moments estimated above. We found that a 10 percentage point decrease in the college admissions rate at top public colleges led to a 0.2 increase in parental hours invested and a 0.22 increase

[21]Note that the SEDA test score data are primarily available for elementary and middle school levels, and so our merge is based on the school quality of a child's elementary or middle school.

[22]We assume that the CES parameters in $j = 1$ are the same as in $j = 2$.

in the price of housing in Q_h^S relative to Q_l^S. To estimate the same effects in the model, we take the baseline calibrated model and shock $\bar{z}$ to induce a change in admissions rates consistent with the data. We then compare the change in parental time investment and house prices between the two model solutions and match this to our above estimates.

Next, we internally calibrate α_S, the curvature of elementary school quality. A larger value of α_S will create starker sorting patterns in the model and magnify the importance of peer effects. Therefore, we target the ratios of parental income, time investment, and child human capital across elementary school qualities.

More directly, α_S affects the productivity (and hence growth rate) at which child human capital is produced. We also pin down α_S using the following indirect inference exercise. We estimate the relationship between human capital growth across $j = 1$ and $j = 2$, and the school attended in $j = 1$. The sample here is composed of those from the PSID for which we have test scores at $j = 1$ and $j = 2$, which is just under a third of our overall sample. We control for parental time investment at $j = 1$, lagged test scores at $j = 1$, and the age difference in years between the two test observations. We run the following regression,

$$\Delta \log(\text{test}) = \beta_0 + \beta_1 Q_S^h + \beta_2 \log \text{test}_{j=1} + \beta_3 \text{time} + \beta_4 \Delta \text{age} + \epsilon \tag{26}$$

Table G.2 presents the results from the above regression. We find that the coefficient on Q_S^h is 0.046 and significant at the 5% level. Controlling for ability (proxied by lagged test scores) and time investment, children in Q_S^h have test scores that grow 4.6% faster than those in Q_S^l. We run the same regression in the model.

Preference Shocks – In the model, preference shocks across elementary quality attendance affect the income sorting into qualities. We discipline the preference shocks using the share of individuals from different income quintiles for each elementary quality, from the PSID.

4.4 Model Fit

We report a summary of model fit in *Table 4*. Our model closely matches moments on income inequality (Gini and standard deviation of earnings) as well as the intergenerational income elasticity. We slightly understate the share of transfers to net worth: our model generates 1.09, while it is 1.26 in the data (Feiveson and Sabelhaus, 2018). In Panel (b), we report moments related to preschool. In our model, 38% of households send their child to preschool, similar to the data.

Panel (c) reports model moments related to public school human capital investment. The population in the high-quality school zone, Q_S^h, is fixed at 0.2. Our calibration slightly overestimates the average household income ratio in school zone Q_S^h versus Q_S^l of 1.72 (1.81 in the model). We closely match the ratio of time investment as well as the test score ratio. The calibration pins down the overall average time investment from ages 0-17 but underestimates time investment at ages 6-11 (0.05 in the model and 0.09 in the data). Our indirect inference exercise on the effect of school quality on test scores gives an estimate of 4.6%, while in our model the value is 5.9%. The last two rows of Panel (c) show how our model does in matching our two causal estimates from the data. We are able to closely match both the effect of college admissions on time investment, in addition to its effect on the house price ratio across school zones.

Panel (d) reports moments related to college. In the data, 45% of high school graduates enroll in college; our model generates a 43% attendance rate. Data from Chetty et al. (2020) show that of individuals who go to a public college, 13% go to a high-quality public college (2000 enrollment) — that translates to 5.9% of the total economy in our model. In addition, we match the average earnings in the data of those who go to low-/high-quality public colleges of 1.82. Lastly, we also match differences in earnings growth by college quality.

In the Online Appendix, *Figure G.1* plots sorting across elementary school quality by parental income quintiles, for both the model and the data. Blue (red) bars are for the low- (high)-school quality. The model does well in generating the observed patterns in the data, though sorting is starker in the model. We underestimate the share of families from the bottom quintile in the high-quality school zone and overestimate the share of families from the top quintile there. *Figure G.2* plots the corresponding figure for college qualities, showing the proportion of the student body by parents of a given income level. Our model has more trouble matching the distribution of family income by college. For instance, there are very few people from the bottom two income quintiles in any college. A potential way of remedying this is to have taste shocks (or psychic costs) for college that are correlated across generations (Lee and Seshadri, 2019).

Table 3: **Internally Calibrated Parameters**

Parameter	Value	Description
θ	0.32	Parental Altruism
ρ_a	0.44	Persistence of abilities
σ_a	0.34	Variance of abilities
σ_ϵ	0.065	Variance of market luck shocks
q_p	0.25	Preschool quality
λ_0	0.25	CES productivity parameter – 0-5
ω_0	0.50	CES elasticity parameter – 0-5
λ_1	0.425	CES productivity parameter – 6-17
ω_1	0.25	CES elasticity parameter – 6-17
ζ	2.0	Anchor of child to adult human capital
α_S	7.0	Curvature of elementary quality
ν	0.40	Curvature of score production function
σ_z	0.60	Noisiness of admissions process
α_C	0.33	Elasticity of college quality to peer-effects
σ_e	0.40	Scale of elementary preference shocks
σ_c	0.25	Scale of college preference shocks

Notes: This table gives model parameters, the internally calibrated value, and a brief description of their role.

Table 4: **Model Fit**

Moment	**Data**	**Model**	**Source**
Panel (a): Aggregate			
Gini	0.40	0.40	OECD
Std. earnings	0.88	0.85	CPS
IGE	0.34	0.34	Chetty et al. (2014)
IGE transfer share	1.26	1.09	SCF
Panel (b): Preschool			
Attendance high	0.37	0.38	NCES
Time invest. – 0-5	0.13	0.16	PSID
Preschool effect on earnings	8%	12%	(Bartik, 2014)
Panel (c): Public school			
Attendance	0.20	0.20	Normalization
Parental inc. ratio	1.72	1.81	PSID
Time invest. ratio	1.10	1.08	PSID
Opportunity time invest. ratio	1.94	1.83	PSID
Test score ratio	1.11	1.15	PSID
School growth effect	0.046	0.059	PSID
Time invest. – 6-11	0.09	0.05	PSID
Time invest. – 12-17	0.07	0.07	PSID
Mean time invest. 0-17	0.09	0.09	PSID
College admissions on time investment	0.19	0.13	Author's estimate
College admissions on house price ratio	0.22	0.20	Author's estimate
Panel (d): College			
Attendance	0.45	0.43	BLS, NCES 2016
Rel. attendance high	0.059	0.059	Normalization
Earnings growth low – 24-35	1.40	1.41	Chetty et al. (2020)
Earnings growth high – 24-35	1.71	1.74	Chetty et al. (2020)
Relative earnings – 24-35	1.82	1.81	Chetty et al. (2020)

Notes: The columns compare the model to the data for selected targeted moments.

4.5 External Validation

We now provide external validation for our model by replicating empirical evidence on the effect of neighborhoods and colleges on adult outcomes.

Chetty et al. (2016) study the impact of child location on future earnings. They do so in the context of the Moving to Opportunity (MTO) experiment, through which families with children living in low-income census tracts were randomly offered rental vouchers to move to higher-income census tracts. Households that did so had to use thirty percent of their income on rent, and the remainder was covered by the voucher. Chetty et al. (2016) find that children who moved before the age of thirteen had 31% higher earnings relative to the control group by their mid-twenties.

We run a similar experiment in our model. At $j = 1$, we randomly offer a housing voucher to parents with below-median income living in school zone Q_S^l, allowing them to move to Q_S^h. The voucher covers remaining rental costs after the agent contributes thirty percent of their income. While the geographical contexts vary slightly between our model (school zones) and the data (census tracts), we believe that one of the main benefits of moving for children lies in school access. Since the MTO experiment was a small-scale randomized controlled trial, we keep prices and spillovers fixed.

We calculate three model statistics to compare to Chetty et al. (2016) in *Table 5*. First, we compute the percentage of families who are offered the vouchers and accept them. We find a take-up rate of 68.4% compared to 48% in the experiment. Next, we calculate the intent-to-treat (ITT) effect on earnings by comparing the average earnings of children in households that were offered vouchers to those eligible but not offered. The ITT in the model is 17% compared to 14.0% in the data. Finally, we calculate the treatment-on-the-treated (TOT) effect by comparing earnings in the treatment and control groups, controlling for initial states. Our model estimates a TOT of 32.9%, compared to 31% in the data.

