Public Education and Intergenerational Housing Wealth Effects

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Abstract

While rising house prices benefit existing homeowners, we document a new channel through which price shocks have intergenerational wealth effects. Using panel data from school zones within a large U.S. school district, we find that higher local house prices lead to improvements in local school quality, thereby increasing child human capital and future incomes. We quantify this housing wealth channel using an overlapping generations model with neighborhood choice, spatial equilibrium, and endogenous school quality. Housing market shocks in the model generate large intra- and intergenerational wealth effects, with the latter accounting for over half of total wealth effects.

Keywords: House prices, intergenerational wealth effects, school quality, neighborhood choice, intergenerational mobility

JEL: E21, E24, I24, J62, R21, R23.

1. Introduction

Rising inequality and low rates of intergenerational mobility in recent decades have prompted researchers to investigate the mechanisms shaping economic opportunity in the United States. Following the pioneering work of Chetty et al. (2014c), many studies have investigated the link between intergenerational income mobility and neighborhood amenities such as school quality and local residential composition (Fogli et al., 2019; Zheng et al., 2021; Gregory et al., 2022; Chyn et al., 2022). Yet, the intergenerational transmission of housing wealth is less well-studied. This is a notable gap in the literature, since housing wealth makes up a large fraction of total household wealth and its value is in large part determined by the quality of neighborhood amenities like local schools.[1] While rising house prices are known to benefit existing homeowners, we investigate the intergenerational transmission of housing wealth shocks with a particular focus on the role of local public schools.[2]

This paper documents a new mechanism by which fluctuations in housing wealth affect economic opportunity through neighborhood sorting and the quality of public education. Local house price growth affects neighborhood sorting and shifts the composition of residents towards those with higher socioeconomic status. This change in student demographics improves local school quality through peer effects and by attracting higher quality teachers. Since schooling is an important input in human capital formation, improvements in school quality increase children's future earnings. Thus, households exposed to house price shocks may receive both direct housing wealth gains as well as intergenerational wealth effects through their children's future incomes.

Our paper proceeds in three stages. First, we provide empirical evidence for the relationship between house price growth and improvements in school quality. Second, we present an illustrative model of the intergenerational transmission of housing price shocks in the presence of the school

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[1]See seminal work on the relationship between school quality and house prices by Black (1999).

[2]A long empirical literature studies housing wealth effects for existing homeowners. See, for example, Mian et al. (2013), Aladangady (2017), Guren et al. (2021), and Graham et al. (2023).

quality channel. Third, we build an overlapping generations model with neighborhood choice, spatial equilibrium, and endogenous school quality to quantify the size of both intra- and intergenerational housing wealth effects.

Our empirical analysis combines student-level administrative data from a large, urban, U.S. school district with housing transaction data from Zillow. We document that faster house price growth in a school attendance zone leads to larger subsequent improvements in local school quality, as measured by school value-added. To alleviate concerns about measurement error and endogeneity, we present estimates using a shift-share instrument that exploits variation in the composition of housing characteristics across school attendance zones (Graham et al., 2023). Our results indicate that a 100 percent increase in house prices over a five-year period leads to a 0.16-standard deviation increase in local school value-added. Given the effect of higher test scores on future child incomes (Chetty et al., 2014b), our estimates imply a $52,660 increase in the present-value of lifetime income in year 2000 dollars.

We then explore mechanisms that explain the effect of house price growth on local school quality. First, we show that faster house price growth alters the composition of local public schools by reducing the share of low socioeconomic status students. Second, we investigate two channels through which changes in student demographics affect school quality: directly through peer effects, and indirectly through the quality of instruction.[3] Using the value-added decomposition of Altonji et al. (2015) and Allende (2019), our estimates indicate that most of the change in school quality is not due to changing peer effects, but is instead due to changes in teacher quality. By exploiting teacher entry and exit across schools, we estimate that changes in teacher quality account for 75 percent of the change in total school quality in response to local house price movements. To explain this, note that teachers face rigid salary schedules and there are no pay differentials across school zones within a district. Instead, teachers sort on the basis of non-pay amenities such as student composition, so that schools with an increasing share of high socioeconomic status students are

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[3]We follow the education literature studying school quality as a function of student body composition (Rothstein, 2006; Allende, 2019).

likely to attract higher quality teachers (Bonhomme et al., 2016).

We explore the implications of this school quality channel of house prices in a simple model of parent decisions in the face of housing wealth shocks. Parents choose consumption, transfers to children, and a neighborhood of residence representing a school zone. Children accumulate human capital according to the quality of their local school. The wealth effects of housing market shocks are traced out through a partial equilibrium exercise where increasing local house prices are mechanically associated with increases in local school quality. Our model demonstrates that these shocks have both intra- and intergenerational wealth effects. On the one hand, higher prices allow parents to sell their house, move to a cheaper neighborhood, and consume or transfer out of their housing wealth. On the other hand, higher local school quality benefits the children of parents that do not sell and remain in place.

Finally, we build an overlapping generations model to quantify the size of intra- and intergenerational housing wealth effects in the presence of the school quality channel. Prior to becoming parents, households choose where to live and purchase a house. When children arrive, parents may choose to move neighborhoods by trading housing. Parents value the life-time wealth they leave to their children, which includes both direct transfers and the value of human capital influenced by local schools. Location decisions then depend on house prices, school quality, and local amenities. In equilibrium, house prices adjust to clear neighborhood housing markets and school quality adjusts endogenously to the composition of local residents. We assume that school quality is a function of average neighborhood incomes, reflecting our empirical findings that it is influenced by the composition of students through teacher sorting.

We calibrate the model to study the wealth effects of housing market shocks. In model experiments, neighborhoods are hit with an exogenous, unexpected, permanent increase in the value of local amenities. Along the equilibrium transition path, the shock generates an increase in housing demand that leads to an increase in neighborhood house prices. Higher prices attract higher income residents and the local school endogenously improves. The wealth effects of these housing market shocks depend on the willingness of parents to consume, transfer wealth directly, and provide their children

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with better schooling opportunities. We find that a one-standard deviation increase in local house prices results in a \$43,000 increase in parent consumption, a \$9,000 increase in transfers to children, and a present-value child income gain of \$64,000. Note that our model-based estimate of the child income effect is similar to the \$53,000 estimate discussed in our empirical work. Overall, intergenerational wealth effects through the school quality channel account for more than half of total housing wealth effects.

Using our model, we also explore heterogeneity in housing wealth effects and decompose the model channels accounting for the intergenerational transmission of housing wealth. First, we consider differences in wealth effects across neighborhood movers and stayers. Following a housing market shock, neighborhood movers experience larger increases in parent consumption and direct wealth transfers to children. In contrast, the children of parents who stay have much larger gains in future income. Second, we show that it is the poorest and wealthiest households that gain most from the school quality channel. Poor households cannot afford to pay the moving costs to leave their current neighborhood, while wealthy households gain little from the extra consumption that would be generated by moving.

1.1. Related Literature

This paper contributes to three broad strands of literature. First, we follow a large body of work studying the relationship between intergenerational inequality, neighborhood choice, school quality, and child human capital accumulation (Benabou, 1994; Benabou, 1996; Durlauf, 1996a; Durlauf, 1996b; Fernández et al., 1996; Fernández et al., 1998). Many of these papers focus on the link between local property taxes and school financing across school districts. High-priced school districts exclude low income families but generate larger property tax revenues that are used to improve the quality of local schools. In contrast, we study differences across school zones within a school district, whereas property taxes are collected at the district level.[4] This allows us to isolate differences in school quality

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[4]Biasi (2023) finds that school district financing reforms have weakened the link between property taxes and school quality in recent decades. The only other sources of funding that may scale with local house prices are donations from parent-teacher associations and school booster clubs. However, these account for just 0.4 percent of

due to local factors such as the composition of students or the quality of teachers at these schools.

Second, our model builds on recent work studying intergenerational inequality with neighborhood sorting and endogenous local school quality (Kotera et al., 2017; Fogli et al., 2019; Eckert et al., 2019; Zheng et al., 2021; Gregory et al., 2022; Chyn et al., 2022). The most closely related papers to our own are Zheng et al. (2021), Fogli et al. (2019), and Chyn et al. (2022). These papers build similar overlapping generations models to our own with neighborhood choice, endogenous sorting, and local spillovers into child human capital accumulation. Additionally, they all study dynamic model responses to shocks that change the patterns of neighborhood sorting and thus endogenously affect the local human capital accumulation channel. Fogli et al. (2019) study a permanent increase in the skill premium that encourages additional human capital investment. Their shock increases neighborhood segregation along income lines and helps explain increasing dispersion of cross-neighborhood intergenerational income mobility since the 1980s. Both Zheng et al. (2021) and Chyn et al. (2022) study model responses to permanent policy changes such as the introduction of school vouchers, transfers, or place based-subsidies. These policies tend to reduce inequality both by directly subsidizing education for low-income families and through general equilibrium channels that tend to equalize school quality and reduce house price differences across neighborhoods. In contrast, our paper pays special attention to the wealth effects generated by housing market shocks. While existing homeowners enjoy higher consumption out of rising house prices, their children benefit from higher future incomes due to endogenous improvements in school quality. Investigating the distribution of these wealth gains within and across families is one of the primary contributions of this paper.

Third, our research is related to a long empirical literature estimating the wealth effects of house price changes (see, for example, Mian et al., 2013; Aladangady, 2017; Guren et al., 2021; Graham et al., 2023). These papers are focused on the direct effects of house price shocks on current homeowners and their contemporaneous consumption behavior. However,

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funding in our district, and around one percent of aggregate spending on education in the U.S. (Brown et al., 2017).

the effects of housing market shocks are much broader, including both the intergenerational transmission of housing wealth and the general equilibrium effects of local housing shocks. In recent work, Daysal et al. (2022) use Danish administration data to show that up to 16 percent of housing wealth shocks experienced by parents are passed into children's future housing wealth. Benetton et al. (2022) use U.S. credit records to show that home-owning parents respond to housing wealth shocks by extracting home equity to provide children with the resources to access their own first homes. Other papers, such as Charles et al. (2018), show that house price shocks can have long-lasting effects on household incomes through general equilibrium channels that influence labor and education decisions. Our paper brings these various literatures together by jointly studying intra- and intergernational housing wealth effects in the presence of an endogenous, general equilibrium school quality channel.

Finally, our paper connects to the education economics literature linking school quality to student body composition (Rothstein, 2006; Allende, 2019). We provide new evidence that teacher sorting is a key driver of the relationship between school quality and student demographics. This sorting is consistent with the view that teachers prefer higher achieving students, which is supported by evidence on teacher preferences across school assignments (Boyd et al., 2011; Bonhomme et al., 2016; Johnston, 2020).

2.   Empirical Analysis

We begin by introducing our data on schools and housing transactions. We focus on a single school district in the United States for which we have high-quality administrative data. We then provide econometric evidence for our novel school quality channel: local house price growth leads to improvements in local schools. Note that throughout our analysis, the unit of observation is a school zone which is defined as a school catchment area: all children in a catchment area can enroll in the local school.

2.1. Data

Education Data: We use administrative data from a large urban school district in the United States. The data cover all students and teachers in public schools in the district from 2003-04 through 2016-17. We observe mathematics and English test scores on standardized end-of-grade exams for each student in each year of schooling, with the exception of 2013-14 when no testing was conducted. The data also provide demographic information for each student. Since our interest is in the relationship between residential location and school quality, and because out-of-zone school choices are much more readily available for high school students, we restrict our sample to students in grades K-5.

Given concerns about the external validity of our results, we note that our school district is similar to others in the U.S. Teachers in the district are paid according to fixed salary schedules, as in 89 percent of school districts in the country (Hansen et al., 2017). Annual teacher turnover rates in the district are comparable to the nationwide average of 16% (Carver-Thomas et al., 2017). And although our focus is on public schools within the district, just 8% of students in our district attend private schools, similar to the nationwide average of 10% (Snyder et al., 2012).

For each elementary school in the district, we construct a measure of school quality called value-added (VA) using standard methods in the economics of education literature.[5] To do this, we prepare the data by first normalizing student test scores within each grade and year to have zero mean and unit variance. Since we also require both current and lagged test scores to construct VA, we exclude all students with invalid scores in the current or previous year, and we exclude data from 2013-14 and 2014-15 due to the lack of testing in 2013-14. Our final sample consists of 1.6 million student-year observations covering around 700,000 unique students across 420 elementary schools. Appendix A.1 provides additional details and summary statistics.

To estimate value-added, we first regress student test scores on school

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[5]School VA methods rely on the assumption that student assignment to schools is uncorrelated with unobserved determinants of achievement, conditional on controls which crucially contain lagged test scores. See Deming (2014) for validation of these measures.

fixed effects and observable determinants of student performance. These controls are: (i) a cubic polynomial in students' prior-year test scores in mathematics and English each interacted with grade dummies, (ii) student-level demographics, including parental education, economically disadvantaged status, ethnicity, gender, limited English status, and age interacted with grade dummies, and (iii) year and grade dummies. School-year fixed effect estimates are then given by the average of students' residualized test scores at a given school in a given year. We then shrink the estimated fixed effects using empirical Bayes (see Morris, 1983) since the raw fixed effect estimates overstate the variance of school VA (Koedel et al., 2015). This produces a VA estimate for each school-year combination.

To interpret the VA measure, note that students moving to a school with a one-unit increase in VA should score one-standard deviation higher in the student test score distribution. Appendix A.2 describes our VA estimation procedure in more detail.

House Price Data: The ZTRAX database provides transaction-level housing data for the US state that contains our school district of interest (Zillow, 2020). We use these data to construct annual house price indexes for each school zone within our school district from 1999 to 2019.

We first convert all house prices into year 2000 dollars by deflating by the Consumer Price Index (U.S. Bureau of Labor Statistics, 2021). The address of each house sold in ZTRAX is matched to a school zone using the latitude-longitude coordinates of the property. Since school zone boundaries may change over time, we use school zone shapefiles from 2009 (The College of William and Mary and the Minnesota Population Center, 2011) and 2016 (National Center for Education Statistics, 2018). Approximately 8 percent of houses cannot be matched to a school zone or change zones across years, and we exclude these houses from our sample. Our house price index is then computed as the median price of houses sold in each school zone in each year. Our final sample covers 424 school zones with an average of 67 houses sold per school zone per year. In a robustness test, we restrict our sample to school zones with at least thirty sales in that year. Table B.2 in Appendix B presents summary statistics for our housing data.

School Zone Demographic and Economic Data: We gather information on school zone-level sociodemographic characteristics from the Amer-

ican Community Survey (ACS) 5-year estimates (U.S. Census Bureau, 2019). Since ACS data are not available for school zones, we construct a cross-walk between census tracts and school zones.[6] We then compute school zone-level averages of statistics using census tract-level population weights. Our demographic controls include information on average educational attainment, homeownership rates, age, and family structure. Our economic controls include unemployment rates and the composition of employment by occupation and industry. Table B.2 in Appendix B reports summary statistics on sociodemographic characteristics for the average school zone in our sample.

2.2. Empirical Strategy

We estimate the relationship between changes in house prices and subsequent changes in school quality using the following regression specification:

$$\Delta VA_{z,t,t+5} = \alpha_z + \alpha_t + \beta \Delta \log HousePrices_{z,t-5,t} + \delta' X_{z,t,t+5} + \epsilon_{z,t} \quad (1)$$

where $\Delta VA_{z,t,t+5}$ is the change in school VA in school zone z between years t and $t+5$, and $\Delta \log HousePrices_{z,t-5,t}$ is the lagged change in log median house prices in school zone z between years $t-5$ and t. Our coefficient of interest is β, which measures the elasticity of school VA with respect to local house prices. The vector $X_{z,t,t+5}$ includes controls for sociodemographic characteristics in school zone z measured between the years t and $t+5$. School zone fixed effects α_z account for school-specific factors affecting average school quality growth. For example, schools with good reputations may improve over time at a faster rate than others. Time fixed effects α_t absorb common trends across school zones such as broader economic forces affecting the entire school district. Thus, our regression specification exploits relative house price changes across school zones within the school district. Throughout our empirical analysis, we cluster standard errors at the school zone level, which is the level of treatment due to house price shocks.

