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ABSTRACT

While rising house prices are known to benefit existing homeowners, we document a new channel through which house 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 children's 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. We find that housing market shocks generate large intergenerational wealth effects that account for around one-third of total housing wealth effects.

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1. Introduction

Recent research has documented strong links between intergenerational mobility and the neighborhood choices of parents.[1] Where a family chooses to live can affect children's future incomes through local factors such as the composition of residents and the quality of schools.[2] In this paper we identify a new mechanism through which local housing market shocks affect economic opportunity across generations: rising local house prices improve the quality of local public schools, which increases children's future earnings potential. We describe this mechanism as an intergenerational housing wealth effect.

We proceed in two stages. First, we provide empirical evidence that local house price growth leads to improvements in local public school quality as measured by school value-added. Second, we build an overlapping generations model that incorporates neighborhood choices, local schools, and spatial equilibrium. Our model enables us to analyze the intra- and intergenerational transmission of housing market shocks. We demonstrate that intergenerational wealth effects due to changing school quality account for nearly one-third of total housing wealth effects. While our empirical findings establish an endogenous relationship between house prices and school quality, the model allows us to investigate its broader implications in the absence of detailed intergenerational data.

Empirically, we show that local house price growth leads to changes in household sorting across neighborhoods, increasing the share of high socioeconomic status residents. This demographic change leads to a more affluent student body and attracts higher-quality teachers, both of which improve local school quality. Importantly, these improvements are independent of changes in school financing mechanisms such as local property taxes.[3] Throughout both our empirical analysis and modeling work, we argue that higher school quality contributes to greater human capital formation among resident children, thereby increasing their future earnings.

[1]See, for example, Chetty et al. (2014c) and Chetty et al. (2016).

[2]Recent modeling work in this area includes work by Fogli et al. (2019), Zheng et al. (2021), Gregory et al. (2022), and Chyn et al. (2022).

[3]For papers studying the link between property taxes and inequality, see Benabou (1994), Benabou (1996a), Benabou (1996b), Durlauf (1996a), Durlauf (1996b), Fernández et al. (1996), Fernández et al. (1998), and Davis et al. (2022).

Consequently, families exposed to positive local housing market shocks benefit from both contemporaneous increases in housing wealth and from higher future earnings of children. These outcomes represent both intra- and intergenerational wealth effects of housing market shocks.

Our first contribution is an empirical analysis combining student-level administrative data from a large, urban, U.S. school district and local house prices constructed from housing transactions data. We document that faster house price growth in a school attendance zone leads to larger subsequent improvements in local public school quality, as measured by school value-added. To alleviate concerns about endogeneity and measurement error, we present estimates using two instruments for house prices: (i) a shift-share instrument that exploits geographic variation in the composition of local housing characteristics, and (ii) local housing supply elasticity estimates.[4] We find that a 100 percent increase in house prices over a five-year period leads to a 0.25-standard deviation increase in local school value-added. Drawing on prior work by Chetty et al. (2014b), we provide a back-of-the-envelope calculation linking these changes in school quality to lifetime gains in child incomes. This exercise suggests that a one standard deviation increase in house price growth is associated with a $37,000 increase in the present-value of lifetime income in year 2000 dollars.

We also explore mechanisms that might account for the empirical relationship between house price growth and school quality changes. First, note that the relationship cannot be explained by changes in local school financing. This is because we study school zones within a school district, while residential property taxes accrue at the school district level. Second, we show that faster house price growth alters the composition of local schools by reducing the share of low socioeconomic status students and increasing the share of students with college-educated parents. Third, we show that improving teacher quality due to teachers switching schools accounts for around two-thirds of the overall change in school quality.[5] We argue that this sorting of teachers across schools is likely to be linked to

[4] See Graham et al. (2023) and Baum-Snow et al. (2024).

[5] To do this we employ methods from Chetty et al. (2014a) to estimate the effect of teachers switching schools following local house price shocks (i.e., teacher entry into and exit from local schools).

the observed changes in student body composition.[6]

Our second contribution is to develop an overlapping generations model that quantifies intra- and intergenerational housing wealth effects in the presence of an endogenous school quality channel. In the model, young households first choose a neighborhood in which to live. Once children arrive, parents have the opportunity to move by selling their existing house and buying a new one in a different neighborhood. Neighborhood choice is of central importance because it determines the local schools that children attend, and school quality is a significant input into human capital formation. Parents value their children's lifetime wealth, which comprises direct transfers and the present discounted value of their future income.

In the spatial equilibrium of the model, house prices adjust to clear neighborhood housing markets, and school qualities adjust to reflect the average incomes of local residents. This latter assumption reflects the relationship between school quality and neighborhood composition explored in our empirical work. A crucial parameter in the model is the elasticity of school quality to local incomes. We estimate this elasticity using our measure of school value-added and data on local household incomes. The remaining model parameters are calibrated to capture cross-neighborhood differences in house prices and incomes. We show that the calibrated model is also able to reproduce the cross-neighborhood patterns of intergenerational income mobility reported in Chetty et al. (2018).

We study intra- and intergenerational housing wealth effects in the model via exogenous neighborhood demand shocks that induce movements in local house prices. Along an equilibrium transition path, positive neighborhood demand shocks increase house prices and attract higher income households thereby improving local school quality. Households that purchased homes prior to the shock must then decide how to allocate their wealth gains. They may adjust consumption, transfers to children, or investments in school quality through decisions to stay in or move across neighborhoods.

Our primary focus is on the marginal change in children's lifetime incomes with respect to house prices, which we estimate to be 1.1 cents in the dollar. Combining this estimate with a $170,000 change in house prices –

[6] See, for example, Bonhomme et al. (2016).

equivalent to the observed standard deviation of 5-year house price growth – incomes are expected be $27,000 higher over their life-times. This estimate is around 70 percent of the income gains from the back-of-the-envelope calculation based on our empirical results. We also report an annualized marginal propensity to consume out of house prices of 1.6 cents in the dollar, which falls within the range of recent estimates in the literature (Mian et al., 2013; Aladangady, 2017; Kaplan et al., 2020; Graham et al., 2023). Additionally, the average annualized marginal propensity to transfer wealth to children is 1.1 cents in the dollar, consistent with recent work on intergenerational transfers of housing wealth shocks by Daysal et al. (2023).

Overall we find that intergenerational wealth effects via higher future child incomes are 30 percent of total housing wealth effects, intergenerational effects through direct transfers are 27 percent of wealth effects, and intra-generational effects through contemporaneous consumption make up 43 percent of total wealth effects. Taken together the intergenerational wealth effects of housing shocks are nearly 60 percent of total housing wealth effects, with half of that coming through the endogenous school quality channel.

Finally, we show that intergenerational housing wealth effects are the result of active parental choices to invest housing gains in additional education. Households benefiting from positive housing market shocks are more likely to stay in their current neighborhoods or move to more expensive ones with better schools. In contrast, households facing negative housing market shocks are more likely to leave their current neighborhoods but tend to move to areas with lower house prices and lower school quality. Our results suggest that parents view education quality as an investment in their children's human capital and leverage housing wealth gains to enhance these investments. This education investment mechanism is reinforced by our endogenous school quality channel. Following a housing market shock, parents may be more or less able to take advantage of improving educational opportunities in their own or other neighborhoods. These strong connections between housing wealth, school quality, and neighborhood choice are central to the intergenerational transmission of housing wealth shocks.

1.1. Related Literature

This paper follows a literature studying the relationship between intergenerational inequality, neighborhood choice, school quality, and child human capital accumulation (Benabou, 1994; Benabou, 1996a; Benabou, 1996b; 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. In this context, house price changes directly impact school revenues and thus quality, as documented by Davis et al. (2022) and modeled in Zheng et al. (2021). In contrast, we study school zones within a school district, whereas property taxes are collected at the district level.[7] This allows us to isolate differences in school quality due to local factors such as the composition of students or the quality of teachers at these schools.

Our model builds on recent work studying intergenerational inequality with neighborhood sorting and endogenous local school quality (Kotera et al., 2017; Aliprantis et al., 2018; 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 with neighborhood choice, endogenous sorting, and local spillovers into child human capital accumulation. 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 dynamic equilibrium responses to policy changes such as the introduction of school vouchers, transfers, or place based-subsidies. In contrast, our paper studies wealth effects following neighborhood-specific housing demand shocks. Our results highlight that even generic fluctuations in house prices can have large effects on intergen-

[7]In any case, property tax revenues in our school district of interest account for just fifteen percent of total school revenues. The only other source of funding that may vary with local house prices are donations from parent-teacher associations and school booster clubs. However, these account for just 0.4 percent of funding in our district, and around one percent of aggregate spending on education in the U.S. (Brown et al., 2017).

erational mobility and the transmission of wealth.

