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HOUSING CROWDING EFFECTS ON CHILDREN'S WELLBEING:

National and Longitudinal Comparisons

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Introduction

Poor living conditions can serve as a mechanism of social stratification, affecting children's wellbeing and resulting in the intergenerational transmission of social inequality. One's housing relates to many aspects of social life including privacy, location, health, security, social relations, and community resources. Stressors of the home environment may affect the life of a child and have lasting consequences throughout the life-course. We utilize data from the Los Angeles Family and Neighborhood Survey and the Panel Study of Income Dynamics' Child Development Supplement to conduct analyses of housing crowding effects on an array of child wellbeing indicators, including academic achievement, behavior problems, and physical health. We seek to understand the effect of housing crowding on children.

Background

Concerns regarding the consequences of population overcrowding began with Malthus in the late 1700s. It was the early 1960s, however, that sparked a wealth of empirical research on the negative effects of population overcrowding. Calhoun's study of laboratory rats found correlations between population density and increased aggression, disruptions in mating patterns and maternal activity, and higher rates of illness (Calhoun 1962). Several studies have cited the negative psychological or pathological effects of housing crowding in adults, including psychological withdrawal (Gove, Hughes, & Galle 1979; Regoeczi 2003), stress (Valins & Baum 1973), aggression (Regoeczi 2003), and loneliness (Wenz 1984). Other studies have also found greater negative parent-child relations (Evans, Lepore, Shejwal, & Palsane 1998), less-responsive parenting (Caldwell & Bradley 1984), and increased child behavioral problems at school (Evans, Saegert, & Harris 2001). We investigate housing crowding effects on several aspects of children's wellbeing which, taken together, have more direct consequences on future social stratification.

The research literature on poverty is rich with information on the social impacts of growing up poor, including negative affects on health, cognitive development, school achievement, and emotional wellbeing (e.g. Duncan & Brooks-Gunn 1997). Indeed, crowded housing can be seen as a socioeconomic indicator because people who cannot afford the price of private space are more likely to live in crowded conditions. Still, it is unclear whether or not housing crowding, net of other socioeconomic indicators, has an effect on child wellbeing.

Despite its likely importance, housing has not been thoroughly investigated as a mechanism of social stratification having impacts on different dimensions of life (Conley, 2001). Housing crowding affects adult educational attainment (by age 25) net of socioeconomic status, making the role of housing intermediary in the transmission of socioeconomic status. In preliminary work, we found that housing crowding has a negative effect on children's math achievement scores, suggesting that this process determining later socioeconomic status begins during childhood (Solari 2005).

Math achievement is one indicator of a child's educational performance and one aspect of general wellbeing. While there is no clear definition of a person's "wellbeing" (Mayer 1997: 40), this study considers the central domains of child wellbeing, including academic achievement, measured using Woodcock-Johnson math and reading test scores; behavioral problems, measured using internal and external behavior problem indices; and physical health, measured using parent-reported health assessments (Hauser, Brown, & Prosser 1997).

There are many possible ways in which living in a crowded home can affect a child's wellbeing. The lack of a comfortable, quiet space can lead children to have difficulties studying and reading, affecting their school performance. Children may sleep less and have irregular sleep patterns due to different schedules of household members. The lack of productive sleep can lead to difficulty concentrating during the day and negatively affect mood and behavior. In addition, children in crowded housing have a higher probability of catching illnesses, which can interfere with their daily routine and interrupt their schooling (Edwards, Fuller, Vorakitphokatorn, & Sermsri 1994; Saegert & Evans 2003; Booth & Johnson 1975).

The lack of privacy for all household members can result in stress, difficult social interactions, and behavioral problems (Evans et al. 1998; Valins & Baum 1973). Parents in overcrowded homes tend to show less responsive parenting (Caldwell & Bradley 1984), which may also translate into less participation in parent-teacher organizations at school, less monitoring of their child's academic performance, or less help with their child's schoolwork. Children in crowded homes have more behavioral problems in school (Evans et al. 2001), which can extend to other social contexts.

Children raised in crowded homes may take their educational, behavioral, and physical health disadvantages with them throughout their lives. Their poor performance in school decreases their chances to access higher education. Their low level of education and educational performance directly affects the occupations and wages for which they are qualified, in turn affecting their socioeconomic attainment. Behavioral problems can lead to difficulties interacting with others. Poor social interactions with teachers, parents, and peers during childhood, can lead to future social challenges forming personal and professional networks in adulthood. Physical health problems can interrupt children's daily routines and keep them behind their peers through adulthood (Booth & Cowell 1976). Ultimately, children growing up in crowded homes are more likely than others to find themselves in a similar situation as their parents, leading to the intergenerational transmission of social inequality.