Our baseline regression in Equation (1) makes two assumptions about

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[6]See cross-walk details in Appendix A.5.

Figure 1: Relationship between House Price Growth and School Quality Growth
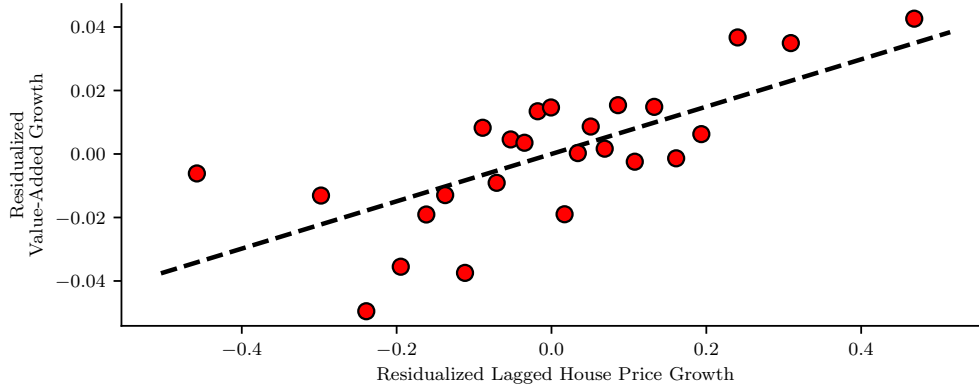
Notes: This figure plots $\Delta \log HousePrices_{z,t-5,t}$ against $\Delta VA_{z,t,t+5}$. Both variables are residualized against school and year fixed effects. The variables are then sorted into bins according to house price growth, and we report average growth in school VA for each bin.

the dynamics of the relationship between school quality and house prices. First, changes in house prices affect school quality with a lag. Second, these changes take place over several years. Both assumptions reflect our view that it takes time for changes in house prices to affect local schools. In Section 2.4, we justify this slow speed of adjustment in addition to reporting the robustness of our results to alternative timing assumptions.

When estimating Equation (1), we have house price data available from 1999 to 2019, while our VA measure is available from 2004 to 2017 excluding the years 2014 and 2015. After constructing 5-year changes in our variables, our sample includes years $t \in \{2004, 2005, 2006, 2007, 2008, 2011, 2012\}$. Figure 1 presents a binscatter plot of the relationship between the residualized variables $\Delta \log HousePrices_{z,t-5,t}$ and $\Delta VA_{z,t,t+5}$. As discussed in detail below, there is a strong positive correlation between house price growth and subsequent increases in school value-added.

2.3. Identification

We face two challenges to identification in estimating Equation (1). First, there is likely to be measurement error in house price growth since we only observe the sample of houses that happen to sell in each school zone

in a given year. Measurement error attenuates our estimates of β. Second, house price growth may be correlated with unobserved variables in the error term $\epsilon_{z,t}$ that are themselves correlated with changes in local school quality. For example, improvements in local amenities could induce higher demand for housing at the same time as predicting higher future school quality. Endogeneity issues such as these will lead us to overestimate the true relationship between house prices and school quality.

To address these concerns, we use a Bartik-style instrument for house prices following Graham et al. (2023). The instrument takes the local share of houses with a given characteristic and interacts that share with an aggregate measure of the marginal price of that house characteristic. For example, we combine the share of two-bedroom houses in each school zone with the aggregate marginal price of two-bedroom houses. We provide a brief summary of the instrument below, but relegate details of the instrument construction to Appendix A.6.

The Bartik-style instrument is constructed in two steps. First, we calculate the local shares of houses with different housing characteristics using three sets of characteristics that are widely reported in the ZTRAX data: decade of construction, number of bedrooms, and number of bathrooms. We compute the local shares by tabulating characteristics from all unique properties sold in each school zone between 1999 and 2019 in the ZTRAX data.

Second, we estimate the aggregate marginal prices of each of these house characteristics, again using ZTRAX. To do this, we estimate a hedonic house price regression with time-varying parameters. The hedonic regression includes three sets of dummy variables capturing our chosen housing characteristics. For example, one set of characteristics includes dummy variables for houses with 1, 2, 3, 4, or 5 bedrooms. Our hedonic regression estimates the time-varying parameter associated with each dummy variable. The growth rate in the marginal price of a given house characteristic is then given by the change in the estimated coefficients on the associated dummy variable. To estimate aggregate marginal prices, we use transactions for all houses in the US state in which our school district is located, but exclude transactions from the school district itself. This is similar to the leave-one-out estimator used for shift-share instruments, but where we

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exclude all sources of variation in house prices that might directly affect school zones in our district (i.e., all other zones within the district).

Identification using our Bartik-like instrument follows from exogeneity of the local housing characteristics shares (Goldsmith-Pinkham et al., 2020). Specifically, cross-sectional variation in local housing characteristic shares must be exogenous to the error term $\epsilon_{z,t}$. In other words, unobserved shocks to local school quality must be uncorrelated with the composition of the local housing stock. We think that this assumption is plausible because house characteristics are largely predetermined at the time of other shocks affecting local school quality. Since it takes time for new residential construction to affect the composition of the total housing stock, housing characteristics are unresponsive to short- or medium-run shocks affecting the quality of local schools. Table 1 presents evidence in favor of this assumption, showing that the correlation of housing characteristics shares within a school zone across a 15 year period are extremely persistent. The transaction-weighted average correlation across bedroom characteristics is 0.84, and the corresponding correlations for bathrooms and decade of construction are 0.88 and 0.94, respectively.

Table 1: Correlation in Share of Housing Characteristics between Sales in 1999-2004 and 2014-2019

Panel (a): Bedrooms and Bathrooms							
	1 Bedroom	2 Bedroom	3 Bedroom	4+ Bedroom	1 Bath	2 Bath	3+ Bath
Correlation	0.69	0.87	0.80	0.88	0.93	0.82	0.94
Transactions Share	0.05	0.31	0.4	0.24	0.24	0.44	0.32
Panel (b): Decade Built							
	<1940	1940-1949	1950-1959	1960-1969	1970-1979	1980-1989	1990-1999
Correlation	0.96	0.95	0.98	0.98	0.93	0.93	0.82
Transactions Share	0.24	0.15	0.22	0.11	0.13	0.10	0.04

Notes: This table presents correlations between school zone-level shares of house characteristics computed for houses sold in 1999-2004 and houses sold in 2014-2019. For decade built, we focus on houses built before 2000, which consist of around 95% of transactions.
Source: Author's calculations using ZTRAX (Zillow, 2020).

2.4. The Effect of House Prices on School Quality

Table 2 presents our estimates of Equation (1). Columns (1) and (2) present OLS estimates, while Columns (3)-(7) present 2SLS estimates using the Bartik-like instrument discussed in Section 2.3. The regression specification in Column (1) includes year fixed effects only, while Column (2)

includes our full set of fixed effects and controls. The OLS estimates are in the range of 0.05 to 0.074 and are statistically significant at the standard confidence levels.

The 2SLS specification in Column (3) includes year fixed effects only. But the use of our instrument for house price growth results in an estimate of 0.155, three times larger than the OLS estimate in Column (1). Columns (3)-(6) progressively add fixed effects and controls. These estimates are stable across specifications, falling in the range of 0.15 to 0.164, and statistically indistinguishable from each other. Note that our first-stage F-statistics are above 200 in every specification, indicating a strong relationship between our instrument and house price growth. Finally, Column (7) restricts the sample to school zone-year observations with at least thirty house sales, which also helps to address concerns about measurement error in house prices. Our estimate increases slightly to 0.202, but is not statistically significantly different from the estimates in Columns (3)-(6).

Our preferred estimate in Column (6) indicates that a 100 percentage point faster house price growth rate is associated with a 0.16 standard deviation increase in school VA. This is the same as 16 percent of a standard deviation gain in average student test scores.

To provide an economic interpretation to our estimates, we conduct a back-of-the-envelope calculation to translate the increase in school VA and student test scores into future earnings. First, a one standard deviation increase in house price growth (65 percentage points) is associated with 0.104 (= 0.16×0.65) of a standard deviation increase in student test scores in each year of schooling. Second, Chetty et al. (2014b) report that a standard deviation increase in test scores in a single grade is associated with a present value gain in lifetime income of \$38,950 in 2000 dollars. Therefore, the initial house price shock is associated with a lifetime income gain of \$4,051 (= $\$38,950 \times 0.104$) for each year of schooling. Third, children typically complete 13 years of schooling and so can expect lifetime income gains of \$52,663 (= $\$4,051 \times 13$) following a standard deviation shock to house prices in their school zone.

Finally, we show robustness to our choice of 5-year growth rates in house prices and school qualities for estimating Equation (1). Table B.3 in Appendix B reports results for regression specifications with changes in

Table 2: Effect of House Price Growth on School Value Added

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	*Dependent variable:* Δ School VA						
Δ log House Price	0.050**	0.074***	0.155***	0.153***	0.150***	0.164***	0.202***
	(0.020)	(0.022)	(0.040)	(0.040)	(0.042)	(0.043)	(0.053)
Method	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	All Zones	All Zones	All Zones	All Zones	All Zones	All Zones	$\geq$ 30 sales
School Zones	424	424	424	424	424	424	325
Observations	2,887	2,887	2,775	2,775	2,775	2,775	1,856
First-Stage F-Stat	–	–	206.20	223.17	249.55	241.52	214.94
School Zone F.E.	No	Yes	No	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	No	Yes	No	No	Yes	Yes	Yes
Economic Controls	No	Yes	No	No	No	Yes	Yes

Notes: This table presents estimates of Equation (1). Columns (1) and (2) are estimated via OLS, and Columns (3)–(7) are IV estimates using the Bartik-like instrument discussed in Section 2.3. Demographic controls include: fraction of residents with a bachelor's degree or higher, median age, homeownership rate, share of families that are married with children. Economic controls include: the unemployment rate, occupational shares of employment in construction and manufacturing, and industry shares of employment in construction, manufacturing, and finance/insurance/real estate. Standard errors and first stage F-statistics are clustered at the school zone-level, and standard errors are reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

prices and school value added over 3-, 4-, 5-, 6-, and 7-year horizons. Our estimates are monotonically increasing with the length of adjustment horizon. Our 3-year estimates are as small as 0.037, while our 7-year estimates are as large as 0.243. These results emphasize that any effect of house price changes on school quality is likely to take place over the medium- to long-run.

2.5.   Mechanisms

We now investigate the mechanisms by which house price growth leads to improvements in school quality. Since we study changes across school zones within a school district, property tax revenues cannot explain this relationship. Instead, we consider the way in which house price growth affects the composition of students, peer- and peer-invariant components of school value added, and the quality of teachers at a school.

Student Composition: Our first hypothesis is that changes in local house prices lead to changes in student sorting across school zones. In Table B.4 in Appendix B we present 2SLS estimates of the effect of house prices on various measures of local student body composition. Column (1) shows that faster house price growth leads to a sizeable reduction in the share of free and reduced-price lunch students. Column (2) indicates that higher house prices generate a moderate reduction in the share of minority students.

However, we do not find any evidence that house price growth causes changes in school or parent resources for education. Column (3) of Table B.4 shows that there is no statistically significant reduction in class sizes, suggesting that local schools do not receive additional funding that could be used to hire more teachers. Column (4) then reveals a null effect on local private school attendance, indicating that house price increases do not cause additional spending on private education.

Peer- and Peer-Invariant Value Added: Our second hypothesis is that changes in student composition affect school quality through two channels: directly through peer effects, and indirectly through changes in the quality of instruction (Rothstein, 2006; Allende, 2019). To explore these channels, we follow Altonji et al. (2015) and Allende (2019) by decomposing school VA into the contributions of the student body (i.e., peer VA) and the contri-

butions of non-peer inputs into school quality such as teachers, principals, class size, infrastructure, and curriculum (i.e., peer-invariant VA).

We give a brief overview of the methodology here and leave a more detailed description to Appendix A.3. The decomposition exercise starts by defining student characteristics that are assumed to have a potential impact on the outcomes of other students. Following Allende, 2019, these characteristics are represented by socioeconomic status and parental education. We then project school-year VA onto these peer characteristics plus a school fixed effect. Intuitively, 'Peer VA' is given by the relationship between year-to-year school-year VA variation and year-to-year changes in peer characteristics. The portion of school quality not coming through peers, 'peer-invariant VA,' is then simply the portion of year-to-year VA changes unexplained by peers.

Table 3 presents 2SLS estimates of the effect of house prices on the two components of school VA. Column (1) first reports our preferred estimate of the effect of prices on total VA from Table 2. Column (2) reports the effect of changes in house prices on the peer component of VA. While the estimated coefficient is 0.005 and statistically significant from zero, it suggests that peer VA accounts for just 3 percent of the change in total VA in response to a house price shock. Column (3) reports the effect of changes in house prices on the peer-invariant component of value added. The estimated coefficient of 0.16 suggests that this is the primary channel through which house prices influence school quality: peer-invariant VA accounts for 97 percent of the change in total VA. The small impact of classroom peers in our setting is consistent with the large literature on peer effects in the classroom which typically finds modest effects (Sacerdote, 2011).

Teacher Quality: Our final hypothesis is that teacher quality is one of the primary drivers of changes to both peer-invariant and overall VA. This would occur if high-quality teachers move schools following a house price shock. Rigid salary schedules across schools within school districts encourage teachers to sort on the basis of perceived amenities such as student composition (Rothstein, 2015; Bonhomme et al., 2016; Bates et al., 2022). Since teachers prefer working with students from advantaged backgrounds (Allensworth et al., 2009; Boyd et al., 2011), they may respond to the effect

of house price changes on local school demographics by moving to those schools. We note that teacher movements across schools are common in the data: Table B.5 in Appendix B reports one- and five-year teacher turnover rates of 20 and 50 percent, respectively.

To test for the effect of house prices on teacher quality, we follow the teacher-switching literature (Chetty et al., 2014a; Bacher-Hicks et al., 2014; Gilraine et al., 2021) and compute changes in teacher VA[7] at each school due to teacher entry and exit. Doing so ensures that the teacher quality gains are not being driven by school improvements such as higher school resources increasing student performance schoolwide. Instead, our teacher quality changes come solely through staffing changes and so are orthogonal to other peer-invariant school inputs (e.g., infrastructure, curriculum, etc).[8] Appendix A.4 provides more details on the calculation of turnover-induced VA changes.

Column (4) of Table 3 reports our estimates of the effect of house prices on school quality through turnover-induced changes in teacher VA. The estimated coefficient of 0.118 suggests that turnover-induced changes in teacher quality account for 74 and 72 percent of peer-invariant and total value-added, respectively. The remaining changes in peer-invariant VA are due to other school-specific factors such as within-teacher improvements, better matching between students and teachers, and higher quality principals, buildings, or school curricula.

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[7]Teacher VA is estimated similarly to school VA where the school fixed effect is replaced by a teacher fixed effect. When estimating teacher VA, however, we also include in our control vector classroom means of prior-year test scores (interacted with grade dummies) and demographics to account for within-classroom peer effects (as is standard in the teacher VA literature).

[8]Careful jack-knifing is required when calculating teacher VA to ensure that school inputs cannot influence the staffing-induced teacher VA measure. Specifically, years where the teacher was at the relevant school need to be excluded from the VA estimation. See Appendix A.4 for further discussion.

Table 3: Effect of House Prices on Peer, Peer-invariant, and Teacher Value-Added

	Dependent variable:			
	Δ School VA	Δ Peer VA	Δ Non-Peer VA	Δ Teacher VA
	(1)	(2)	(3)	(4)
Δ log House Price	0.164***	0.005**	0.160***	0.118***
	(0.043)	(0.002)	(0.043)	(0.030)
Method	2SLS	2SLS	2SLS	2SLS
Sample	All Zones	All Zones	All Zones	All Zones
School Zones	424	424	424	424
Observations	2,775	2,775	2,775	2,763
School Zone F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
First-Stage F Stat	241.52	241.52	241.52	240.18
Demographic Controls	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes

Notes: This table presents estimates of Equation (1), where the dependent variable is replaced with different measures of school value added. Column (1) estimates effects on total school VA. Column (2) estimates effects on the peer component of school VA. Column (3) estimates effects on the peer-invariant component of school VA. Column (4) estimates effects on school VA through changes in teacher quality induced by teacher entry and exit. All columns report 2SLS estimates using the Bartik-like instrument discussed in Section 2.3. Standard errors and first stage F-statistics are clustered at the school zone-level, and standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

3. Illustrative Model

To illustrate the intergenerational wealth effects of house prices, we start with a simple partial equilibrium model of parent-household decisions. Parents choose consumption, transfers to children, and a neighborhood of residence. A child's human capital is determined by the quality of the school in the neighborhood chosen by the parent. We then trace out the wealth effects of housing market shocks through a partial equilibrium exercise where an increase in local house prices is mechanically associated with an increase in local school quality. We defer a general equilibrium analysis to Section 4.