Additionally, our research is related to a long empirical literature estimating the contemporaneous wealth effects of house price changes on current homeowners (Mian et al., 2013; Aladangady, 2017; Kaplan et al., 2020; Graham et al., 2023). In recent work, Daysal et al. (2023) use Danish administration data to study the intergenerational transmission of wealth via house price shocks to parent homeowners. 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. Relatedly, Brandsaas (2021) builds a life-cycle housing model to study how transfers of wealth to adult children help them enter the housing market. In our paper we jointly study intra- and intergernational housing wealth effects in the context of local housing market shocks with an endogenous local school quality response.

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; Karbownik, 2020).

2. Empirical Analysis

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 for academic years 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.

Regarding external validity, our school district is broadly 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 while we focus on public schools, we note that our district's private school share is 8%, 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.[8] 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 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 fixed effects and observable determinants of student performance. These controls are: (i) year and grade dummies, (ii) cubic polynomials in students' prior-year test scores in mathematics and English, each interacted with grade dummies, and (iii) student-level demographics, including parental education, economically disadvantaged status, ethnicity, gender, limited English status, and age, all interacted with 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 an empirical Bayes method (see Morris, 1983) since the raw fixed effect estimates overstate the variance of school VA (Koedel et al., 2015). Appendix A.2 describes our VA estimation procedure in more

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

detail.

Our procedure produces VA estimates for each school-year combination. To interpret the VA measure, note that students moving to a school with a one-unit increase in VA would be expected to score one-standard deviation higher in the overall student test score distribution.

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 real annual house price indexes for each school zone within our school district for academic years 1998-99 to 2018-19.

The address of each house sold within our district 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 2008-09 (The College of William and Mary and the Minnesota Population Center, 2011) and 2015-16 (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 final sample covers 393 school zones with at least thirty house sales per year.

We deflate all nominal house values by the CPI (U.S. Bureau of Labor Statistics, 2021) and then construct an arithmetic repeat-sales house price index following Shiller (1991). In contrast with a median sales price index, the repeat-sales index holds constant the composition of the housing stock over time. Table B.2 in Appendix C presents summary statistics for our housing data.

School Zone Demographic Data: We gather information on school zone-level sociodemographic characteristics from the American Community Survey (ACS) 5-year estimates (U.S. Census Bureau, 2019). This demographic information includes average educational attainment, homeownership rates, and family structure. Since ACS data are not available for school zones, we construct a cross-walk between census tracts and school zones. The cross-walk aggregates census tract-level demographics to the school zone level using census tract-level population weights. Appendix A.5 provides additional details. Table B.2 in Appendix C 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:

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

where $\Delta \text{VA}_{z,t,t+5}$ 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 the log of the repeat-sales index 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 $t+5$, such as the homeownership rate and the share of married families with children. 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.

Our baseline regression in Equation (1) makes two assumptions about 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 report the sensitivity of our results to alternative timing assumptions.

To estimate Equation (1) we use house price data from 1998-99 to 2018-19, while our VA measure is available from 2003-04 to 2016-17 excluding the years 2013-14 and 2014-15. After constructing 5-year growth rates, our sample consists of years $t \in \{$2003-04, 2004-05, 2005-06, 2006-07, 2007-08, 2010-11, 2011-12 $\}$. As motivating evidence, Figure 6 in Section C presents a binscatter plot of the relationship between $\Delta \log HousePrices_{z,t-5,t}$ (in percentiles) and $\Delta VA_{z,t,t+5}$, residualized against year and school zone fixed effects. We now turn to discussing causal estimation of Equation (1).

2.3. Identification

We face two challenges to identification in estimating Equation (1). First, 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. Second, there may 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.

To address these concerns, we use an instrumental variable estimation strategy employing two instruments from the recent housing literature: (i) a Bartik-style or shift-share instrument following Graham et al. (2023), and (ii) local housing supply elasticities from Baum-Snow et al. (2024). The first instrument exploits geographic variation in the composition of the housing stock given aggregate changes in the demand for different kinds of housing. The second instrument exploits geographic variation in the ease of constructing new housing given changes in aggregate demand for all types of housing.

Bartik-Style House Price Instrument: Following Graham et al. (2023), the Bartik-style instrument is constructed by taking the local share of houses with given physical characteristics and interacting those shares with aggregate estimates of the marginal prices of those characteristics. For example, we combine the share of two-bedroom houses in each school zone with the aggregate marginal price of two-bedroom houses. Again making use of the ZTRAX data, we proceed in two stages. First, we use three house characteristics that are widely reported in the data: decade of construction, number of bedrooms, and number of bathrooms. We compute the local shares of houses possessing each characteristic using the set of unique properties sold between 1999 and 2019.

Second, we estimate the aggregate marginal prices of each characteristic with a hedonic house price regression. The regression features time-varying coefficients on a set of dummy variables capturing our chosen characteristics. For example, bedroom characteristics are represented by dummy variables for houses with 1, 2, 3, 4, or 5+ bedrooms. The growth rate in the marginal price of a given house characteristic is the change in the estimated time-varying coefficient on the associated dummy variable. To capture aggregate marginal prices, we use transactions for all houses in the state containing our school district, but exclude transactions from the school district itself. This is similar to the leave-one-out estimator used for shift-share instruments, expcept 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). For further details on instrument construction, see Appendix A.6.

Identification of Equation (1) 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 house characteristics 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 this is plausible because house characteristics are largely predetermined at the time of other shocks affecting local school quality. Table B.3 in Appendix C shows that the composition of the housing stock is extremely persistent. The transaction-weighted average of 15-year within-zone correlations for our characteristics shares is 0.84 for number of bedrooms, 0.88 for number of bathrooms, and 0.94 for decade of construction. Since it takes time for new residential construction to affect the composition of the total housing stock, it seems likely that housing characteristics are unresponsive to short- or medium-run shocks affecting the quality of local schools.

Housing Supply Elasticity Instrument: Our second instrument uses local housing supply elasticities from Baum-Snow et al. (2024).[9] Baum-Snow et al. (2024) identify these elasticities by combining an urban economic geography model with estimated changes in housing demand due to labor income shocks across nearby commuting destinations. As suggested

[9]This follows seminal work by Saiz (2010) who produces housing supply elasticities for larger Metropolitan Statistical Areas.

by the authors we use estimates from their quadratic finite mixture model, we use their supply elasticities for housing units, and we use their estimates for 2001 which occurs prior to the start of our own sample period. Since they provide estimates for census tracts, we again make use of our crosswalk to aggregate up to the school zone level (see Appendix A.5). In order to produce time series variation in the instrument, we interact the cross-sectional housing supply elasticities with the aggregate 5-year growth rate of real house prices for the state in which our school district is located.[10]

Identification of Equation (1) using the housing supply elasticity instrument requires that unobserved shocks to local school quality are uncorrelated with the sensitivity of local housing provision to house price changes. As discussed in Gyourko et al. (2008), Saiz (2010), and Baum-Snow et al. (2024), elasticities of housing supply are functions of local land topography and local land use regulations. Existing features of the local landscape, such as the presence of local water features or whether the land is on an incline, are almost certainly unrelated to the growth rate of local school quality. Local regulations could be related to changes in school quality to the extent that local politics influence both regulation and school policies. However, both land use and school policies are generally determined at higher levels of geography, such as the city or school district, rather than at the level of the local school zone.

2.4. The Effect of House Prices on School Quality

Table 1 presents our estimates of the effect of house prices on school quality from Equation (1). Columns (1)–(2) report OLS estimates, Columns (3)–(4) report 2SLS estimates using the Bartik-style instrument, Columns (5)–(6) report 2SLS estimates using the housing supply elasticity instrument, and Columns (7)–(8) report 2SLS estimates from an overidentified specification using both instruments. Each specification is estimated first with year fixed effects only, and then with a full set of fixed effects and controls.

Our OLS specification produces statistically significant estimates in the

[10] Aladangady (2017) interacts housing supply elasticities with changes in national interest rates, and Graham et al. (2023) interacts housing supply elasticities with broad, regional house price changes.