Next, we show that our model generates reasonable predictions about the importance

Table 5: MTO in Model and Data

	Data	Model
Take-up	48%	68.4%
Intent-to-Treat	14%	17.0%
Treatment-on-Treated	31%	32.9%

Notes: Earnings measured when individuals are in their mid-twenties. Data from Chetty et al. (2016).

of college quality for earnings. We follow Hoekstra (2009), who studies the causal effect of attending a flagship state university on future earnings. He uses a regression discontinuity design for individuals who were just above versus below the admissions threshold and finds intent-to-treat effects of 11-17%. In our model, we compare the average earnings of agents who were just above and just below the admissions threshold for Q_H^C, $\bar{z}$. The ITT effect on earnings in the model is 21.7%. Overall, our model is able to produce reasonable estimates of the effects of housing vouchers and attendance at flagship colleges. We now turn to running policy experiments with the model.

5 Policy Counterfactuals

We use our model to assess the effects of education policies at three different stages: elementary school, secondary school, and college.

Income Affirmative Action at College – We consider an income-based affirmative action policy that provides students from low-income families with an increased probability of attending the high-quality college. Children from families with below-median income receive extra bonus points when calculating their admission scores. This is equivalent to a policy where the high-quality college has a quota of spots for low-income students, with a higher level of bonus points implying more spots allocated to low-income applicants.[23] We

[23]See Brotherhood et al. (2023) for a proof of this equivalency. We use bonus points as they are more computationally tractable.

consider a conservative policy in which low-income students receive an additional 20% of the admission score cutoff required in the baseline equilibrium. Since colleges admit more low-income students, their per-pupil expenditure falls as they must pay out more in financial aid. However, college quality may increase or decrease depending on whether more high-ability students attend.

Integration at the Public School Level – We study a rezoning policy in which 4% of students are moved across school boundaries. The policy consists of randomly taking 2.5% of children living in the low-quality school zone and sending them to the high-quality school. Conversely, we randomly send 10% of children in the high-quality school zone to the low-quality school. We do this at the elementary school level and/or at the secondary school level. Rezoning weakens the relationship between house prices and school quality since buying a house in Q_S^h does not come with guaranteed school quality. The realization of the elementary (secondary) school shock takes place at the start of the period when the child is age $j = 1$ ($j = 2$), so that parents know the realized school quality when making time investment decisions.

Equilibrium – For each policy experiment, we run two versions. First, we solve the model when the policy is anticipated in a partial equilibrium setting. Agents update their choices in response to the policy, and spillovers from peer effects readjust, but the house price of Q_S^h and the college cutoff $\bar{z}$ are held constant. Next, we solve the model in general equilibrium, when the policy is anticipated and all equilibrium objects are allowed to adjust.

In the experiments, we keep the tax schedule fixed and government expenditures G adjust. Quantitatively, we find that government revenues rise in each policy experiment, and so G rises. An alternative would be to hold government expenditures fixed and vary a level shifter in the progressive tax schedule. However, this would conflate changes in IGE and inequality stemming from the educational policy with changes to the tax rates. We have experimented with this alternative and find it has negligible effects on our results, as the level decrease in the tax function necessary to hold government expenditures constant is small.

5.1 General Equilibrium Effects

Table 6 presents the partial and general equilibrium percent changes in the following variables: Q_C^h, the share who attend the high-quality college; Q_S^h, the share who live in the high-quality school zone; the intergenerational elasticity of income; the Gini coefficient of income; $\bar{z}$, the admissions score that clears the high-quality college; and P_S^h, the price of the high-quality school zone. All percent changes are computed relative to the initial baseline steady-state equilibrium.

We begin by discussing how the rezoning policy unfolds throughout public school. Panels (a) and (b) of *Table 6* present our findings for the elementary school and secondary school rezoning policies, respectively. Rezoning at the elementary school level has only minor effects. In partial equilibrium, the demand for Q_S^h falls by 1%. Since the expected school quality of Q_S^h is lower, fewer households are willing to pay the higher cost to live there. In general equilibrium (row (ii)), there is a 1.1% decrease in P_S^h as the house price must fall to clear the housing market. In general equilibrium, the intergenerational elasticity of earnings and the Gini coefficient decrease, since there is a weaker relationship between house prices and school quality, and less of a difference between the two school zones.

In Panel (b), we turn to the effects of rezoning at the secondary school level. In row (i) of Panel (b), we see that the share of people in Q_S^h falls by roughly eight percent in partial equilibrium. This translates to a three percent decrease in the price P_S^h and a 1.7% decrease in the IGE in general equilibrium. Note that even though the rezoning policies at the elementary and secondary school levels move the same population share, the secondary school rezoning has larger effects. A parent choosing between schools Q_S^h and Q_S^l faces more uncertainty in the case of the secondary school policy. When their child is aged $j = 2$, the parent faces uncertainty both in terms of school quality and the income shock. However, in the elementary school policy, the parent can insure against a bad school shock in $j = 1$ by adjusting time investment in $j = 2$. Therefore, the value of the high-quality school zones falls more under the secondary school rezoning policy, leading to larger improvements in intergenerational mobility.

Panel (c) contains results for the combined K–12 policy. In general equilibrium, the policy produces the largest decrease in the IGE (i.e., the highest increase in mobility), with a 2.2% drop. There is also a large fall in P_S^h as the expected value of the school zone's quality decreases.

Panel (d) presents results for the college affirmative action policy, which helps low-income families with children whose test scores were just below the baseline admission cutoff. Row (i) contains the partial equilibrium results, which show college attendance at Q_C^h increasing by 28%, as more people have enough points to be admitted. Row (ii) of Panel (d) presents the general equilibrium effects, where $\bar{z}$ and P_S^h are allowed to adjust. Since Q_C^h has a fixed supply of seats and is now accepting more low-income children, the admissions score that clears the college market, $\bar{z}$, increases by 11.5%. As college becomes more competitive, the value of a guaranteed good elementary and secondary school increases, which is reflected in a 1.8% increase in P_S^h. In general equilibrium, the IGE increases by 2.3% (lower income mobility) due to increased sorting at the elementary and secondary levels. This policy experiment highlights how efforts to promote socioeconomic diversity at the college level can have unintended consequences that affect earlier stages of human capital development.

In Panel (e), we add the college affirmative action policy to the K–12 policy. In the general equilibrium case, the fall in the IGE is cut by nearly half compared to Panel (c). The reason is that while rezoning at K–12 improves income mobility, the college policy increases competition, pushing up the admission score. There is also a smaller reduction in P_S^h compared to Panel (c). Our results indicate that integration policies are less effective when implemented at both the K–12 and college levels than at the K–12 level alone.

Table 6: **Effect of Policies on Population**

	Q_C^h pop. (1)	Q_S^h pop. (2)	IGE (3)	Gini (4)	$\bar{z}$ (5)	P_S^h (6)
Panel (a): Elementary School						
(i) Partial Eqm.	-0.3	-1.0	-1.2	-0.5	–	–
(ii) General Eqm.	–	–	-1.1	-0.3	-0.5	-1.1
Panel (b): Secondary School						
(i) Partial Eqm.	-2.7	-7.8	-1.6	-0.6	–	–
(ii) General Eqm.	–	–	-1.7	-0.4	-0.7	-2.9
Panel (c): K-12:						
(i) Partial Eqm.	-2.1	-8.3	-2.3	-0.9	–	–
(ii) General Eqm.	–	–	-2.2	-0.5	-1.0	-5.5
Panel (d): College						
(i) Partial Eqm.	28.3	0.6	0.2	1.1	–	–
(ii) General Eqm.	–	–	2.3	-0.1	11.5	1.8
Panel (e): K-12, College:						
(i) Partial Eqm.	22.2	-7.8	-2.0	0.3	–	–
(ii) General Eqm.	–	–	-1.1	-0.9	10.2	-5.1

Notes: This table presents results for our policy experiments in partial and general equilibrium. Each panel lists a different policy experiment. Columns (1) through (6) present different moments. Q_C^h pop. is the share of agents in the high-quality college. Q_S^h pop. is the share of households living in the high-quality school zone. IGE is the intergenerational elasticity of income. Column (4) presents the Gini coefficient of income. $\bar{z}$ is the admissions score to get into the high-quality college. P_S^h is the price of the high-quality school zone. The last two variables are held fixed in partial equilibrium. Moments are presented in percent changes relative to the baseline steady-state equilibrium.