Note that throughout our analysis we abstract from direct parental investments, such as time or other resources, in child education. Much of the previous literature explores the importance of these factors for explaining human capital accumulation during childhood (Cunha et al., 2010). Extending the model to allow for direct investments in education will dampen intergenerational inequality to the extent that investments are substitutes for school quality (Greaves et al., 2023), and will amplify intergenerational

inequality to the extent that investments are complementary with school quality (Attanasio et al., 2022) or financial constraints are tighter for the poorest households (Daruich et al., 2020). We leave such extensions for future research.

3.1. Environment

Parents' decisions are divided into two sub-problems. First, parents choose consumption and transfers conditional on a choice of neighborhood. Second, parents choose whether to move neighborhoods knowing their optimal decisions under each neighborhood choice.

First, consider the decision problem for a parent conditional on having chosen a new neighborhood:

$$V(w, n; n') = \max_{c, b_k} \log c + \psi \log(y_k + b_k)$$

$$\text{s.t.} \quad c + b_k = w + P_n - P_{n'}$$

$$y_k = Q(P_{n'})$$

where w is initial parent wealth, n is the current neighborhood of a parent, n' is the new choice of neighborhood, c is parent consumption, b_k is a transfer to children, P_n and $P_{n'}$ are the prices of houses in neighborhoods n and n', and ψ is the strength of altruistic preferences over a child's total future wealth $y_k + b_k$. Child human capital y_k is determined by the quality of the local school where quality $Q(P)$ is an increasing function of the local house price, $Q'(P) \equiv \partial Q / \partial P > 0$.

The first order conditions yield optimal decisions as functions of the choice of neighborhood n':

$$c(n') = \frac{1}{1 + \psi} \left(w + (P_n - P_{n'}) + Q(P_{n'}) \right) \tag{2}$$

$$b_k(n') = \frac{\psi}{1 + \psi} \left(w + (P_n - P_{n'}) \right) - \frac{1}{1 + \psi} Q(P_{n'}) \tag{3}$$

$$y_k(n') = Q(P_{n'}) \tag{4}$$

Both consumption and transfers are functions of initial wealth, the housing equity extracted by moving neighborhoods $P_n - P_{n'}$, and local school quality

in the chosen neighborhood. Child human capital is a function of local school quality only.

Second, consider the neighborhood choice problem of the parent. For illustration, we restrict to the case of two neighborhoods: $n \in \{A, B\}$. Parents face idiosyncratic neighborhood preference shocks ε_n, which follow an extreme value distribution with variance σ_n. The neighborhood choice problem is:

$$V(w, n) = \max_{n' \in \{A, B\}} \{V(w, n; n') + \sigma_n \varepsilon_{n'}\}$$

The extreme value distribution assumption leads to the familiar logistic functional form for the probability that a parent chooses a new neighborhood $n' \neq n$:

$$\mathbb{P}(n'|w, n) = \left[1 + \exp\left(\frac{V(w, n; n) - V(w, n; n')}{\sigma_n}\right)\right]^{-1}$$

$$= \left[1 + \left(\frac{w + Q(P_n)}{w + P_n - P_{n'} + Q(P_{n'})}\right)^{\frac{1+\psi}{\sigma_n}}\right]^{-1} \quad (5)$$

where $V(w, n; n)$ is the value of remaining in neighborhood n, and $V(w, n; n')$ is the value of moving to the other neighborhood $n' \neq n$. The second equality follows from the optimal decisions in Equations (2)–(4), and the detailed derivation is reported in Appendix C.1. As is the case for consumption and transfer decisions, neighborhood choices are functions of initial wealth and the value of housing equity extracted if moving $P_n - P_{n'}$. Additionally, the moving decision is a function of the differences in school quality across neighborhoods, $Q(P_n)$ and $Q(P_{n'})$.

3.2. Wealth Effects of House Price Movements

Consider a partial equilibrium exercise where we exogenously increase the price of houses P_n in a single neighborhood n. Because local school quality is an increasing function of local prices, the school in neighborhood n also improves as P_n rises.

First, consider the effects of the change in neighborhood price P_n on

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households that choose to move to a new neighborhood $n' \neq n$:

$$\frac{\partial c}{\partial P_n}\bigg|_{n' \neq n} = \frac{1}{1+\psi}, \quad \frac{\partial b_k}{\partial P_n}\bigg|_{n' \neq n} = \frac{\psi}{1+\psi}, \quad \frac{\partial y_k}{\partial P_n}\bigg|_{n' \neq n} = 0$$

Conditional on moving, the increase in initial house price means that parents earn more from the sale of their house. Parents spend this additional wealth by consuming more and transferring additional wealth to their children. However, since parents are moving, an isolated increase in the the initial neighborhood price has no effect on the quality of schools in the new neighborhood nor on the human capital accumulation of children.

Second, consider the effects of the change in neighborhood price P_n on households staying in their initial neighborhood $n' = n$:

$$\frac{\partial c}{\partial P_n}\bigg|_{n'=n} = \frac{1}{1+\psi}Q'(P_n), \quad \frac{\partial b_k}{\partial P_n}\bigg|_{n'=n} = -\frac{1}{1+\psi}Q'(P_n), \quad \frac{\partial y_k}{\partial P_n}\bigg|_{n'=n} = Q'(P_n)$$

Conditional on staying, households do not sell their house and so cannot spend out of the increase in the value of their housing equity. However, as local house prices rise the quality of local schools improves, $Q'(P_n) > 0$, which increases child human capital. Since children are wealthier in the future, parents can increase their own consumption by reducing transfers. Notice that wealth effects for non-moving households depend entirely on the response of local school quality to house prices. If $Q'(P_n) = 0$, then stayers are unresponsive to house price movements.

Now consider the effect of the change in neighborhood price P_n on neighborhood location choices. We restrict attention to the case where neighborhoods are initially identical, and report results for the general case in Appendix C.2. With initially identical neighborhoods, we have that $P_n = P$ and $Q(P_n) = Q(P)$ for $n \in \{A, B\}$. It follows from Equation (5) that $\mathbb{P}(n'|w,n) = \mathbb{P}(n|w,n) = \frac{1}{2}$, and the effect of an increase in house prices on the likelihood of moving is

$$\frac{\partial \mathbb{P}(n'|w,n)}{\partial P_n} = \frac{1}{4}\frac{1+\psi}{\sigma_n}\left(\frac{1-Q'(P)}{w+Q(P)}\right) \tag{6}$$

Suppose local prices have no influence on school quality: $Q'(P) = 0$. Then $\partial \mathbb{P}(n'|w,n)/\partial P_n > 0$ and households are more likely to move following

an increase in local prices. This is because households can only directly benefit from higher prices by selling their current house, moving to a new neighborhood, and spending out of the housing equity gain. In contrast, when $Q'(P) > 0$ the change in the probability of moving is smaller than when the school quality channel is absent. When school quality improves following the increase in house prices, households are more likely to take advantage of faster child human capital accumulation by staying in their initial neighborhood.

Finally, we derive precise expressions for the intra-generational and intergenerational wealth effects of house price movements. In order to compute wealth effects we first take expectations over each variable of interest x with respect to the neighborhood preference shocks: $\mathbb{E}[x] = \sum_{n'} \mathbb{P}(n'|w, n)x(n')$. We then compute changes in the expected values of consumption, transfers, and child human capital with respect to changes in initial neighborhood price P_n. We relegate the detailed derivation to Appendix C.2. Our wealth effects are characterized by:

$$\frac{\partial \mathbb{E}[c]}{\partial P_n} = \frac{1}{2}\frac{1}{1+\psi}\left(1 + Q'(P)\right), \quad \frac{\partial \mathbb{E}[b_k]}{\partial P_n} = \frac{1}{2}\frac{1}{1+\psi}\left(\psi - Q'(P)\right), \quad \frac{\partial \mathbb{E}[y_k]}{\partial P_n} = \frac{1}{2}Q'(P)$$

In the case of initially identical neighborhoods, wealth effects are simple weighted averages of the mover and stayer wealth effects reported above. Note, however, that the size of these wealth effects depends crucially on the strength of both intergenerational links and the school quality channel. When parents are altruistic $\psi > 0$, the response of consumption may be larger or smaller than for a non-altruistic household depending on the sensitivity of school quality to house prices. The stronger is the altruistic motive, the more a parent prefers to transfer wealth to children and the smaller is the contemporaneous consumption response to house price movements. But a high sensitivity of school quality to house prices reduces the amount that parents need to transfer to children, which increases the amount they can consume out of rising house prices.

Overall, our simple model illustrates the presence of both intra-generational and intergenerational wealth effects of house price movements. As documented extensively in the existing literature, current homeowners respond to increasing house prices by consuming more out of the rising
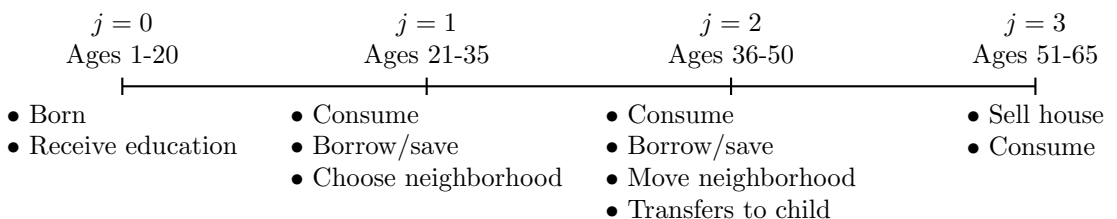
value of their home equity. But homeowners may also consider their children when deciding how to respond. On the one hand, parents can transfer housing wealth gains to their children directly. On the other hand, parents may indirectly transfer wealth to their children through improvements in the quality of local schools in their neighborhood. Thus parents face a trade-off about the use of rising house wealth. Parents can either sell up and move neighborhoods in order to access home equity, or they can remain in place so that their children benefit from the increasing quality of their local schools.

4. Quantitative Model

4.1. Environment

Overview: The model features overlapping generations of parent-child households. Households live for four periods, where age is denoted $j \in \{0, 1, 2, 3\}$. The timing of events and decisions is summarized in Figure 2. Across the life-cycle, households build human capital, earn income, consume, borrow and save, leave transfers to their children, and choose a neighborhood in which to live. The desirability of a neighborhood varies with local house prices, school qualities, common amenity values, and idiosyncratic taste shocks. In equilibrium, house prices adjust to ensure that the demand for housing satisfies the availability of houses in each neighborhood. In addition, local school quality is endogenously determined by the average incomes of the residents choosing to live in each neighborhood.

Figure 2: Timing of Decisions in the Model

$j = 0$	$j = 1$	$j = 2$	$j = 3$
Ages 1-20	Ages 21-35	Ages 36-50	Ages 51-65

- Born
- Receive education

- Consume
- Borrow/save
- Choose neighborhood

- Consume
- Borrow/save
- Move neighborhood
- Transfers to child

- Sell house
- Consume

Neighborhoods and Housing: There are three neighborhoods denoted $n \in \{A, B, C\}$. Households purchase one unit of housing at a neighborhood-specific price P_n. House purchases may be financed with

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mortgage debt, as discussed in more detail below. Housing is traded at ages $j = 1$ and $j = 2$, and all housing is sold at age $j = 3$. At age $j = 2$, households decide whether to leave their initial neighborhood and purchase housing elsewhere. If a household chooses to move, it faces a moving cost proportional to the value of their current house κP_n. The stock of houses in each neighborhood H_n is supplied inelastically.

We think of neighborhoods as school attendance zones within the same school district. Each neighborhood is associated with a local school that all children in the neighborhood attend. School quality Q_n is determined by the average income of residents in a neighborhood $\overline{Y}_n$ relative to the average income of all residents $\overline{Y}$:

$$Q_n = \left(\frac{\overline{Y}_n}{\overline{Y}} \right)^\alpha \tag{7}$$

where $\overline{Y}_n = \frac{1}{H_n} \sum_{j=1,2} \int \mathbb{1}_n y d\lambda_j$ is average income across age $j = 1, 2$ households in neighborhood n, $\overline{Y} = \sum_{j=1,2} \int y d\lambda_j$ is average income across all age $j = 1, 2$ households in the population, $\mathbb{1}_n$ is equal to one if a household resides in neighborhood n, y is the income of a given household, λ_j is the distribution over households at age j, and we make the normalization that $\sum_{j=1,2} \int d\lambda_j = 1$. The parameter α is the elasticity of school quality to local average incomes. Our simple functional form is convenient for calibration and computing equilibria, as discussed in Appendix D.

As part of the empirical analysis we found that higher local house prices appear to attract higher socioeconomic status students and families as well as higher performing teachers to local schools. It seems likely that both student and teacher composition is positively correlated with the incomes of households in which they are family members. Thus, Equation (7) posits a simple mechanism describing the relationship between between local average incomes and local school quality.[9]

Finally, recall that we are interested in differences between school zones within a given school district. For this reason we assume that school quality depends on neighborhood composition only and is unrelated to local

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[9]Fogli et al. (2019) model a similar reduced-form relationship between local school quality, average child ability, and average parent income.

property tax revenues.[10]

Human Capital and Household Income: Human capital is developed as a child and is a simple function of ability and school quality:

$$y_k = a_k Q_n \tag{8}$$

Children are born with innate ability a_k, which is imperfectly inherited from their parents. Ability follows a log-AR(1) process:

$$\ln a_k = (1 - \rho_a)\mu_a + \rho_a \ln a + \varepsilon_a \tag{9}$$

where a is the ability of a parent, μ_a is the average of log-ability, ρ_a governs the intergenerational persistence of ability, and ε_a is an IID normal shock with mean zero and standard deviation σ_a. The second component of human capital is determined by school quality Q_n in the neighborhood in which a child grows up. Since parents decide which neighborhood to live in while raising children, they influence the accumulation of human capital via the local school their child attends.

Initial human capital is known at age $j = 1$. Between ages $j = 1$ and $j = 2$, human capital is subject to idiosyncratic shocks and follows a log-random walk:

$$\ln y_2 = \ln y_k + \varepsilon_y$$

where ε_y is IID normal with standard deviation σ_y and mean $\mu_y = -\frac{1}{2}\sigma_y^2$. Finally, household income at each age is a combination of human capital and a deterministic, age-specific factor χ_j that captures the life-cycle profile of income. Thus, age j income is given by $\chi_j y_j$.

4.2.   Household Decision Problems

We next describe the decision making process of households at each age j, starting with old adults and working backwards. Households enter each period with the state vector $\{b, y, a, n\}$, reflecting current assets or debt b,

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[10]See Section 1.1 for a discussion of prior research in which differences in tax revenues are the primary driver of school quality differences across school districts.

human capital y, ability a, and current neighborhood of residence n.

Decision Problem for Old Adults: Households enter a terminal period at age $j = 3$. The old household consumes all available resources including income, the proceeds from the sale of their house, and the return on assets determined by the interest rate r. The decision problem is:

$$V_3(b, y, n) = \log(c_3) \qquad (10)$$
$$\text{s.t.} \quad c_3 = \chi_3 y + (1 + r)b + P_n$$

Decision Problem for Middle-Aged Adults: At age $j = 2$ households solve a decision problem similar to the simple model in Section 3. The household problem is divided into two sub-periods. First, children are born and their ability is revealed, idiosyncratic taste shocks over neighborhoods are realized, and adults may choose a new neighborhood to live in. Second, conditional on their choice of neighborhood, parents consume, borrow or save, and leave transfers for their children.