Table 1: Effect of House Price Growth on School Value Added

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ House Price	0.088***	0.126***	0.212***	0.250***	0.291	0.351*	0.217***	0.253***
	(0.028)	(0.030)	(0.062)	(0.063)	(0.187)	(0.211)	(0.060)	(0.062)
School Zones	393	393	393	393	393	393	393	393
Specification	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Instrument	–	–	G&M	G&M	BS&H	BS&H	Both	Both
1st Stage F-Stat	–	–	174.10	212.23	11.17	9.25	94.81	112.5
Sargan Stat.	–	–	–	–	–	–	0.45	0.75
Zone F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,873	1,873	1,873	1,873	1,873	1,873	1,873	1,873

Notes: This table presents estimates of Equation (1). Columns (1) and (2) are estimated via OLS, Columns (3) and (4) are IV estimates using the Shift-Share instruments, Columns (5) and (6) are estimates using the BSH instrument, and Columns (7) and (8) use both instruments. School zone controls include: homeownership rate, percentage of individuals with a bachelor's degree or higher, and share of families that are married with children. 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

range of 0.088 to 0.126. Using our Bartik-style instrument for house prices, we estimate larger coefficients of 0.212 to 0.250. First-stage F-statistics for these regressions are in the range of 174 to 212, indicating a strong relationship between our instrument and house price growth. Using our housing supply elasticity instrument, we estimate slightly larger coefficients of 0.291 to 0.351. These estimates are statistically noisy, and only the specification with all controls is statistically significantly different from zero at the 10 percent level. Additionally, the housing supply elasticity instrument is much weaker than the Bartik-style instrument: first-stage F-statistics are in the range of 9 to 11.[11] Finally, our overidentified specification with both instruments produces statistically significant estimates of 0.217 to 0.253, which is very similar to our estimates with the Bartik-style instrument alone. Under this specification we conduct overidentification tests, which produce Sargan statistics of 0.45 to 0.75. Given a critical value at the 5% level of 3.84, we cannot reject the null hypothesis that the instruments are jointly valid instruments.

Our preferred estimate in Column (8) indicates that 100 percentage point faster house price growth rate is associated with a 0.253 standard

[11] This is consistent with Graham et al. (2023) who also find that housing supply elasticity instruments are weak predictors of house price growth in a panel data context.

deviation increase in school VA. This is the same as 25 percent of a standard deviation gain in average student test scores.

To provide an economic interpretation of our estimates, we conduct a back-of-the-envelope calculation to translate the increase in school VA and student test scores into future income gains. First, a one standard deviation increase in house price growth (65 percentage points) is associated with 0.16 ($= 0.253 \times 0.65$) 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 during a single grade year 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 \$6,232 ($= \$38,950 \times 0.16$) for each year of schooling. Finally, a child that completes six years of elementary schooling can expect lifetime income gains of \$37,392 (=\$6,232×6) following a standard deviation shock to house prices in their school zone.

Finally, we illustrate the sensitivity of our results to our choice of 5-year growth rates in house prices and school qualities for estimating Equation (1). Table B.4 in Appendix C estimates the effect of house price changes on school VA over 3-, 4-, 5-, 6-, and 7-year horizons. Our estimates are always statistically significant and monotonically increasing with the length of adjustment horizon. Our 3-year estimates are as small as 0.14, while our 7-year estimates are as large as 0.389. 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 could lead to improvements in school quality. Since we study changes across school zones within a school district, differences in property tax revenues cannot explain this relationship. Additionally, we do not think that changes in local school or parent resources associated with house price growth are directly associated with higher quality schooling. Column (4) of Table 2 shows that house price shocks do not lead to changes in average class sizes, suggesting that local schools do not receive additional funding that could be used to hire more teachers. Column (5) shows that house price shocks do not lead to changes in private school enrollment shares, suggesting that house price rises do not induce additional parent spending on private education.

Table 2: Effect of House Prices on School Characteristics

	Share FRL	Share College	Share Black	Class Size	Private/Public
	(1)	(2)	(3)	(4)	(5)
Δ log House Price	−0.569***	0.053*	−0.013	0.100	0.008
	(0.091)	(0.028)	(0.009)	(0.928)	(0.029)
School Zone F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
First-Stage F-stat	96.5	107.93	93.4	89.7	98.1
Number of Schools	396	393	394	392	396
Observations	2,203	1,873	2,680	2,372	2,683

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) looks at the change in students whose parents have college education. Column (3) 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 (4) the dependent variable is the change in average class size in the school zone, while in Column (5) it is 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 zone over the number of students attending the public catchment school. All estimates are computed via 2SLS using the shift-share and BSH instruments. *p<0.1; **p<0.05; ***p<0.01

Instead, we consider the way in which house price growth affects the composition of students in the local school zone. Column (1) of Table 2 shows that faster house price growth leads to a sizeable reduction in the share of free and reduced-price lunch students. Column (2) shows that the share of students whose parents have college education increases. And Column (3) indicates that higher house prices may also reduce the share of visible minority students, though the estimate is statistically insignificant.

Peer- and Peer-Invariant Value Added: We now test whether faster house price growth is associated with improving school quality (i) directly through peer effects, or (ii) 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 contributions 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 relegate a detailed description to Appendix A.3. The peer component of school VA is derived from student characteristics that may affect the outcomes of other students. We follow Allende (2019) in assuming that these characteristics are well-represented by socioeconomic status and parents' education level. We then project school-year VA onto these peer characteristics plus a school fixed effect. Peer VA is then given by the relationship between year-to-year variation in school VA and year-to-year changes in peer characteristics. The residual component of school VA is labelled peer-invariant VA.

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

	Δ School VA	Δ PeerVA	Δ Fixed VA	Δ Teacher VA
	(1)	(2)	(3)	(4)
Δ House Price	0.253***	0.010***	0.243***	0.184***
	(0.062)	(0.0027)	(0.061)	(0.047)
School Zones	393	393	393	393
First-Stage F Stat	112.52	112.52	112.52	111.9
School Zone F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
School Zone Controls	Yes	Yes	Yes	Yes
Observations	1,873	1,873	1,873	1,867

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 teacher VA through changes in teacher quality induced by teacher entry and exit. All columns report 2SLS estimates using the shift-share and BSH instrument. 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

Table 3 presents 2SLS estimates of the effect of house prices on the two components of school VA. Column (1) repeats our preferred estimate of the effect of prices on school VA from Table 1. Column (2) reports the effect of changes in house prices on the peer component of VA, with an estimated coefficient of 0.010 that is statistically significant from zero. Column (3) reports the effect of changes in house prices on the peer-invariant component of value-added, with an estimated coefficient of 0.243. These results suggest that peer VA accounts for just 4 percent of the change in total VA following a house price shock, while the remainder is due to changes in the peer-invariant component of VA. Our finding of a small direct impact of school peers on school quality is consistent with a large literature documenting fairly modest effects of peers on child outcomes (Sacerdote, 2011).

Teacher Quality: We now investigate the extent to which changes in peer-invariant VA is due to changes in teacher quality. We are interested in identifying changes in teacher quality due to teacher sorting across schools rather than due to within-teacher quality changes at a given school. Within-teacher quality changes may be difficult to disentangle from changing student demographics if teachers find it easier or more rewarding to teach advantaged students. We therefore follow the teacher-switching literature (Chetty et al., 2014a; Bacher-Hicks et al., 2014; Gilraine et al., 2021) and compute changes in teacher VA at each school due solely to changes in staff (i.e., teacher entry to and exit from a particular school). Note that teacher movements across schools are fairly common: Table B.5 in Appendix C reports one- and five-year teacher turnover rates in our school district of 20 and 50 percent, respectively.

We first estimate teacher-level VA for each teacher and year in our data set.[12] We then compute changes in school VA using a jackknife procedure that excludes data for teachers while they remain at a given school but includes data for teachers when they switch schools. Changes in a school's VA are then computed from the enrollment-weighted means of additions of teacher VA when new teachers enter and subtractions of teacher VA when old teachers exit. Appendix A.4 provides details of the estimation.

Column (4) of Table 3 reports our estimate of the effect of house prices on school quality through teacher switching. We estimate a statistically significant coefficient of 0.18. Comparing Columns (3) and (4), our results suggest that turnover-induced changes in teacher quality account for three-fourths of peer-invariant value-added. The remaining small changes in peer-invariant VA are due to other school-specific factors such as within-teacher improvements, better matching between students and teachers, higher quality principals, and changes in school curricula.

