The Effect of the Price of Housing on Child and Young Adult Achievement

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Abstract

Unprecedented swings in the real price of owner-occupied housing may have affected child development. We merge longitudinal data on child and young adult outcomes with information on local house prices and market rents, and analyze both the short- and long-term effects of the price of housing experienced during childhood. The results indicate that the price of owner-occupied housing has a small negative effect on children's mathematical achievement, but no consistent impact on reading achievement, behavior problems, or a child's body mass index. A higher average price of housing experienced during childhood has a negative effect on the wage rate of young adults, consistent with the negative effect on childhood mathematical achievement.

Housing expenditures comprise a substantial share of household budgets, averaging 33% in the United States (Bureau of Labor Statistics, 2015).[1] The quantity and quality of housing consumed has a large impact on household wellbeing. Substandard and crowded housing can have significant adverse effects on households as a result of exposure to allergens, toxins, lead paint, poor lighting, and poor heating. These effects are especially important for children, who are more vulnerable to the deleterious consequences of poor housing. Furthermore, the effects of poor quality housing on children may persist into adulthood. In addition to the health consequences of the exposures cited above, overcrowded and substandard housing may constrain the ability of children to study for school and develop their cognitive skills (Goux and Maurin, 2005).[2] The price of housing is therefore a potentially important determinant of child outcomes.

In this paper, we estimate the effect of the price of housing on child cognitive achievement, health, and longer run outcomes such as educational attainment and wages. A key advantage of this reduced form approach is that identification of the effects of housing prices is relatively straightforward. We use plausibly exogenous variation over time in the price of housing within metropolitan statistical areas (MSAs) for identification. In contrast, the more direct approach of estimating the effects of housing and other inputs on child development must deal with the very likely possibility that inputs are endogenous. It is difficult to find plausibly exogenous sources of variation in the many important housing characteristics and other inputs that affect child outcomes. The disadvantage of the reduced form approach is that it does not identify the specific channels through which the price of housing affects children. The price of housing could affect child outcomes by influencing the quality and quantity of housing demanded, which in turn affect child outcomes. However, the price of housing could affect demand for other inputs as well, such as parental time, child care, and health care. We have limited data for exploring such channels, but we analyze the effect of the price of housing on the channels we are able to measure.

The impact of the price of housing on children has been evaluated in two studies. Harkness and Newman (2005) find that the physical health, behavior, and grade promotion of poor children are negatively affected by local area housing prices. They use cross-sectional data from the 1997 National Survey of America's Families (NSAF), and restrict the sample to families with income less than 200% of the federal poverty line, finding mixed results that are discussed in more detail below. Harkness, Newman, and Holupka (2009) also measure the effects of local housing prices on education, health, and behavioral outcomes for children. They use longitudinal data from the Panel Study of Income Dynamics, again restricting the sample to families with income less than 200% of the federal poverty line. This study finds no evidence that the price of housing affects outcomes for poor children.

We build on and extend these studies in several ways. First, we explore a wider variety of child outcomes including cognitive development, measured by mathematical and reading achievement, behavior problems, and physical health. Second, we do not select the sample on the basis of family income. Third, we use data from a different source, the National Longitudinal Survey of Youth, 1979 cohort (NLSY79), and the associated Child and Young Adult surveys. These data are much richer in key dimensions than both the NSAF and the PSID. Child outcomes have been recorded in great detail every two years since 1986. Fourth, the main deficiency of the NLSY79 for our purposes is absence of data on housing. We deal with this by collecting additional data from public sources on the dwellings of respondents, and merging these data with the main NLSY79 data.[3] We use these data along with a small amount of qualitative information about the dwellings recorded by NLSY interviewers to identify potential channels through which the price of housing affects child outcomes. Fifth, we analyze longer term effects of the price of housing experienced during childhood by studying young adult outcomes including educational attainment, labor force participation, and earnings. Sixth, the NLSY79 survey oversampled minority households, yielding samples sufficiently large to permit reliable inferences based on separate analyses for children of black and Hispanic mothers. Finally, we use a different approach to estimation that accounts for the dynamic nature of child development, follows directly from a simple economic model of the household, and allows for persistent sources of unobserved heterogeneity. We also test whether the effect of the price of housing on child outcomes differs by race, ethnicity, child age, and the mother's cognitive ability.

The estimation results indicate that the price of owner-occupied housing has a small negative and statistically significant effect on mathematical achievement, while the price of rental housing has a small and statistically insignificant negative coefficient. The estimate implies that a $10,000 increase in the real price of owner-occupied housing would cause a decline of 0.1 percentile points in the math achievement test score. There is some evidence that the effect is larger in absolute value for the children of Hispanic mothers and for children of mothers with below average cognitive skill. It also is larger for girls, the children of older mothers, and at ages 6 to 10. We do not find any consistent impacts on reading achievement or behavioral problems. Finally, we find mixed results on the long run effects of housing prices experienced during childhood. The price of owner-occupied housing, averaged over the entire period of childhood, is estimated to have negative effects on the hourly wage rate, while the rental price of housing has a positive effect on work experience. Given the small effects of the price of housing on child outcomes, it is not surprising that we also find small effects of the price of housing on the limited number of dwelling characteristics and other inputs available in our data.

One might argue that changes in the MSA-average price of housing are unlikely to affect children, because, as pointed out by a referee, a child may live in the same house for years, which remains unchanged despite fluctuations in the price of housing or even the value of the house. This is a valid point, but there are several counterarguments. First, the price of rental housing can have a more immediate effect on the dwelling occupied. Second, the average owner-occupied dwelling turned over every six years during the sample period, so children may experience several changes in residence during childhood. Third, homeowners can extract equity from their homes, as evidenced by Lovenheim's (2011) finding of a positive impact of the price of housing on college attendance.

One possible explanation for the absence of effects on child outcomes is wealth effects. A higher price of housing makes the quantity and quality of housing more expensive, implying substitution away from housing inputs. But a higher price of housing causes an increase in the value of an asset owned by the majority of households. As expected, we find that an increase in the price of owner-occupied housing has a positive moderately large impact on home equity and on non-housing wealth. However, household wealth has a very small effect on child outcomes, so wealth effects do not seem to be an explanation for the lack of effects of the price of housing on child outcomes.

In the remainder of the paper, we provide a literature review, a discussion of the conceptual framework and empirical approach, a description of the data, a discussion of results, and concluding remarks.

Background and Literature Review

Harkness and Newman (2005) find that the physical health, behavior, and grade promotion of poor children are affected by local area housing prices. Using cross-sectional data restricted to families with incomes less than 200% of the federal poverty line, they find that child health and behavior problems are worse in higher-priced housing markets, while school grade completion is highest for children living at the extremes in areas with either very high or very low housing prices. Harkness, Newman, and Holupka (2009) use longitudinal data, restricting the sample to families with incomes less than 200% of the federal poverty line. They find no evidence that the price of housing affects any outcomes for poor children. It may be the case that families living in high-priced housing markets experience offsetting effects from living in better neighborhoods but having less income for other expenditures (Leventhal and Newman, 2010). Lovenheim (2011) found that changes in house prices, which affect household wealth, influence college attendance. Specifically, each $10,000 increase in home equity was estimated to increase college enrollment by 5.7 percentage points for low resource families.

The price of housing has been shown to affect household decisions that may in turn influence child development. The price elasticity of demand for housing has been estimated to be roughly −0.5 (Polinsky, 1977). Thus, the quantity of housing consumed in localities with a higher price of housing should be lower, ceteris paribus, and expenditure on housing will be higher. Both the size of a dwelling and the amount of expenditures on housing rather than other goods may affect child outcomes. The ratio of the asset price of housing to the rental price affects the likelihood of a household selecting to own or rent their residence (Hendershott and Shilling, 1982) and tenure choice may affect child outcomes. The price of housing affects the savings rates of renters, especially when the required down payment for a home is at least 20% of house value (Engelhardt, 1994; Sheiner, 1995), and household wealth may affect child outcomes. Multiple studies have shown that increases in house prices cause an increase in the home equity of owner-occupiers, leading to an increase in household consumption (Campbell and Cocco, 2007; Mian and Sufi, 2011), some of which may benefit children.