We begin our analysis focusing on the effects of crowding in Los Angeles, a major metropolitan area with particularly high rates of crowded housing. In the 1980's, reductions in government housing support in both public housing and voucher programs came in combination with the decline of affordable housing due to gentrification, urban renewal, and increases in housing prices and rents throughout the country. These affordability problems were more severe in Los Angeles than in the U.S. overall (Wolch & Li 1997). Of all large cities in the nation, five of the top ten most crowded are in Los Angeles County according to the 2000 Census. The percentage of occupied housing units with greater than one person per room in L.A. County increased between 1990 and 2000, from 19.3 percent to 22.9 percent (see Table 1a). Compared to the U.S., with 5.7 percent of occupied housing units containing greater than one person per room in 2000 (U.S. Census), L.A. County has consistently faced dramatically larger proportions of crowding. In 2000, L.A. County had over four times more crowded occupied housing units with over one person per room than the nation (U.S. Census). Of all counties in the nation, L.A. County is the second most crowded (greater than one occupant per room of all occupied housing units) according to the 2004 American Community Survey. Most reported estimates of crowding focus on the household level, but children are facing much higher rates of housing crowding (See Table 1b). Children's experience with housing crowding in L.A. County has also increased over time. The difference in crowding rates between L.A. County and the nation is much greater for children than households, as shown in both the Census and PSID-CDS crowding distributions (see Table 1b and 1c).

Los Angeles has an especially high immigrant population – a group at particular risk of housing crowding (Krivo 1995; Myers et al. 1996; Clark, Deurloo, & Dieleman 2000; Friedman & Rosenbaum 2004). Myers (1999) explains that an increase in overcrowding in the U.S. and especially in California[1] in the most recent census decade could be attributed to high levels of immigration of Latinos (Clark et al. 2000). Myers and Lee (1996) also show that Hispanic immigrants in Southern California become more crowded as their stay in the U.S. lengthens.

We first determine whether or not housing crowding in Los Angeles affects children's academic achievement, behavior problems, and/or physical health. To determine whether Los Angeles is unique in its effects, we use similar models using a nationally representative dataset of children.

We address the following questions: 1) What is the effect size of housing crowding on child wellbeing in the U.S. compared to LA County? 2) Does the effect size change once other socioeconomic factors are controlled? 3) Do crowding effects vary across child outcomes? and 4) What are the mechanisms through which housing crowding affects children's outcomes?

Data

In order to investigate the effects of housing crowding on child wellbeing, we use the Los Angeles Family and Neighborhood Survey (LAFANS) and the Panel Study of Income Dynamics' Child Development Supplement (PSID-CDS). The LAFANS is a

[1] According to the 2003 American Community Survey, California is the second most crowded state in the nation (after Hawaii), measured by the percent of occupied housing units with greater than one occupant per room. California is also over 2.5 times more crowded than the U.S. overall.

multi-stage stratified cluster sample specially designed to capture family effects of child development and educational performance. The first wave of data was collected in 2000 from a representative sample of about 3,200 households in 65 neighborhoods, allowing for a diverse set of neighborhoods - from densely populated central city areas to rural areas. The LAFANS over-samples poor neighborhoods and households with children, making these data well suited for the study of children most vulnerable to living in crowded conditions (Sastry et al. 2003).

LAFANS offers information on a variety of outcomes for randomly selected children and siblings. Woodcock-Johnson Revised cognitive tests on math and reading for 2,433 and 1,940 children, respectively, ages 3 to 17 assess academic achievement. A battery of behavioral questions combine into indices on internal and external behavior problems for 2,369 and 2,366 children, respectively, ages 3 to 15. The parents of 2,454 children ages 3 to 17 offer personal assessments of their child's general physical health. Since the condition of housing crowding is so closely connected to socioeconomic status, we control for variables related to socioeconomic and demographic characteristics detailed in the Methods section.

The PSID-CDS serves as a logical comparison dataset for our LAFANS investigations. The PSID is a longitudinal, nationally representative survey of individuals and families. The PSID began with a sample in 1968 and has followed these families/individuals and their new families lineages annually until 1997 and biannually thereafter. The CDS is a supplement to the PSID focused on garnering a detailed understanding of the children. The CDS has two waves of data, one in 1997 on 3,563 children ages 0 to 12 and a second in 2002-03 on 2,908 children/adolescents ages 5 to 18. The PSID-CDS has child wellbeing measures similar to those in LAFANS, including

Woodcock-Johnson test scores, behavior problem indices, and a physical health assessment, making it ideal for comparison. The CDS also includes measures of mechanisms through which crowding may affect child outcomes, such as level of noise inside the home. The 1997 and 2001 PSID show crowding rates comparable to the 2000 Census U.S. rates, assuring us that these data can accurately measure our focal process.

Methods

Dependent Variables

LAFANS

We consider five child outcomes that serve as indicators of wellbeing. The first two outcomes are measures of educational achievement from the Woodcock-Johnson Revised tests, a battery of exams that assess individual scholastic achievement (Peterson et al. 2003, p. 89). Children ages 3 to 17 were administered the Applied Problems test measuring skills in analyzing and solving practical mathematics problems. This serves as an assessment of math reasoning. A Letter-Word Identification test, measuring symbolic learning and reading identification skills, combines with a Passage Comprehension test[2] to indicate broad reading achievement. The Passage Comprehension test involves multiple-choice items that require the child to indicate the picture representing a phrase, and short passage items in which the child identifies a missing key word. The math and reading tests are scored using the Woodcock Compuscore and Profiles Program Version 1.0. Scores were computed in relation to age. We utilize the percentile rank score, which indicates the percentage of subjects in the selected age group or grade that had the same

[2] Children ages 3 to 5 were only administered the Letter-Word Identification test.

or lower scores (Peterson et al. 2003), for its ease in interpretation.[3]