Our results suggest that house price growth largely drives school quality improvements through a teacher sorting mechanism. Note that there are rigid teacher salary schedules within the school district that preclude cross-zone wage adjustments that might attract better teachers (see Hansen et al., 2017) and changes to school zone house prices do not affect teachers' real

[12]This is similar to our estimates of school VA, and follows standard procedures in the VA literature. Details are provided in Appendix A.4.

wages since most teachers commute from outside their school zone (Arturo Santelli et al., 2022). Instead, previous work has shown that teachers sort across schools on the basis of student composition (Rothstein, 2015; Bonhomme et al., 2016; Karbownik, 2020; Bates et al., 2022). Since teachers prefer working with students from advantaged backgrounds (Allensworth et al., 2009; Boyd et al., 2011), they likely respond to house price shocks by moving to schools with an increasing share of high socioeconomic status students. This is consistent with the results in Table 2. Note that teachers will value this amenity even in the absence of peer effects, since it improves their workplace experience even if it does not influence workplace productivity.

3. Quantitative Model

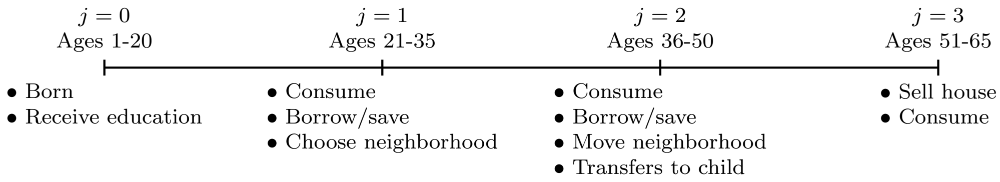
Our empirical results show that rising local house prices are associated with improvements in local school quality. We now build a quantitative model to study the intra- and intergenerational wealth effects of house price shocks in the presence of an endogenous local school quality channel.

3.1. Environment

Overview: The model features overlapping generations of parent-child households. Households live for four periods, where age is denoted $j \in \{0, 1, 2, 3\}$. Figure 1 summarizes the timeline of life events including schooling, earnings, consumption, borrowing and saving, leaving transfers to children, and choosing neighborhoods in which to live. The desirability of each neighborhood varies with the price of housing, school quality, common neighborhood preference shifters, and idiosyncratic preference shocks. In equilibrium, house prices adjust to clear local housing markets and school quality is endogenously determined by the characteristics of neighborhood residents.

Neighborhoods and Housing: There are five model neighborhoods denoted $n \in \{A, B, C, D, E\}$. Households purchase one unit of housing at a neighborhood-specific price P_n. House purchases may be financed with mortgage debt, as explained below. Housing is traded at ages $j = 1$ and

Figure 1: Timeline of Household Events and Decisions



$j = 2$, 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. Movers face costs 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 attended by all children in the neighborhood. The quality of a local school Q_n is endogenously determined by the characteristics of residents in n.[13] This mechanism reflects our empirical findings that higher socioeconomic status students and higher-quality teachers are attracted to local schools in neighborhoods with faster house price growth (see Section 2). For tractability, we assume a simple relationship between between average local resident incomes and local school quality.[14] Specifically, school quality is given by the average income of local residents $\overline{Y}_n$ relative to the average income of all households $\overline{Y}$:

$$Q_n = \left(\frac{\overline{Y}_n}{\overline{Y}} \right)^{\alpha} \tag{2}$$

where α is the elasticity of school quality to local average incomes, average income in the population is $\overline{Y} = \sum_{j=1,2} \int y d\lambda_j$, average income in neighborhood n is $\overline{Y}_n = \frac{1}{H_n} \sum_{j=1,2} \int \mathbb{1}_n y d\lambda_j$, $\mathbb{1}_n$ indicates if a given household lives in neighborhood n, y is household income, λ_j is the distribution over households at age j.

Human Capital and Household Income: Human capital is developed

[13] Note that quality within a school zone is independent of local property tax revenues since these are received and allocated by the larger school district. Zheng et al. (2021) model district-level school quality as a function of local tax revenues.

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

as a child and is a simple function of ability and school quality:

$$y_k = a_k Q_n \tag{3}$$

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

$$\ln a_k = (1 - \rho_a)\mu_a + \rho_a \ln a + \varepsilon_a \tag{4}$$

where a is the ability of a parent, μ_a is average log-ability, ρ_a governs intergenerational persistence, and ε_a is an IID normal shock with mean zero and standard deviation σ_a. The second component of human capital is local school quality Q_n where a child grows up. Parents influence human capital accumulation via the local school their child attends.[15]

Initial human capital y_k is known upon entry to the labor force at age $j = 1$. Between ages $j = 1$ and $j = 2$, human capital 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 $\chi_j y_j$.

3.2. Household Decision Problems

At each age j, the household state vector $\{b, y, a, n\}$ consists of assets or debt b, human capital y, ability a, and current neighborhood n.

Decision Problem for Young Adults: At age $j = 1$, young adults are endowed with transfers provided by their parents b, human capital y, and their own ability a. Young adults do not have children or own housing.

[15] For tractability we abstract from direct parent investments in child education such as parental time or other resources (Cunha et al., 2010). Allowing for direct investments will dampen intergenerational inequality to the extent that investments are substitutes for school quality (Greaves et al., 2023), but will amplify intergenerational inequality if investments are complementary with school quality (Attanasio et al., 2022) or if financial constraints are more binding on poor households (Daruich et al., 2020).

Their decision problem is divided into two sub-periods. First, idiosyncratic taste shocks over neighborhoods are realized and young adults choose a neighborhood to live in. Second, given a choice of neighborhood young adults consume c_1, and borrow or save b_1'.

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

$$
\begin{aligned}
V_1(b, y, a; n') = \max_{c_1, b_1'} \; & \log(c_1) + \beta \mathbb{E}\left[V_2(b_1', y', a_k, n')\right] \\
\text{s.t.} \quad & c_1 + b_1' + P_{n'} = \chi_1 y + b \\
& \ln a_k = (1 - \rho_a)\mu_a + \rho_a \ln a + \varepsilon_a \\
& \ln y' = \ln y + \varepsilon_y \\
& b_1' \geq -\theta P_{n'}
\end{aligned}
\tag{5}
$$

where a_k is uncertain future child ability, and y' is next period human capital. When $b_1' < 0$ the household uses a mortgage to finance the house purchase. Borrowing is subject to a loan to value constraint, where θ is the maximum loan to value ratio. Expectations over future values $\mathbb{E}[V_2]$ are taken over the evolution of child ability a_k, income shocks ε_y, and idiosyncratic neighborhood taste shocks $\varepsilon_{n'}$ arriving at age $j = 2$. Future values are discounted at rate β.

In the first sub-problem households choose a neighborhood n_1' given common preference shifters Z_n and idiosyncratic taste shocks ε_n, both of which are unrelated to housing costs and school quality. Common preferences capture differences across neighborhoods valued by all households, such as the quality of housing stock or local amenities, while taste shocks reflect differences valued by individual households. The choice problem is:

$$
V_1(b, y, a) = \max_{n_1'} \left\{ V_1(b, y, a; n_1') + Z_{n_1'} + \sigma_n \varepsilon_{n_1'} \right\} \tag{6}
$$

where Z_n are fixed and ε_n are drawn from a Type 1 Extreme Value distribution with scale parameter σ_n.

Decision Problem for Middle-Aged Adults: The age $j = 2$ problem is also 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 choice of neighborhood, parents consume c_2, borrow or save b_2', and leave transfers for their children b_k'.

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

$$\begin{aligned} V_2(b, y, a_k, n; n') = \max_{c_2, b_2', b_k'} \;& \log(c_2) + \beta V_3(b_2', y, n') + \varphi \log\left(b_k' + Y_k\right) \quad (7) \\ \text{s.t.} \quad & c_2 + b_2' + b_k' = \chi_2 y + (1+r)b + \mathbb{1}_{n' \neq n}\left(P_n - P_{n'} - \kappa P_n\right) \\ & y_k = a_k Q_{n'} \\ & Y_k = \chi_1 y_k + \frac{\chi_2 y_k}{1+r} + \frac{\chi_3 y_k}{(1+r)^2} \\ & b_2' \geq -\theta P_{n'}, \; b_k' \geq 0 \end{aligned}$$

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 across neighborhoods, the household receives the proceeds from selling its old house and buying a new house $P_n - P_{n'}$ less the moving cost κP_n. The household can also borrow $b_2' < 0$ subject to the loan to value constraint.