The results of two recent studies suggest that the price of housing affects the composition of families. Curtis (2011) provides evidence that a higher price of housing is associated with a greater likelihood of shared living arrangements for mothers, including marriage, cohabitation, and living with an extended family. Farnham, Schmidt, and Sevak (2011) find that the price of housing has an asymmetric effect on divorce rates. The share of divorced families is unaffected by a rising price of housing. However, a falling price of housing appears to reduce divorce rates among highly educated households, perhaps because home owners are locked into their houses by the loss in equity. To the extent that family structure and divorce affect children either through inputs of time, resources, or tension between parents, this may serve as an additional channel through which the price of housing influences child outcomes.[4]

Yoshikawa and Ohtaka (1989) find that savings and labor supply are affected by the price of housing in Japan, and labor supply may affect child outcomes. House prices may affect parents' accumulation of human capital, which may affect child outcomes. Price changes also may affect the probability of geographic mobility. Hanushek, Kain, and Rivkin (2004) find a "significant externality from moves" where "students in schools with high turnover suffer a disadvantage, and the cost is largest for lower income and minority students who typically attend much higher turnover schools."

The impact of housing subsidies on child outcomes is reported in related literature. Public policy in the United States subsidizes housing expenses via the tax deduction for mortgage interest and property taxes, rent subsidies for low-income households, and many other programs at all levels of government. Often, a component of the rationalization for these programs to promote homeownership and make housing more affordable is the presumed positive impact of high-quality housing on children. There have been many studies of the effect of housing subsidies on child and adult outcomes, but most of these studies take the form of a program evaluation. Such evaluations are very useful for measuring the impact of specific programs, but it is difficult to generalize the results to other program configurations, contexts, and populations [see, for example, Currie and Yelowitz (2000) for an evaluation of the impact of public housing on child outcomes].

Finally, a large literature studies the impact of dwelling characteristics and homeownership on child outcomes. This literature is clearly related to our analysis, but we do not estimate provide any evidence on these impacts, so we do not discuss this literature.[5]

Conceptual Framework and Empirical Specification

In this section, we briefly sketch a simple conceptual framework for modeling housing choices and their impact on child outcomes. We specify an empirical model of child outcomes based on the framework. We then discuss the implications of the framework for obtaining consistent estimates of the effect of the price of housing on child outcomes.

We use the household production function framework (Becker, 1965; Todd and Wolpin, 2003, 2006) to model the production of a child outcome, such as cognitive achievement, denoted q_{it+1} for child i in period $t + 1$. q_{it+1} is produced by the household with inputs of housing, h_{it}, other purchased inputs, and time inputs, conditional on a set of predetermined variables, including the period-t level of the child outcome, q_{it}. h_{it} is an index of the features of the dwelling occupied by the family that matter for children, such as indoor space, outdoor space for play, number of bedrooms, soundness of the structure, and so forth.

The family's objective is to choose the allocation of time and money each period to maximize the expected present discounted value of remaining lifetime utility, subject to time and budget constraints, and the production function. The optimization problem can be solved for an implicit housing demand function of the form:

$$h_{it} = h(q_{it}, A_{it}, w_{it}, p_{it}, R_{it}, E_{it}, x_{it}, \mu_i, \eta_{it}). \tag{1}$$

Here, A_{it} is non-housing wealth, w_{it} is the mother's wage rate, p_{it} is the ownership price of a unit of housing, R_{it} is the price of renting a unit of housing, E_{it} is home equity at the beginning of period t, x_{it} is a set of control variables, μ_i is a permanent error component, and η_{it} is a transitory shock to housing demand. Substituting the housing demand function and similar demand functions for the other inputs into the production function yields a derived demand equation for the child outcome, conditional on the state variables:

$$q_{it+1} = q^*(q_{it}, A_{it}, w_{it}, p_{it}, R_{it}, E_{it}, x_{it}, \mu_i, \eta_{it}). \tag{2}$$

This is the equation we are interested in estimating. It does not identify the direct effect of housing on child development, as the parameters (which are implicit here) are combinations of parameters of preferences and production functions, as well as the expectations formation process. It does identify the effect of the price of housing on child outcomes, which can be estimated consistently without imposing as many assumptions as would be required to obtain estimates of the production function.

A key point about equation (2) is that it does not condition on home ownership status or other choices made by the family. It includes both the rental price, R_{it}, and the ownership price, p_{it}, because both of these variables influence the ownership decision. Thus, the rental and owner prices affect child development both through their influence on the ownership decision, which may have a direct impact on the child outcome, and through their influence on the quality of home demanded, conditional on ownership status.[6] Assume a linear form for estimation:

$$\begin{aligned} q_{it+1} = {} & \beta_0 + \beta_1 q_{it} + \beta_2 A_{it} + \beta_3 w_{it} + \beta_4 p_{it} + \beta_5 R_{it} \\ & + \beta_6 E_{it} + \beta_7 x_{it} + \mu_i + \theta_{it}, \end{aligned} \tag{3}$$

where θ_{it} combines the transitory preference shock η_{it} and transitory measurement error in the child outcome. Ordinary least squares (OLS) estimates of this regression equation will yield inconsistent parameter estimates as a result of the presence of the permanent unobserved error component, μ_i, which is correlated with q_{it}, as can be seen from the once lagged version of (3):

$$q_{it} = \beta_0 + \beta_1 q_{it-1} + \beta_2 A_{it-1} + \beta_3 w_{it-1} + \beta_4 p_{it-1} + \beta_5 R_{it-1} + \beta_6 E_{it-1} + \beta_7 x_{it-1} + \mu_i + \theta_{it-1}. \quad (4)$$

With access to at least three periods of data on each child, we can eliminate μ_i by first-differencing, yielding:

$$\Delta q_{it+1} = \beta_1 \Delta q_{it} + \beta_2 \Delta A_{it} + \beta_3 \Delta w_{it} + \beta_4 \Delta p_{it} + \beta_5 \Delta R_{it} + \beta_6 \Delta E_{it} + \beta_7 \Delta x_{it} + \Delta \theta_{it}, \quad (5)$$

where $\Delta z_{it} = z_{it} - z_{it-1}$ for any variable z_{it}.[7] First differencing eliminates endogeneity due to μ_i, but differencing a dynamic model induces correlation between $\Delta q_{it} = q_{it} - q_{it-1}$ and the error $\Delta \theta_{it} = \theta_{it} - \theta_{it-1}$ in (5).[8] To deal with this we need an instrument for Δq_{it} that is uncorrelated with $\Delta \theta_{it}$. A natural candidate is q_{it-1}, which is correlated with Δq_{it} by construction, but uncorrelated with $\eta_{it} - \eta_{it-1}$ as long as θ_{it} is serially uncorrelated. Thus the identifying assumption is that any persistence in unobserved heterogeneity is fully captured by μ_i; that is, there is no serial correlation in transitory shocks.[9] Following Arellano and Bond (1991), this fixed effects instrumental variable estimator is implemented by the generalized method of moments (GMM) in order to increase efficiency in estimation. Note that Δq_{it} is the only variable that is instrumented; Δp_{it} and ΔR_{it} are exogenous and do not require instrumenting.

The coefficients of interest, β_4 and β_5, are the short run impacts of changes in the owner and rental prices of housing. If a change in the price of owner-occupied housing is transitory, its long run cumulative impact on q is $\beta_4(1 + \beta_1 + \beta_1^2 + \dots \beta_1^T)$, where T is the number of periods remaining until the child's outcome is no longer affected by the housing input. If the change is permanent, its long run impact is $T\beta_4(1 + \beta_1 + \beta_1^2 + \dots \beta_1^T)$.