5.1.1 Mechanisms

Our policy experiments show that while elementary and secondary school rezoning policies improve intergenerational mobility, a college affirmative action policy that aims to improve access to the high-quality college for low-income students decreases average income mobility. In this section we discuss the model mechanisms underlying this result.

We have shown empirically that high-quality colleges have a fixed supply of seats. When these colleges implement an affirmative action policy, competition rises for those not targeted by the policy. Parents respond by investing more in their child's human capital production, both in terms of time, and monetarily, by moving to the high-quality school zone, Q_S^h. The higher demand for Q_S^h causes prices to rise, pricing out low-income families on the margin. The net effect is to lower intergenerational mobility on average. This result is a direct consequence of our novel modeling structure, where parent decisions respond to changes in college competition. Under a version of the affirmative action counterfactual exercise where parent policy functions are kept constant from the benchmark solution, IGE falls by 0.5%. A key factor driving the rise in the IGE is the fixed supply of seats. We find that for IGE to remain constant during the college affirmative action policy, capacity at the high-quality colleges would need to rise by 19.5 percentage points.

We now highlight additional differences between the PE and GE college affirmative action policies. In particular, we define two types of agents, between the PE and GE counterfactuals: (1) "stayers" and (2) "leavers". *Stayers* are individuals who attended Q_C^h in the partial equilibrium version and also attend Q_C^h when P_S^h and $\bar{z}$ adjust. *Leavers* are those who attend Q_C^h in the partial equilibrium setting but do not in general equilibrium.

Table 7 reports the ratio of average moments for *leavers* divided by *stayers*. From row (1) we see that *leavers* and *stayers* are of very similar ability, with a ratio near one. Additionally, from row (2) *leavers* and *stayers* have quite similar human capital levels as children in partial equilibrium. This is not surprising, as both attended the high-quality college in partial equilibrium.

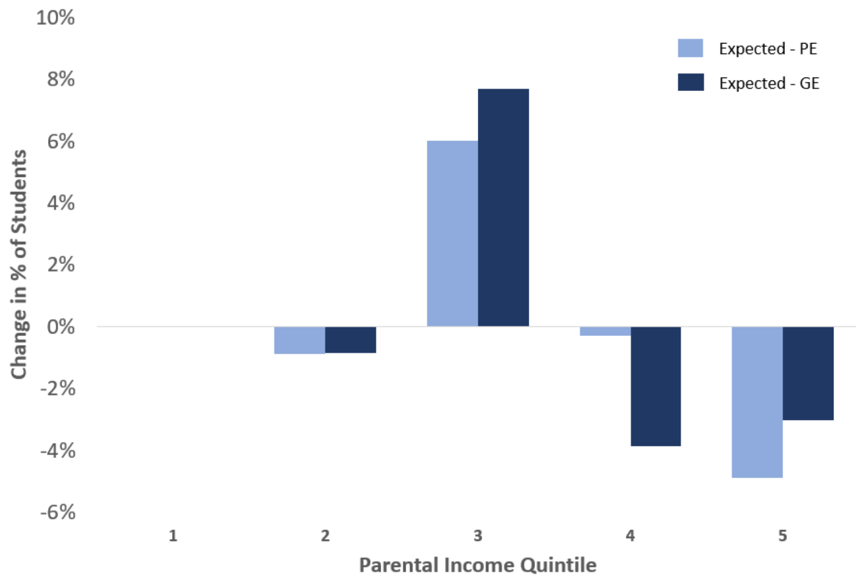
Table 7: **Ratio of High-quality College Leavers over Stayers for Selected Moments**

Moment	**Ratio**
(1) Child ability, $\hat{a}$	0.98
(2) PE child human capital, $\hat{h}$	0.95
(3) GE child human capital, $\hat{h}$	0.59
(4) Probability of leaving high-quality school zone, Q_S^h	3.12
(5) Parental income, y	0.82

Notes: This table reports average moments for the "Leavers" relative to (divided by) the "Stayers" in the general equilibrium version of the income affirmative action policy. "Stayers" are individuals who attended Q_C^h in the partial equilibrium version and also attend Q_C^h when P_S^h and $\bar{z}$ adjust. "Leavers" are those who attend Q_C^h in the partial equilibrium setting but do not in general equilibrium.

However, looking at child human capital in GE, *leavers* now have significantly less human capital than *stayers* at 0.59. This is because *leavers* no longer attend the high-quality college but *stayers* do. However, looking at row (4) we see that the reduction in human capital stems from more than changes in college quality. Row (4) compares the probability of leaving the high-quality school zone between PE and GE. *Leavers* are also three times more likely to leave the high-quality school zone in addition to the high-quality college. Row (5) shows that, on average, *leavers* have lower parental income than *stayers* with a ratio of 0.82. Hence, it is these types of agents who are no longer able to afford to live in the high-quality neighborhood when prices rise in the GE college affirmative action counterfactual. *Figure 5* shows that these lower-income *leavers* are (on average) from the second parental income quintile. These students are crowded out on the margin at the high-quality neighborhood and are no longer able to meet admission standards at the high-quality college. Moreover, those in the lowest income quintile are unable to effectively take advantage of the college affirmative action policy. It is overwhelmingly those in the third income quintile who see increases in enrollment at the high-quality college under this policy.

Figure 5: **Income Sorting for High-Quality College, by Counterfactuals**



Notes: This figure shows the sorting of parental income into Q_C^h for the college integration policy in partial equilibrium and general equilibrium. The bars are the level changes in the percentage of students who are from each parental income quintile relative to the baseline general equilibrium.

5.2 Welfare

Table 8 reports the aggregate consumption equivalent welfare changes for three general equilibrium integration policies, relative to the benchmark calibrated U.S. economy.[24] Column (1) reports the change in welfare from the K-12 rezoning policy discussed in *Section 5*. Here welfare falls on aggregate by 0.17%. Welfare could rise of fall, depending on changing K-12 qualities, and the welfare losses of those moved out of the neighborhood relative to the welfare gains of those moved into the neighborhood. However, given that the policy is conducted for a random set of households, it is natural that welfare falls on average.

In column (2), we find that the college affirmative action policy increases welfare by 0.11%. This is a quantitative result showing that on average, reducing inefficiencies for lower income agents sees larger welfare gains than the crowding out of higher income students.

Finally, column (3) combines the college and K-12 policies. We find that (unlike IGE)

[24] Welfare is calculated as an expected value *before* the uncertainty over college admissions is resolved.

Table 8: Welfare Changes over Benchmark Model

	K-12, GE	College, GE	College + K-12, GE
	(1)	(2)	(3)
Δ Welfare	-0.17%	0.11%	0.21%

Notes: This table reports the consumption equivalent welfare effects of three integration policies, in general equilibrium.

these policies are complementary with respect to aggregate welfare, which now rises by 0.21%. Here, some agents who could not "take advantage of" the college affirmative action policy due to a lower-quality K-12 education, now are able to and attend the high-quality college. These agents see large welfare gains on average, driving up the aggregate.

6 Discussion and Conclusion

This paper studies the effect of integration policies across different stages of human capital development. Our work is the first to feature a dynamic lifecycle heterogeneous agent model with endogenous sorting and qualities at both the K-12 and college levels. To make credible predictions on the interaction of integration policies, the model is calibrated to match the sensitivity of parental human capital investments (through time spent and school zone choice) to changes in competition at future schooling levels in the data. We use a novel strategy to causally estimate these moments in the data.

At the aggregate level, we find that integration policies are effective at improving intergenerational mobility at the public school level but not at the college level. At the elementary and secondary school levels, rezoning policies reduce inequality between school zones. The average ability of students in Q_S^l rises, increasing school quality there. Since lower-income children are more likely to reside in Q_S^l, intergenerational mobility improves as these children accumulate higher levels of human capital. Additionally, Intergenerational mobility improves because a rezoning policy reduces the expected school quality in the expensive school zone, leading to a drop in the house price. Lower-income families can move in, increasing the human capital of their children.