The second household sub-problem given neighborhood choice n' is:

$$V_2(b, y, a_k, n; n') = \max_{c_2, b'_2, b'_k} \log(c_2) + \beta V_3(b'_2, y, n') + \varphi \log(b'_k + Y_k) \qquad (11)$$
$$\text{s.t.} \quad c_2 + b'_2 + b'_k = \chi_2 y + (1 + r)b + \mathbb{1}_{n' \neq n} ((1 - \kappa)P_n - P_{n'})$$
$$y_k = a_k Q_{n'}$$
$$Y_k = \chi_1 y_k + \frac{\chi_2 y_k}{1 + r} + \frac{\chi_3 y_k}{(1 + r)^2}$$
$$b'_2 \geq -\theta P_{n'}, \ b'_k \geq 0$$

where b'_2 is the choice of savings or debt, b'_k are transfers to children, y_k is child human capital, and Y_k is the present value of a child's life-time income discounted at the interest rate r. If moving to a new neighborhood, the household receives the proceeds from selling its old house and buying a new house $(1 - \kappa)P_n - P_{n'}$, subject to the moving cost. When $b'_2 < 0$ the household uses a mortgage to finance housing. Mortgage borrowing is subject to a loan to value constraint, where θ is the maximum loan to value ratio. The parameters β and φ reflect weights on the adult's own future utility and its altruistic utility over child outcomes, respectively.

As in Section 3, we assume that parents care about the life-time wealth

of their children. This includes transfers b'_k and the present value of lifetime income Y_k. For tractability, in the model, parents ignore uncertainty over child income and focus only on the permanent component of human capital y_k.[11] Furthermore, as in Fogli et al. (2019), parents value child outcomes via the same log-utility function over their own consumption. These assumptions simplify computation as the model only needs to be solved backwards from age $j = 3$ once. That is, we do not need to recursively iterate over the solutions to parent and child value functions.

Next, consider the problem of an age $j = 2$ household choosing a neighborhood to live in. Households enjoy common amenities $Z_{n'}$ in each neighborhood n. But they also face idiosyncratic taste shocks $\varepsilon_{n,2}$ over their neighborhood choices n'. The idiosyncratic shocks reflect preferences for locations that are unrelated to housing costs, school quality, or local amenities. The taste shocks are distributed according to a Type 1 Extreme Value distribution with scale parameter σ_n. The neighborhood choice problem is:

$$V_2(b, y, a_k, n) = \max_{n'} \left\{ V_2(b, y, a_k, n; n') + Z_{n'} + \sigma_n \varepsilon_{n',2} \right\} \qquad (12)$$

Decision Problem for Young Adults: At age $j = 1$, young adults enter the period with transfers provided by their parents b, human capital y, and their own ability a. Young adults do not yet have children or own housing. Again, household decisions are divided into two sub-problems.

The second household sub-problem given neighborhood choice n' is:

$$V_1(b, y, a; n') = \max_{c_1, b'_1} \ \log(c_1) + \beta \mathbb{E} \left[V_2(b'_1, y', a_k, n') \right] \qquad (13)$$

$$\text{s.t.} \quad c_1 + b'_1 + P_{n'} = \chi_1 y + b$$

$$\ln a_k = (1 - \rho_a)\mu_a + \rho_a \ln a + \varepsilon_a$$

$$\ln y' = \ln y + \varepsilon_y$$

$$b'_1 \geq -\theta P_{n'}, \ \geq 0$$

where b'_1 is either savings or debt, and a_k is uncertain future child ability. Again, mortgage borrowing is constrained by a maximum loan to value ratio. Expectations are taken over the evolution of child ability a_k, income

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[11]Our assumptions preclude the possibility of a dynastic precautionary savings mechanism as, for example, discussed by Boar (2021).

shocks ε_y, and idiosyncratic neighborhood taste shocks $\varepsilon_{n'}$ arriving at age $j = 2$.

As is the case for middle-aged adults, young households enjoy common amenities $Z_{n'}$ and face idiosyncratic neighborhood taste shocks $\varepsilon_{n,1}$ with scale parameter σ_n. The neighborhood choice problem is:

$$V_1(b, y, a) = \max_{n'} \{V_1(b, y, a; n') + Z_{n'} + \sigma_n \varepsilon_{n',1}\} \qquad (14)$$

4.3. Equilibrium

A stationary equilibrium consists of common amenities $\{Z_n\}$, house prices $\{P_n\}$, decision rules for consumption $\{c_1, c_2, c_3\}$, borrowing, savings, and transfers $\{b'_1, b'_2, b'_k\}$, and neighborhood choices $\{\mathbb{1}_{1,n}, \mathbb{1}_{2,n}\}$, and invariant distributions $\{\lambda_1, \lambda_2, \lambda_3\}$, such that: (i) given house prices, the decision rules solve the household problems in Equations (10), (11), (12), (13), and (14); (ii) housing markets clear in each neighborhood

$$\sum_{j=1,2} \int \mathbb{1}_{j,n} d\lambda_j = H_n;$$

(iii) school quality in each neighborhood is given by Equation (7); (iv) and the stationary distributions satisfy

$$\lambda_1 = \int Q_{2,K} d\lambda_2, \quad \lambda_2 = \int Q_{1,2} d\lambda_1, \quad \lambda_3 = \int Q_{2,3} d\lambda_2$$

where $Q_{j,j'}$ are the distribution transition functions from age j to j', and $Q_{2,K}$ is the transition function from parents at age $j = 2$ to children at age $j = 1$.

4.4. Calibration

First, we choose parameters using information external to the model. Second, we calibrate the remaining model parameters via a simulated method of moments algorithm to match selected cross-sectional statistics on wealth and income inequality and mobility.

A model period is 15 years, model ages $j = 1, 2, 3$ represent households aged 21–35, 36–50, and 51–65, and the population size of each cohort is

normalized to one. Model neighborhoods are distinguished by their house prices such that $P_A < P_B < P_C$. We set the price in neighborhood A to the numeraire: $P_A = 1$. Housing supply is fixed so that neighborhood population sizes are equal: $H_n = \frac{1}{3}$ for all n.

To map data to model neighborhoods, school zones are grouped by house price and population-weighted averages of statistics are computed within each group. Our groups are school zones with: prices below the first tertile of prices ($n = A$); prices between the first and second tertiles of prices ($n = B$); and prices above the second tertile of prices ($n = C$). Each price threshold is the population-weighted percentile of the median house prices observed across school zones. Median house prices are taken from ZTRAX for the years 2010-2015 (Zillow, 2020).

Other statistics of interest are not typically reported for school zones. Instead, we make use of a crosswalk between 2010 census tracts and school zones.[12] Aggregation up to school zones is done by computing the population-weighted averages of census tract-level statistics. Finally, we allocate school zone-level statistics to our model neighborhoods according to the house price thresholds described above.

Table 4 reports our model parameters. Panel (a) shows parameters calibrated externally. The life-cycle profile of income $\{\chi_j\}_{j=1,2,3}$ is taken from the ratios of average incomes between ages 36–50 and 51–65 relative to average incomes between ages 21–35 using data from the 2010 Survey of Consumer Finances (Board of Governors of the Federal Reserve System, 2010). The real annual interest rate is 2 percent, and for simplicity we assume that the interest rate on savings is the same as the interest rate on mortgages. In the data, the median LTV ratio at origination is 80 percent. Since a typical mortgage maturity is 30 years and one model period is 15 years, we assume that households repay half of their mortgage principal within a model period. Hence, we set the maximum LTV ratio θ to 0.4. Finally, we normalize the mean of the ability process μ_a to ensure that the lowest income household at age $j = 1$ can afford to purchase a house in the cheapest neighborhood. See Appendix D.2 for details.

Panel (b) of Table 4 reports internally calibrated parameters, chosen via a simulated method of moments algorithm. We choose the parameters

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[12]See Appendix A.5 for details.

Table 4: Model Parameters

Description	Parameter	Value	Source
Panel (a): Externally Calibrated Parameters			
Life-cycle income profile	$\{\chi_j\}$	$\{1.00, 1.71, 2.00\}$	SCF, 2010
Annual interest rate	r	0.020	See text
Maximum LTV ratio	θ	0.400	See text
Average ability	μ_a	1.504	Normalization
Panel (b): Internally Calibrated Parameters			
Annual discount factor	$\beta^{\frac{1}{15}}$	0.877	Calibrated
Altruism	φ	3.427	Calibrated
Local income elasticity of school quality	α	0.591	Calibrated
Std. dev. neighborhood taste shocks	σ_n	1.277	Calibrated
Std. dev. ability shocks	σ_a	0.353	Calibrated
Intergenerational persistence of ability	ρ_a	0.050	Calibrated
Std. dev. income shocks	σ_y	0.820	Calibrated
Moving cost	κ	0.540	Calibrated
Neighborhood amenity, $n = B$	Z_B	0.758	Calibrated
Neighborhood amenity, $n = C$	Z_C	2.257	Calibrated

Table 5: Moments used in Model Calibration

Moment	Model	Data	Source
Aggregate networth-to-labor income	1.301	1.300	SCF, 2010
Transfers share of networth	0.259	0.260	Feiveson et al. (2018)
Average income ratio, B/A	1.316	1.310	ACS, 2010–2014
Average income ratio, C/A	2.295	2.300	ACS, 2010–2014
Income transition, $\mathbb{P}(q_5|p_{25}, n = A)$	0.086	0.110	Chetty et al. (2014c)
Income transition, $\mathbb{P}(q_5|p_{25}, n = C)$	0.250	0.240	Chetty et al. (2014c)
Variance log-income, $j = 2$	0.847	0.848	SCF, 2010
Move probability, $j = 2$	0.389	0.383	CPS, 2004–2016
House price ratio, B/A	1.550	1.550	Zillow, 2005–2015
House price ratio, C/A	3.020	3.020	Zillow, 2005–2015

$\{\beta, \varphi, \alpha, \sigma_n, \sigma_a, \rho_a, \sigma_y, \kappa, Z_B, Z_C\}$ to match the statistics reported in Table 5. Although each parameter affects multiple model moments, we discuss the primary channels through which these parameters are identified by the data.

We set the discount factor β to target the ratio of aggregate networth

to aggregate income for households aged 21–65, using data from the 2010 Survey of Consumer Finances (Board of Governors of the Federal Reserve System, 2010).[13] The weight on child utility φ is set to target the aggregate ratio of life-time within-family transfers to networth, as reported by Feiveson et al. (2018).

Next we set the standard deviation of neighborhood taste shocks σ_n, the standard deviation of ability shocks σ_a, the persistence of child ability ρ_a, and the elasticity of the school quality function α. These parameters jointly determine neighborhood sorting behavior and intergenerational income mobility. Thus, we target relative average incomes across neighborhoods, as computed using data from the 2010–2014 waves of the American Community Survey (U.S. Census Bureau, 2019). We also target the statistics $\mathbb{P}(q_5|p_{25}, n = A)$ and $\mathbb{P}(q_5|p_{25}, n = C)$, which are the probabilities that a child of parents at the 25th percentile of the income distribution living in neighborhood n are in the top income quintile by the time they themselves reach adulthood, as reported by Chetty et al. (2014c). The standard deviation of income shocks σ_y is set to match the variance of log income for households aged 36–50, using data from the 2010 Survey of Consumer Finances (Board of Governors of the Federal Reserve System, 2010).

The proportional moving cost κ targets the probability of moving across neighborhoods at age $j = 2$, computed using the Public Use Microdata from the 2004–2016 waves of the Current Population Survey (Flood et al., 2023). To align with parent-households in the model, we restrict observations in the data to married homeowners aged 35–50, and define cross-neighborhood moves as within-county moves over the last year. Assuming that households move at most once between ages 35 and 50, the probability of moving at any time in a 15-year period is given by $\sum_{j=35}^{50} \pi_j \times \prod_{s=35}^{j-1}(1 - \pi_s)$. Z_A is normalized to zero, and Z_B and Z_C target house prices in neighborhoods B and C relative to A.

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[13]Since the only assets in our model are savings, housing, and mortgages, we take networth in the data to be: the value of owner-occupied housing less mortgages plus liquid assets minus credit card balances.

4.5. Intra- and Intergenerational Wealth Effects of Housing Market Shocks

We run model experiments to study the wealth effects of shocks to the housing market. Our experiments are exogenous, unexpected, permanent shocks to common neighborhood amenity values Z_n, followed by a transition of the economy to a new steady state equilibrium. For ease of exposition, results are reported for the experiment featuring amenity shocks to the middle-priced neighborhood, B. However, our results are similar for shocks to other neighborhoods, and we report these results in Appendix D.4.

First, we solve for a new steady state equilibrium under the change to amenity value Z_n. The new value of Z_n is chosen such that the equilibrium price in neighborhood n increases by 10 percent. However, Walras' Law implies that only two out of three neighborhood prices need to adjust to satisfy the housing market conditions in the new equilibrium. To generate changes in all three house prices an additional restriction on house price movements is required. We impose that the log-change in house prices is the same for each neighborhood that is not affected by the amenity shock, for example, $\Delta \log P_A = \Delta \log P_C$. Additionally, school quality Q_n in each neighborhood adjusts to satisfy Equation (7) in equilibrium. We then solve for the dynamic transition path of the economy to the new steady state by finding the time paths for prices and qualities $\{P_{n,t}, Q_{n,t}\}_{n,t}$ that satisfy the market clearing conditions in each neighborhood n and period t.

Figure 3 illustrates the transition paths of amenities, prices, and qualities following the shock to neighborhood B. After the increase in amenity value of neighborhood B, housing demand rises in B and falls in neighborhoods A and C. Prices in B rise by 10 percent in the long run, and prices in A and C fall by 5 percent in the long run. While higher amenity values make B more attractive for all households, higher prices result in relatively higher income residents moving in than in the initial steady state. As a result, school quality in B rises by around 5 percent in the long run. Neighborhoods A and C lose some of their relatively high income residents to neighborhood B, and so school quality in these neighborhoods falls by around 2 percent in the long run.

Figure 3: Transition Paths Following Amenity Shock to Neighborhood B

(a) Amenities   (b) House prices   (c) School qualities

$n = A$ $n = B$ $n = C$
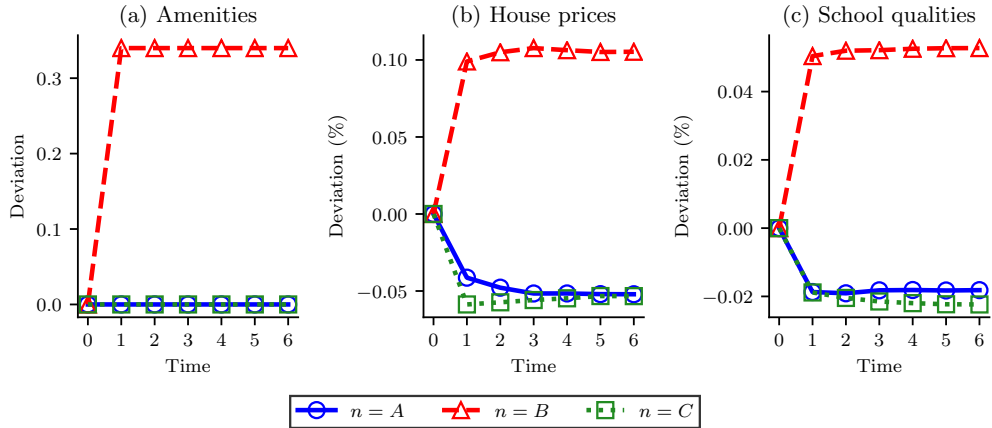
Drawing on the household-level responses to these changes, we now study the various wealth effects of housing market shocks. The responses of parent consumption, transfers to children, child incomes, and probabilities of moving neighborhoods are computed for households aged $j = 2$ in the first period of the shock.

First, Table 6 provides a simple summary of our results by reporting the real dollar value of wealth effects in response to a standard deviation-sized house price shock observed in the data. To do this, we first compute the marginal changes in consumption, transfers, and net present values of child incomes with respect to local house price changes (see Table 7 and the discussion below). We then multiply these marginal effects by the standard deviation of real 15-year house price changes within our school distrct of interest, which is $123,800 measured in year 2000 dollars.