It is of considerable interest to determine whether the price of housing experienced during childhood has consequences that extend beyond childhood. For example, effects on cognitive development during childhood could, if persistent, have implications for educational attainment and earnings in adulthood. We use a reduced form approach to analyzing the long run effects of the price of housing, estimating models of educational attainment, employment, and wages as a function of the average price of housing experienced during childhood. This approach is consistent with the conceptual model described above.[10]

Data

The data are from the National Longitudinal Survey of Youth–1979 (NLSY79) and the associated child and young adult surveys. In this study, a cohort of 12,686 people ages 14 to 22 were interviewed in 1979, and they have been interviewed annually or biennially through the present. The survey content is quite broad, including education, training, employment, income, childbearing, marriage, and many other items. In even-numbered survey years beginning in 1986, the children of female respondents have been administered a battery of cognitive, social, and emotional development assessments, and a large amount of additional information about the children has been collected from the mothers and the children. Beginning in 1994, children who were at least 15 years old have been interviewed directly as part of the young adult study. These interviews collect data on many of the same items as the surveys administered to original sample members: education, employment, marital and other relationships, and fertility. The sample of mothers is large, and the retention rate is remarkably high after more than 30 years. We use data collected through the 2008 survey round.

NLSY Sample

The original NLSY79 sample included 6,283 women. The sample consisted of a representative cross-section of youth aged 14–22 at the beginning of 1979, and supplementary oversamples of blacks, Hispanics, low-income whites, and members of the military. Most of the military oversample was dropped from the survey after 1984, and the low-income white oversample was dropped after 1990. In 2008, 3,975 women were interviewed and of these 3,352 were mothers. As of the 2008 interview round, the NLSY79 women were ages 43 to 51, and their childbearing is close to complete (Center for Human Resource Research, 2009).

A drawback of the NLSY79 Child and Young Adult data is that the children are not a representative sample of the overall U.S. population of children from any particular birth cohort. Their mothers are representative of the cohorts born in 1957–1964 who were living in the U.S. in 1979, but the sample has not been refreshed to reflect changing population characteristics resulting from immigration. This will mainly be a concern for the analysis of the children of Hispanic mothers. Also, the oldest children were born to younger mothers, a self-selected group. For example, a youth observed at age 23 in 1998 and born in 1975 must have been born to a teenager, because the oldest NLSY79 respondents were aged 18 in 1975. However, with each new round of data collection, this becomes less of a limitation.

The full sample includes 14,802 observations from 6,681 different children. Note that one observation in our analysis represents two surveys because of the lagged dependent variable in the regression; 19.5% of the sample children have one observation, 39.4% have two observations, and 41.1% have three observations.

Child Outcomes

The outcome measures in the NLSY79 fall into several broad domains, including behavioral/psychological, cognitive, and health. These are described in turn, followed by discussion of the measures available from the Young Adult surveys.

Behavioral/Psychological Measures. A Behavior Problems Index (BPI) is derived from 28 questions asked of the mother about children aged four and older. This scale is widely used in psychological research, and has been nationally normed based on the National Health Interview Survey in 1981. Examples of items included in the scale are: has sudden mood changes, is high strung, tense, and nervous, is impulsive or acts without thinking, feels worthless, is disobedient at school.

Cognitive Measures. The Peabody Individual Achievement Tests (PIATs) provide a broad measure of academic achievement for children aged five and over.[11] The PIAT Mathematics assessment measures a child's attainment in mathematics as taught in mainstream education. The PIAT Reading Recognition subtest measures word recognition and pronunciation ability. The PIAT Reading Comprehension subtest measures a child's ability to derive meaning from sentences that are read silently.

Health Measures. Extensive information on child health has been collected regularly in the NLSY79. Mothers report on accidents, injuries, or illnesses requiring medical attention, and on whether the child has been diagnosed with various conditions. In each survey round, the child's height and body weight are either measured by the interviewer or reported by the mother. Here, we focus on the mother's report of the child's body mass index (BMI).[12] The BMI is a proxy for body fat percentage and can be used to categorize potential problems with being overweight and underweight.

Young Adult Measures. We focus on the impact of the average price of housing during childhood on a young adult's wages, employment, and years of education.

Price of Housing. We use two measures of the price of housing: the price of an owner-occupied dwelling of a given quality and the rental price of a dwelling of a given quality. Both MSA level prices are measured at the metropolitan level and are therefore taken as given by households.[13] In contrast, intra-metropolitan differences in house prices are closely linked to neighborhood choice, yielding endogenous house prices. While there is some evidence that a household's choice of MSA is influenced by housing affordability, the linkage is substantially weaker than at the neighborhood level (Gabriel, Shack-Marquez, and Wascher, 1992; Sasser, 2010). Both dwelling prices (rental and owner-occupied) are relevant because they may influence multiple household decisions (own or rent, household composition, labor supply) and these decisions may affect child outcomes. Ownership and rental prices are positively correlated (as we show below), but the correlation over time and across space is far from perfect (Davis, Lehnert, and Martin, 2008).

The price of housing differs across metro areas for many reasons, including differences in population and growth, amenities such as climate, and local government regulations. These differences may affect other determinants of child outcomes, such as labor markets and school quality. Our framework includes controls for two of the main channels through which labor markets affect child outcomes: the wage rate and wealth. We also include geographic fixed effects that absorb time-invariant and slow-moving factors such as climate.

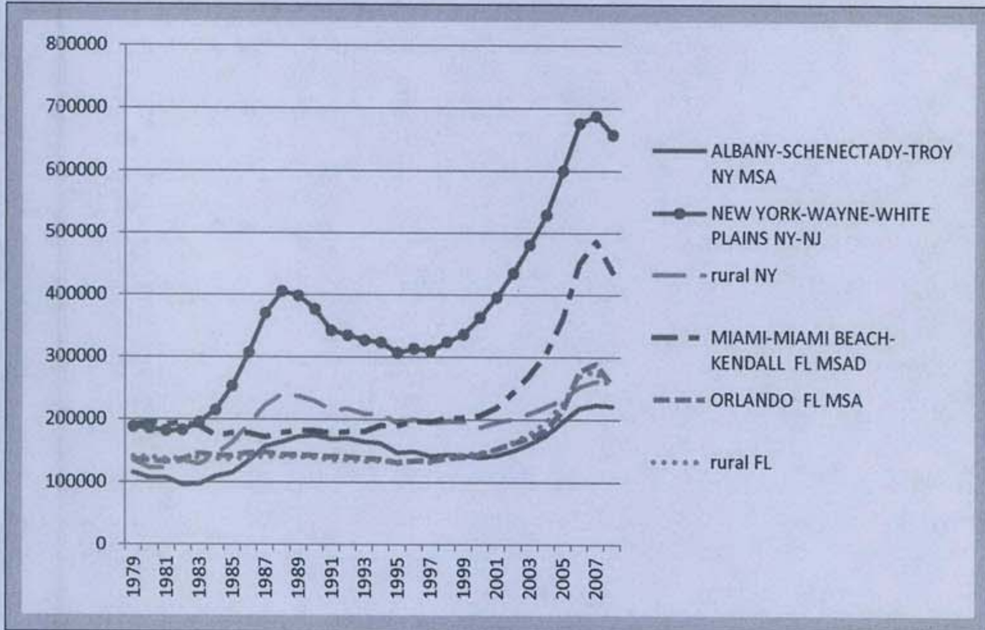
Ownership Price. We begin with the Freddie Mac House Price Index (FMHPI), which uses the repeat sales method (Case and Shiller, 1990) to create a constant-quality price index for owner-occupied properties for each state and for 367 MSAs, with coverage beginning in 1975.[14] We changed the base year for the index to 2008, and obtained from Freddie Mac a price index for the rural areas of states. We use the value of the index from the first quarter, which best corresponds to annual NLSY79 survey dates. The index was then deflated using the national CPI-U. The result is a constant-quality house price index for each locality. However, in this form the index cannot be compared across localities because it is designed to measure only changes in prices within each locality.