We assume that parents care about the life-time wealth of their children. This includes transfers b_k' and the present value of life-time income Y_k. For tractability, parents ignore uncertainty over child income and focus only on the permanent component of human capital y_k.[16] As in Fogli et al. (2019), parents value child outcomes via the same log-utility function over their own consumption, and the parameter φ governs the strength of their altruism.[17]

As is the case for young adults, age $j = 2$ households choose a neighborhood n_2' given common preferences Z_n and taste shocks ε_n:

$$V_2(b, y, a_k, n) = \max_{n_2'} \left\{ V_2(b, y, a_k, n; n_2') + Z_{n_2'} + \sigma_n \varepsilon_{n_2'} \right\} \quad (8)$$

Decision Problem for Old Adults: Age $j = 3$ households consume income, the proceeds from selling their house, and remaining assets. They

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

[17]These assumptions significantly simplify our computations 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.

solve the problem:

$$
\begin{aligned}
V_3(b, y, n) = & \ \log(c_3) \\
\text{s.t.} \quad & c_3 = \chi_3 y + (1+r)b + P_n
\end{aligned}
\tag{9}
$$

3.3. Equilibrium

A stationary equilibrium consists of house prices $\{P_n\}$, decision rules for consumption $\{c_1, c_2, c_3\}$, borrowing or saving, and transfers $\{b'_1, b'_2, b'_k\}$, neighborhood choices $\{n'_1, n'_2\}$, and invariant distributions $\{\lambda_1, \lambda_2, \lambda_3\}$, such that: (i) given house prices, the decision rules solve the household problems (5)–(9); (ii) housing markets clear in each neighborhood

$$
\sum_{j=1,2} \int \mathbb{1}_{j,n} d\lambda_j = H_n \tag{10}
$$

(iii) school quality in each neighborhood is determined by Equation (2); (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 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 $j = 1$. For further details on computation, see Appendix B.

3.4. Calibration

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. Neighborhoods are distinguished by their house prices such that $P_A < P_B < P_C < P_D < P_E$. We normalize $P_A = 1$. Housing supply is fixed and neighborhood sizes are equal: $H_n = \frac{1}{5}$ 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. We compute the median house prices for each school zone using ZTRAX data from 2010-2015 (Zillow, 2020) and then group

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	2.147	Normalization
Local income elasticity of school quality	α	0.200	Authors
Panel (b): Internally Calibrated Parameters			
Annual discount factor	$\beta^{\frac{1}{15}}$	0.880	Calibrated
Altruism	φ	4.014	Calibrated
Std. dev. neighborhood taste shocks	σ_n	1.281	Calibrated
Std. dev. ability shocks	σ_a	0.371	Calibrated
Intergenerational persistence of ability	ρ_a	0.609	Calibrated
Std. dev. income shocks	σ_y	0.932	Calibrated
Moving cost	κ	0.684	Calibrated
Neighborhood demand shifter, B	Z_B	0.488	Calibrated
Neighborhood demand shifter, C	Z_C	0.900	Calibrated
Neighborhood demand shifter, D	Z_D	1.566	Calibrated
Neighborhood demand shifter, E	Z_E	2.577	Calibrated

zones according to population-weighted quintiles of the house price distribution. Since many statistics of interest are not reported for school zones, we use a crosswalk between 2010 census tracts and school zones.[18] We aggregate census tract statistics to the school zone level by computing population-weighted averages. Finally, we allocate school zone-level statistics to model neighborhoods according to the house price quintiles computed above.

Table 4 reports model parameters. Panel (a) shows externally calibrated parameters. The life-cycle profile of income $\{\chi_j\}_{j=1,2,3}$ is computed 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 (SCF) (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

[18] See Appendix A.5 for details.

Table 5: Moments used in Model Calibration

Moment	Model	Data	Source
Aggregate networth-to-labor income	1.329	1.300	SCF, 2010
Transfers share of networth	0.336	0.260	Feiveson et al. (2018)
Average income ratio, B/A	1.227	1.350	ACS, 2010–2014
Average income ratio, C/A	1.443	1.360	ACS, 2010–2014
Average income ratio, D/A	1.838	1.930	ACS, 2010–2014
Income transition, $\mathbb{P}(q_5\|p_{25})$	0.144	0.150	Chetty et al. (2014c)
Move probability, $j = 2$	0.438	0.383	CPS, 2004–2016
House price ratio, B/A	1.420	1.420	Zillow, 2005–2015
House price ratio, C/A	1.780	1.780	Zillow, 2005–2015
House price ratio, D/A	2.580	2.580	Zillow, 2005–2015
House price ratio, E/A	4.190	4.190	Zillow, 2005–2015

house in the cheapest neighborhood A.[19] See Appendix B.2 for details.

The elasticity of school quality to local income, α, is a key parameter in the model that we estimate directly. To do this, we first take the log-transformation of Equation (2): $\log Q_n = \alpha \log \left(\overline{Y}_n/\overline{Y}\right)$. We assume that school quality $\log Q_n$ corresponds to our school value-added measure constructed in Section 2.1, and relative average incomes $\overline{Y}_n/\overline{Y}$ are taken from the American Community Survey (U.S. Census Bureau, 2019).[20] Table B.6 in Appendix C reports our regression results. Across several specifications our estimated elasticity α is stable at around 0.2.

Panel (b) of Table 4 reports model parameters chosen via a simulated method of moments algorithm. We choose the parameters $\{\beta, \varphi, \sigma_n, \sigma_a, \rho_a, \sigma_y, \kappa, Z_B, Z_C, Z_D, Z_E\}$ to target the statistics reported in Table 5. On average, our calibration produces a reasonable fit between model and data across a range of targeted statistics.

We set the discount factor β to target the ratio of aggregate networth to aggregate earnings for households aged 21–65, using data from the 2010 SCF.[21] 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 choose the parameters governing the idiosyncratic shocks in

[19]Similarly, Fogli et al. (2019) assume that all households are renters and they normalize rent in the cheapest neighborhood to zero.

[20]School value-added enters in levels, as in our empirical estimates of Equation (1).

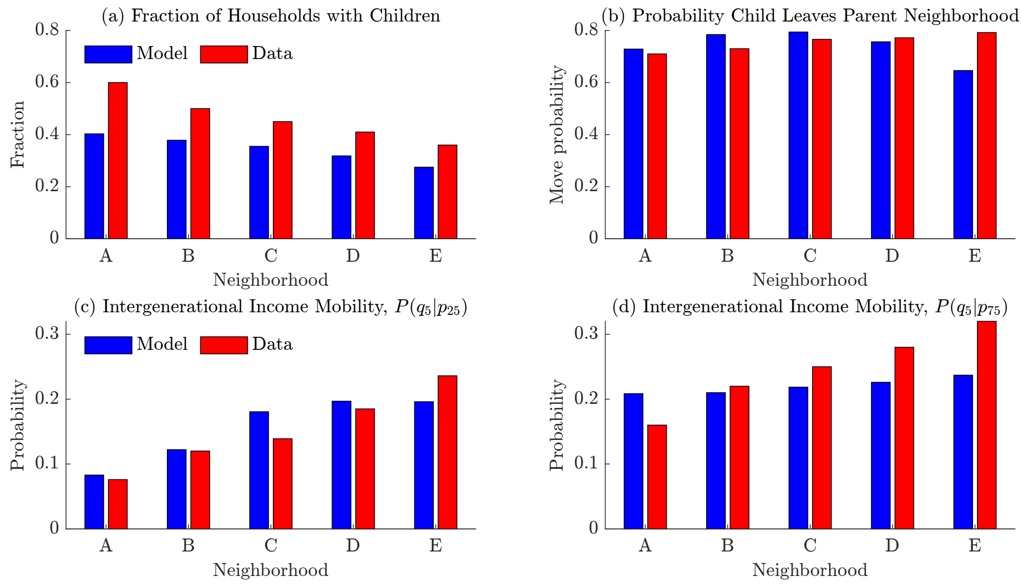
[21]Since the only assets in our model are savings, housing, and mortgages, we take networth in the data to be: the value of owner-occupied housing less mortgages plus liquid assets minus credit card balances.

the model. These parameters jointly determine differences in average incomes across neighborhoods as well as the rate of intergenerational income mobility. We set the standard deviation of neighborhood taste shocks σ_n and the standard deviation and persistence of ability shocks σ_a, ρ_a to target average incomes in the middle three neighborhoods B, C, and D relative to the lowest-price neigborhood, A. Average incomes are constructed using the 2010–2014 waves of the American Community Survey (U.S. Census Bureau, 2019). The standard deviation of human capital shocks during working life σ_y is set to target the probability that a child with parents at the 25^{th} percentile of the income distribution will be in the top income quintile as an adult. We denote this statistic $\mathbb{P}(q_5|p_{25})$ and take its value from Chetty et al. (2014c), who calculates mobility statistics for children born in the 1980s, with earnings measured in 2011-2012.