We find that parent consumption rises by around $43,000, transfers to children rise by over $9,000, and present value of life-time child incomes rise by nearly $64,000. Intra-generational wealth effects through contemporaneous parent consumption make up 37 percent of the total housing wealth effect. Intergenerational wealth effects through future child incomes constitute 55 percent of the total wealth effect of a housing market shock, while transfers to children make up just 8 percent. The sum of the intergenerational effects through both transfers and higher child incomes constitutes nearly two-thirds of the total effect of shocks to the housing market.

Note that the $64,000 increase in average child incomes following a

Table 6: Total Housing Wealth Effects of Amenity Shocks to Neighborhood B

	Parent consumption	Transfers to child	Child income	Total
Dollar value	$43,138	$9,409	$63,878	$116,425
Fraction of total	0.37	0.08	0.55	1.00

Notes: Marginal effects computed for age $j = 2$ households across the 15-year model period and evaluated at the empirical standard deviation of 15-year real house price changes.

housing market shock is very similar to our back-of-the-envelope calculation of $52,660 in Section 2.4. Although no feature of our model is calibrated to match the dynamic interaction between house prices and school quality, we find it reassuring that our empirical- and model-implied numbers are of similar magnitudes.

Next, we study the wealth effects of housing market shocks in more detail. Table 7 reports marginal responses for different groups of households and under different conditions. Each of these marginal responses is reported as the annualized change in the relevant variable scaled by the change in local house prices, and averaged across a given group of households.

In Panel (a) we report marginal effects averaged across all households. Households display a marginal propensity to consume (MPC) out of house prices of 0.023 (that is, 2.3 cents in the dollar). This result is consistent with recent estimates of MPCs out of housing wealth from the empirical literature.[14] Households have a smaller marginal propensity to transfer (MPT) housing wealth to children of 0.005. MPTs out of housing wealth are little-studied in the literature. However, recent empirical work by Daysal et al. (2022) estimates that 8 to 16 percent of housing wealth shocks experienced by parents are transmitted to the housing wealth of children.[15] The marginal change in life-time income for children (MPY) is 0.034. As noted above, this is consistent with the implications of our own empirical work in

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[14]Estimates of MPCs for non-durable goods are in the range of 0.01 to 0.03 (Mian et al., 2013; Aladangady, 2017; Guren et al., 2021; Graham et al., 2023).

[15]Additionally, Benetton et al. (2022) find that parental home equity extraction is associated with a high probability that adult children transition to homeownership.

Table 7: Marginal Housing Wealth Effects of Amenity Shocks to Neighborhood B

	Parent consumption	Transfers to child	Child income	Moving probability
Panel (a): All households				
All	0.023	0.005	0.034	0.046
Panel (b): Households from neighborhood B				
All	0.031	0.012	0.040	-0.014
Stayers only	0.026	-0.000	0.103	–
Movers only	0.038	0.030	-0.052	–
Panel (c): Households from neighborhoods A and C				
All	0.019	0.001	0.031	0.054
Stayers only	0.023	0.003	0.083	–
Movers only	0.011	-0.002	-0.056	–
Panel (d): Partial equilibrium effects				
Amenity shocks only	0.000	-0.000	0.000	-0.029
Price changes only	0.017	0.007	0.000	0.078
Quality changes only	0.004	-0.004	0.030	-0.020

Notes: All statistics computed for age $j = 2$ households and reported in annualized terms. Marginal effects computed as changes in a given variable divided by the change in local house price. Partial equilibrium statistics computed as changes in a given variable divided by the change local house prices observed along the general equilbrium transition path.

Section 2. Finally, the probability that households move neighborhoods is positively correlated with local house price movements (0.046). Since two thirds of the population live in neighborhoods experiencing house price declines, our results suggest a significant decrease in cross-neighborhood mobility overall.

In Panel (b) we consider wealth effects experienced by households from neighborhood B only. These households experience combined increases in their local amenity value, house price, and school quality. MPCs are around 30 percent higher for households in neighborhood B than for households overall (0.031 vs. 0.023), while MPTs are more than twice as large (0.012 vs. 0.005). Effects on child incomes are also somewhat larger (MPY of 0.04 vs. 0.034). The marginal change in moving probability is negative for neigh-
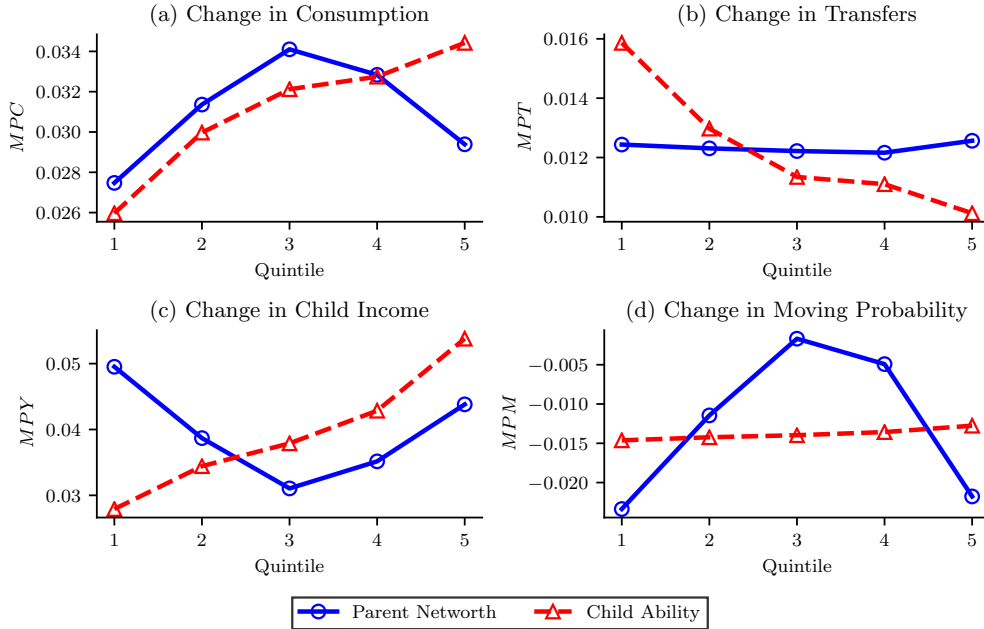
borhood B households. This is consistent with our simple model in Section 3, where parents are more likely to remain in their current neighborhood to take advantage of rising school quality.

In Panel (b) we also compare marginal wealth effects for households staying in neighborhood B and those moving from B to another neighborhood. The MPC out of housing wealth is about 50 percent larger for movers compared to stayers (0.038 vs. 0.026) while the MPT is zero for stayers but as high as 0.03 for movers. Changes in child incomes are very large for stayers (MPY of 0.1), but negative for movers (MPY of -0.05). This latter result is mechanical. Because there is positive co-movement between prices and school quality in equilibrium, households leaving neighborhood B are necessarily moving to another neighborhood with falling school quality. Higher house prices are primarily enjoyed by movers, who both consume more and leave larger transfers out of the increase in housing equity. Stayers gain less from an increase in house prices but their children benefit more from improvements in local school quality.

Panel (c) shows the wealth effects experienced by households from either neighborhood A or C. These households experience no change in amenity value, but suffer from decreases in both house values and local school quality. For neighborhood A and C households, average MPCs, MPTs, and MPYs are smaller than for households from neighborhood B. A and C households have large and positive marginal changes in the probability of moving, suggesting that households are much less likely to move given decreasing local house prices. In addition, MPCs are smaller for movers than stayers, while MPTs are small and positive for stayers but small and negative for movers. Marginal changes in child incomes are large and positive for stayers and negative for movers. For neighborhood A and C households, the lower likelihood of moving combined with the large MPY for stayers implies that children born into these neighborhoods will be worse off in the future due to declining local school quality.

Panel (d) reports wealth effects from partial equilibrium exercises where changes in amenities, house prices, and school qualities are fed through the model one at a time. For ease of comparison, we compute marginal changes in each variable with respect to the general equilibrium house price movements in each neighborhood (i.e. quasi-marginal propensities). We find

Figure 4: Heterogeneity in Wealth Effects of Amenity Shocks to
Neighborhood B

(a) Change in Consumption   (b) Change in Transfers

(c) Change in Child Income   (d) Change in Moving Probability

Notes: Wealth effects reported for households living in neighborhood B prior to shock.

that changes in amenities have no effect on household consumption, transfers, or child incomes, but they do reduce the probability of moving. Isolated changes in house prices generate an MPC that is 75 percent of the size of the average MPC in general equilibrium (0.017 vs. 0.023), while the MPT is 40 percent larger than the average MPT in general equilibrium (0.007 vs. 0.005). These results are due to the fact that in the absence of school quality changes, households would like to pass more of their housing wealth gains to children in the form of transfers. Finally, we find that isolated changes in school quality produce small MPCs, negative MPTs, and a similar sized MPY to that observed in general equilibrium (0.030 vs. 0.034). Overall, these results show that movements in house prices are primarily responsible for housing wealth effects through parental consumption and transfers to children, while changes in school quality are solely responsible for intergenerational wealth effects through changes in child incomes.

Figure 4 illustrates additional results on the heterogeneity in housing wealth effects. We report marginal wealth effects for households across

the distributions of parental networth and child ability. The focus here is on households initially living in neighborhood B, which are those exposed to the positive amenity shock, increase in house prices, and rising school quality. Across the distribution of parental networth, we find hump-shaped MPCs, MPYs, and changes in moving probability. Low-wealth households find it costly to move neighborhoods and so are more likely to stay, less likely to consume out of their housing wealth, but have children that benefit from rising local school quality. Middle-wealth households can afford to move, consume more out of their rising housing wealth, but benefit less from rising local school quality. High-wealth parents can afford to move, however they place more weight on their children's outcomes than they do on their own consumption. These households are more likely to stay, consume less out of their housing wealth, and their children gain more from rising local school quality.
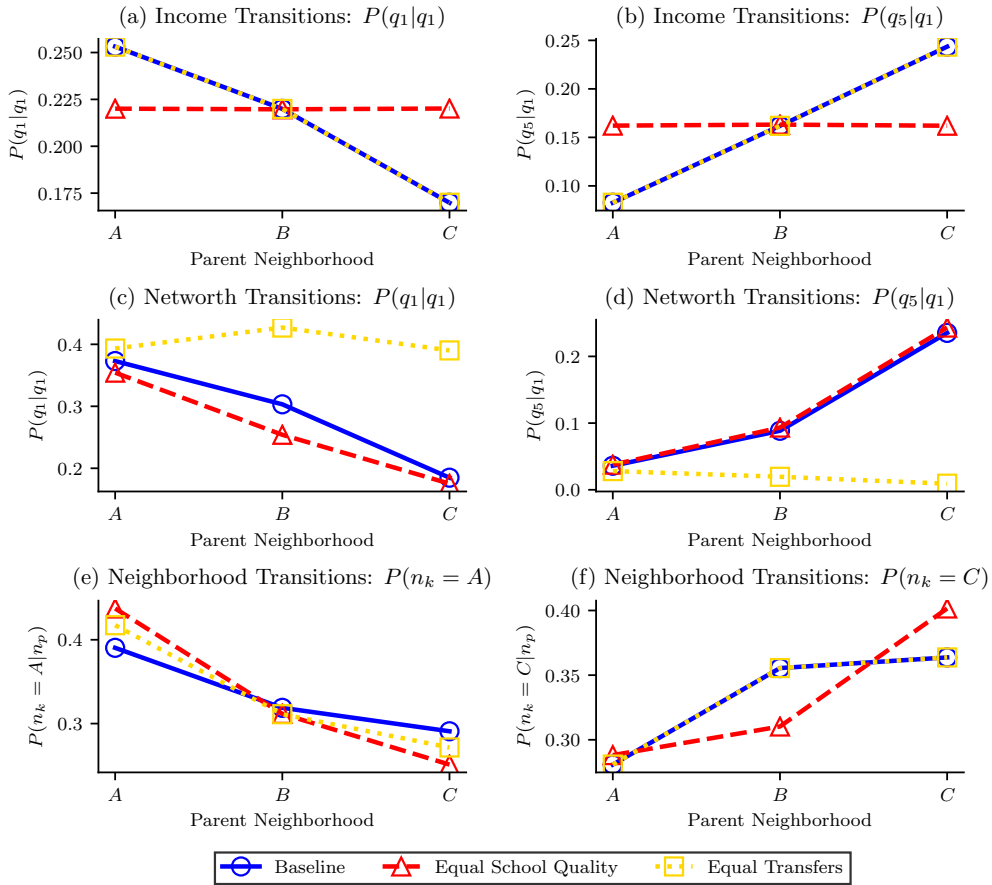
Figure 4 also shows interesting patterns of housing wealth effects across the distribution of child ability. High ability children benefit most from rising school quality, so the change in child incomes following the shocks is increasing in ability. Parents of high ability children compensate for these benefits to their children by reducing transfers and increasing their own consumption.

4.6. Model Mechanisms

We now explore our model mechanisms to understand how economic opportunity is propagated across generations. In particular, we study the way in which children's incomes, wealth, and own neighborhood choices are influenced by the circumstances and choices of their parents.

Figure 5 illustrates intergenerational transition probabilities for income, wealth, and neighborhood choice. In each panel, the horizontal axis indicates transition probabilities for children conditional on their parents having chosen to live in neighborhoods A, B, or C. The solid blue lines report transition probabilities in the steady state of our baseline model. The dashed red lines and dotted yellow lines illustrate counterfactual model transition probabilities. Starting from the initial steady state equilibrium, we fix all parent decision rules but shut down dispersion in the school qual-

Figure 5: Effect of Model Mechanisms on Intergenerational Mobility

(a) Income Transitions: $P(q_1|q_1)$

(b) Income Transitions: $P(q_5|q_1)$

(c) Networth Transitions: $P(q_1|q_1)$

(d) Networth Transitions: $P(q_5|q_1)$

(e) Neighborhood Transitions: $P(n_k = A)$

(f) Neighborhood Transitions: $P(n_k = C)$

Baseline   Equal School Quality   Equal Transfers

ity and parental transfers mechanisms, one at a time. To do this, we set the relevant endogenous variable – school quality or parent transfers – to its median value in the baseline equilibrium. We then compute parent-to-child income, wealth, and neighborhood transition probabilities for the subsequent generation of children.

Panels (a) and (b) illustrate the relationship between parent location choice and intergenerational income mobility.[16] In the baseline model, we can see that parent neighborhood choices have a very strong influence on children's future incomes. For low-income families, children growing up in neighborhood A are 7.5 percentage points more likely to remain at the bottom of the income distribution than children growing up in neighborhood

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[16]$\mathbb{P}(q_x|q_1)$ is the probability that a child born to parents in the bottom quintile q_1 of the income distribution end up in the q_x^{th} quintile of the income distribution at age $j = 2$.

C. In contrast, low-income children growing up in neighborhood C are more than 15 percentage points more likely to reach the top of the income distribution than children from neigborhood A.

Panels (a) and (b) also show that school quality accounts for the entirety of the relationship between parent neighborhood and the intergenerational transmission of income. The red dashed lines show the results of shutting down the school quality channel, thereby equalizing quality across neighborhoods. In Panel (a) we can see that the children of low-income parents from low-priced neighborhoods (e.g. A) are just as likely to grow up with low incomes as children from high-priced neighborhoods (e.g. C). In Panel (b), we can see that low-income families are just as likely to have their children reach the top of the income distribution whether they live in low- or high-priced neighborhoods.

Panels (c) and (d) illustrate the relationship between parent location choice and intergenerational wealth mobility.[17] The baseline model shows that parent neighborhood choices are also strongly related to children's future wealth. For low-wealth families, growing up in neighborhood A means that a child is 20 percentage points more likely to remain at the bottom of the wealth distribution than children from neighborhood C. Low-wealth children growing up in neighborhood C are around 25 percentage points more likely to reach the top of the wealth distribution than children from neigborhood A.

Panels (c) and (d) also show that parent transfers account for most of relationship between parent neighborhood choice and the intergenerational transmission of wealth. When all children receive the median-sized transfer, children from low-wealth families in high-priced neighborhoods (e.g. C) are just as likely to grow up with low wealth as children from low-priced neighborhoods (e.g. A). Similarly, low-wealth families are just as unlikely to send their children to the top of the wealth distribution whether they live in low- or high-priced neighborhoods.