To create cross-sectionally comparable price indexes, we estimated a national hedonic price regression using data from the 2000 Census (1% sample).[15] We used the results to create a year-2000 cross-sectionally comparable house price index, with the characteristics of the house set equal to the national median characteristics. This year-2000 index was then combined with the Freddie Mac time series index to create a cross-sectionally and intertemporally comparable index of the price of owner-occupied housing (HPI). The final step was to assign respondents' locations to either an MSA or the rural area of their state of residence.

In our specification we control for state fixed effects, so identification of the effect of the price of housing is from variation of within-state price trends over time. During the house price boom and bust, many localities exhibited substantially different house price trends when comparing rural areas with mid-sized and large cities within a given state. Also, MSAs along the coasts exhibited different price trends than inland cities in the same state. Exhibit 1 displays an example of these different house price trends in New York and Florida, comparing for each state a large MSA (New York City and Miami), an inland MSA (Albany and Orlando), and a rural areas. The differences in price trends within states are notable. The mean percentage change between observations (two years) in the HPI is 7.9%, with the 25th percentile being 4.5%, and the 75th percentile being 11.2%.

Rental Price. A MSA-level constant quality rental price index comparable to the Freddie Mac index for owner-occupied properties does not exist. Instead, we use the HUD index of fair market rents (FMR).[16] This index measures rents for dwellings of various characteristics (we selected two-bedroom apartments, which is the most common size for rental units) for MSAs and other counties. The standard definition of the FMR is "the 40th percentile of gross rents for typical,

Exhibit 1 | Real House Price Trends in Six Localities



Notes: The deflated owner-occupied house price indexes are derived from the Freddie Mac MSA level house price index (Freddie Mac, 2012).

non-substandard rental units occupied by recent movers in a local housing market."[17] The mean percentage change between observations (two years) in the rental price is -0.6%, with the 25th percentile being -3.7% and the 75th percentile being 2.8%.

Theories that view housing as an investment good argue that the asset price of a dwelling should equal the discounted value of future rents (Capozza and Helsley, 1990). Thus, one would expect a strong positive correlation between our owner (HPI) and renter (FMR) house price indexes. However, the indexes should not be perfectly correlated because some factors affect asset prices more so than rents, such as the expected population and income growth of an MSA and the house price bubble in the 2000s. Exhibit 2 reports the cross-sectional correlation of the two indexes. The correlation is stronger in MSAs than non-MSA areas and is fairly constant over time at about 0.80.

One test of the robustness of our results is to use alternative measures of HPI and FMR. These alternative indexes use multiple years of the American Housing Survey in place of the Census as the source of house price and home characteristic data.[18]

Exhibit 2 | Correlation of the House Price Index (HPI) and Fair Market Rent (FMR) Indexes

Year	All Areas	In MSAs	Not in MSAs
1986	0.77	0.79	0.50
1988	0.79	0.80	0.44
1990	0.79	0.82	0.44
1992	0.77	0.80	0.50
1994	0.77	0.79	0.31
1996	0.79	0.81	0.40
1998	0.71	0.71	0.57
2000	0.74	0.76	0.59
2002	0.76	0.79	0.42
2004	0.80	0.81	0.61
2006	0.86	0.88	0.38
2008	0.83	0.85	0.42

Other Control Variables

The price of housing is only one of many factors that might affect child development, and it is important to control for as many of these other influences as possible in order to avoid attributing the effects of other variables to housing. However, as indicated above, it is *not* appropriate to control for inputs to the child development production function, because we are not estimating that function. Rather, we should control for exogenous variables that affect child development but are not household choices. We control for the child's gender, age, and birth order, and the mother's age, race, ethnicity, and marital status, Armed Forces Qualification Test (AFQT) score, location (central city or not), and the number of children in each of six age-sex categories (0–4, 5–11, 12–17).[19] Marital status categories include married, cohabiting, divorced, separated, single, and widowed.[20] The AFQT score is the sum of scores from the arithmetical reasoning, word knowledge, paragraph comprehension, and numerical operations sections of the Armed Services Vocational Aptitude Battery, administered in 1980. The AFQT is similar although not identical to an IQ test. It has been widely used in analyses of adult earnings (e.g., Heckman, Stixrud, and Urzua, 2006) and as a predictor of cognitive development of children (e.g., Blau, 1999; Todd and Wolpin, 2003; Bernal and Keane, 2011). It provides a measure of maternal cognitive ability and achievement that is strongly correlated with child cognitive development, and is therefore a very useful control variable. Because AFQT rises with age, we adjust the variable for age at the time of test administration.

The measures of the economic environment in which the child resides include the mother's predicted wage rate, the household's non-housing net worth, and its home equity. The predicted wage rate is used because the mother's observed wage depends on her labor supply decision (e.g., part-time work, no work).[21] The mother's wage depends on the local labor market, thus controlling for any influence of the labor market on child outcomes. Home equity is measured as the difference between the respondent's estimate of home value and mortgage debt.[22] Finally, full sets of state and year dummy variables are included. The means for the primary explanatory variables and outcomes of interest are reported in Appendix 2.

Results

Child Outcomes

We focus first on the results for the PIAT-Math score, a measure of cognitive achievement. Exhibit 3 reports selected coefficient estimates from Arellano-Bond estimates of equation (5), the first-differenced model of derived demand for the child outcome, with Δq_{it} instrumented by q_{it-1}. The control variables are listed in the note to the exhibit. Total assets are separated into home equity and non-housing assets, as implied by the conceptual framework. Row 1 shows the estimated impact of the HPI (measured in units of millions of 2008 dollars), the index of the price of owner-occupied housing, in a specification in which it is the only house price variable. The coefficient estimate is -11.85 and the estimate is significantly different from zero. The negative sign indicates that an increase in the price of housing causes a decrease in child development. Row 2 shows the estimated effect of the Fair Market Rent index (measured in units of thousands of 2008 dollars), in a specification in which it appears as the only house price variable. The coefficient estimate is -3.84, and the estimate is not significantly different from zero.

Row 3 of Exhibit 3 reports results from a specification that includes both the HPI and the FMR as explanatory variables. The coefficient estimates are slightly smaller but similar in magnitude and precision to those in rows 1 and 2, suggesting that there is enough independent variation in the HPI and FMR to identify the effects of both prices.[23]

Rows 3a and 3b report estimates for a specification that allows the effects of price increases and decreases to differ.[24] Three of the four coefficient estimates are similar in magnitude to those in row 3, although less precise, but the effect of a decrease in the HPI is estimated to be 66, significantly different from zero. The sign is as expected, but the large magnitude is surprising.

Row 4 of Exhibit 3 shows results from a child fixed effects estimator that does not account for endogeneity induced by first differencing a dynamic model. The coefficient estimates are a bit larger in absolute value compared to the GMM estimates in row 3, and both are significantly different from zero. However, the

Exhibit 3 | Selected Coefficient Estimates for PIAT-Math

PIAT-Math	HPI	FMR	Non-housing Net Worth	Home Equity	Lagged PIAT-Math Score
1. Arellano-Bond Estimates	−11.85**		0.12	−0.10	0.03**
	(4.86)		(0.09)	(0.21)	(0.02)
2.		−3.84	0.12	−0.05	0.03**
		(2.53)	(0.10)	(0.21)	(0.02)
3.	−11.09**	−3.31	0.12	−0.09	0.03**
	(4.90)	(2.55)	(0.09)	(0.21)	(0.02)
3a. Increases	−14	−6			
	(16)	(5)			
3b. Decreases	66	−3			
	(25)	(5)			
4. Child Fixed Effects	−14.4***	−6.1***	0.12	0.01	−0.14***
	(4.4)	(2.2)	(0.08)	(0.20)	(0.01)
5. No Fixed Effects (OLS)	−3.0	0.8	0.20	0.28	0.54***
	(3.3)	(1.1)	(0.08)	(0.18)	(0.01)

Notes: PIAT-Math is measured in percentiles. HPI is measured in millions of dollars, and FMR is measured in thousands of dollars per month. All specifications include the following additional explanatory variables: the lagged PIAT Math score, the child's age, sex, and birth order, the mother's age, race, ethnicity, marital status (6 categories), AFQT, central city, predicted wage rate, household net worth, an indicator for whether net worth is missing, the number of children in each of six age-sex categories (0–4, 5–11, 12–17), and full sets of state and year dummies. The standard errors reported in parentheses, are clustered at the child level. The R^2 for the model in row 5 is 0.48. The sample size is reported for the Arellano-Bond estimation. All regressions start with the 22,383 observations (7,542 children) described in Appendix 2, but the Arellano-Bond and child FE methods lose a number of observations due to the additional lag of the dependent variable used in these methods. The OLS regression in row 5 has a sample size of 21,168 observations (7,313 children and 3,273 mothers). The overall sample size is 14,802, which includes 6,681 children.