Our second two outcomes are internal and external measures of children's behavior problems based on 28 questions asked to parents about their child. The internal scale asks 11 questions about withdrawal and sadness, while the external scale asks 17 questions about aggression.[4] We use the natural log of these scales as our measure because most children rank at the lower end of the behavior problem scales.[5] Our final outcome is a measure of children's general health. Parents rank their child's general health as excellent, very good, good, fair, or poor.[6]

PSID-CDS

We utilize the most similar measures to those in the LAFANS models for our 1997 and 2002 PSID-CDS models. We use Woodcock-Johnson math and reading test scores, comprising of a raw, age-adjusted Applied Problems test score and a broad reading score, called standard scores. The CDS has similar internal and external behavior problem indices as the LAFANS. In addition, the PSID asks the primary care-giver the

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[3] This measure is similar to an SAT percentile rank score which colleges use as a basis for admission standards. Mathematics and reading scores are good measures of academic performance because they are considered primary skills in the education of children through the end of high school. The SAT test also has sections devoted to mathematics, problem-solving, and reading comprehension. The percentile rank scores allow values between 0 and 100.

[4] Parents responded to these questions using a three-point Likert scale of how true each statement was of their child – "1" if often true, "2" if sometimes true, and "3" if not true. In order to calculate the index scale, the coding was changed (often true=2, sometimes true=1, not true=0) and each response across all appropriate items for that scale was summed. A score was not computed if any item was missing.

[5] There is little variation of internal behavior problems along levels of crowding, with most observations showing low numbers of problems. A comparison of models with a continuous versus logged scale of internal behavior problems shows a preference (higher R-squared) for the model with the logged form. This is repeated for external behavior problems with similar results. Our models use the natural log form of these variables.

[6] There are other questions asked of parents about their children's health, two of which could be related to crowded housing or poor housing conditions– asthma and high levels of lead in the blood; there is not enough variability in the answers, however, to study these health assessments. We also noticed that much of the distribution of health status was concentrated near the excellent and good end of the scale. So, we tested a model using the natural log of health against the linear form and BIC statistics revealed a better fit for the linear form.

same questions concerning the child's general physical health as the LAFANS. These child outcomes are all measured in 1997 and 2002.

Independent Variables

LAFANS

Crowding

The focal independent variable is housing crowding, a continuous measure of persons per room.[7] The effects of crowding on a child's wellbeing may begin to affect that child at a higher ratio of persons per room. A continuous measure enables us to capture these possibilities. This measure was calculated by dividing the total number of household members by the total number of rooms, the sum of bedrooms and other rooms.[8] Rooms are determined by two survey questions. The first asks for the number of bedrooms in the house or apartment. The second asks for the number of other rooms, not including bedrooms, bathrooms or the kitchen.

Demographic variables

We include demographic control variables to model the association between housing crowding and child wellbeing. Child's gender may affect the association because males are typically better performers in mathematics than females (Hyde,

[7] Solari (2005) experiments with different forms of crowding, including a dichotomous measure of 0-1.0 versus greater than 1.0 person(s) per room, and an interviewer assessment of whether or not they believe too may people occupy the space available in their home. She finds the continuous measure of persons per room to fit the data best. LAFANS does not have data on housing unit square footage, thus we were unable to include a density measure in the analysis.

[8] We prefer the measure persons per room to persons per bedroom because of inconsistencies on how people define bedrooms. A den could be converted into a bedroom, for instance, and people may define these rooms inconsistently.

Fennema, & Lamon 1990). Boys are also more likely to express their behavior problems through aggression than girls (Maccoby & Jacklin 1980). Child's age is included because behavior problems can manifest in different manners and at different stages of development (Evans 2006).

Marital status of the child's mother serves as another demographic indicator. Female-headed households are over-represented in lower income groups (Duncan & Brooks-Gunn 1997). Single mothers may have more responsibilities, leaving less time to monitor children, help their children with school work, and care for their children's physical health.[9]

New immigrants to Southern California are typically of Latino descent. They have lower educational attainment compared to natives and limited understanding of English and American culture, putting Latinos at an economic disadvantage. It is difficult to get a well-paying job with little education and poor English skills. Also, immigrants are more likely to live in crowded housing conditions for many reasons, including having poor English-language skills, lacking knowledge of the housing market, settling in same-ethnicity enclaves, and having lower incomes (Krivo 1995; Myers et al. 1996; Clark et al. 2000; Friedman & Rosenbaum 2004). We include a measure of nativity in our model.

Socioeconomic control variables

Various dimensions of family socioeconomic position may be correlated with housing crowding. We include socioeconomic measures in our model to determine the independent effect of housing crowding on child wellbeing. These variables are primary

[9] We also investigate the number of other children in the household because those children could absorb parental resources, such as time and money; this neither affects the magnitude nor the significance of the crowding coefficient, however. We do not present the results here because we favor a more parsimonious model.

caregiver's educational attainment,[10] family income,[11] and race/ethnicity. Those of "mixed race" identify a primary race. We collapse Pacific Islander, Native American, and other race together due to small sample sizes. We combine these other races into the Latino category, the largest group and most similar in levels of crowding, leaving us with four race/ethnicity categories (Latino/other, white, black, Asian). We use a measure of mother's race/ethnicity rather than the child's because much of the negative or positive consequences of race/ethnicity for a child occur through the mother. For instance, the location and quality of their housing unit is more strongly related to the mother's race/ethnicity rather than the child's.