Panels (e) and (f) illustrate intergenerational neighborhood mobility.[18] The baseline model displays strong intergenerational persistence of neigh-

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[17]$\mathbb{P}(q_x|q_1)$ is the probability that a child born to parents in the bottom quintile q_1 of the wealth distribution end up in the q_x^{th} quintile of the wealth distribution at age $j = 2$.

[18]$\mathbb{P}(n_k = N)$ is the probability that a child at age $j = 2$ chooses to live in neighborhood $n_k = N$ given their parent's choice of neighborhood.

borhood choice, with children much more likely to live in the same neighborhood as their parents than any other neighborhood. These results suggest that the model generates strong multi-generational dependence of incomes through neighborhood choices. Panels (e) and (f) also show that both school quality and parent transfers have a moderate influence on intergenerational neighborhood choice, but much of this mechanism is determined by other model mechanisms – for example, child ability and income shocks.

Overall, we find that intergenerational income and wealth mobility is strongly tied to spatial inequality. Parents in high-priced neighborhoods provide their children with significant advantages. Those children are much less likely to grow up with low incomes, low wealth, or to live in low price neighborhoods when adults. Moreover, these spatial patterns of intergenerational mobility are strongly tied to endogenous differences in school quality as well as parental transfers of wealth. Since high-priced neighborhoods feature high-quality schools, children growing up in these neighborhoods benefit from higher incomes as adults. Additionally, high-priced neighborhoods also attract parents willing to leave more wealth to their children, so children growing up in these neighborhoods tend to receive larger transfers and to benefit from higher wealth as adults.

5. Conclusion

We study intra- and intergenerational housing wealth effects in the presence of an endogenous school quality channel. Using data from a large US school district, we show that rising local house prices are associated with subsequent improvements in local school quality. Taking this relationship as given, we argue that parents tradeoff the direct benefits of rising house prices with the intergenerational benefit of rising local school quality. We then quantify the size of the intra- and intergenerational housing wealth effects in an overlapping generations model with neighborhood choice, spatial equilibrium, and endogenous local school quality. Importantly, the school quality channel accounts for over half of the total wealth effect of a housing market shock.

In our empirical work, we study the mechanisms behind the school quality response to house price shocks. We find that teacher sorting across

schools accounts for most of the observed changes in local school quality. Since teachers typically face constant salary schedules within school districts, high performing teachers are attracted to schools with higher socioeconomic status students. One policy implication of our results is that school districts could use financial incentives to attract and retain high-quality teachers at under-performing schools (see, for example, Dee et al., 2015; Morgan et al., 2023). These policies would dampen the rise in intergenerational inequality following adverse local housing market shocks.

Our paper also has implications for the role of heterogeneity in asset returns, particularly housing, in propagating wealth inequality. Prior research shows that there is significant variation in the return on housing across household demographics such as initial wealth, race, and gender (Landvoigt et al., 2015; Perry et al., 2018; Goldsmith-Pinkham et al., 2023). Our research suggests that the positive co-movement between local house prices and public school quality amplifies both heterogeneity in the returns to housing as well as the intergenerational return to housing.

These results have two important policy implications. First, capital gains taxes are unlikely to significantly dampen wealth inequality. This is because the price component of housing returns results in small direct transfers of wealth. In contrast, the school quality component of housing returns accounts for the bulk of the intergenerational transmission of housing wealth. While capital gains taxes could be used to redistribute wealth among existing homeowners, they will have little effect on intergenerational inequality.

Second, policymakers may wish to consider offsetting the school quality channel for neighborhoods affected by adverse housing market shocks. For example, policies could provide opportunities for children to attend schools outside their local attendance zone through open-enrollment policies or the establishment of charter schools. These mechanisms would ameliorate wealth inequality by breaking the link between house prices and local school quality (see, for example, Zheng, 2022). We hope to explore such policy proposals in future research.

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For Online Publication: Appendix

A. Empirical Analysis Details

This appendix provides additional details about our sample construction, estimation of school and teacher value-added (VA), and construction of our house price instrument.

A.1. Education Sample Construction

Our data cover elementary grades for a large urban school district for school years 2002-03 through 2016-17. Given the requirement for lagged test scores, we start with the entire enrollment history of students in the district in grades 3-5 for the school years 2003-04 through 2016-17. We then drop academic years 2013-14 and 2014-15 from the dataset along with third grade after 2012-13 due to missing data.[19] Our analysis sample therefore cover grades 4-5 from 2003-04 through 2012-13 and 2015-16 through 2016-17 school years and third grade from 2003-04 through 2012-13. These data cover roughly 800,000 students with 1.7 million student-year observations.

Our data also include detailed demographic information. Specifically, we have information about parental education (five education groups), economically disadvantaged status, ethnicity (seven ethnic groups), gender, limited English status, and age. Demographic coverage is near-universal for all demographic variables with the exception of parental education, which is missing for twenty-nine percent of the sample. Whenever demographic information is missing, we create a missing indicator for that variable.

We make several data restrictions to arrive at our final VA samples. To start, we exclude roughly 200,000 student-year observations that lack a valid current or lagged mathematics test score; these data then constitute our sample used to estimate school VA. To arrive at our teacher VA sample, we make two additional sample restrictions. First, we drop approximately 90,000 student-year observations that cannot be matched to a

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[19]Data are missing for 2013-14 and 2014-15 due to a change in the statewide testing regime that occurred in 2013-14, which resulted in no test score data that year and also eliminated the second grade test thereafter. As lagged test scores are required when computing value-added, we drop academic years 2013-14 and 2014-15 from the dataset, as well as third grade after 2012-13.

teacher. Second, we only include classes with more than seven but fewer than forty students with valid current and lagged mathematics scores, losing an additional 8,500 observations.

Table B.1 reports summary statistics. Our school district is majority-hispanic and consists of a relatively low-income student body with over two-thirds of students qualifying for free or reduced price lunch.[20] Columns (2) and (3) then show the samples used to estimate VA. The VA samples are similar to the full sample, although are somewhat positively selected with student test scores being about 0.02 standard deviations higher than the full sample.[21]

A.2. Constructing School Value-Added

Using the school VA sample, we estimate estimate school VA using the following equation:

$$y_{ist} = \phi X_{ist} + \mu_{st} + \epsilon_{ist}, \qquad (A.1)$$

where y_{ist} is the mathematics score of student i in school s at time t, X_{ist} captures observed characteristics of the student (demographics, past academic performance, and family background), and μ_{st} is the school's contribution to student test scores in year t, or simply school VA. The error term ϵ_{ist} is assumed to be independently and identically distributed normal with variance σ_ϵ^2. A key requirement for school VA, μ_{st}, to be unbiased is that the control vector X_{ist} is sufficiently rich, with lagged test scores acting as the key control (Chetty et al., 2014a). We therefore follow this literature and include a rich set of controls in X_{ist}, including: (i) cubic polynomial in prior-year scores in mathematics and English interacted with grade dummies,[22] (ii) individual-level demographics, including parental education (five education groups), economically disadvantaged status, ethnicity

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[20]Free or reduced price lunch eligibility is often used as a poverty indicator in education data sets as students are only eligible if their family income is at or below 185 percent of the poverty level.

[21]The positive selection is driven by the requirement that students have a lagged test score, as students without lagged test scores tend to be lower-performing. This moderate positive selection into the VA analysis sample is ubiquitous in the VA literature.

[22]When prior English test scores are missing, we set the English score to zero and include an indicator for missing data interacted with the cubic polynomial in prior-year mathematics scores.

(seven ethnic groups), gender, limited English status, and age interacted with grade dummies, and (iii) grade and year dummies. In contrast to much of the VA literature, however, we do not include school or school-grade level means of prior-year test scores or individual covariates so that we can decompose school VA into the portion coming from the school itself and the portion coming through peer effects (see Section 2.4).

The parameters of interest in equation (A.1), μ_{st}, can be estimated via the maximum likelihood estimator (often referred to as the fixed effect estimator) which is given by:

$$\mu_{st} = \frac{1}{n_{st}} \sum_{i=1}^{n_{st}} (y_{ist} - \hat{\phi} X_{ist}), \qquad (A.2)$$

where n_{st} is the total number of students in the VA sample at school s in year t.[23] While the estimator given by equation (A.2) is consistent, it is rarely used in practice due to finite sample considerations. Instead, the VA literature uses empirical Bayes methods to leverage additional information about the distribution of school VA to modify poor-quality estimates for some schools based on observations for other schools. We follow the lead of this well-developed literature and employ the parametric empirical Bayes estimator (see Morris, 1983), which takes the following form:

$$\delta_{st} = \mu_{st} \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\epsilon^2 / n_{st}}, \qquad (A.3)$$

where σ_μ^2 and σ_ϵ^2 represent the variance of school value-added and idiosyncratic student shocks, respectively. These model parameters are estimated via maximum likelihood and then plugged-in to equation (A.3) to get our school VA estimates, $\hat{\delta}_{st}$.

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[23]We follow much of the VA literature and estimate $\hat{\phi}$ in a first step where we regress $y_{ist} = \phi X_{ist} + \mu_s + \epsilon_{ist}$ to estimate $\hat{\phi}$ and then construct the fixed effects estimates using equation (A.2) in the second step. Alternatively, one could estimate the fixed effects in a single step, although results are near-identical. See Koedel et al., 2015 for a discussion of one- versus two-step estimators in the context of VA.

A.3. Decomposing School Value-Added into Peer and Peer-Invariant VA

This subsection describes in greater detail our decomposition – using a methodology borrowed from Altonji et al. (2015) and Allende (2019) – of school VA into its peer and peer-invariant components (see Section 2.5). Formally, let VA_{st} denote the VA of school s in year t and let the vector $\boldsymbol{x}_i$ include characteristics that are assumed to have a potential impact on the outcomes of other students. Following Allende, 2019, we define $\boldsymbol{x}_i$ as a two-dimensional socioeconomic type $\boldsymbol{x}_i = (x_i^y, x_i^e)$, composed by the binary variables x_i^y and x_i^e that indicate whether the student is socioeconomically disadvantaged and/or has educated parents. Specifically, we define a socioeconomically disadvantaged student as one who is eligible for free or reduced price lunch and students with educated parents as those whose parents are high school graduates.

We then characterize the peers in the school as a vector, $\boldsymbol{z}_{st}$, that includes the mean for the characteristics in $\boldsymbol{x}_i$ for school s at time t. We then decompose the peer and peer-invariants components of school VA by projecting (estimated) school VA, $\widehat{VA}_{st}$, onto the peers vector, $\boldsymbol{z}_{st}$, plus a school fixed effect:

$$\widehat{VA}_{st} = \boldsymbol{z}_{st}' \pi^z + \alpha_s + \epsilon_{st}. \tag{A.4}$$

The portion of school quality coming directly through peers, 'Peer VA,' is given by $\boldsymbol{z}_{st}' \hat{\pi}^z$. The portion of school quality not coming through peers, 'peer-invariant VA,' is then the portion of VA unexplained by peers and so is recovered by subtracting $\boldsymbol{z}_{st}' \hat{\pi}^z$ from $\widehat{VA}_{st}$.

A.4. Constructing Teacher Value-Added

Constructing Teacher Value-Added: The procedure to estimate teacher quality is near-identical to our school VA estimation procedure. Using the teacher VA sample, we estimate teacher VA using the following equation:

$$y_{ijt} = \phi X_{ijt} + \alpha_j + \epsilon_{ijt}, \tag{A.5}$$

where y_{ijt} is the mathematics score of student i assigned to teacher j at time t, X_{ijt} captures observed characteristics of the student (we use the same control vector as for school VA, although also include school-grade and classroom level means of prior-year test scores and individual covariates), and α_j is teacher j's (time-invariant) contribution to student test scores, or simply teacher VA. Once again, the error term ϵ_{ist} is assumed to be independently and identically distributed normal with variance σ_ϵ^2.

We then construct our estimate of teacher VA, μ_j, using the empirical Bayes estimator:

$$\mu_j = \alpha_j \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\epsilon^2 / \sum_t n_{jt}}, \tag{A.6}$$

where $\alpha_j \equiv \sum_t \sum_{i=1}^{n_{jt}} (y_{ijt} - \hat{\phi} X_{ijt}) / \sum_t n_{jt}$ where n_{jt} is the size of the class taught by teacher j in year t. As before, σ_α^2 and σ_ϵ^2 represent the variance of teacher value-added and idiosyncratic student shocks, respectively. These model parameters are estimated via maximum likelihood and then plugged-in to equation (A.6) to get our teacher VA estimates, $\hat{\mu}_j$.

Calculating Turnover-Induced Teacher Value-Added Changes: The turnover-induced change in teacher VA is then calculated over the relevant time period by finding the VA of teachers that are entering and exiting a given school. Specifically, let n_{jt} denote the enrollment of teacher j's class in period t and let μ_j^{-s} denote teacher j's value-added excluding years where they taught at school s. (The exclusion of years where the teacher taught at school s ensures that the changes in teacher VA at school s solely come from teacher staffing changes and not from within-teacher quality changes.)

We then take all teachers who enter school s in period t from another school s' in $t-1$[24] and find the enrollment-weighted VA, $\hat{Z}_{st}^{enter}$, of these teachers in school s:

$$\hat{Z}_{st}^{enter} = \frac{\sum_j n_{jt} \hat{\mu}_j^{-s} \mathbb{1}\{st \neq s', t-1\}}{\sum_j n_{jt}}. \tag{A.7}$$

Analogously, we take all teachers who exited school s in period $t-1$ and

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[24]The set s' also includes the option of not teaching. We therefore include teachers who enter school s but did not teach in the prior year as part of our identifying variation.

find the enrollment-weighted VA, $\hat{Z}_{st}^{exit}$, that these teachers would have contributed to school s in period t had they not left:

$$\hat{Z}_{st}^{exit} = \frac{\sum_j n_{j,t-1} \hat{\mu}_j^{-s} \mathbb{1}\{s't \neq st - 1\}}{\sum_j n_{jt}} \ . \tag{A.8}$$

The change in VA at school s in year t, Z_{st}, is then given as the change in VA in school s coming from teachers that enter and exit school s in year t: $\hat{Z}_{st} = \hat{Z}_{st}^{enter} - \hat{Z}_{st}^{exit}$.

Note that equations (A.7) and (A.8) use jack-knife teacher VA estimates. These VA estimates are constructed by simply removing the jack-knife years from the calculation of teacher VA. Thereore, if we wish to remove years t and $t - 1$ from the VA calculation, our jack-knife VA estimator, $\mu_j^{-\{t-1,t\}}$, would be:

$$\mu_j^{-\{t-1,t\}} = \alpha_j^{-\{t-1,t\}} \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\epsilon^2 / \sum_{\substack{t \neq t-1 \\ t \neq t}} n_{jt}} \ , \tag{A.9}$$

where $\alpha_j^{-\{t-1,t\}} \equiv \sum_{\substack{t \neq t-1 \\ t \neq t}} \sum_{i=1}^{n_{jt}} (y_{ijt} - \hat{\phi} X_{ijt}) / \sum_{\substack{t \neq t-1 \\ t \neq t}} n_{jt}.$

A.5. Constructing Cross-Walk between Census Tracts and School Zones

We construct the cross-walk using school attendance boundaries from 2015-16 (National Center for Education Statistics, 2018) and census tract files for 2010 from IPUMS.

We construct a mapping from census tracts to school zones as follows. Let $c_1...c_N$ be all the census tracts that intersect school zone z. Then x_z, the value for a sociodemographic characteristic x in school zone z, is a weighted average of $x_i, i = 1, ..., N$, the sociodemographic values for census tract i. Precisely, $x_z = \sum_{i=1}^N \omega_{z,i} x_i$. The weight, $\omega_{z,i}$ is the share of the school zone area z that intersects with census tract c_i. The cross-walk reports the population share of a given school zone that falls into each intersecting census tract.