At the college level, however, a policy aimed at increasing socioeconomic diversity has minimal effect on the IGE in partial equilibrium and actually decreases mobility in general equilibrium. This occurs because the policy increases competition for college seats, which exacerbates inequality earlier in the human capital accumulation process.

The key assumption driving this result is the capacity constraint at the high-quality college. It follows that expanding opportunity at the public school versus the college stage requires different policy levers. While integration increases mobility at the school level, it does not do so at the college level. In both cases, the supply of seats is limited, but the crucial difference is that college admissions impose a human capital floor. As such, colleges may be better able to improve mobility by expanding the number of available seats.

Finally, our model underscores the importance of understanding both the timing and interaction of policies. An elementary school rezoning policy reduces inequality between school zones less than an otherwise equivalent policy at the secondary level. This is because access to a quality secondary school remains guaranteed, which keeps the price of that school zone elevated. Regarding policy interactions, we find that implementing college affirmative action alongside school rezoning may not be effective. In fact, the affirmative action policy partially offsets the positive intergenerational mobility gains from public school integration. Our work highlights that improving education opportunity requires coordination of policies.

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Online Appendix

Appendix A Institutional Context

We begin by discussing the institutional details that motivate our research question. For each schooling stage, we highlight the existing inequalities and give examples of recent integration policies.

Within the elementary and secondary school system, two levels of public school institutions exist: school districts and individual schools. School districts are administrative bodies that are responsible for the management and finances of a group of individual schools. The current focus of integration policies is on reducing economic segregation among schools within a single district (Potter and Burris, 2020).[25] Within a school district, assignment to public schools is mostly determined by residential address through school attendance zones. While school choice options have become more common, the percentage of public school students who attended a school assigned based on their location of residence was nearly 70% in 2016 (Wang et al., 2019). The link between location of residence and school assignment implies that access to high-quality public schools is a function of real estate prices, and therefore, family socioeconomic status (Black, 1999).

We present evidence on income segregation for Chicago Public Schools and New York City Public Schools. *Figure A.1* in the Online Appendix highlights economic segregation in the Chicago Public School District using free and reduced-lunch status, a program that provides no-cost or reduced-cost meals to children at school.The maps indicate stark income segregation with clusters of higher-income areas at both the elementary (left map) and secondary school (right map) levels. In *Figure A.2* we highlight the relation between the share of free and reduced-lunch students and other covariates for New York City Geographic District #2. The top left map shows the share of free and reduced-lunch students, which

[25] School districts span large geographic areas, and desegregation policies across districts would be logistically challenging.

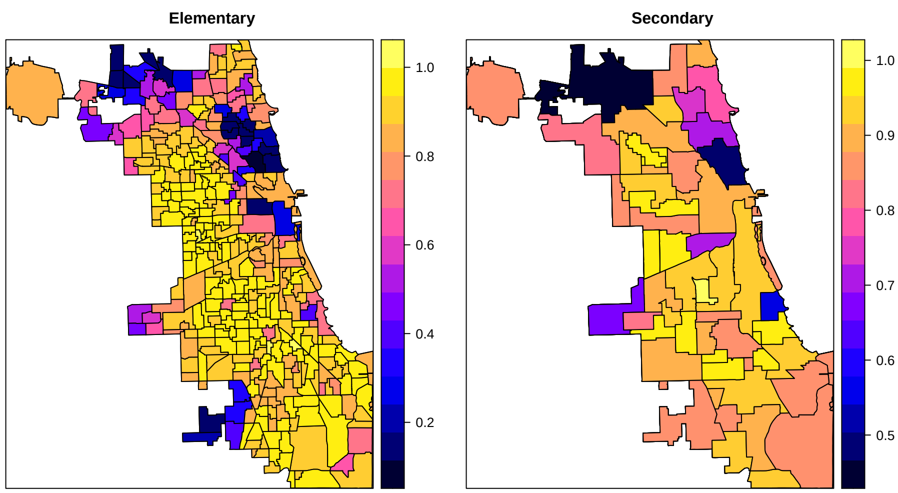
positively correlates with the share of white students in the top right map. In the bottom left map, we plot the per-pupil expenditures in each school, showing that within the district, low-income schools actually have higher spending. Lastly, the bottom right figure plots the share of students who score above proficiency on standardized tests. There is a strong correlation between income and test score performance. These figures emphasize that low-income students tend to attend lower-performing schools, despite these schools receiving more funding.

While some integration plans stem from the result of federal or state government grants, the majority are implemented at the local government level (Potter and Burris, 2020). A recent report by The Century Foundation identified 185 school districts that have student integration plans outlined in their district policies. These 185 districts enroll about 14% of public school students, and about a quarter of their policies were implemented in 2017 or later (Potter and Burris, 2020). Examples of integration plans include frequent redrawing of attendance zone boundaries to balance socioeconomic status, giving higher weight to transfer requests from low-SES students, and school choice programs that prioritize a balanced SES distribution. As a specific example, at the middle school level in 2019, NYC Geographic District 15 in Brooklyn implemented a program to reduce segregation among low-income and English Language Learner students by giving them priority seats at every school in the district (Meckler, 2019).

Finally, at the college level, recent work from Chetty et al. (2020) finds family income segregation across colleges that is comparable in magnitude to that across neighborhoods. In addition, Chetty et al. (2020) show that even conditional on the same SAT scores, students from higher-income families have a higher probability of attending selective colleges than those from lower-income families. The recent decision to strike down race-based affirmative action has left policymakers focused on continuing to improve access to good colleges for those from underrepresented backgrounds. The previous federal administration issued directives to states and colleges to improve outreach to minorities and to consider financial hardship, secondary school, and neighborhood during admissions.[26] One such example is the Texas "Top 10%" rule, in which the top seniors of each high school in the state are admitted to public state schools. The states of Florida, California, and Illinois also have similar percentage plans.

To conclude, there are a variety of integration policies across different stages of child development. A complete understanding of the effects of these policies requires studying how they interact with each other across the lifecycle. To this end, we turn to developing a structural model of human capital development.

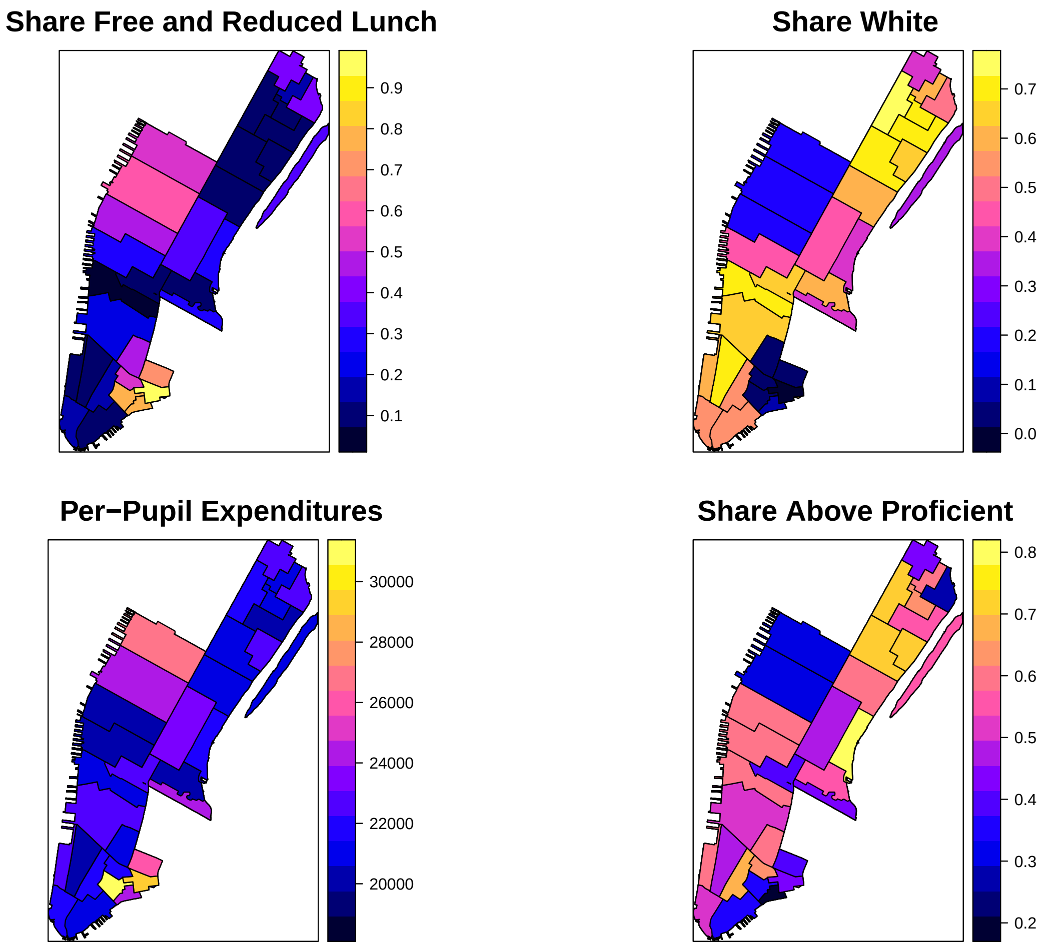
Figure A.1: **Chicago Elementary School Zones**