PSID-CDS

The independent variables in our PSID-CDS analysis all originate from the PSID rather than the CDS. The time-varying covariates, like crowding, age, mother's marital status, and family income, are measured in 1997 and 2001.[12] We utilize other years of the PSID to create a four-year average value of crowding, discussed below. The time-invariant controls, such as race/ethnicity, immigrant status, and mother's educational attainment, are measured in 1997.

[10] We choose primary caregiver's education over mother's or father's education because the benefit of a parent's education is best gained through contact with the child (Coleman 1988). The adult with the most child contact is defined as the primary caregiver, making this a superior control measure. Still, most primary caregivers in this sample are the child's mother (96.4%), so we will refer to this as mother's education from this point forward.

[11] Income is an obvious indicator of socioeconomic status (Duncan & Brooks-Gunn 1997), though there were a number of measures from which to choose in this dataset. We prefer to capture a measure of household income. Though there is literature that suggests non-family members do not share their income with the extended household (Bauman 1999), non-family members are likely to contribute towards rent/mortgage. The LAFANS do not contain the finances of non-family household members; we thus settle for family income. Income data were not available in all cases. To minimize missing values from the analysis, we use an imputed income measure (See Bitler & Peterson (2004) for discussion of the imputation procedures).

[12] We refer to this second wave of data as the 2002 PSID-CDS, although the independent variables are collected in 2001 and the dependent variables are collected in 2002.

Crowding

The PSID has a long history of information on families and the household, as well as the housing unit. We construct a continuous measure of persons per room for both survey waves. The numerator is a sum of the number of people in the family and the number of non-family members living in the housing unit. The denominator is the number of bedrooms and other rooms in the housing unit, not including the kitchen.[13]

We also take advantage of the PSID history by constructing four-year average housing crowding measures that correspond to the two CDS waves. Average crowding for wave I consists of four PSID data points in 1994, 1995, 1996, and 1997. For wave II, the average crowding measure consists of two PSID data points over the last four years, in 1999 and 2001.[14]

Demographic variables

We include demographic control variables in our PSID-CDS analysis that are similar to those in the LAFANS analysis. We use a measure of child's gender and age. Age is measured generally at the year of each survey wave. We include mother's marital status at both waves, and a measure of immigrant status. Due to the genealogical survey design of the PSID, it does not incorporate new families to the sample unless there is a new birth to a pre-existing sample member. In 1997, the PSID included a special sub-

[13] We subtract the kitchen unit, a value of one, from the total number of rooms variable in the PSID for all units with two or more rooms. Because there was no separate kitchen indicator, we investigated the 2001 American Housing Survey to reference which types of units never had kitchens, and which did. We found that 100 percent of one room units did not have a kitchen, but 93 percent of all two room units and 100 percent of units with more than 2 rooms had at least one kitchen. Though some larger room units had more than one kitchen, we did not adjust for this because of its inconsistency.
[14] To avoid excessive missing data, we average only the values within the four-year period of non-missing values.

sample of immigrants that have been in the U.S. since 1968 to address this sample design limitation. We use an indicator of being part of this sub-sample as our measure of nativity.

Socioeconomic control variables

We utilize measures of mother's education, race/ethnicity, and family income as indicators of SES. We use a continuous measure of mother's education and three categories of mother's race/ethnicity (white, black, and Latino/other), measured in 1997. Although we keep Asians as a separate category in the LAFANS, the sample is too small in the PSID. We fold other races and Asians into the Latino category because they have the most similar housing crowding characteristics. We include a continuous measure of 1997 and 2001 total family income (in thousands).

Sample

LAFANS

The children sampled in LAFANS include a randomly selected child (RSC) and the RSC's randomly selected sibling (SIB), if available, from each of the sampled households with children. Children ages 3 to 17 were tested for the Woodcock-Johnson Assessments. Parents of children ages 3 to 17 were asked about their child's general health and parents of children ages 3 to 15 were surveyed for information concerning behavior problems. The availability of data varies for each of the outcome measures. The sample sizes range from 1,940 to 2,454.[15] RSCs make up 62 percent of the children analyzed in this study, and the balance is SIBs. We use listwise deletion of cases with

[15] The observations are distributed as follows: 2433 for math achievement, 1940 for reading achievement, 2369 for internal behavior problems, 2366 for external behavior problems, and 2454 for physical health.

missing data on any of the independent variables in the separate child outcome models, reducing the sample sizes between 6.3 and 7.3 percent, depending upon the outcome.[16] This leaves us with a range of unweighted sample sizes from 1,808 to 2,304 children for the models in this study.[17]

We use survey estimation procedures to account for the multi-stage stratified cluster design of the LAFANS. We weight the data to correct for over-sampling poor strata, over-sampling households with children, and household non-response (Peterson et al. 2003). An adjustment for the difference in selection probabilities of RSCs and SIBs is embedded in the weight. The sample is clustered on the census tract. Because the RSCs and SIBs are not independent, we correct for this by computing robust standard errors (StataCorp 2005).