**Significantly different from zero at the 5% level.

***Significantly different from zero at the 1% level.

hypothesis that the HPI and FMR coefficients in rows 3 and 4 differ cannot be rejected. The OLS estimates shown in row 5 that do not account for endogeneity yield much smaller effects. These results indicate that ignoring permanent unobserved heterogeneity leads to bias toward zero.[25]

The negative signs on the coefficient estimates are consistent with the expected effect of the price of housing on housing demand and child outcomes. If a higher cost of housing leads families to purchase less housing, and if housing is a productive input to child development, we would expect a negative effect of the price of housing on child outcomes. However, the economic magnitude of the estimated effect is small. The coefficient estimates in row 3 imply elasticities at the means of −0.03 for the HPI and −0.05 for the FMR. For example, a 20% drop in the HPI from its mean implies an increase in mathematical achievement of 0.29 percentile points, or 0.01 standard deviations. If this change were permanent, it would cumulate to an effect of 1.19 percentile points after four periods (eight years). Another way to characterize the magnitude of the effect is to compute the predicted change in PIAT math score as a result of a given change in house prices. The change in the median value of the house price index from 2000 to 2006 was $60,000. The estimate in row 3 of Exhibit 3 implies that this would have caused a decline in the average PIAT math reading score by 0.7 percentile points with a 95% confidence interval of 0.1 to 1.3 percentile points. The large coefficient estimate on declines in HPI implies a much larger impact: an increase of 4 percentile points.

Exhibit 4 presents results for other child outcomes: PIAT Reading Recognition, PIAT Reading Comprehension, the Behavior Problems Index (BPI), and the Body Mass Index (BMI). The estimation method and control variables are the same as in row 3 of Exhibit 3. The effects of HPI and FMR are relatively small in all cases, and insignificantly different from zero.[26]

The contrasting results for math and reading (−11.1 for math; 4.3 and 0.4 for reading comprehension and recognition) raise the question of why house prices affect one but not the other. We have found little discussion of this specific issue in the literature. The literature on differential achievement in math and reading is primarily concentrated on gender differences (Hyde and Linn, 1988; Else-Quest, Hyde, and Linn, 2010). Hart, Petrill, and Thompson (2010) use a sample of twins to identify genetic and environmental influences on math and reading ability. They conclude that there is a single genetic factor that influences both outcomes, and there are additional genetic factors that separately influence math and reading; the twins also were exposed to common household and school environments. Dobbie and Fryer (2011) found that an intervention, the Harlem Children's Zone, had a bigger effect on mathematical ability compared to reading outcomes for low-income children.

Heterogeneous Effects

Exhibit 5 presents estimates of the PIAT-Math model for several subgroups of the population, defined by the mother's race and ethnicity, her age, her AFQT score, and the child's gender and age. There is some evidence of heterogeneity in the effect of house prices. The effect of HPI is larger in absolute value for girls than for boys. The effect of HPI is much larger for children whose mothers are in the lower half of the AFQT distribution and for children of Hispanic mothers. The latter two findings suggest that outcomes of children in relatively disadvantaged families are more sensitive to the price of housing.[27] There is also evidence that the effects are larger for younger children (ages 6–10) relative to older children (11–14) and the very young.[28]

Exhibit 4 | Selected Coefficient Estimates from Models for Other Child Outcomes

Outcome	HPI	FMR	Non-housing Net Worth	Home Equity	Lagged Dept. Variable	Sample Size (# Children)
PIAT-Reading Recognition	4.31	0.74	0.04	0.03	0.21***	14,702
	(4.20)	(2.19)	(0.08)	(0.18)	(0.02)	(6,661)
PIAT Reading Comprehension	0.41	−3.88	0.16	−0.20	0.19***	10,796
	(5.98)	(3.25)	(0.12)	(0.26)	(0.03)	(6,018)
Behavior Problems Index	−2.03	−0.92	−0.06	−0.12	0.16***	17,609
	(5.08)	(2.60)	(0.10)	(0.21)	(0.02)	(7,216)
Body Mass Index	0.26	0.49	−0.01	−0.02	0.17***	19,251
	(1.92)	(0.44)	(0.02)	(0.06)	(0.01)	(7,001)

Note: All results are from models estimated by the Arellano-Bond method. See the notes to Exhibit 2 for a list of the other regressors.
***Significantly different from zero at the 1% level.

Exhibit 5 | Selected Coefficient Estimates from Models of PIAT-Math for Subgroups

Group	HPI	FMR	*N* (# Children)
Boys	−8.08	−4.19	7,400
	(6.86)	(3.78)	(3,362)
Girls	−14.13**	−2.92	7,402
	(7.01)	(3.51)	(3,319)
Black (non-Hispanic)	12.23	−4.94	4,633
	(10.98)	(5.41)	(2,145)
White (non-Hispanic)	0.18	1.24	7,242
	(6.74)	(3.69)	(3,161)
Hispanic	−35.80***	−8.81	2,927
	(10.59)	(5.37)	(1,375)
Mother's age: 21–28	5.18	−28.38	314
	(85.06)	(29.59)	(280)
Mother's age: 29–37	−21.59	−4.22	8,011
	(17.40)	(3.72)	(4,247)
Mother's age: 38+	−8.86*	0.23	6,477
	(5.22)	(3.73)	(3,528)
Child's age: 6–10	−30.04***	−2.84	5,017
	(8.59)	(4.32)	(4,751)
Child's age: 11–14	−2.78	−2.97	9,439
	(6.14)	(3.14)	(5,949)
AFQT above median	−1.96	−1.91	7,195
	(6.18)	(3.48)	(3,175)
AFQT below median	−23.55***	−4.52	7,208
	(8.33)	(4.14)	(3,306)

Note: All results are from models estimated by the Arellano-Bond method. See the notes to Exhibit 2 for a list of the other regressors.
*Significantly different from zero at the 10% level.
**Significantly different from zero at the 5% level.
***Significantly different from zero at the 1% level.

Young Adult Outcomes

Child development outcomes have a strong influence on subsequent adult outcomes (e.g., Cunha and Heckman, 2008), so it is of interest to explore whether the effects (or lack thereof) of the price of housing experienced during childhood persist into adulthood. As of 2008, the latest year of data in our sample, nearly 4,500 children have been observed and assessed throughout childhood and into adulthood. Exhibit 6 presents mother fixed effects estimates of the cumulative impact of the price of housing during childhood on three important young adult

Exhibit 6 | Selected Coefficient Estimates from Regression Models of Young Adult Outcomes

	Mean	HPI	FMR	N
High school graduation by age 20	0.78	0.34 (1.4)	−0.24 (0.31)	4,789
Ever college by age 20	0.58	−1.6 (1.9)	−0.02 (0.41)	4,269
Bachelor's degree by age 25	0.12	0.43 (2.1)	−0.25 (0.63)	2,147
Mean log wage 21+	2.36	−3.6** (1.7)	0.60 (0.40)	3,704
Years of work experience by age 25	3.0	16.5 (15.1)	8.3** (4.1)	2,069

Notes: All regressions are estimated using mother fixed effects. All specifications include the following additional explanatory variables: the child's age, sex, and birth order, the mother's age, marital status (6 categories), central city, predicted wage rate, household net worth, an indicator for whether net worth is missing, the number of children in each of six age-sex categories (0–4, 5–11, 12–17), and full sets of state and birth year dummies. The standard errors reported in parentheses are clustered at the child level. The within-R^2 for the model in the first row is 0.05.
**Significantly different from zero at the 5% level.

outcomes.[29] Because the outcomes we examine are realized after the end of childhood and form a single observation, we cannot use the Arellano-Bond or child fixed effects estimators, so mother fixed effects estimates are presented instead. For each outcome, the sample is limited to families with at least two children who have reached the age criterion indicated in Exhibit 6.