Notes: These two maps present school zones in the Chicago Public School District 299 at the elementary level (left map) and high school level (right map). Each area represents a school zone. School zones are shaded by the share of free and reduced-lunch students. School attendance zone boundaries are from the School Attendance Boundary Survey (SABS) 2015–16. Free and reduced-lunch statistics are from the National Center for Education Statistics.

[26]See https://www.ed.gov/news/press-releases/biden-harris-administration-outlines-strategies-increase-diversity-and-opportunity-higher-education.

Figure A.2: **New York City Elementary School Zones**



Notes: These maps present different statistics for elementary school zones in New York City Geographic District #2. Each area is a school zone. The top left figure shows the share of free and reduced-lunch students. The top right figure shows the share of white students. Per-pupil expenditures at each school are shown in the bottom left figure, while the bottom right figure shows the share of students who score above proficient on standardized tests. School attendance zone boundaries are from the School Attendance Boundary Survey (SABS) 2015-2016. Free and reduced-lunch and race statistics are from the National Center for Education Statistics. Per-pupil expenditures are from the U.S. Department of Education. Standardized test scores are from the New York State Department of Education.

Appendix B Capacity at Colleges and K-12 Schools

B.1 College Enrollment

We focus on states that have the highest ranked top public colleges: California, Michigan, Florida, North Carolina and Virginia. *Figure B.1* plots the ratio of in-state first-time freshman enrollment at top public universities to the total number of high school graduates in that state, annually from 2006 to 2015. Enrollment data come from the IPEDS fall enrollment surveys, restricted to first-time freshmen reporting a state of residence equal to the institution's state. High school graduate counts are drawn from NCES Digest of Education Statistics and Common Core of Data.[27] The universe of top public universities is defined using a fixed list of flagship and highly selective public institutions, described further in *Appendix C* and listed in *Table G.4*.

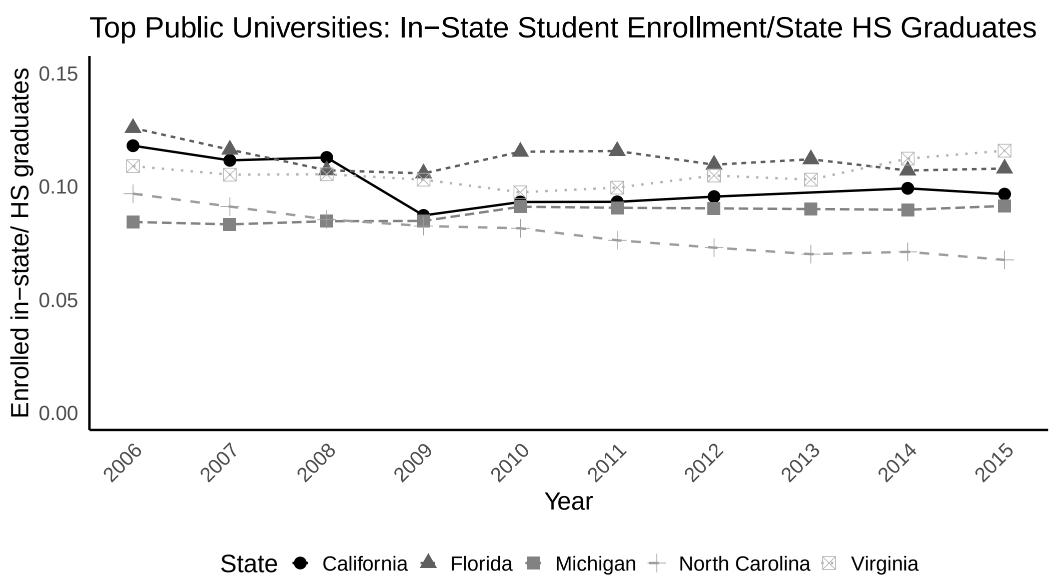


Figure B.1: In-state freshman enrollment at top public universities as a share of state high school graduates, 2006–2015.

[27]Texas, along with California observations for 2003 and 2013 are excluded due to non-reporting in IPEDS.

B.2 Elementary School Enrollment

Figure B.2 plots the share of grade 5 public school enrollment in top-quintile elementary schools for the same five states. School quality is measured using the Stanford Education Data Archive (SEDA), which provides pooled cross-sectional estimates of average test scores at the school level. Schools are ranked into within-state quintiles and we focus on the share of students within state who attend top quintile schools. Grade 5 enrollment by school and year comes from the NCES Common Core of Data. The outcome is each state's total grade 5 enrollment in top-quintile schools as a share of statewide grade 5 enrollment.

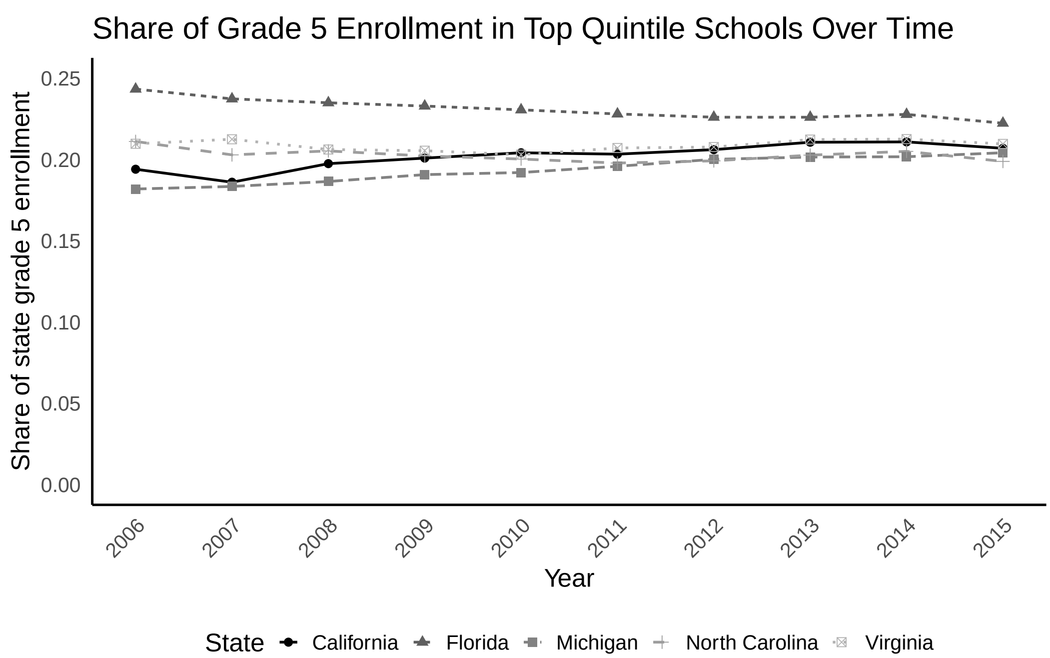


Figure B.2: Share of state grade 5 public school enrollment in within-state top-quintile schools, 2006–2015.

Appendix C Data

C.1 Panel Study of Income Dynamics

The primary data source we use is the Child Development Study (1997, 2002, 2007, 2014) from the Panel Study of Income Dynamics. In the main PSID sample, we extract information on all family heads and their partner (using the "relation to head" variable) including age, marital status, labor and taxable income, and hours worked. We deal with top-coding as in Lee and Seshadri (2019).