The moving cost κ targets the probability of moving across neighborhoods between ages $j = 1$ and $j = 2$. We use data 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 this 15-year period is: $\pi_{35} + \sum_{j=36}^{50} \pi_j \times \prod_{s=35}^{j-1}(1 - \pi_s)$. The common neighborhood preference shifter Z_A is normalized to zero. We set the remaining preference shifters Z_n to target house prices relative to neighborhood A, P_n/P_A for $n \in \{B, C, D, E\}$.

Figure 2 illustrates a range of untargeted cross-neighborhood statistics. Panel (a) shows that the proportion of households with children declines with neighborhood house price in both the model and data (American Community Survey). Panel (b) illustrates the probability that a child leaves the neighborhood that their parents raised them in by the time they are adults. In the data, this probability starts at around 70% and rises with neighborhood price. In the model, the probability is similar in levels, but slightly hump-shaped with respect to neighborhood income. Panels (c) and (d) illustrate statistics for upward income mobility and upward income persistence, respectively. That is, we report the probabilities that children of parents at the 25^{th} and 75^{th} percentiles of the income distribution will

Figure 2: Cross-Neighborhood Statistics in Model and Data



Source: Authors' calculations using statistics reported in Chetty et al. (2018). The statistics on fraction of households with children are from the 2010-2014 wave of the American Community Survey.

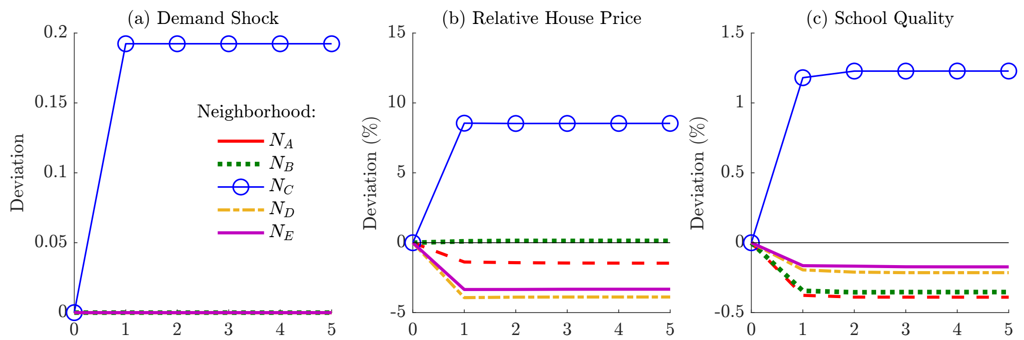
reach the top income quintile as adults. In both the model and the data, upward income mobility $P(q_5|p_{25})$ rises significantly with neighborhood price. Upward income persistence $P(q_5|p_{75})$ also rises with neighborhood price, although the cross-neighborhood slope is noticeably flatter in the model. Our model moments show that variation in public school quality can explain a significant proportion of the variation in $P(q_5|p_{25})$ across neighborhoods.

3.5. Intra- and Intergenerational Wealth Effects

We now run a set of experiments to quantify the wealth effects of housing market shocks through the school quality channel. There are five simulation experiments, with one shock for each of the five neighborhoods. The housing shock is modelled as an exogenous, unexpected, permanent, common neighborhood demand shock, ΔZ_n. We first solve for new steady state equilibria under each neighborhood demand shock. The new value of Z_n is chosen such that the equilibrium price in neighborhood n increases by ten percent. The remaining neighborhood prices adjust to clear their respective housing markets. Additionally, school quality Q_n in each neighborhood adjusts to satisfy the equilibrium condition in Equation (2). 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 each time t along the transition path.

Figure 3 illustrates the transition paths following a demand shock to neighborhood C as an example of one of our experiments. Following the shock, demand to live in neighborhood C rises while demand for the other neighborhoods falls. These changes in demand are mirrored in the observed house price changes across the neighborhoods. While the higher common demand shifter Z_C makes C more attractive for all households, higher prices select for relatively higher income residents than in the initial steady state. As a result, school quality in C endogenously rises over the long run. Other neighborhoods lose some of their relatively high income residents to neighborhood C, and school quality in these neighborhoods falls over the long run.

Figure 3: Transition Paths Following Neighborhood Demand Shock to N_C



As in our empirical results in Section 2, equilibrium house price changes are strongly correlated with changes in local school quality. We compare the model to the data in this regard by running regression Equation (1) on the model generated data. We take model data from all five experiments and compute changes in house prices and school quality for each school between the initial steady state and first period of the shock. Table 6 compares our empirical results to our model regression results. We report both OLS and 2SLS specifications, where we instrument for model house price changes with the neighborhood demand shocks ΔZ_n. Our model generates school quality responses to house prices that are about half as large as our (instrumented) empirical estimates.

Table 6: House Price Growth and School Quality Growth

	(1) Data	(2) Data	(3) Model	(4) Model
Δ log House Price	0.13	0.25	0.11	0.12
Specification	OLS	2SLS	OLS	2SLS

Notes: Columns (1) and (2) are from Table 1. Columns (2) and (3) are regressions using data pooled across all experiments, in which each neighborhood receives a positive demand shock in turn. School quality is Q_n, and the instrument for house prices is the local demand shock Z_n. All specifications include neighborhood fixed effects.

We now quantify the intra- and intergenerational wealth effects of housing market shocks. To do this, we use the responses of aged $j = 2$ households in the first period of the transition path. The response of consumption and transfers to the shocks reflect intra- and intergenerational wealth effects, respectively. The neighborhood choice response affects the child's school quality and their future income, reflecting an additional intergenerational wealth effect of the housing shock.

Because we solve for model equilibria by simulating the distribution of households directly, we compute wealth effects using the household decision rules. From the household problem in Equation (7), let $x_2(b, y, a_k, n; n')$ denote a decision or outcome given the current idiosyncratic state and conditional on neighborhood choice n'. Let $x_{2,t}(b, y, a_k, n; n')$ denote the same decision or outcome along the transition path at date t. Now denote the relative house price in neighborhood n by $P_{n,t} - \overline{P}_t$ where $\overline{P}_t$ is the average price across all neighborhoods. We compute wealth effects as the marginal effect of house prices on decision or outcome x:

$$\frac{x_{2,t}(b, y, a_k, n; n') - x_2(b, y, a_k, n; n')}{(P_{n,t} - \overline{P}_t) - (P_n - \overline{P})}$$

We compute averages of these effects across household groups using the initial distribution over idiosyncratic states $\lambda_2(b, y, a_k, n)$ and the probability of choosing a given neighborhood n' at the time of the shock $\mathbb{P}_{2,t}(n'|b, y, a_k, n)$. This probability is computed from the neighborhood choice problem in Equation (8). Finally, all marginal effects are reported at an annual frequency by dividing by the 15-year model period.

Table 7: Housing Wealth Effects of Neighborhood Demand Shocks

	Marginal propensity to consume	Marginal propensity to transfer	Marginal change in child income	Marginal propensity to move
Panel (a): All households				
All	0.016	0.010	0.011	0.012
Panel (b): Households from shocked neighborhoods				
All	0.019	0.011	0.012	-0.003
Stayers only	0.021	0.010	0.026	–
Movers only	0.016	0.013	-0.007	–
Panel (c): Households from unshocked neighborhoods				
All	0.015	0.010	0.010	0.016
Stayers only	0.008	0.003	0.024	–
Movers only	0.023	0.019	-0.007	–

Notes: Statistics computed for age $j = 2$ households and reported in annualized terms. Marginal effects computed as changes in a given variable divided by the relative change in local house prices. Statistics computed as averages across all experiments, in which each neighborhood receives a positive demand shock in turn.

Table 7 reports our housing wealth effects. Panel (a) shows average annualized marginal propensities across all households. The marginal propensity to consume (MPC) out of house prices is 0.016 (that is, 1.6 cents in the dollar), the marginal propensity to transfer (MPT) housing wealth to children is 0.01 (1 cent in the dollar), and the marginal change in life-time income for children (MPY) is 0.011 (1.1 cents in the dollar). Additionally, the marginal propensity to move neighborhoods (MPM) is 0.012.

Panel (b) reports average wealth effects for households living in neighborhoods that experience the positive demand shock. These households benefit from higher exogenous neighborhood quality, higher prices of the houses they already own, and rising local school quality. MPCs for these households are nearly 20 percent higher than for households overall (0.019 vs. 0.016), while MPTs and MPCs are of a similar size to those for all households. The MPM is negative for shocked neighborhoods, suggesting that households are less likely to move following a positive housing wealth shock and instead prefer to stay to take advantage of improving local schools.