The coefficient estimates in Exhibit 6 imply rather large effects, but the pattern of effects is difficult to interpret, and most of the estimates are imprecise. Recall that the change in the median value of the house price index from 2000 to 2006 was \$60,000, and that HPI is measured in units of millions of dollars in the regression. The coefficient estimate of −1.6 for the effect of the HPI on the probability of ever attending college by age 20 implies a change of −0.096 as a result of the change in the price of housing (.06 ∗ 1.6). However, the coefficient estimate of 0.43 for the effect of the HPI on the probability of college completion by age 25 implies a change of 0.026 as a result of the change in the price of housing from 2000 to 2006. There is a negative effect of the HPI on the logarithm of the mean wage rate, with an implied effect of the 2000–2006 increase in the HPI of −.216 (0.06 ∗ −3.6).[30] This result is qualitatively consistent with the negative effect on PIAT-Math, but the magnitude is far too large to be accounted for by the small estimated effect of the HPI on the PIAT-Math. The positive effects of the HPI on education and experience are inconsistent with the negative effect on the wage rate. Similarly, the negative effects of the FMR on educational attainment are inconsistent with a positive wage effect. On the other hand, the positive effects of the FMR on work experience and the wage rate are consistent, and the magnitudes imply that if the effect of FMR on the wage operated only via the effect on experience, a one-year increase in experience would cause a 7% increase in the wage rate, a plausible magnitude early in the career. Nevertheless, the overall message of Exhibit 6 is that there is no consistent pattern of effects, and most of the 95% confidence intervals include zero.[31]

Mechanisms

An important question about the effects of the price of housing on child outcomes is the mechanisms through which they operate. It is natural to think of the mechanisms as housing quality and quantity, so we explore price effects on several measures of house quality and quantity. However, as discussed above, the price of housing could affect other household decisions that affect children, including labor supply, wealth, and residential mobility.

The upper panel of Exhibit 7 reports estimates of the effects of the HPI and the FMR on several dwelling characteristics that can be considered as indicators of house quality, based on interviewer observations. The results show that the effects of the HPI and the FMR on these characteristics are generally small and imprecisely estimated. The largest coefficient estimate on the HPI (in absolute value) is the effect on safety of the play area: -0.71 (standard error $= 0.81$). Recall that the HPI is measured in millions of dollars, so this coefficient indicates that the \$60,000 increase in the HPI observed from 2000 to 2006 would have caused a decline in the probability of a safe play area of .043 ($-0.71 * 0.06$). The largest coefficient estimate on the FMR is the effect on interviewer-reported structural and health hazards in the dwelling: 0.45 (standard error $= 0.12$). The FMR is measured in thousands of dollars per month, with a mean of 0.78 and a standard deviation of 0.22. A one standard deviation increase in the FMR would therefore cause an increase in the probability of a safe building of 0.10. This is not negligible, but the sign of the coefficient estimate is puzzling.

The lower panel of Exhibit 7 shows results for two measures of housing quantity: the number of bedrooms and the square feet of living space, derived from public records as described above. These characteristics are available only for owner-occupied homes, but we use the same specification for these models (including both the HPI and the FMR) in order to maintain comparability. The signs of the coefficients are all negative as expected (a higher price of housing leads to lower housing quantity demanded), but again small in magnitude and not precisely estimated. The effect of a \$60,000 increase in the HPI would be to reduce demand for bedrooms by 0.01 and reduce demand for living space by 18 square feet (1% of the mean).

Exhibit 8 reports estimates of the impact of the price of housing on the mother's labor supply and household net worth, disaggregated into non-home net assets

Exhibit 7 | Selected Coefficient Estimates from Models of Home Inputs

Dependent Variable	Mean (Std. Dev.)	HPI	FMR	Sample Size (# of Kids)
Panel A: Interviewer observations				
Safe Play Area	0.94 (0.23)	−0.71 (0.81)	0.04 (0.29)	490 (489)
Minimal Clutter in Home	0.84 (0.37)	−0.22** (0.11)	−0.03 (0.08)	5,934 (3,087)
Dark and Monotonous Home	0.06 (0.23)	−0.01 (0.07)	−0.04 (0.05)	5,938 (3,090)
Clean Home	0.92 (0.28)	0.10 (0.07)	0.03 (0.05)	5,933 (3,086)
Safe Building	0.77 (0.42)	0.06 (0.15)	0.45*** (0.12)	3,568 (2,624)
	Mean (Std. Dev.)	HPI	FMR	Sample Size (# of Mothers)
Panel B: Dwelling characteristics				
Number of bedrooms	3.34 (0.98)	−0.15 (0.29)	−0.24 (0.17)	3,461 (1,237)
Square feet of living space (000's)	1.82 (1.03)	−0.30 (0.23)	−0.17 (0.15)	4,653 (1,237)

Note: All results are from models estimated by the Arellano-Bond method. The dependent variables are the survey interviewer's observations (first five rows) and dwelling characteristics (last two rows) from publically available sources. The survey questions are: "Child's play environment is safe?" "All visible rooms of house/apartment are minimally cluttered?" "Interior of the home is dark or perceptually monotonous?" "All visible rooms of house/apartment are reasonably clean?" "Building has no structural/health hazards?" The square feet variable has been trimmed to remove values less than 300 and greater than 15,000 square feet. Observations with 0 or more than 8 bedrooms also are excluded. Each row reports results from a different regression. All specifications include the following additional explanatory variables: the lagged dependent variable, the child's age, sex, and birth order, the mother's age, race, ethnicity, marital status (6 categories), AFQT, central city, predicted wage rate, household non-housing net worth, home equity, the number of children in each of six age-sex categories (0–4, 5–11, 12–17), and full sets of state and year dummies. Also included are the home state's welfare benefits, three child support enforcement variables, dummies for the presence of state welfare waiver and for federal welfare reform, and the average tax rate (calculated as a combination of both federal and state taxes) at median income. The standard errors reported in parentheses are clustered at the child level, except for those in the last two rows, which are clustered at the mother level. Unit of observation for interviewer observations is a child-year. Unit of observation for home characteristics is a mother-year.

**Significantly different from zero at the 5% level.

***Significantly different from zero at the 1% level.

Exhibit 8 | Selected Coefficient Estimates from Models of Labor Supply and Net Worth

Dependent Variable	Mean (Std. Dev.)	HPI	FMR	Sample Size (# of Mothers)
Mother's weeks worked per year / 52	0.59 (0.41)	0.052 (0.080)	0.042 (0.042)	12,237 (3,109)
Mother is employed	0.76 (0.43)	0.007 (0.092)	−0.012 (0.048)	12,086 (3,088)
Non-home net worth ($000)	58 (221)	235*** (58)	−69** (31)	12,237 (3,109)
Home equity ($000)	39 (114)	125***	−32*** (11)	12,237 (3,109)
Home equity|homeowner ($000)	84 (155)	232*** (41)	8 (22)	5,695 (2,156)

Note: All results are from models estimated by the Arellano-Bond method. See the note to Exhibit 6 for a list of the other explanatory variables. The models for the wealth variables do not include wealth as explanatory variables. The standard errors reported in parentheses are clustered at the child level.