A.6. Constructing Instrument for House Prices

We construct a Bartik-style instrument following Graham et al. (2023). Let $B_{z,t-5,t}$ denote the instrument for local house price growth between t and $t-5$. The instrument is constructed as the interaction between the local shares $\lambda_{z,c}$ of houses with a given characteristics c with the change in the aggregated marginal price of those characteristics $\Delta q_{c,t-5,t}$. The instrument is given by:

$$B_{z,t-5,t} = \sum_{d \in \mathcal{D}} \lambda_{z,d} \Delta q_{d,t-5,t} + \sum_{b \in \mathcal{B}} \lambda_{z,b} \Delta q_{b,t-5,t} + \sum_{h \in \mathcal{H}} \lambda_{z,h} \Delta q_{h,t-5,t} \quad \text{(A.10)}$$

where $d \in \mathcal{D}$, $b \in \mathcal{B}$, and $h \in \mathcal{H}$ denote distinct sets of house characteristics described in detail below, $\lambda_{z,c}$ is the share of houses in zone z with generic characteristic c, and $\Delta q_{c,t-5,t}$ is the 5-year change in the aggregate marginal price of a generic characteristic c. The local characteristic shares satisfy the adding up constraints $\Sigma_{c \in \mathcal{C}} \lambda_{z,c} = 1$ for each set of characteristics $\mathcal{C} \in \{\mathcal{D}, \mathcal{B}, \mathcal{H}\}$.

We use three sets of house characteristics that are widely reported in the ZTRAX data (Zillow, 2020). These characteristics are: the decade of construction $\mathcal{D} \equiv \{pre-1939, 1940-1949, 1950-1959, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2009, 2009-2018\}$; the number of bedrooms $\mathcal{B} \equiv \{1, 2, 3, 4, 5+\}$; and number of bathrooms $\mathcal{H} \equiv \{1, 2, 3, 4+\}$.[25] We compute the local shares using ZTRAX data by tabulating characteristics from all unique properties sold between 1998 and 2019. We present the shares of physical characteristics for the average school zone in our sample in Table B.2 below.

In order to construct the aggregate marginal prices of house characteristics we estimate a hedonic pricing regression using the ZTRAX housing transactions data. The regression takes the form

$$p_{j,t} = \gamma_k + \sum_{d \in \mathcal{D}} q_{d,t} \mathbb{1}(d_j = d) + \sum_{b \in \mathcal{B}} q_{b,t} \mathbb{1}(b_j = b) + \sum_{h \in \mathcal{H}} q_{h,t} \mathbb{1}(h_j = h) + \eta_{j,t}$$

$$\text{(A.11)}$$

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[25]Graham et al. (2023) also considers an extension of the instrument to include characteristics describing house floor size and property lot size. They find that this extended instrument provides little additional information relative to year, bedroom, and bathroom characteristics.

where $p_{j,t}$ is the price of property j in year t, and the dummy variables $\mathbb{1}(d_j = d)$, $\mathbb{1}(b_j = b)$, $\mathbb{1}(h_j = h)$ are equal to one for a property j with the relevant construction age, number of bedrooms, and number of bathrooms. We include county-level fixed effects γ_k to absorb average differences in the level of house prices across broad geographic areas. The time-varying coefficients $q_{d,t}$, $q_{b,t}$, and $q_{h,t}$ measure the marginal prices of house characteristics for decade built, number of bathrooms, and number of bedrooms, respectively. We compute 5-year changes in these marginal prices to construct the growth rates $\Delta q_{c,t-5,t}$ in Equation (A.10).

We estimate Equation (A.11) using house transactions from a broad geographic area in order to capture aggregate movements in the marginal prices of house characteristics. We use transactions for all houses in the US state in which our school district is located, but exclude all transactions from the school district itself. This is similar to the common leave-one-out estimator used for shift-share instruments, except that we exclude all sources of variation in house prices that might directly affect school zones in our district (i.e., all other zones within the district). This removes any mechanical correlation between changes in local house prices and our aggregate marginal house characteristic prices. As a result, we avoid the possibility of reverse causality between local price movements and the aggregate time-series variation in our instrument.

Let $B_{z,t-5,t}$ denote the Bartik-like instrument for local house price growth between t and $t-5$. Identification requires that the instrument $B_{z,t-5,t}$ does not affect local school quality growth except through its effects on local house price growth:

$$\text{Cov}(B_{z,t-5,t}, \epsilon_{z,t} | \alpha_z, \alpha_t, X_{z,t,t+5}) = 0$$

Following Goldsmith-Pinkham et al. (2020), we assume that that identification follows from exogeneity of the local shares embedded in our instrument. Specifically, cross-sectional variation in local housing characteristic shares $\lambda_{z,c}$ is exogenous to the error term $\epsilon_{z,t}$. In other words, unobserved shocks to local school quality must be uncorrelated with the composition of the local housing stock.

B. Additional Tables

Table B.1: Summary Statistics for Calculating Value-Added

	Full Sample (1)	School Value-Added Sample[1] (2)	Teacher Value-Added Sample[2] (3)
Mean of Student Characteristics			
Mathematics Score (σ)	0.00	0.02	0.02
Reading Score (σ)	0.00	0.02	0.02
Lagged Mathematics Score (σ)	0.02	0.03	0.04
Lagged Reading Score (σ)	0.02	0.03	0.03
% White	9.2	9.3	8.9
% Black	9.9	9.1	9.0
% Hispanic	74.2	75.0	75.4
% Asian	4.2	4.3	4.3
% Free or Reduced Price Lunch	69.5	70.0	70.9
% English Learners	30.2	30.4	30.5
Parental Education:[3]			
% High School Dropout	34.4	34.6	34.7
% High School Graduate	45.5	45.3	45.6
% College Graduate	20.1	20.1	19.7
# of Students	839,248	743,727	717,023
# of Teachers	-	-	14,536
Observations (student-year)	1,772,731	1,558,687	1,461,842

Notes: This table presents summary statistics for the variables in our administrative education data set that we use to calculate value-added. We then compare the full sample of students in our data to the samples used to calculate school and teacher value-added.

[1] Same as the full sample, but dropping students with missing current or lagged mathematics scores.

[2] Same as the school value-added sample in column (2), but dropping students who cannot be uniquely matched to a teacher.

[3] The 'High School Graduate' category also includes parents with 'Some College,' while 'College Graduate' also incorporates those with graduate school degrees. Roughly thirty percent of observations are missing parental education data or have parental education recorded as "Decline to Answer."

Table B.2: Housing and School Zone Characteristics

Panel A: Housing Characteristics

Number of Houses	Average Sale Price	Average Bedrooms	Average # Bathrooms	Average Year Built	Median Lot Size (sq feet)	Average log House Price Change (5-yr)
717,528	386,938	2.9	2.2	1958	7500	0.23

Panel B: School Zone Demographics

% Bachelor's	Median Age	% Homeownership	% Married with Kids	% Unemployed	% Manufacturing	% Service
30	34	40	32	10	11	21

Panel C: Average School Zone Physical Characteristics Share

% Pre 1939	% 1940-1970	% 1970-2000	% Post 2000	% 1 Bedroom	% 2 Bedroom	% 3 + Bedroom
39	39	18	6.5	4.5	34	62

Notes: Panel A presents summary statistics for the sample of houses that sold in our district from 1999 to 2019. House characteristic data is from (Zillow, 2020). Panel B presents average demographics across school zones in the dataset. "% Bachelor's" refers to people with a Bachelor's degree or higher. "% Manufacturing" refers to the percentage of people who work in the manufacturing industry while "% Service" refer to the percentage of people that have an occupation in the service sector. Demographics are from the American Community Survey. Panel C presents the average percent of houses in school zones with certain characteristics that are used to construct the instrument. The first four columns refer to the time period of construction.

Table B.3: Different Time Windows for House Price and School Value-Added Changes

| | 3-year | 4-year | 5-year | 6-year | 7-year |
	Dependent variable:				
	(1)	(2)	(3)	(4)	(5)
Δ log House Price	0.037	0.113**	0.164***	0.185***	0.243***
	(0.033)	(0.045)	(0.043)	(0.052)	(0.077)
Method	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	All Zones	All Zones	All Zones	All Zones	All Zones
School Zones	423	424	424	424	424
Observations	2,411	2,794	2,775	2,374	1,972
First-Stage F Stat	320.57	261.21	241.52	328.62	169.92
School Zone F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates of Δ log House Price from Equation (1) using different time periods of house price and school value-added changes. The dependent variable is Δ log $HousePrice$. Column (1) uses 3-year windows, and Column (2) uses 4 years. In Column (3) we present our baseline estimate using a 5-year time period. Column (4) uses 6-years and Column (5) uses 7-years. All estimates are computed via instrumental variables. Demographic controls include: percentage of individual with a bachelor's degree or higher, median age, homeownership rate, share of families that are married with children. Economic controls include: unemployment rate, percent in service occupations, percent in construction occupations, percent in manufacturing industry, percent in finance/insurance/real estate industry, and percent in construction industry. The row "First-Stage F Stat" reports the F statistics from the first stage of the IV estimation. *p<0.1; **p<0.05; ***p<0.01

Table B.4

	Dependent variable:			
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	Share FRL	Share Black	Class Size	Private School to Public School Ratio
	(1)	(2)	(3)	(4)
Δ log House Price	−0.671***	−0.012**	−0.376	−0.007
	(0.063)	(0.006)	(0.617)	(0.018)
Sample	All Zones	All Zones	All Zones	All Zones
Method	2SLS	2SLS	2SLS	2SLS
Number of Schools	427	427	423	427
Observations	3,304	3,639	3,303	3,663
First-Stage F-stat	301.23	278.72	217.45	310.23
School Zone F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes

Notes: This table presents coefficients on Δ log House Price estimated from Equation (1) with different dependent variables. In Column (1), the dependent variable is ΔFRL, the change in the share of free and reduced lunch students from t to $t+5$. Column (2) estimates the effect of Δ log House Price on $\Delta Black$, the change in the share of Black students in a school zone from t to $t+5$. In Column (3) the dependent variable is the change in average class size in the school zone. Column (4) estimates the effect of Δ log House Price on the ratio of students in private to public school. Private school ratio is defined as the number of students attending a private school in a school zone over the number of students attending the public catchment school. Private school enrolment numbers are from the NCES. Demographic controls include: percentage of individual with a bachelor's degree or higher, median age, homeownership rate, share of families that are married with children. Economic controls include: unemployment rate, percent in service occupations, percent in construction occupations, percent in manufacturing industry, percent in finance/insurance/real estate industry, and percent in construction industry.
*p<0.1; **p<0.05; ***p<0.01

Table B.5: Teacher Turnover Across 1,3, and 5-year Horizons

% of Teachers that:	Time Horizon		
	1-year	3-year	5-year
Stay in the Same School	83.5	66.0	54.3
Leave To Another School	6.0	11.2	13.9
Leave District	10.5	22.8	31.8

Notes: The numbers in each column sum to one-hundred percent. We consider a teacher to have left the district if we do not observe them in our data after the relevant time horizon and the year after. Similarly, we consider a teacher to have switched schools if they appear in a different school after the relevant time horizon or one year later but were missing in the data after the relevant time horizon. Adding the extra year is done to account for 1-year teacher leaves (e.g., maternity leave) where the teacher leaves the data for one year, but has not truly left the school. We exclude the appropriate number of years at the end of our data period so that these 1-year leaves are consistently allowed.

C. Illustrative Model Proofs

C.1. Location Choice Probabilities

Combining the definition of the value function and the the optimal decisions from Equations (2), (3), and (4) we find:

$$V(w, n; n') = \log c(n') + \psi \log(y_k(n') + b_k(n'))$$
$$= \log\left(\frac{1}{1+\psi}\right) + \psi \log\left(\frac{\psi}{1+\psi}\right) + (1+\psi)\log\left(w + (P_n - P_{n'}) + Q(P_{n'})\right)$$

Then the value functions for moving ($n' \neq n$) and non-moving ($n' = n$) households are:

$$V(w, n; n') = \log\left(\frac{1}{1+\psi}\right) + \psi \log\left(\frac{\psi}{1+\psi}\right) + (1+\psi)\log\left(w + (P_n - P_{n'}) + Q(P_{n'})\right)$$
$$V(w, n; n) = \log\left(\frac{1}{1+\psi}\right) + \psi \log\left(\frac{\psi}{1+\psi}\right) + (1+\psi)\log\left(w + Q(P_n)\right)$$

Substituting these value functions into the probability of choosing neighborhood n' we have:

$$\mathbb{P}(n'|w,n) = \left[1 + \exp\left(\frac{V(w,n;n) - V(w,n;n')}{\sigma_n}\right)\right]^{-1}$$

$$= \left[1 + \exp\left(\frac{1+\psi}{\sigma_n}\log\left(w + Q(P_n)\right) - \frac{1+\psi}{\sigma_n}\log\left(w + (P_n - P_{n'}) + Q(P_{n'})\right)\right)\right]^{-1}$$

$$= \left[1 + \left(\frac{w + Q(P_n)}{w + P_n - P_{n'} + Q(P_{n'})}\right)^{\frac{1+\psi}{\sigma_n}}\right]^{-1}$$

C.2. Wealth Effects of House Price Movements

Changes in neighborhood choice probabilities. Using the equation above for $\mathbb{P}(n'|w,n)$, we can show that the change in the probability of a parent choosing neighborhood n' is:

$$\frac{\partial \mathbb{P}(n'|w,n)}{\partial P_n} = \mathbb{P}(n'|w,n)(1 - \mathbb{P}(n'|w,n))\frac{1+\psi}{\sigma_n}\left(\frac{1}{w + P_n - P_{n'} + Q(P_{n'})} - \frac{Q'(P_n)}{w + Q(P_n)}\right)$$

Consumption wealth effect. Average consumption expenditure is given by:

$$\mathbb{E}[c|w,n] = \sum_{n' \in \{A,B\}} \mathbb{P}(n'|w,n)c(n')$$

The change in consumption given a change in initial house price P_n is:

$$\frac{\partial \mathbb{E}[c|w,n]}{\partial P_n} = \sum_{n' \in \{A,B\}}\left(\frac{\partial \mathbb{P}(n'|w,n)}{\partial P_n}c(n') + \mathbb{P}(n'|w,n)\frac{\partial c(n')}{\partial P_n}\right)$$

$$= \frac{\partial \mathbb{P}(n'|w,n)}{\partial P_n}c(n') + \mathbb{P}(n'|w,n)\frac{\partial c(n')}{\partial P_n}$$

$$+ \frac{\partial(1 - \mathbb{P}(n'|w,n))}{\partial P_n}c(n) + (1 - \mathbb{P}(n'|w,n))\frac{\partial c(n)}{\partial P_n}$$

where we use the Leibniz rule to find the derivative of the product within the summation term, and make use of the fact that $\mathbb{P}(n|w,n) = 1 - \mathbb{P}(n'|w,n)$. Substituting in the conditional wealth effects on consumption from Section 3.2 and the equation for the change in neighborhood

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choice probabilities from above:

$$\frac{\partial \mathbb{E}[c|w,n]}{\partial P_n} = \left[\frac{\mathbb{P}(n'|w,n)\mathbb{P}(n|w,n)}{\sigma_n}\left(1 - Q'(P_n)\frac{w + P_n - P_{n'} + Q(P_{n'})}{w + Q(P_n)}\right) + \frac{\mathbb{P}(n'|w,n)}{1+\psi}\right]$$
$$+ \left[-\frac{\mathbb{P}(n'|w,n)\mathbb{P}(n|w,n)}{\sigma_n}\left(\frac{w + Q(P_n)}{w + P_n - P_{n'} + Q(P_{n'})} - Q'(P_{n'})\right) + \frac{\mathbb{P}(n|w,n)}{1+\psi}Q'(P_n)\right]$$

And simplifying yields:

$$\frac{\partial \mathbb{E}[c|w,n]}{\partial P_n} = \frac{\mathbb{P}(n'|w,n)\mathbb{P}(n|w,n)}{\sigma_n}(\mathcal{A} + \mathcal{B}) + \frac{1}{1+\psi}\left(\mathbb{P}(n'|w,n) + \mathbb{P}(n|w,n)Q'(P_n)\right)$$

where

$$\mathcal{A} = \frac{(P_n - P_{n'}) + [Q(P_{n'}) - Q(P_n)]}{w + P_n - P_{n'} + Q(P_{n'})}$$
$$\mathcal{B} = Q'(P_{n'})\frac{[Q(P_n) - Q(P_{n'})] - (P_n - P_{n'})}{w + Q(P_n)}$$