In Panel (b) we also compare wealth effects conditional on staying or moving. MPYs are much larger for stayers as their children enjoy the benefits of the strong positive correlation between local house prices and local school qualities. Movers have small negative MPYs on average as they experience positive housing wealth shocks in their initial neighborhood but typically move to neighborhoods with declining school quality. This means that the children of movers are worse off than they would have been had they made the same move in the initial steady state. However, these children may still be better off in absolute terms than they would have been if they stayed. As we show in Section 3.6, movers spend some of their housing wealth gains on moving to more expensive neighborhoods with higher school quality than in their initial neighborhood. This is also the reason why movers have smaller MPCs than stayers (0.016 vs. 0.021).

Panel (c) reports wealth effects for households living in neighborhoods that did not experience the demand shock. These households generally experience falling house prices and declining local school quality. Across all households in these neighborhoods, wealth effects are similar to the effects for all households reported in Panel (a), and only slightly smaller than the wealth effects for positively shocked households reported in Panel (b). However, stayers in these neighborhoods have very small MPCs (0.008) and MPTs (0.003) but large MPYs (0.024). Stayers are not forced to realize their housing wealth losses right away, but they cannot avoid the decline in local school quality and their children suffer from this change. In contrast, movers have large MPCs (0.023) and large MPTs (0.019) as these households are forced to absorb realized housing wealth losses after house sale.

Table 8: Dollar-Valued Housing Wealth Effects

	Consumption	Transfers	Child income	Total
Dollar Values	\$40,005	\$25,363	\$27,488	\$92,856
Fraction of total	0.43	0.27	0.30	1.00

Notes: Real, dollar-valued wealth effects computed from marginal effects in Table 7 and evaluated at the empirical standard deviation of 5-year real house price changes.

Table 8 provides a simple summary of our main results by computing real, dollar-valued wealth effects given the empirical standard deviation of house price changes. For comparison with our empirical results in Section 2, we use the standard deviation of real 5-year growth rates (63 percent) multiplied by the median house price in our school district in 2010 (\$269,646). That is, we consider a \$169,877 house price increase. We then multiply this house price change by the wealth effects reported in Panel (a) of Table 7.

Household consumption rises by around \$40,000, transfers to children rise by around \$25,000, and the present value of life-time child incomes rises by around \$27,000. Intra-generational wealth effects through contemporaneous consumption make up 43 percent of the total housing wealth effect. Intergenerational wealth effects through future child incomes are 30 percent of the total wealth effect, and transfers to children are 27 percent. The sum of the intergenerational effects through both transfers and higher child incomes constitutes nearly 60 percent of the total effect of shocks to the housing market.

We can now compare our model-based wealth effects to our empirical results. Again, Our model results suggest that a one standard deviation increase in local house prices is associated with a \$27,000 increase in life-time income for a child. In Section 2.4 our back-of-the-envelope calculation suggested a one standard deviation increase in local house prices is associated with a \$37,392 increase in life-time incomes for children. Thus, housing wealth shocks in our model generate around 70 percent of the observed life-time income gains for children. 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.

Finally, our other model-based wealth effects, although untargeted, are also consistent with estimates from prior literature. In Table 7 we report an average MPC out of housing wealth of 0.016 which is similar to recent estimates for non-durable goods in the range of 0.01 to 0.03 (Mian et al., 2013; Aladangady, 2017; Kaplan et al., 2020; Graham et al., 2023). MPTs out of housing wealth are little-studied in the literature, however recent empirical work by Daysal et al. (2023) estimates that 8 to 16 percent of housing wealth shocks experienced by parents are transmitted to the housing wealth of children.[22] To compare to our own results, note that Table 8 reports that households transfer \$25,000 to children out of an initial \$170,000 increase in house prices. This suggests that 15 percent of housing

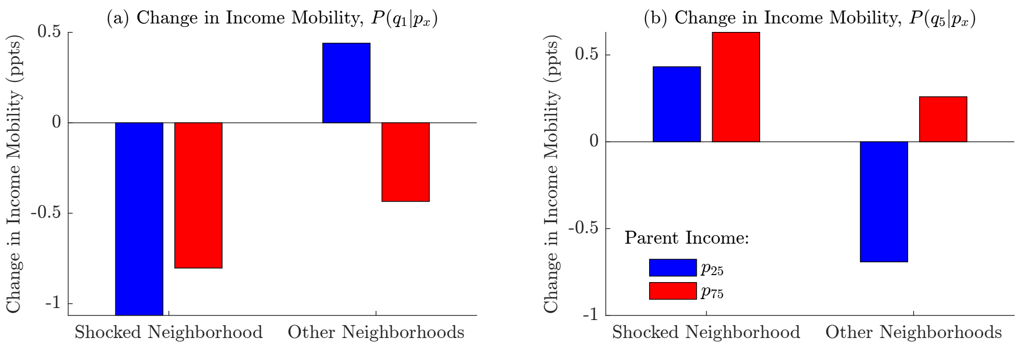
[22]Benetton et al. (2022) find that parental home equity extraction out of housing wealth gains is associated with a high probability that adult children transition to homeownership.

wealth shocks are transmitted to children via direct transfers from parents.

3.6. Additional Channels of Housing Wealth Effects

In our final exercises we use the model to further explore the channels of intra- and intergenerational housing wealth effects. Consider again the model experiments in which each neighborhood faces a permanent positive demand shock ΔZ_n and we solve for the equilibrium transition path to the new steady state.

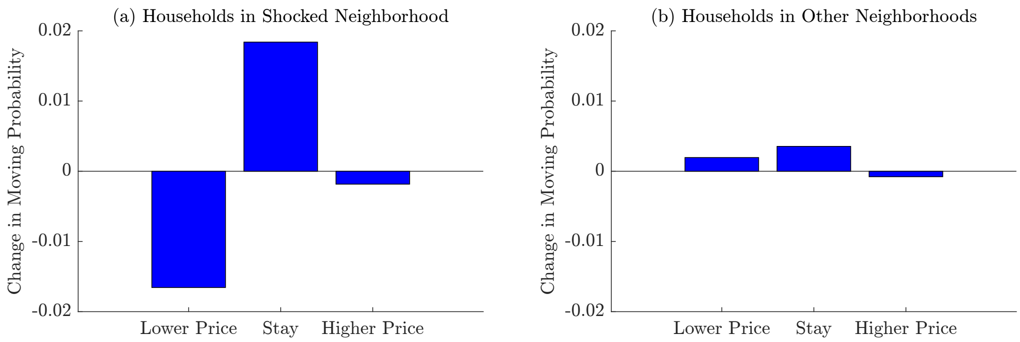
Figure 4: Changes in Income Mobility Following Neighborhood Demand Shocks



In Figure 4 we show how these housing market shocks affect intergenerational income mobility relative to the initial steady state. Panel (a) shows changes in the probability that a child grows up to be in the bottom quantile of the income distribution, and Panel (b) shows changes in the probability of a child ending up in the top quintile of the income distribution. We show these changes in income mobility conditional on parents at the 25^{th} and 75^{th} percentiles of the income distribution, and for households in the shocked neighborhood compared to all other neighborhoods.

Neighborhoods that benefit from the positive housing market shock experience large declines in downward mobility $P(q_1|p_x)$ and moderate increases in upward mobility $P(q_5|p_x)$. These benefits are enjoyed by the children of parents at both the bottom and top of the income distribution. Effects on other neighborhoods are more mixed. The children of low income parents are more likely to fall to the bottom of the income distribution and less likely to reach the top, while the opposite is true for children of high income parents. This is largely because low income parents are more likely to live in low priced neighborhoods that have worse school quality to begin with. A similar sized decline in school quality across neighborhoods has a larger impact on families that are already at the bottom of the school quality distribution.

Figure 5: Changes in Moving Probabilities Following Neighborhood Demand Shocks



These changes in intergenerational mobility are conditional on parents remaining in their initial neighborhoods and their children facing the effect of changes in local school quality. However, the increases in intergenerational inequality may be mitigated if households are willing to change neighborhoods in response to the shock. Figure 5 illustrates how housing market shocks affect household moving decisions. Panel (a) shows that households experiencing the positive demand shock are much more likely to stay in their initial neighborhood, and conditional on moving they are much less likely to move to lower priced neighborhoods. Panel (b) shows that households not hit by the shock are somewhat more likely to stay in their initial neighborhood, but conditional on moving they are more likely to move to a lower priced neighborhood.