The Child Development Study raw data comes in multiple files. We merge the "Assessment" file (child test score information), the "Demographics" file (child age) and the "Time Diary" file. For each child-year observation, we link the child to their primary caregiver (in some waves there is also an "other" caregiver) from the main study. For each child-year we have the following information: age, human capital scores, time per week with parent, and caregiver information and earnings.

There are fifty-seven letter-word questions in the Child Development Study, which are increasing in difficulty. The raw scores are out of fifty-seven, and we normalize them to being out of one hundred. These raw scores only allow us to account for differences in cognitive skills among children of the same age. In order to compare test scores across ages, we use the adjustment mechanism in Lee and Seshadri (2019), where each of the fifty-seven questions is given a weight equal to the inverse of the share who got that question correct.

C.1.1 Sample Selection

We make the following refinements to the sample. First, as in Lee and Seshadri (2019), we drop children who are noted as not being in the household (seqno greater than 50). We only keep caregivers who are listed in relation to the child as being either a parent or a stepparent. Next, we drop families where the caregiver is not in the household or the caregiver is not listed as either the "Head" or the "Wife". The reason for the latter is we need to know the caregiver's labor market earnings in order to account for opportunity cost of time when investing in children.

Table C.1: **PSID Sample Summary Statistics**

	Full Sample (1)	Human Capital Scores (2)	School Information (3)
Age	10.10	10.85	10.51
log Household Income	10.76	10.77	10.76
Active Hours	28.22	26.31	26.33
Age of Household Head	38.20	38.80	38.35
% Head: Male	70	69	69
Adjusted score	–	46.08	45.70
Number of Unique Children	4,673	4,490	2,201
Number of Child-Year Obs.	7,612	6,877	3,202

Notes: Column (1) presents the full sample of children in the Child Development Study. Column (2) conditions on children with human capital scores. Column (3) conditions on those with school information.

Appendix D Model Calibration

D.1 Adult Human Capital

D.1.1 Production

Depreciation of human capital is taken to be 1.5%, which is standard in the literature. Weber (2014) reviews the literature and finds a value in the range of 0.5% to 4.5%. We set the elasticity of investment in the human capital production function, η, to 0.5. Estimates of this parameter are reviewed in Browning et al. (1999) and range from 0.5 to 0.9. The value is chosen to be at the lower end of this range, as 0.5 is standard in more recent literature and similar models (see for instance Lee and Seshadri (2019)).

D.1.2 Earnings Volatility

The mean of the market luck shocks is set to zero. We follow Lee and Seshadri (2019) when estimating the variance of market luck shocks, σ_{ϵ_m}. Their method relies on the fact that in Ben-Porath models, agents cease investing time accumulating human capital near the end of the lifecycle. Given that market luck shocks are i.i.d., we can estimate σ_{ϵ_m} by simply calculating the variance of old-age ($j = 10$ and $j = 11$) household labor earnings using our PSID sample. This produces an estimated σ_{ϵ_m} of 0.17.

D.1.3 Earnings Taxation

Following Guvenen et al. (2014) and Herrington (2015), we estimated tax functions using data from the Organization for Economic Co-operation and Development (OECD). The data include central and local government taxes, family tax benefits, and social security tax contributions levied on income. The data are comparable across countries and publicly available. The net average tax function is estimated using the form,

$$\tau({}^{y}/_{AW}) = a_0 + a_1({}^{y}/_{AW}) + a_2({}^{y}/_{AW})^{\phi} \tag{27}$$

where AW denotes average earnings for the given country. Our estimated tax functions are reported in *Table G.1*. We bound the tax function from below at -0.1 to ensure that some agents do not receive arbitrarily large transfers from the government.

D.1.4 Colleges

Student Loans – We set our repayment length to two periods, as the statutory repayment length of student loans under Fixed Repayments is ten years in the United States. Following Matsuda and Mazur (2022), we set the student loan premium, ι, to 0.02. We do not allow agents to default on student loans.

There are several types of income-contingent loans (ICLs) in the United States, all with slightly different income repayment options. The plan modeled here is Pay-As-You-Earn (PAYE), which is the most common ICL. Under PAYE, agents making less than 150% of the federal poverty level make no repayments. This means that $\hat{y}$ is set to $18,060. Someone making more than $\hat{y}$ pays 10% of discretionary income, i.e., $\chi = 0.1$.[28]

Loan limits are either: (1) the total cost of attending college less expected financial contribution, or (2) the federal undergraduate loan limit of $57,500. Together, these two components define the function governing loan levels, $D(Q_C, b) = \min\{t(Q_C) - g(Q_C, b), \bar{D}\}$.

Tuition Schedules – The function $t(Q_C)$ is calculated by taking the average sticker tuition price in 2013, weighted by college enrollment for each college group (Chetty et al., 2020). Next, $g(b, Q_C)$ is set by computing the average needs-based grants from all sources across our two levels of Q_C and four income quartiles. In the NPSAS, income quartiles are classified for all students within the same dependency status (whether students depend financially on their

[28]Discretionary income is defined as after-tax income in excess of $\hat{y}$.

parents' income or not).[29] Lastly, the merit-based grant, $s(a, Q_C)$, is set by calculating the average merit grant awarded by three ranges of SAT scores (400–800, 801–1200, 1201–1600) and by college quality Q_C, again using the NPSAS. All functions are nearly linear and are linearized using endpoint values.

D.2 Child Human Capital Development

D.2.1 Preschool

The cost of preschool, t_P, is externally set as the population-weighted average of median preschool cost across counties from the National Database of Childcare Prices (US Dept of Labor 2016–2018). We assume that if a parent does not send their child to preschool, they must spend the equivalent of a full-time 40-hour work week caring for the child. This implies that $n_P = 0.24$.

We have three parameters governing human capital accumulation while of preschool age, which we internally calibrate to jointly match three moments from the data. The parameters are the quality of preschool Q_P, and λ_0 and ω_0, the CES parameters for the first period of human capital development.

The first moment we match is the share of children under five who are in some form of center-based care in 2019, using the National Center for Education Statistics. The higher the value of Q_P, and the lower the values of λ_0 and ω_0, the more parents will find it worthwhile to pay the cost of preschool. Our second moment, which these three parameters sharply affect, is the level of parental time investment made for children aged 0–5 ($\hat{j} = 0$). For our third moment, we target the literature's estimate of the causal effect of Chicago Child-Parent Center Pre-K programs on earnings (Bartik, 2014).

[29] Ideally, we would use wealth quartiles to line up with the model, but the NPSAS only reports income quartiles.

Appendix E Additional Model Results

E.1 Unexpected Policies

To further highlight how the model works, we show here the importance of having these educational policies be anticipated. We compare responses when the policies come as a surprise—that is, agents do not anticipate the change. We simulate a new stationary distribution of agents under the new policy experiment, using the same policy functions as in the baseline equilibrium. Next, we study how agents respond when the policy is unexpected versus expected. The unexpected case is only well defined in the partial equilibrium environment, when P_S and $\bar{z}$ are fixed.

The right panel of *Figure G.3* in the Online Appendix presents the percent change in average time investment in Q_S^l over ages $j = 1, 2$ in each policy experiment relative to the baseline steady-state equilibrium. Red bars represent the case when the policy is unexpected, and blue bars represent when the policy is expected. Across the three policies, there are limited changes in average time investment in the unexpected case. However, when the policy is expected, there are larger changes. For example, under the college integration policy, residents in Q_S^l, who are on average lower-income, know that their child has a better chance of being accepted to a high-quality college. Parents of children whose scores were close to the Q_C^h threshold find it worthwhile to invest more in their child's human capital. Average time investment increases by 2.5% in Q_S^l. We see similar patterns in the elementary and secondary school rezoning cases. When the elementary school policy is a surprise, average time investment in Q_S^l changes by -0.3%. However, in the partial equilibrium case, that same statistic increases by 2.8%, with parents again anticipating that their child has higher expected school quality.

The left panel of *Figure G.3* in the Online Appendix shows the average change in school quality for Q_S^l, measured as the average ability of children in the school, across the three integration policies. When elementary integration is unexpected, average ability in Q^l_S rises by 0.5%; it rises by 0.4% in the unexpected secondary rezoning case. On the other hand, the rise is four (two) percent when the elementary (secondary) rezoning policy is expected. In anticipation of the policy, some agents with high-ability children on the margin of living between Q^l_S and Q^h_S in the baseline equilibrium now choose to live in Q^l_S due to the rise in expected school quality. These results highlight the importance of expectations in creating effective policies to improve mobility. Agents cannot optimally change their decisions when policies are a surprise, which limits the potential gains in intergenerational mobility.