PSID-CDS

The wave I CDS children originate from a sample of selected PSID families with children ages 0-12. Up to two children per family were randomly selected for the 1997 CDS. Families who participated in the 1997 CDS and were active in the 2001 PSID were re-contacted for the CDS wave II. Children ages 3-12 in wave I and ages 8-17 in wave II who have data in both waves are included in this analysis.

We use listwise deletion for cases with missing data on less than 2 percent of the sample for any of the independent variables across all child outcome models. For those independent variables with more than 2 percent missing, we impute the missings to the

[16] In examining the missing values, we determine that none of the independent variables have an especially high number of case on which values are missing. Listwise deletion of cases with missing data, therefore, did not result in the loss of a significant number of cases.
[17] The observations are distributed as follows: 2268 for math achievement, 1808 for reading achievement, 2227 for internal behavior problems, 2225 for external behavior problems, and 2304 for physical health.

group mean and include a dummy variable indicating whether or not they were originally missing. This results in unweighted sample sizes of children ranging from 998 and 2,084.

We use survey estimation procedures to account for the PSID sample selection. The PSID sample is a combination of two separate probability samples: a cross-sectional national sample and a national sample of low-income families; once combined, this results in unequal selection in the final PSID sample. The original structure of the sample was also altered in 1997 through a reduction in the sample size and the inclusion of an immigrant household sample, which changed the original sample recruitment rules. We weight the data to correct for unequal selection probabilities, differential attrition, and changes in the proportion of families undergoing follow-up and sample recruitment structure. We calculate robust standard errors to compensate for differential child selection within families (StataCorp 2005).

Statistical Methods and Models

We estimate the effects of housing crowding on children's wellbeing using ordinary least squares (OLS) regression analyses for both the LAFANS and PSID-CDS. Three models predict each of the five indicators of wellbeing – mathematics and reading scores, internal and external problem behavior indices, and parental assessment of child's physical health. Model 1 has the zero-order effect of crowding. Model 2 includes the effects of crowding plus the effects of child's sex and age, and mother's marital status and nativity status. Model 3 includes all of the variables included in Model 2 plus the mother’s educational attainment, family income, and mother’s race/ethnicity. These three models show, for each outcome, the gross and net effects of crowding.[18]

We take advantage of the PSID-CDS longitudinal structure by pooling the two waves and conducting pooled OLS and fixed effects estimation for Model 3. Here, each child has two records of information thereby doubling the sample size and increasing our statistical power. In the fixed effects procedure, we include only time-varying covariates – crowding, age, marital status, and income - as predictors in this model, because all time-invariant covariates, such as gender, nativity, mother's education, and race, are automatically controlled by differencing the effects between waves.

Single equation estimates of the effects of crowding and other covariates are unparsimonious and may result in relatively imprecise estimates of the effects of crowding. Inasmuch as these effects may be small and of marginal statistical significance in moderate sized samples, they may be difficult to detect. We explore whether child wellbeing can be simplified into a smaller number of dimensions than the five measured in our LAFANS analysis.[19] Thus, we estimate housing crowding effects using several specifications of a Multiple Indicators, Multiple Causes (MIMIC) model (Bollen 1989; Hauser and Goldberger 1971). In this model, we specify that crowding and the other independent variables affect the five indicators of child wellbeing through one or more latent variables. Let y_{ij} denote the value on the jth measured indicator of wellbeing for

[18] In additional analyses for which results are not reported in this paper, we examine a number of alternate measures of crowding, the effects of household poverty, and possible interactions between crowding and the other independent variables including age, gender, race, nativity, and housing type. None of these investigations produced results at variance with the ones reported in this paper.

For each outcome we also estimate a model that includes the socioeconomic factors but excludes the effects of crowding. When compared to Model 3, this model shows the degree to which household crowding accounts for the advantages enjoyed by white children with highly educated parents and from higher income families. In results not shown here, however, we find that crowding accounts for a very small fraction of the total effects of family socioeconomic and race/ethnic factors on child wellbeing.

[19] As shown in the results section, the PSID-CDS does not show consistent significant effects of crowding across the outcomes. This suggests that the effects of crowding on these outcomes in the PSID-CDS behave differently, and should not be grouped together to summarize one latent measure.

the ith child ($i = 1,\ldots, N$; $j = 1, \ldots, 5$); X_{ik} denote the value on the kth measured independent variable for the ith child ($k = 1, \ldots, K$); η_{is} denote the value on the sth latent dimension of child wellbeing for the ith child; λ_{js}, μ_j, and γ_{ks} are parameters to be estimated, and ε_{ij} and φ_{is} are random disturbances. Then the MIMIC model is:

$$y_{ij} = \mu_j + \lambda_{js}\eta_{is} + \varepsilon_{ij}$$

and

$$\eta_{is} = \gamma_{ks} X_{ik} + \varphi_{is}\,.$$

The λ_{js} denote the effects of the common latent factor(s) for child wellbeing on the specific measures of wellbeing, and the γ_{ks} denote the effects of the independent variables on the latent factor(s) for child wellbeing. This model is more parsimonious than the separate OLS models because, compared to the $5K$ parameters in OLS, the MIMIC model has $5 + K$ parameters.[20]

We consider two forms of the MIMIC model. The first allows a single dimension of child wellbeing; that is, $S = 1$ and a single factor accounts for the correlations among the indicators of wellbeing (Figure 1a). In this case, the effect of each independent variable has proportional effects on the five indicators of wellbeing. In the second form, we specify two latent variables; one represents cognitive outcomes based on mathematics and reading, and another represents health based on internal and external behavior problems and a physical health assessment (Figure 1b). As discussed further below, this second specification fits the data better than the first, yet is still more parsimonious than the five separate OLS regression models.