** Significantly different from zero at the 5% level.

*** Significantly different from zero at the 1% level.

and home equity.[32] The price effects on the mother's labor supply, as measured by weeks worked per year and whether employed, are very small. The HPI effects on wealth are positive, as expected, and significantly different from zero, and the FMR effects are negative and also significantly different from zero. A $1,000 increase in the HPI is estimated to increase non-home net worth by $235 and to increase home equity by $125 for the entire sample, and $232 for the subsample of homeowners.[33] These are fairly sizeable effects, but what do they imply for child outcomes? The estimates of wealth effects on PIAT-Math in Exhibit 3 (row 3) are 0.12 per $100,000 increase in non-home net worth and −0.09 per $100,000 increase in home equity. Accounting for the effects of the HPI that operate via wealth, the net effect of the HPI on PIAT-Math is virtually identical to the direct effect of −11.09.[34]

Our exploration of possible mechanisms for the effects of the price of housing has been largely unsuccessful. But in this case a null result is useful because it rules out some of the more obvious mechanisms. It will take data even richer than ours to make further progress in teasing out mechanisms.

Conclusion

Our main results indicate that the net effects of the price of housing on child and young adult outcomes are small and generally are not significantly different than zero. For some population subgroups and for certain outcomes, the effects are larger, but these are exceptions. The finding most consistent with our expectations is that a higher price of owner-occupied housing has a negative effect on a child's mathematics achievement. The most striking result is the asymmetry in the effects of house price increases and decreases, with the effect of a decrease almost five times as large in absolute value as the effect of an increase. Overall, our results suggest that the price of housing is not a major determinant of child outcomes. We find little evidence to support the view that lower house prices during childhood result in better young adult outcomes.

The literature on housing indicates that the quantity and quality of housing demanded depends on the price of housing. Goux and Maurin (2005) and others have found that less space per person in a household negatively affects child outcomes. However, we do not find a strong relation between house price and the quantity or quality of housing demanded. How can we reconcile these findings? One possibility is that the most important feature of a dwelling regarding child outcomes is not the amount of space per person, but rather the quality of the interior space (home environment), which has been previously found to be an important determinant of child outcomes. A second possibility is that the quantity of housing is less important than whether it is owned or rented. A third argument explaining why the price of housing does not affect child outcomes via our measures of the quantity and quality of housing is that there are offsetting effects of the price of housing on other inputs that affect children. Child outcomes are influenced by many factors, including parental time, family structure, locational choice, and expenditures on goods. We explored the effects of the price of housing on two such factors, maternal labor supply and net worth, but found small effects. Recent research has found that the price of housing has effects on marriage, divorce, and neighborhood choice. Thus, even if the direct effect of a lower price is to improve housing that in turn benefits children, there may be offsetting effects on other aspects of the family or its allocation of time for children. In summary, the impact of the price of housing is complex, and many factors affected by house prices also affect child outcomes.

Can our results be used to make judgments about specific housing subsidies? In general, they cannot. Our study is of the overall effect of MSA house prices on child outcomes, not subsidies for specific aspects of housing. Often, subsidies result in large changes in the net price of housing, much larger than the changes experienced by the typical household in our sample. Out-of-sample extrapolation would be required to draw conclusions about the impact of policies that yielded large changes in house prices.

Appendix 1

Description of the Peabody Individual Achievement Tests

The PIAT is a widely used brief assessment of academic achievement, with demonstrably high test-retest reliability and concurrent validity (Baker, Keck, Mott, and Quinlan, 1993). It is administered to children aged 5–14. We use percentile scores based on national norms.

The PIAT-Mathematics test consists of 84 multiple choice items of increasing difficulty. The items begin with early skills, such as recognizing numerals, and progress to measuring advanced concepts in geometry and trigonometry. The child looks at each problem and then chooses an answer by pointing to or naming one of four options. In the PIAT-Reading Recognition test children read a word silently, and then say it aloud. It contains 84 items, each with four options, which increase in difficulty from preschool to high school levels. Skills assessed include matching letters, naming names, and reading single words aloud. In the PIAT-Reading Comprehension test the child silently reads a sentence once and then selects one of four pictures that best portrays the meaning of the sentence. It consists of 66 items.

Appendix 2

Selected Sample Characteristics

Outcomes of Interest	Mean (Std. Dev.)
PIAT-Math Score (Percentile)	52.37 (27.89)
PIAT-Reading Score (Percentile)	57.65 (28.94)
Behavioral Problems Index Score (Percentile)	59.50 (28.05)
Body Mass Index	18.39 (4.69)
High School Degree by Age 20 (Binary)	0.79 (0.41)
Average Hourly Wage, ages 21+	11.50 (4.81)
Selected Explanatory Variables	
Fair Market Rent (thousands of dollars / month)	0.78 (0.22)
House Price Index (millions of dollars)	0.13 (0.10)
Black	0.32 (0.47)
Hispanic	0.20 (0.40)

Appendix 2 (continued)
Selected Sample Characteristics

Outcomes of Interest	Mean (Std. Dev.)
Mother's AFQT Score (Percentile, age adjusted)	35.27 (27.74)
Mother's Predicted Hourly Wage Rate	15.43 (9.01)
Net Worth ($ hundred thousands)	0.98 (2.99)
Non-housing Net Worth ($ hundred thousands)	0.60 (2.27)
Home Equity ($ hundred thousands)	0.40 (1.16)

Note: The explanatory variable means and standard deviations are reported for the regression sample used for the PIAT-Math regression that includes Home Equity. These means differ slightly from the regression sample used for other outcomes. Only a select few of the explanatory variables used in the regression are reported above. The base year for deflation was 2008. AFQT scores were adjusted for differences in the age the respondent when the test was administered. Home equity is the mean for all households. Mother's wage is predicted using a regression of log wages on work experience, work experience squared, state fixed effects, year fixed effects, and individual fixed effects. We then take the exponential of predicted log wages to get predicted wages. Note that wages and work experience includes both part-time and full-time jobs. The sample size is 22,383. The number of children is 7,542 and the number of mothers is 3,340.

Endnotes

1 The Consumer Expenditure Survey (Bureau of Labor Statistics, 2015) reports that in 2015, for all consumer units, average housing expenditures were $18,409 and average total household expenditures were $55,978. For households in the lowest quintile of income, housing expenditures were 40.4% of total expenditures.

2 Foreclosures of mortgages may affect household members' health. Currie and Tekin (2015) argue that within a neighborhood an increase in the number of foreclosures is correlated with an increase in emergency room visits and hospitalizations for stress-related medical conditions such as hypertension and depression.

3 The data on house characteristics were gathered by the Center for Human Resource Research at Ohio State University. They matched NLSY79 respondent addresses to house characteristics reported on publically available websites. The data were provided to us without the addresses, which are obviously confidential.

4 See Gruber (2004), Amato (2010), and Tartari (2015), among others.

[5] See, for example, Holupka and Newman (2012), Barker (2013), and Green (2013) for recent analyses of the effect of homeownership on child outcomes, and Goux and Maurin (2005) for a study of the effect of crowding on child achievement.

[6] They may also affect outcomes through their influence on expectations of future values of R and p and their influence on other household demand functions.

[7] First differencing or child fixed effects estimation approaches are commonly applied to analyses of child achievement. See Todd and Wolpin (2003) for a general discussion, and Dahl and Lochner (2012) for a recent example. It is well known that these approaches can result in a reduction in the signal-to-noise ratio in the dependent variable in the presence of classical measurement error (θ_{it}). This tends to reduce the precision of the estimates but does not affect the consistency of the estimator (see Cameron and Trivedi, 2005, p. 913). However, the reduction in the signal-to-noise ratio caused by first differencing the explanatory variables will aggravate measurement error bias. This is not a major concern for the key explanatory variables of interest here (price of housing and rent), because they are measured at the local area level, and are less subject to measurement error than are household-level variables such as assets.

[8] The same logic implies that ΔA_{it} and ΔE_{it} are correlated with $\Delta \eta_{it+1}$ and should be treated as endogenous.

[9] This assumption could be relaxed by using q_{it-2} as an instrument instead of q_{it-1}, but at the cost of requiring at least four observations per child instead of three. This approach would use up too many degrees of freedom, so we do not pursue it.