Appendix F Computation

The dynamic programming problem is solved by backwards induction beginning with the terminal condition $V(j = 12, Q_C, a, b, h) = 0$. Given that ability and college quality are static over an individual's lifecycle, the problem is broken apart and solved separately. This is done to easily facilitate parallelization of the computer code. The model is solved with three college qualities (including no college option). The model can be solved for a larger number of qualities, however distinguishing between many more college qualities in the data becomes difficult.

The AR(1) process for abilities is approximated using five ability levels and the Rouwenhorst discretization method. The model solution is invariant to the number of abilities used. The distributions for market luck shocks are discretized using the equal-mass approach.

For all periods where the child is present in the household an expanding rectangular grid is set over continuous variables $(h_j, \hat{h}_j, b_j)$ and a uniform grid is set over discrete variables $(a, \hat{a}, Q_c)$, with an additional state variable for either preschool, Q_P, or elementary school, Q_S. During period $j = 9$ there is an additional continuous choice variable $\hat{b}_j$. When solving for optimal policies we interpolate using cubic splines over next periods value functions. We solve for policy functions using a modified Nelder-Mead algorithm to allow for rectangular box constraints.

Given the altruistic motives of parents to children a single round of backwards induction is insufficient to solve the model. Solving the model proceeds by guessing a value function V_3, a mean income level $\bar{y}$, elementary school quality Q_S, and college qualities Q_C. Additionally, guesses for the price of the high quality neighborhood, P, and the high quality college admission cut off, $\bar{z}$, are given. The model is then solved via backwards induction, obtaining a new guess for V_3. Once a convergence criterion is satisfied on V_3, we simulate to solve for the additional three fixed points of $\bar{y}$, Q_S, and Q_C, then updating guesses. The new guesses are then fed into the model, and the model is solved by backwards induction until once more achieving convergence on V_3. This process is repeated until we obtain convergence on $\bar{y}$, Q_S, and Q_S. Finally, we then update guesses for P and $\bar{z}$ and proceed again as above, until convergence is achieved for all five fixed points.

To simulate moments from the model we take some arbitrary vector of parameters Θ and solve the model to obtain all decision rules. we then simulate $N = 1,000,000$ agents for $T = 20$ generations and discard all but the last two generations. The model converges to a steady state quickly and increasing the number of generations to $T = 100$ has no effect on results. Similarly, simulating $N = 2,000,000$ agents has negligible effects on results.

Appendix G Additional Tables and Figures

Table G.1: **Estimated Tax Function Parameters**

Parameter	**Value**
a_0	0.623
	(0.010)
a_1	-0.005
	(0.0003)
a_2	-0.516
	(0.010)
ϕ	-0.448
	(0.010)
R^2	0.998

Notes: This table reports the regression results of equation (13). P-values are reported in brackets.

Table G.2: **Effect of School Quality on Human Capital Growth**

Variable	**Coefficient**
Q_S^h	0.0461
	(0.0145)
$\log test_{j=1}$	-0.730
	(0.0152)
$time$	0.000531
	(0.00029)
Δage	0.0758
	(0.009)
$Intercept$	2.73
	(0.093)
Number obs.	805
Adjusted R^2	0.85

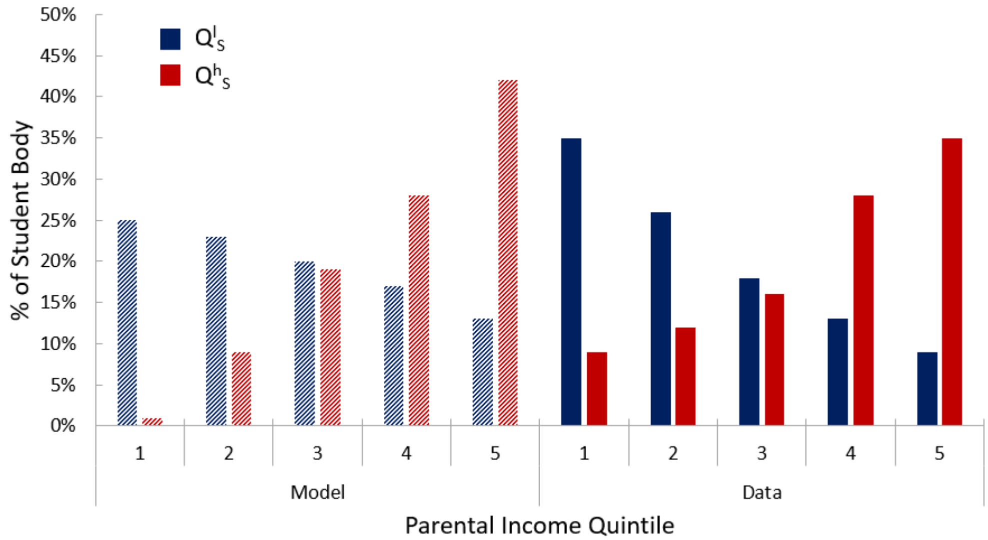
Notes: This table presents coefficient estimates from equation (26). The dependent variable is the logged difference in test scores for individuals from age $j = 1$ to $j = 2$. Q_S^h is an indicator for whether the individual was in a high-quality school zone during $j = 1$. $\log test_{j=1}$ is the logged test score of the individual at $j = 1$. $time$ is active time investment at $j = 1$, and Δage is the difference in ages, in years, between when the two test scores were observed. Standard errors are in parentheses.

Table G.3: **Externally Calibrated Parameters**

Parameter	**Description**	**Value**	**Source**
(a) Preferences			
J	Model periods	11	Biological life, 0-72
β	Discount factor	0.98	Risk free rate, 0.02
σ	Relative risk aversion	1.0	Ln utility
(b) Prices			
r	Risk free rate	0.02	Risk free rate, 2019
ι	Student loan premium	0.02	Standard loan
w	Wage rate	1.0	Normalization
(c) Preschool			
t_p	Cost of preschool	0.18	NDCP
n_p	Time investment, no-preschool	0.24	Full-time care
(d) Tuition			
$t(q_l)$	Sticker tuition low-Q college	0.11	NPSAS
$t(q_h)$	Sticker tuition high-Q college	0.31	NPSAS
$g(\bar{b}, q_l)$	Needs aid: top quartile, low-Q	0.07	NPSAS
$g(\underline{b}, q_l)$	Needs aid: bottom quartile, low-Q	0.01	NPSAS
$g(\bar{b}, q_h)$	Needs aid: top quartile, high-Q	0.19	NPSAS
$g(\underline{b}, q_h)$	Needs aid: bottom quartile, high-Q	0.04	NPSAS
$s(\bar{a})$	Merit aid by college quality	0.06	NPSAS
$s(\underline{a})$	Merit aid by college quality	0.01	NPSAS
f	Fixed cost of attending college	0.10	Belley et al. (2014)
(e) Student Loans			
$\hat{y}$	No repayment threshold	0.35	PAYE terms
χ	Proportional repayment	0.10	PAYE terms
$\bar{D}$	Federal student loan limit	0.28	PAYE terms
(f) Adult Human capital			
δ	Depreciation	0.015	Weber (2014)
η	Production elasticity	0.50	Browning et al. (1999)

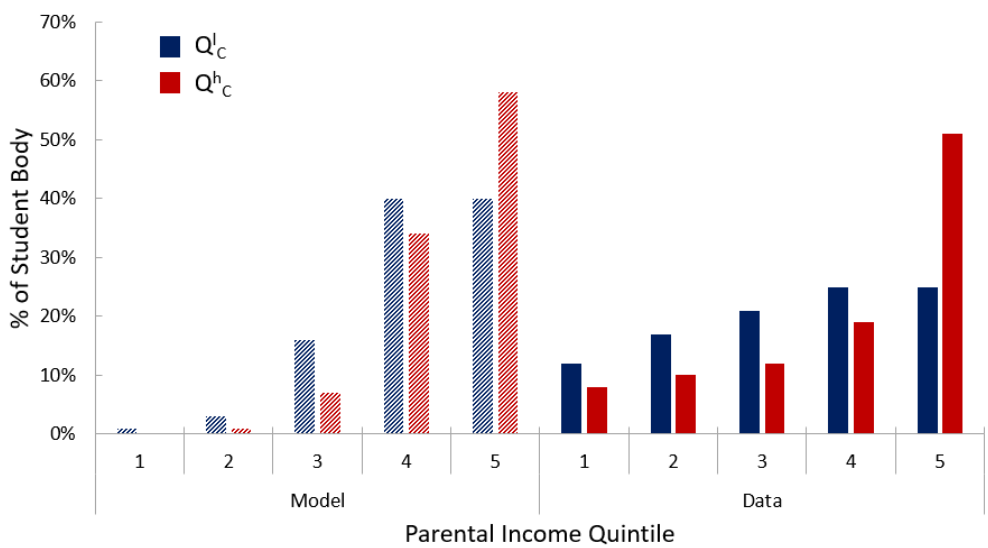
Notes: This table gives model parameters, a brief description of their role, the externally calibrated value, and the source. All monetary values are expressed as a proportion of average income.