[20] In practice, to identify the variance of the latent variable(s), it is necessary to fix one of the λ_{js} for each latent variable or place some other restriction(s) on the model. We follow the convention of assuming $\lambda_{1s} = 1$ for each latent variable.

Results

Descriptive Characteristics

Tables 2a and 2b present correlations, weighted means, and standard deviations of the variables involved in the models, based on the largest estimated sample.[21] The overall average math reasoning and broad reading percentile rank scores for the sample of 2,304 children in LAFANS are 53.4 and 50.1. The average numbers of logged internal and external behavior problems are 2 and 2.3, respectively. An average child in the sample has "very good" health (4.2), lives in a home with about one and half people per room, and is about nine and half years old. Most children in the sample live in two-parent families, with about 35 percent in single-parent families. About 44 percent of the sampled households are first generation immigrants (the child's mother is born outside the U.S.). The average child has a mother with a high school education and a family income of about $53,000. More than half (55 percent) of the sampled children have Latina mothers.

There are many similarities between the LAFANS and PSID-CDS samples, but there are also some key differences. Table 2b shows correlations, means, and standard deviations for the 2002 PSID-CDS sample.[22] The most striking difference between the LAFANS and PSID-CDS is in their average levels of crowding. The Los Angeles sample has a higher average crowding level (1.48) compared to the PSID-CDS sample (.94). Some other notable differences are in the marital status distribution, proportion Latino, proportion immigrants, and average family income. The PSID-CDS has a large sample

[21] These statistics are based on the 2304 children in LAFANS and the 2170 children from PSID-CDS estimated in the physical health models. Statistics may vary slightly for other child outcome models due to differences in sample sizes.
[22] Although only standard (raw, age-adjusted) math and reading scores are available in the PSID-CDS, the averages remain comparable to the percentile rank values in LAFANS (See Table 4.20 in Peterson et al. 2003, pg. 91, for a comparison of standard scores and percentile ranks).

of married mothers and fewer never married mothers than the LAFANS. The PSID-CDS also has a substantially smaller proportion of Latinos (20 percent) compared to LAFANS (55 percent). Not surprisingly, the LAFANS has a much higher proportion of immigrants (44 percent) than the PSID-CDS (16 percent). In addition, the children used in our PSID-CDS analyses have a higher total family income (about $73,000) than children's families in LAFANS (about $53,000). Children in the LAFANS and CDS have similar achievement scores, with children in the CDS having slightly more behavioral problems and slightly better health on average.

Table 3 shows the average housing crowding level, standard deviation, and percentage for each of the independent variables in the LAFANS and both PSID-CDS waves. In the LAFANS, younger children in the sample live in more crowded housing than older children. Crowding levels monotonically decline as age increases. Children whose mothers were never married live in more crowded housing than those whose mothers are married or were formerly married. Natives tend to live in less crowded housing on average compared to immigrants. There is a monotonic inverse relationship between mother's education and crowding. Children with poorly educated mothers tend to live in housing with 1.95 persons per room, while those with highly educated mothers live with 0.90 persons per room. There is also a monotonic inverse relationship between income groups and crowding. On average, the poorest group (< $20,000) lives with 1.86 persons per room, compared to an average of 1.01 persons per room for the wealthiest group (> $45,000). Whites and Asians live in the least crowded housing on average compared to blacks and Latinos. Still, Latinos experience one and a half times as much crowding on average compared to blacks.

The PSID-CDS sample experiences patterns in average crowding levels across its other characteristics that are similar to those in the LAFANS. There is a monotonic decrease in average crowding as mother's education increases and as income increases, similar to patterns found in the LAFANS. Though the average levels of crowding tend to be lower in the PSID-CDS than the LAFANS overall, the trends remain the same. Children whose mothers never married live in more crowded housing than those with mothers in other marital statuses. Immigrants at the national level also tend to live in more crowded housing on average than natives, just as they do in Los Angeles. Whites also continue to have the lowest crowding levels, and Latinos the highest, at the national level.

Figures 2a to 2c portray the relationship between housing crowding and the child wellbeing indicators in the LAFANS sample. The box graphs of math and reading scores (Figure 2a) and the log of internal and external behavior problems (Figure 2b) by intervals of crowding levels (in increments of .5 persons per room) show a linear relationship across the earlier crowding intervals, with more inconsistency towards the higher levels of crowding. This suggests a non-linear relationship between housing crowding and academic test scores and behavioral problems. We do not, however, have sufficient evidence to support a non-linear treatment of housing crowding.[23]

Figure 2c displays the relationship between housing crowding and physical health. Due to the limited number of health categories, we present a stacked bar graph displaying the percentage levels of health across intervals of housing crowding. This graph clearly shows that reports of excellent health for children are most prevalent at the lowest levels of crowding. The proportion with excellent health diminishes as crowding