Now we assume that neighborhoods are initially identical: $P_{n'} = P_n = P$. In that case, $\mathcal{A} = 0$ and $\mathcal{B} = 0$, and $\mathbb{P}(n'|w,n) = \mathbb{P}(n|w,n) = \frac{1}{2}$. Then the change in consumption is given by:

$$\frac{\partial \mathbb{E}[c|w,n]}{\partial P_n} = \frac{1}{2}\frac{1}{1+\psi}\left(1 + Q'(P)\right)$$

Transfer wealth effect. Average parental transfers are given by:

$$\mathbb{E}[b_k|w,n] = \sum_{n' \in \{A,B\}} \mathbb{P}(n'|w,n)b_k(n')$$

Following the same steps as above for consumption, we find an expression for the change in trasnfers given a change in initial house price P_n:

$$\frac{\partial \mathbb{E}[b_k|w,n]}{\partial P_n} = \frac{\mathbb{P}(n'|w,n)\mathbb{P}(n|w,n)}{\sigma_n} \times \mathcal{C} \times \mathcal{D}$$
$$+ \frac{1}{1+\psi}\left(\mathbb{P}(n'|w,n) + \mathbb{P}(n|w,n)Q'(P_n)\right)$$

where

$$\mathcal{C} = \frac{1}{w + P_n - P_{n'} + Q(P_{n'})} - \frac{Q'(P_{n'})}{w + Q(P_n)}$$
$$\mathcal{D} = \psi(P_n - P_{n'}) + [Q(P_n) - Q(P_{n'})]$$

Now we assume that neighborhoods are initially identical: $P_{n'} = P_n = P$. In that case, $\mathcal{D} = 0$, and $\mathbb{P}(n'|w,n) = \mathbb{P}(n|w,n) = \frac{1}{2}$. Then the change in trasnfers is given by:

$$\frac{\partial \mathbb{E}[b_k|w,n]}{\partial P_n} = \frac{1}{2}\frac{1}{1+\psi}\left(\psi - Q'(P)\right)$$

Child human capital wealth effect. Average child human capital is given by:

$$\mathbb{E}[y_k|w,n] = \sum_{n'\in\{A,B\}} \mathbb{P}(n'|w,n)y_k(n')$$

Following the same steps as above for consumption, we find an expression for the change in child human capital given a change in initial house price P_n:

$$\frac{\partial \mathbb{E}[y_k|w,n]}{\partial P_n} = \frac{\mathbb{P}(n'|w,n)\mathbb{P}(n|w,n)(1+\psi)}{\sigma_n} \times \mathcal{C} \times [Q(P_{n'}) - Q(P_n)] + \mathbb{P}(n|w,n)Q'(P_n)$$

where $\mathcal{C}$ is as above. Now we assume that neighborhoods are initially identical: $P_{n'} = P_n = P$. In that case, $Q(P_{n'}) = Q(P_n)$, and $\mathbb{P}(n'|w,n) = \mathbb{P}(n|w,n) = \frac{1}{2}$. Then the change in child human capital is given by:

$$\frac{\partial \mathbb{E}[y_k|w,n]}{\partial P_n} = \frac{1}{2}Q'(P)$$

D. Quantitative Model Details

D.1. Model Discretization

The model statespace is given by $\mathbf{s} = \{b, y, a, n\}$. The number of grid points in each dimension are N_b, N_y, N_a, and N_n. We set the number of neighborhoods $N_n = 3$, and the grid points $[1, 2, 3]$ act as simple numerical labels for neighborhoods A, B, and C. Child ability a follows an AR(1) process as in Equation (9) with parameters μ_a, ρ_a, and σ_a. We discretize the process using the Rouwenhorst (1995) method with $N_a = 5$ grid points.

Recall from Equation (8) that child human capital is given by $y_k = a_k Q_n$. So at age $j = 1$, human capital is entirely determined by ability and parent neighborhood choices. At age $j = 2$ adults receive log-normally distributed income shocks ε_y. We discretize the shocks process using a Gauss-Hermite method with $N_{\varepsilon_y} = 5$ nodes. We compute all possible values of y for households at age $j = 1$ by taking the Kronecker product of the grids for a and Q_n. To compute the possible values of y for households at age $j = 2$, we construct an additional Kronecker product with the discretized grid for ε_y. To construct the final grid space we then take the unique values of y across both ages $j = 1, 2$. This yields a grid space of size $N_y = N_a \times N_n \times (1 + N_{\varepsilon_y}) = 90$.

Liquid assets b are negative when the household borrows to finance housing, and positive when the household is saving. The minimum grid size is given by $\underline{b} = -\theta \overline{P_n}$ where $\overline{P_n}$ is the maximum value of housing and θ is the maximum loan to value ratio for borrowing. In our dynamic experiments in Section 4.5, house prices can be higher than they are in steady state. Therefore, we set $\overline{P_n}$ to the largest value for any neighborhood across all of our experiments. In practice, these prices are no more than 10 percent higher than prices in steady state. We set the maximum liquid asset grid point equal to the maximum possible income realization plus the proceeds of selling the most expensive house to purchase the least expensive house. We set the number of grid points to $N_b = 100$. We split the grid evenly between negative and positive values. Finally, we distribute grid points polynomially within the negative and positive parts of the asset space.

D.2. Scaling the Ability Process

One difficulty in computing equilibria of our model is that households may not be able to afford to purchase a house given their income. For a given income distribution, nothing guarantees that houses are affordable for all households. Other papers in the literature ensure minimum housing affordability by allowing for an intensive margin or house size choice, or by assuming households can only rent and that the lowest rental rate is normalized to zero (see, for example, Fogli et al., 2019).

We address this problem by normalizing the mean of the child ability process μ_a to ensure that the very poorest household in the model can afford to purchase a house in the least expensive neighborhood. Since households first purchase a house at age $j = 1$, minimum housing affordability requires that the poorest household can afford the downpayment on a house in the lowest price neighborhood. That is,

$$(1 - \theta)\underline{P_n} \leq \underline{y_k} = \underline{a_k}\underline{Q_n}$$

where underlined variables are the minimum values for house prices, income, ability, and school quality, respectively. We take the minimum value for child ability a_k from smallest grid value in the discretized AR(1) process for the ability process. Since we discretize the process using the Rouwenhorst (1995) method, the smallest value of a_k on the grid is given by:

$$\underline{a_k} = \exp\left(\log(\mu_a) - \frac{1}{2}\frac{\sigma_a^2}{(1 + \rho_a)(1 - \rho_a)} - \frac{\sigma_a}{\sqrt{1 - \rho_a^2}}\sqrt{N_a - 1}\right)$$

where μ_a, ρ_a, and σ_a are the mean, persistence, and standard deviation of the AR(1) process, respectively, and N_a is the number of grid points used in discretization. Thus, to ensure minimum housing affordability we set the mean of the ability process to its lower bound, which is given by:

$$\mu_a = \exp\left(\log((1 - \theta)\underline{P_n}) - \log(\underline{Q_n}) + \frac{1}{2}\frac{\sigma_a^2}{(1 + \rho_a)(1 - \rho_a)} + \frac{\sigma_a}{\sqrt{1 - \rho_a^2}}\sqrt{N_a - 1}\right)$$

By construction, our steady state equilibrium is such that $\underline{P_n} = P_A = 1$ and $\underline{Q_n} = Q_A$. The parameters ρ_a, σ_a, μ_y, and school quality Q_A are all determined by the simulated method of moments algorithm used in

calibration, so μ_a is updated enodgenously during the calibration process.

D.3.   Equilibrium and Calibration

Recall that an equilibrium of our model requires that housing markets clear

$$\sum_{j=1,2} \int \mathbb{1}_{j,n} d\lambda_j = H_n \tag{D.1}$$

and that school quality is governed by

$$Q_n = \left(\frac{\overline{Y}_n}{\overline{Y}}\right)^\alpha = \left(\frac{\frac{1}{H_n}\sum_{j=1,2}\int \mathbb{1}_n y d\lambda_j}{\sum_{j=1,2}\int y d\lambda_j}\right)^\alpha \tag{D.2}$$

A simple implementation of our model would solve an inner loop over the market clearing conditions for any given set of parameters considered during the calibration process. In order to speed up calibration, we avoid this inner loop by incorporating the market clearing conditions in the calibration process directly.

First, we normalize the price of housing in neighborhood A so that $P_A = 1$. Second, we assume that housing market clearing holds at the relative neighborhood prices targeted in the calibration. That is, we impose that $P_B/P_A = 1.740$ and $P_C/P_A = 3.120$ (see Table 5). Third, we assume that the school quality equation holds at the relative neighborhood average incomes targeted in the calibration. That is, we impose that $Y_B/Y_A = 1.31$ and $Y_C/Y_A = 2.30$ (also see Table 5).

We then rewrite the local school quality function as

$$\begin{aligned}
Q_n &= \left(\frac{\frac{1}{H_n}\sum_{j=1,2}\int \mathbb{1}_n y d\lambda_j}{\sum_{j=1,2}\int y d\lambda_j}\right)^\alpha \\
&= \left(\frac{\frac{1}{H_n}\sum_{j=1,2}\int \mathbb{1}_n y d\lambda_j}{\sum_n H_n\left(\frac{1}{H_n}\sum_{j=1,2}\int \mathbb{1}_n y d\lambda_j\right)}\right)^\alpha \\
&= \left(\frac{\frac{\overline{Y}_n}{\overline{Y}_A}}{\sum_n H_n\left(\frac{\overline{Y}_n}{\overline{Y}_A}\right)}\right)^\alpha
\end{aligned}$$

and we impose the targeted ratios for $\overline{Y}_B/\overline{Y}_A$ and $\overline{Y}_C/\overline{Y}_A$.

Since the price and quality vector $\{P_n, Q_n\}_{n=A,B,C}$ is available prior to solving the model, market clearing is instead computed as part of the calibration process. That is, the market clearing conditions enter the simulated method of moments algorithm as model moment conditions. We use two housing market clearing conditions from (D.1), while the third market clears automatically via Walras' Law. We use two of the school quality conditions from (D.2),

$$Q_n - \left(\frac{\overline{Y}_n}{\overline{Y}}\right)^\alpha = 0$$

where $\overline{Y}_n$ and $\overline{Y}$ are computed in the model. Note that the third school quality function automatically holds due to the relationship

$$\sum_n H_n Q_n^{\frac{1}{\alpha}} = 1$$

As long as the model generates the same relative average incomes $\overline{Y}_B/\overline{Y}_A$ and $\overline{Y}_C/\overline{Y}_A$ as in the data, the equilibrium school quality equations hold.

D.4. Additional Model Results

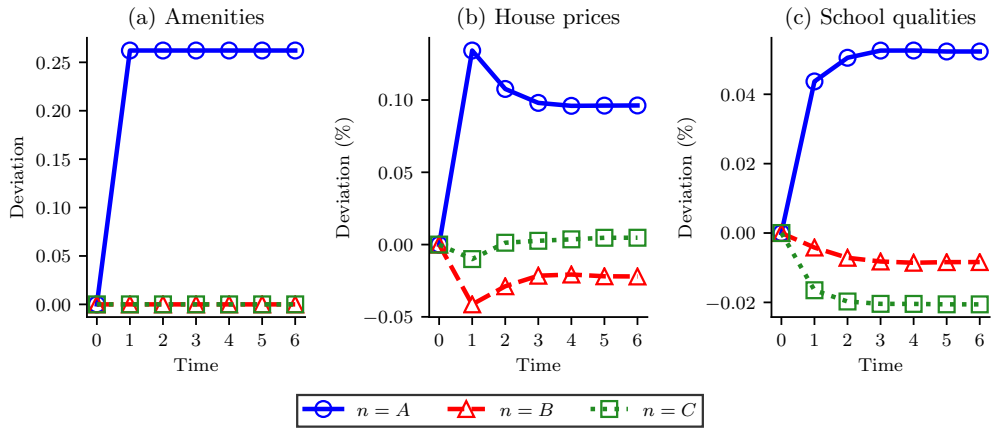Figure 6: Transition Paths Following Amenity Shock to Neighborhood A

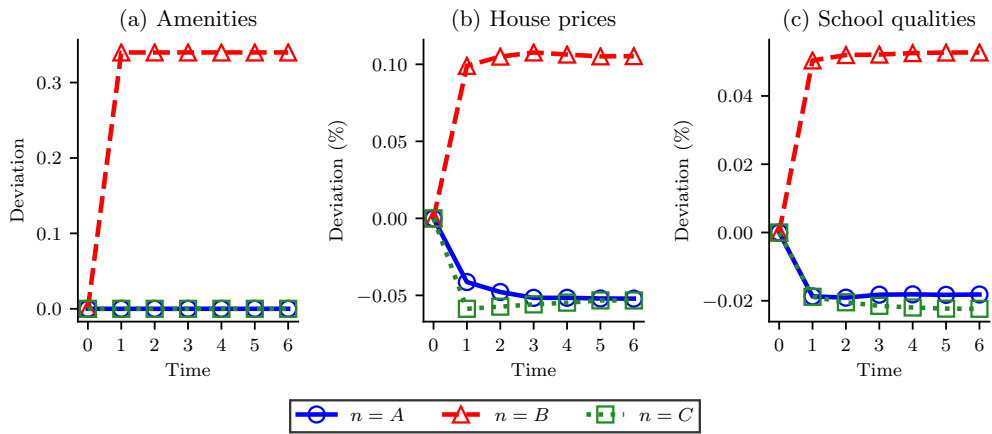Figure 7: Transition Paths Following Amenity Shock to Neighborhood B

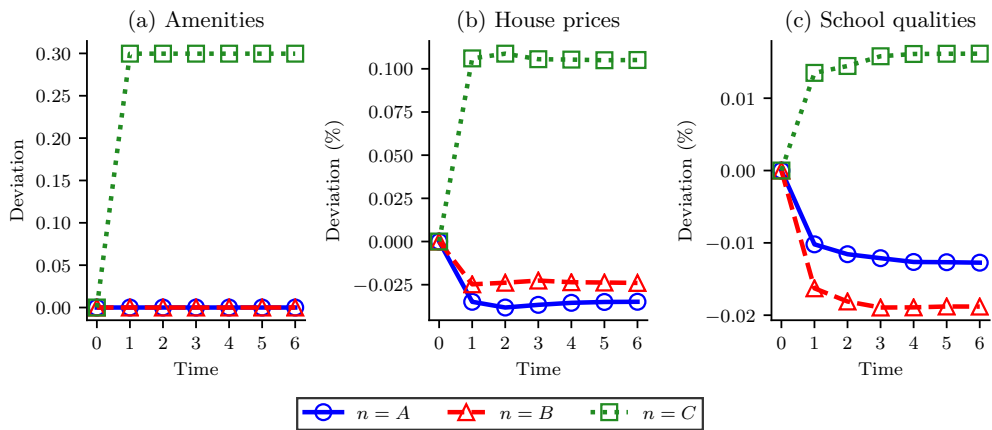Figure 8: Transition Paths Following Amenity Shock to Neighborhood C

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Table B.6: Marginal Housing Wealth Effects of Amenity Shocks to Each Neighborhood

	Parent consumption	Transfers to child	Child income	Moving probability
Panel (a): Amenity shock to neighborhood A				
All households	0.027	0.005	0.066	-0.003
Stayers only	0.029	-0.003	0.117	–
Movers only	0.025	0.017	-0.013	–
Panel (b): Amenity shock to neighborhood B				
All households	0.023	0.005	0.034	0.046
Stayers	0.024	0.002	0.090	–
Movers	0.021	0.010	-0.055	–
Panel (c): Amenity shock to neighborhood C				
All households	0.062	0.039	0.026	0.007
Stayers only	0.024	0.003	0.077	–
Movers only	0.125	0.097	-0.057	–

Notes: All statistics computed for households at age $j = 2$ and reported in annualized terms. Statistics computed as changes in a given variable divided by the change in house price in a household's initial neighborhood. Averages for each statistic computed using probability weights from the stationary distribution.