Figure G.1: **Share of Students Attending a K-12 Quality by Parental Income Ranks**



Notes: This figure plots sorting across elementary school quality by parental income quintiles, for both the model and the data. Blue (red) bars are for the low- (high)-school quality.

Figure G.2: **Share of Students Attending a College Quality by Parental Income Ranks**



Notes: This figure plots sorting across the high and low-quality colleges by parental income quintile. Blue (red) bars are for the low- (high)-college quality.

Table G.4: **List of Top Public Colleges**

State	School Name	State	School Name	State	School Name
CA	UCLA	FL	University of Florida	CA	UC Davis
CA	UC-Berkeley	TX	UT Austin	CA	UC Irvine
MI	Umichigan-Ann Arbor	GA	Georgia Institute of Technology	IL	University Illinois Urbana Champaign
VA	University Virginia	CA	UC Santa Barbara	WI	UC Wisconsin-Madison
NC	University North Carolina Chapel Hill	OH	Ohio State	NJ	Rutgers
CA	UC San Diego	MD	University Maryland	IN	Purdue
GA	University of Georgia	WA	University Washington	TX	Texas A & M
VA	Virginia Tech	FL	Florida State	MN	University Minnesota
VA	William & Mary	NC	North Carolina State Raleigh	NY	Stonybrook
CA	UC Merced	MA	University Massachusetts Amherst	MI	Michigan State
PA	Penn State	CT	University of Connecticut	PA	University of Pittsburgh
NY	Binghamton University	IN	Indiana University-Bloomington	CO	Colorado School of Mines
NY	University at Buffalo	CA	UC Riverside	SC	Clemson University
NJ	Rutgers - Newark	IL	University Illinois Chicago	NJ	NJ Institute of Technology
CA	UC Santa Cruz	DE	University Delaware	FL	University South Florida
FL	Florida International University	NJ	Rutgers-Camden	PA	Temple University
CO	UC Boulder	IA	University Iowa	AL	Auburn University
CA	Cal State-Long Beach	VA	George Mason	CA	San Diego State
AZ	University of Arizona	MO	University of Missouri	AL	University of Alabama
AK	University of Alaska Fairbanks	AR	University of Arkansas	ID	University of Idaho
IA	University of Iowa	KS	University of Kansas	KY	University of Kentucky
LA	University of Louisiana	NE	University Nebraska-Lincoln	NV	University Nevada
NH	University of New Hampshire	NM	University of New Mexico	ND	University North Dakota
OK	University of Oklahoma	OR	University of Oregon	RI	University of Rhode Island
SC	University South Carolina	TN	University Tennessee	UT	University of Utah
VT	University of Vermont	WY	University Wyoming	ME	University of Maine
MS	University of Mississippi	MT	University of Montana	SD	University of South Dakota
WV	West Virginia	TX	University of Texas at Dallas		

Notes: This table presents the list of top public schools from US News and flagship schools for each state that are used in the calculation of the shift-share instrument.

Table G.5: **Instrument Validity − Correlation of Shares**

	Pop.	% Wht	% Blk	% Asn	% Foreign	Unemp	medhhinc
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share foreign	0.15	-0.01	-0.20	0.15	0.27	0.14	0.19

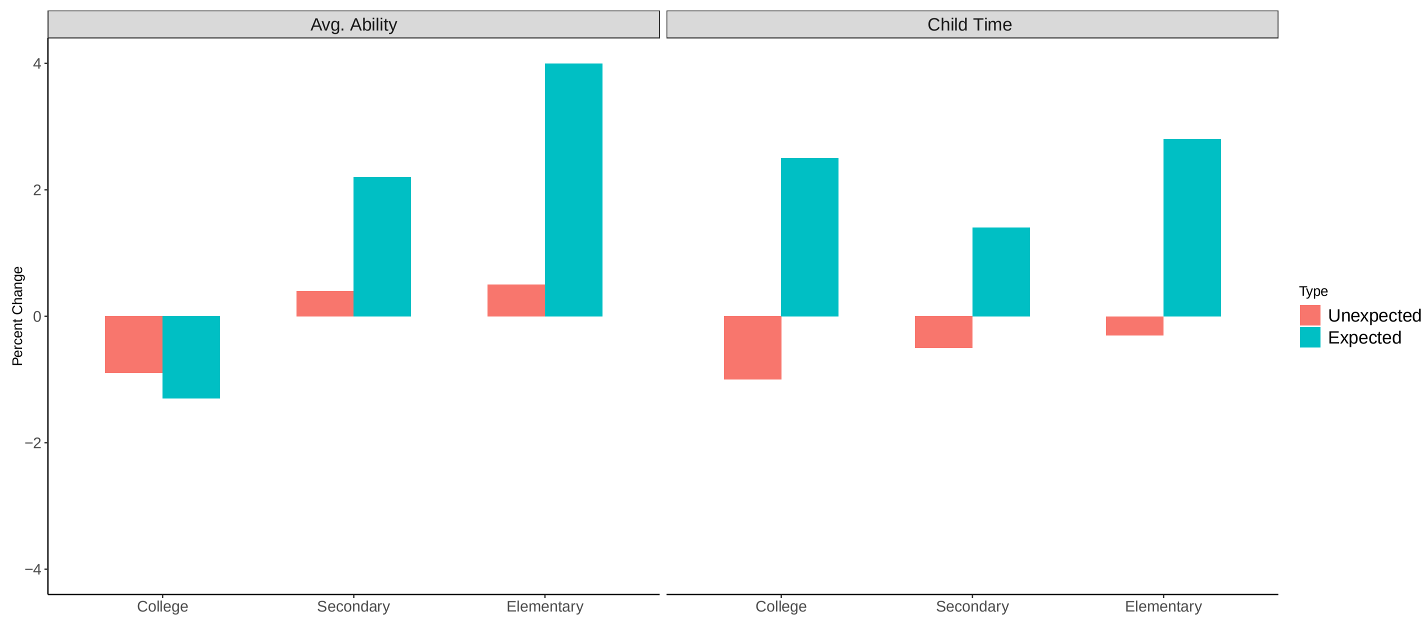
Notes: This table presents the correlation between the average share of foreign students in 2000 at top public schools by state and other state demographics in 2005–2009. Column (1) is state population. Columns (2), (3), and (4) are percentage of state who are White, Black and Asian, respectively. Column (5) is percent foreign-born. Column (6) is the unemployment rate and Column (7) is median household income. *Source:* American Community Survey, 2005–2009.

Table G.6: **In-State Enrollment Shares**

State	**Share of College Attendees who are In-State**
AZ	0.89
CA	0.92
FL	0.91
GA	0.84
MI	0.90
NY	0.83
NC	0.90
OH	0.86
PA	0.85
TX	0.90

Notes: This table presents the share of students in each of the most populous states who attend a post-secondary institution in their own state of residence. Data is taken from IPEDS, 2006.

Figure G.3: **Expected versus Unexpected Policies**



Notes: This figure presents effect of the unexpected (red bars) and the expected policies (blue bars) in partial equilibrium. The right graph is for average time investment in the low-quality school zone. The left graph is average ability in the low-quality school zone. All moments are presented as percent changes relative to the baseline steady-state equilibrium.