[23] We test other functional forms of household crowding, including logarithmic, quadratic, and exponential specifications, but Wald and BIC statistics indicate that the linear specification is adequate. Most of the sample falls into the first four crowding intervals where the linear relationship holds. Though the pattern for the remaining intervals strays from a linear form, the sample sizes are relatively small and unreliable.

increases. The pattern begins as a linear relationship and appears to have diminishing negative effects of crowding on children's health at higher levels of crowding. Statistical tests comparing different functional forms of crowding, however, indicate that the linear form is adequate to summarize the relationship between crowding and health in this sample.[24]

Regression Analysis

In the first stage of our analyses, we examine the gross effect of housing crowding for each child wellbeing indicator (See Table 4). We then examine the change in the coefficient as we add demographic and then socioeconomic variables. For each child outcome in the LAFANS, housing crowding negatively affects wellbeing. In Model 1, each additional person per room decreases math and reading test scores by 7.6 and 5.9 percentage points, respectively. A child in a household where everyone has a room to themselves, for instance, is expected to have a math score of 57 percentile points, while a child in a household where everyone has to share a room with another person is expected to get 49 percentile points. Child behavior problems increase with more housing crowding. An additional person per room is expected to increase children's internal behavior problems by 7.2 percent and increase the expected external behavior problems by 5.6 percent in Model 1. General physical health declines by .18 on a scale of 1 to 5 with a unit increase in housing crowding in Model 1. All of these gross effects are highly statistically significant (p<.000).

The results for the PSID-CDS are similar. In 1997, an additional person per room

[24]We repeat this process of testing the functional form of crowding on the outcomes for the PSID-CDS samples in both waves. We arrive at similar conclusions to those using the LAFANS. The patterns for math, reading, and health are clearly linear, with a vaguely linear pattern for the behavior problems. We do not present those figures here but are available upon request from the authors.

decreases children's math and reading scores by 11.3 and 11.8 standard points, respectively, in Model 1. Children's behavioral problems tend to increase with an increase in crowding, however even the gross relationship is moderately statistically significant for internal and not significant for external behavior problems. In fact, the effects of crowding on external behavior problems in the 1997 CDS are never statistically significant, with inconsistency in the direction of the effect. General physical health declines by .18 on the 1 to 5 scale with an increase in crowding. The story is similar for 2002, except the crowding coefficient for math scores is a bit lower than in 1997. A unit increase in housing crowding decreases a child's math scores by 6.2 standard points.

Once we include demographic variables in our model, the effects of crowding decline for each child outcome. Model 2 adds child's sex, age, mother's marital status, and immigrant status to Model 1. In LAFANS, the coefficient for housing crowding predicting math scores declines by 17 percent, from -7.6 to -6.3, once we add demographic controls. A unit increase in housing crowding corresponds to a decrease in child math scores by 6.3 percentile points, net of demographics. An additional person per room decreases reading scores by 5.7 points, controlling for demographic variables, a reduction of 3 percent from the gross coefficient in Model 1. In the PSID-CDS, the crowding coefficient for math and reading drop by a similar amount. Our demographic indicators account for 6.8 and 12 percent of the crowding effect on math and reading respectively in 1997. In 2002, the crowding coefficient drops 5.5 and 7 percent for math and reading respectively once we add demographic controls. There is still a substantial amount of the crowding coefficient on academic achievement that has not been explained away by this first set of controls.

Adding demographic control variables to the internal behavior problems model in

LAFANS diminishes the housing crowding coefficient by 35 percent. An additional person per room is expected to increase a child's internal behavior problems by 4.6 percent, net of the demographic variables. An additional unit in housing crowding is expected to increase a child's external behavior problems by 5.5 percent controlling for demographic variables, reducing the crowding coefficient by 2 percent from the gross model. The patterns across models 1 and 2 in the PSID-CDS for internal and external behavior problems fluctuate and are all statistically insignificant, with the exception of internal behavior problems in 1997 for Model 2. A unit increase in crowding corresponds to a 3.5 percent increase in internal behavior problems.

In the LAFANS physical health model, the housing crowding coefficient diminishes by 31 percent from Model 1 once we control for demographic variables. An additional person per room harms a child's physical health by .13 points on the 1 to 5 scale, net of demographics. The effect of crowding on health in the 1997 and 2002 PSID-CDS also decline by 26 and 60 percent respectively once we add demographic controls. Despite declines in the coefficients' magnitude, housing crowding remains statistically significant ($p<.05$) for each of the child outcomes in LAFANS, and all but the behavioral problems in the PSID-CDS waves I and II. The coefficient for housing crowding changes more dramatically, however, once we control for socioeconomic status.