[10] In principle, the model implies that we should allow the price of housing experienced at each age to have a different impact on the young adult outcome. However, this approach results in a severe collinearity problem, as the price of housing tends to be highly serially correlated. Using the childhood average price of housing is a natural restriction to deal with the collinearity problem, and is consistent with the commonly used approach of analyzing the effect of "permanent income" (i.e., average childhood income) on child outcomes (e.g., Blau, 1999; Dahl and Lochner, 2012).

[11] See Appendix 1 for additional details about these tests.

[12] BMI is computed as body mass in kilograms divided by the square of height in meters.

[13] Intra-metropolitan differences in house prices are closely linked to neighborhood choice, which is likely endogenous. While there is some evidence that household choice of MSA is influenced by housing affordability, the linkage is substantially weaker than at the neighborhood level (Gabriel, Shack-Marquez, and Wascher, 1992; Sasser, 2010).

[14] The method compares price changes of dwellings for which repeat sales are observed. It is described in detail at Freddie Mac (2012). The sample exceeds 25 million observations.

[15] The dependent variable is the log of the house price. Explanatory variables include state dummies, MSA dummies, the number of bedrooms (third-order polynomial), total rooms (third-order polynomial), categorical dummies for the year built (8 categories), and lot size (2 categories).

[16] A detailed description is at http://www.huduser.org/periodicals/USHMC/winter98/summary-2.html.

[17] Before 1995, the FMR was measured at the 45th percentile level. After 1995, some MSAs have FMRs reported at different percentiles (e.g., the 50th percentile), while most

MSA's FMRs are measured at the 40th percentile. The implication is that even if the distribution of quality of rental dwellings remained constant, the change in the percentile selected would imply a change in the quality of the dwelling. We estimate the following equation for each MSA:

$$FMR_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 I(t \geq 1995) + \beta_4 I(50th) + \varepsilon_t$$

The FMR measurement change in 1995 was universal and thus the fourth term picks up the effect of the change in percentiles. After 1995 about 5% of MSAs report FMRs at the 50th percentile and the fifth term in the regression captures this adjustment. We use the fitted values from the regression to adjust the HUD FMR data to use the 45th percentile for all MSAs (i.e., set the fourth and fifth terms to zero).

[18] We create house prices and rental price indices from AHS data through a series of steps. First, we estimate two hedonic price functions, one for rented units and one for owned units, with MSA fixed effects. Second, we establish national market baskets for renter-occupied and owner-occupied samples. Finally, we predict the owner price and renter price in each MSA by pricing the owners' basket and renters' basket using the hedonic price functions described in the first step. We made a number of additional corrections before merging these prices with our NLSY data because the AHS data are reported by MSA for odd years, while the NLSY data are reported using CBSAs in even years. We lose some observations as a result of implementing a crosswalk between MSAs and CBSAs in order to get the AHS data matched with the appropriate CBSA. Then we impute AHS rent and price variables for even years using MSA-specific FMHPI and FMR prices series.

[19] The non-time-varying variables drop out when the child fixed effects and Arellano-Bond estimators are used.

[20] Marital status may be endogenous, so we estimated a specification that excludes it, and the results were similar to those reported. We exclude the mother's education in the main results reported here, but the results were unaffected when education was included.

[21] The wage rate is predicted from a fixed effect log wage regression using all available wage observations for each woman, after trimming outliers (less than $1.50 and greater than $150.00 per hour). The regressors include work experience and its square, year dummies, and state dummies. The fixed effects and observed work experience are used in the prediction, while year and state dummies are set equal to the sample means in the prediction. The predicted log wage is then exponentiated.

[22] We omit a number of variables that had very little effect on the results in preliminary estimates, including the education of grandparents, an indicator for whether the mother resided in the U.S. at age 14, highest grade completed, family structure of the mother's household when she was age 14, mother's immigration status, dummies for missing parental education, and the number of her siblings.

[23] The price of housing could have a nonlinear effect on child outcomes. We estimated a specification with quadratic effects of the HPI and the FMR, and quadratic terms for equity, but none of the coefficients estimates on the quadratic terms were significantly different from zero. We explored several other specifications of the PIAT-Math equation. A spline function in the HPI did not reveal any evidence of nonlinearity. We also re-estimated the models treating home equity and non-housing financial assets as

endogenous. The instruments were the lagged values of home equity and non-housing financial assets. The results were qualitatively quite similar to those reported; for example the estimated effects of the HPI and the FMR corresponding to the specification in row 3 of Exhibit 3 are −7.3 (5.9) for the HPI and −4.1 (2.7) for the FMR, compared to −11.1 (4.9) and −3.3 (2.6), respectively in Exhibit 3. We estimated a specification in which home equity and non-housing assets were dropped, yielding results similar to the main findings. We also estimated a set of more parsimonious specifications of the PIAT-Math outcome equation. If the lagged dependent variable is omitted, the coefficients of HPI and FMR are positive and neither is statistically significant. If we drop the state dummy variables, thus incorporating between state price variation (and other between state differences), then the coefficient of the HPI remains statistically insignificant but that of the FMR is positive and statistically significant, contrary to expectations. Thus it seems that controlling for the lagged outcome and for state fixed effects is quite important.

[24] The results are from a single model, with the two house price variables interacted with dummies indicating price increases and price decreases.

[25] If MSA fixed effects are used rather than state fixed effects, the results are substantially the same. Another specification omitted respondents living in rural areas. The coefficient on the HPI was larger in this case. The results did not differ substantially if the alternative owner-occupied and rental price series described above were used.

[26] We tested alternative specifications for the BMI including dummy variables for being overweight (BMI $\geq$ 22), being obese (BMI $\geq$ 30), being severely obese (BMI $\geq$ 35), and being underweight (BMI $<$ 13). In none of these cases were the effects of the HPI or the FMR much larger or significantly different from zero.

[27] This is consistent with the results of Dahl and Lochner (2012) for the effect of income on child outcomes: larger effects for families with characteristics associated with low income.

[28] To explore the issue of heterogeneous effects further, we estimated a model of PIAT-Math for the sample of low-AFQT Hispanic mothers, with female children age 6–10 (sample size 304). The HPI coefficient is −106 with a standard error of 35. The elasticity of PIAT-Math with respect to HPI is −0.38 for this subgroup (the means of PIAT-Math and HPI are 42.8 and 0.15, respectively). A one-year 20% increase in the HPI would reduce math scores by 3.25 percentile points, which is 0.13 of a standard deviation. The coefficient of lagged PIAT-Math is 0.15, so a four-period change in the HPI by 20% would reduce PIAT-Math by 15.3 percentile points.

[29] For young adult outcomes, the explanatory variables, including house price measures, are averaged over ages 0 to 15 so that we can capture the effects of early-life and childhood housing conditions.

[30] The mean wage is constructed by averaging real wage rates observed at ages 21 and above. Cases with no observed wage at ages 21 and above are dropped. Of all cases in which an individual is observed at least once at ages 21 and above, 94% have at least one wage observation.

[31] As mentioned, we use data from an alternative source, the American Housing Survey (AHS), to create hedonic price indices for owner-occupied houses and rental units. The coefficient estimates for the child and YA outcomes were almost always of the same signs but are less precisely estimated, likely due to the smaller sample sizes. The AHS identifies fewer MSAs than does the Census.

[32] Naturally, these models omit home equity and non-home net worth as explanatory variables.

[33] Recall that the HPI is measured in millions and net worth in hundreds of thousands of dollars. A coefficient estimate of 2.35 implies that a one million dollar increase in the HPI would cause a $0.235 million increase in non-home net worth. Note that an increase in the HPI causes a decline in homeownership, so we cannot give the estimate for the subsample of owners a causal interpretation, since it is based on a selected sample.

[34] Converting units to be comparable, ∂PIAT-Math/∂HPI $= -11.09 + 0.12*0.235 - 0.09 * 0.125 = -11.07$.

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