These results suggest that households enjoying positive housing wealth shocks largely forgo the immediate use of that wealth in order to stay in place and take advantage of rising local school quality. If these households do move, they are now relatively more likely to move to higher priced neighborhoods that have better schools. Overall, positive wealth shocks are effectively reinvested into improving education for children. In contrast, households facing negative housing wealth shocks are less likely to sell their current home and realize those losses right away. But in choosing not to move the children of these households bear a cost in terms of declining education quality. For households that do sell, they are more likely to move to lower priced neighborhoods, but this also comes at the cost of sending children to lower quality schools than they would otherwise have been enrolled in.

Overall, we find that the intergenerational wealth effects of housing market shocks have strong spatial implications. Households enjoying positive house price shocks typically allocate gains to greater educational opportunities for their children, and these children benefit significantly by climbing the income distribution when older. Households experiencing negative house price shocks often cannot afford to move or are forced to move to cheaper neighborhoods with lower school quality. Children of all backgrounds suffer real income losses from this decline in educational opportunities, but in relative terms the children of low income families do the worst as they are much more likely to fall down the income distribution when older.

Essentially, education quality is a form of investment in child human capital and parents capitalize on housing wealth gains to make more of these investments. This mechanism is reinforced by our endogeneous school quality channel. Following a housing market shock, parents may be more or less able to take advantage of improving educational opportunities in their own or other neighborhoods. These strong connections between housing wealth, school quality, and neighborhood choice are central to the intergenerational transmission of housing wealth shocks.

4. Conclusion

In this paper we study intra- and intergenerational housing wealth effects in the presence of an endogenous school quality channel. First, using data from a large US school district we show that rising local house prices are associated with subsequent improvements in local school quality. Second, we quantify the wealth effects of house price shocks in an overlapping generations model with neighborhood choice, spatial equilibrium, and endogenous local school quality. Given an increase in house prices parents may consume, directly transfer wealth to children, or provide better educational opportunities for children through access to improving local schools.

We find that the intergenerational wealth effects are large, with the effect of the school quality channel on children's future incomes accounting for one-third of the total wealth effect of a housing market shock.

Having documented this new channel for housing wealth effects, future research might consider the policy implications that follow. Importantly, policies need to account for our finding that the consequences of housing market shocks are broader than just the contemporaneous effects on current homeowners. For example, policies such as capital gain taxes would only target contemporaneous wealth gains and not the changes in intergenerational inequality. Instead, policies would need to find a way to break the link between local house prices and local school quality. For example, school districts could allow students to attend public schools outside the school zone in which they live. Alternatively, schools and school districts could use counter-cyclical financial incentives to keep high-quality teachers in place following adverse local wealth shocks.

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Online 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.[23] 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

[23] 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.[24] 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.[25]

A.2. Constructing School Value-Added

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

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

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^2_ϵ. 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,[26] (ii) individual-level demographics, including parental education (five education groups), economically disadvantaged status, ethnicity

[24] 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.

[25] 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.

[26] 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:

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

where n_{st} is the total number of students in the VA sample at school s in year t.[27] 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:

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

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, $\hat{\delta}_{st}$.

[27]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 $t-1$[28] 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

[28]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:

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

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

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 Bartik 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:

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

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 $\mathcal{H} \equiv \{1, 2, 3, 4+\}$.[29] 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

[29] 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.

transactions data. The regression takes the form

$$p_{j,t} = \gamma_k + \sum_{d \in \mathcal{D}} q_{d,t} \mathbb{1}(d_j = d) + \sum_{b \in \mathcal{B}} q_{b,t} \mathbb{1}(b_j = b) + \sum_{h \in \mathcal{H}} q_{h,t} \mathbb{1}(h_j = h) + \eta_{j,t} \tag{A.11}$$

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:

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

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. Quantitative Model Details

B.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 $N_n = 5$. Child ability a follows an AR(1) process as in Equation (4) with parameters μ_a, ρ_a, and σ_a. We set $N_a = 5$ and discretize the process using the Rouwenhorst method.

Recall from Equation (3) that child human capital is given by $y_k = a_k Q_n$. 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 $N_y = N_a \times N_n \times (1 + N_{\varepsilon_y}) = 90$.

We set the minimum liquid asset grid size to $\underline{b} = -\theta\overline{P_n}$ where $\overline{P_n}$ is the maximum house price and θ is the maximum mortgage LTV ratio. We set $\overline{P_n}$ to the largest house price in any neighborhood across all of our dynamic experiments from Section 3.5. 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 $N_b = 100$, and 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.

B.2. Scaling the Ability Process

Following the literature, we might ensure minimum housing affordability by allowing for an intensive margin of 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).

One difficulty in computing equilibria of our model is that for a given income distribution, nothing guarantees that houses are affordable for all households. To address this problem we normalize the mean of the child ability process μ_a to ensure that the poorest household at age $j = 1$ can afford the downpayment on a house in the least expensive neighborhood:

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

where underlines denote minimum values in the model. Since we discretize the ability process using the Rouwenhorst method, the smallest value of a_k is given by the grid point:

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

Combining (D.1) and (D.2), we solve for the μ_a that ensures minimum housing affordability:

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

where $\underline{P_n} = P_A = 1$ and $\underline{Q_n} = Q_A$ by assumption. The parameter μ_a is then updated enodgenously during the calibration process used to determine ρ_a, σ_a, μ_y, and Q_A.

C. Additional Tables and Figures

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

	Full Sample	School Value-Added Sample[1]	Teacher Value-Added Sample[2]
	(1)	(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: 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 1998-99 through 2003-04 and houses sold in 2013-14 through 2018-19. 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).

Table B.4: Different Time Windows for House Price and School Value-Added Changes

	Dependent variable:				
	3-year	4-year	5-year	6-year	7-year
	(1)	(2)	(3)	(4)	(5)
Δ House Price	0.138**	0.244***	0.253***	0.317***	0.389**
	(0.066)	(0.086)	(0.062)	(0.087)	(0.179)
School Zones	395	396	393	393	390
Specification	2SLS	2SLS	2SLS	2SLS	2SLS
First-Stage F Stat	80.4	57.5	112.5	71.6	23.4
School Zone Controls	Yes	Yes	Yes	Yes	Yes
School Zone F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	1,531	1,736	1,873	1,673	1,353

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. Column (1) uses 3-year windows and Column (2) uses 4-year. 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 2SLS using the shift-share and BSH instruments. *p<0.1; **p<0.05; ***p<0.01

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

	Time Horizon		
% of Teachers that:	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

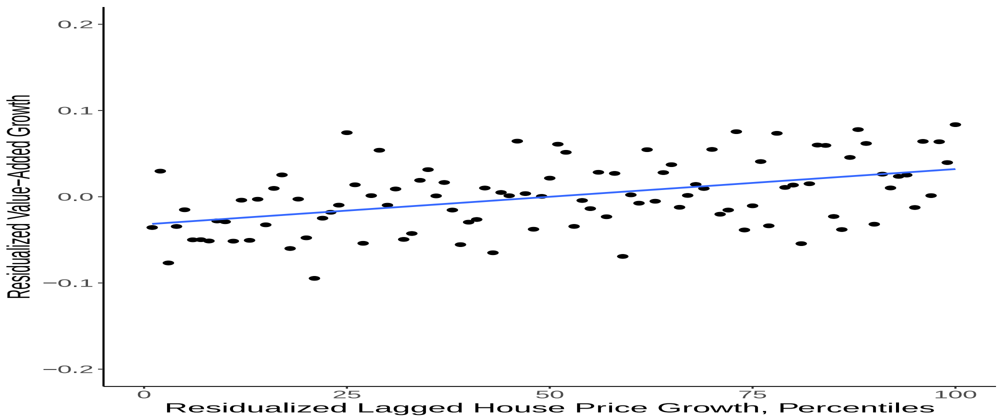
Notes: The numbers in each column sum to one-hundred percent. We consider a teacher to have left the district if we do not observe them in our data after the relevant time horizon and the year after. Similarly, we consider a teacher to have switched schools if they appear in a different school after 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.

Table B.6

	Dependent variable:			
	School Value-Added			
	(1)	(2)	(3)	(4)
log Relative Income	0.189***	0.189***	0.211***	0.211***
	(0.011)	(0.011)	(0.009)	(0.009)
Time Range	2010-2014	2010-2014	All Years	All Years
Year F.E.	No	Yes	No	Yes
Observations	1,880	1,880	3,298	3,298
Adjusted R^2	0.139	0.139	0.165	0.167

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 6: Relationship between House Price Growth and School Quality Growth



Notes: This figure plots percentiles of $\Delta \log HousePrices_{z,t-5,t}$ against $\Delta VA_{z,t,t+5}$. Both variables are residualized against school and year fixed effects. The residualized house price growths are then sorted into percentiles, and we report average growth in school VA for each bin.