In Model 3, we add socioeconomic variables- mother's educational attainment, family income, and race/ethnicity - to Model 2 for each measure of child wellbeing. These SES variables account for most of the crowding effect on math scores across the datasets. The housing crowding coefficient in LAFANS is reduced by almost three quarters (73 percent) from the gross math model; however, housing crowding is still statistically significant (p<.05).[25] An additional person per room reduces a child's math scores by 2.1 percentile points. Similar to the math model, a unit increase in housing crowding reduces a child's reading score by two percentile points; this coefficient is moderately significant (p<.10).[26]

In the PSID-CDS, SES accounts for much, but not all, of the crowding effect on academic achievement. The effect of crowding on math and reading scores is reduced by 53 and 61 percent respectively in 1997, and 73 and 64 percent in 2002, once we control for demographic and SES characteristics. However, there is still a statistically significant effect of crowding on academic achievement. An additional person per room is associated with a decline in math and reading by 5.3 and 4.6 standard points respectively in 1997. In 2002, the crowding effect on reading scores (-4.2) is very similar to that in 1997, however the effect on math scores is much lower (-1.6) in 2002 than in 1997. The crowding coefficient predicting math in 2002 for Model 3 is also marginally statistically significant (p=.104).

Estimates of housing crowding on internal and external behavior problems are substantially reduced in Model 3 from Model 1 in LAFANS. The housing crowding coefficient predicting internal behavior problems in Model 3 is 36 percent smaller than its corresponding coefficient in Model 1. An additional person per room is expected to increase a child's internal behavior problems, such as withdrawal or depression, by 2.6 percent. Although the magnitude of the housing crowding coefficient drops from 7.2

[25] In prior work, we also expanded Model 3 in the LAFANS to include measures of neighborhood crowding to study its effects on child wellbeing. We defined neighborhood as a Census tract, and used two different measures of crowding based on 2000 Census data for Los Angeles County. One was a measure of persons per square mile, and the other was a ratio of the average household size by the average number of rooms per housing unit in the tract. We found no significant effects of neighborhood crowding on any child wellbeing indicators.
[26] Estimates of Model 3 for each independent variable are available in Appendix A.

percent in Model 1 to 2.6 percent in Model 3, it remains statistically significant (*p*<.05). This is also true for external behavior problems. The housing crowding coefficient drops 21 percent from Model 1 once we control for demographic and SES variables, but it remains statistically significant (*p*<.05). A unit increase in housing crowding is expected to increase the number of external behavior problems, such as a strong temper, by 4.4 percent.[27] The results for the PSID-CDS are not statistically significant, except for the 1997 Model 3 predicting internal behavioral problems. An increase in housing crowding corresponds to a 4 percent increase in children's internal behavior problems.

The estimate of housing crowding also drops substantially with the addition of demographic and SES control variables in the model predicting children's physical health. In LAFANS, an additional person per room reduces a child's health rating by .04 on the 1 to 5 scale, a reduction in the coefficient's magnitude by over three quarters (77 percent) from Model 1. Despite the small effect size of crowding on health, it remains statistically significant (*p*<.05). The story is different for the PSID-CDS samples. These models show that the SES and demographic controls account for the relationship between housing crowding and health. The crowding coefficients in the 1997 and 2002 models suggest a negative effect but are not statistically significant.

We take the PSID-CDS analysis of Model 3 three steps further by taking advantage of the extensive family history in the PSID and its longitudinal structure. First, we use a calculation of average crowding over a four year period for both waves of the PSID-CDS to compare its effects on child wellbeing with the single year measure of

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[27] A comparison of the relative effects of household crowding across the five outcomes in LAFANS for Model 3 reveals that internal behavior problems are most strongly affected by an additional person per room, with a -.09 standard deviation change. In Model 3, the standardized housing crowding coefficients are -.069 for math scores, -.068 for reading scores, .076 external behavior problems, and -.048 for physical health.

crowding. We then stack the two waves of data to form a pooled dataset and use pooled OLS estimation. Finally, we run fixed effects models looking at within child differences over time.

Table 5 shows the single year and four-year average crowding results for each wave of the PSID-CDS separately, as well as the pooled and fixed effects estimates. Average crowding makes better use of the data by looking at the child's history of crowdedness and averaging it over a four-year period. This measure will average out children with short episodes of living in crowded housing and emphasize those children with more exposure to crowded living conditions.

Focusing on the 1997 and 2002 results, we see some differences in the single year versus four year average crowding coefficients for academic achievement. The magnitude of the average crowding coefficient is 33 to 48 percent larger in both waves predicting math and reading scores compared to their single year crowding counterpart. Averaging crowding does not affect the results for internal or external behavior problems or physical health.

Table 5 also introduces the pooled OLS analysis for both single year and four year average crowding.[28] The single year pooled results show significant crowding estimators for math and reading. A unit increase in crowding corresponds to a decline in math and reading scores by 3.3 and 4.7 standard points, respectively. The crowding effects on internal and external behavior problems are still insignificant, but in the correct direction, suggesting that an increase in crowding increases the number of internal and external behavior problems. Housing crowding still does not show significant effects on health using pooled OLS however the direction of the effect is the same across datasets and

[28] We use 1997 weights for the pooled OLS estimates.

waves. The results suggest that increases in housing crowding have a negative effect on children's physical health.

Moving from the pooled single year crowding analysis to the pooled average crowding analysis in Table 5, we see a consistent increase in the magnitude of the coefficients. A unit increase in average crowding significantly decrease math and reading scores by 4.3 and 6.7 standard points, respectively. Although the effects of average crowding on behavior problems and physical health remain insignificant ($p<.05$), the coefficients are larger than single year crowding.

Finally, we conduct fixed effect estimates of Model 3 in the PSID-CDS. We estimate the effect of a unit increase in single year crowding and average crowding between the two waves on the five child wellbeing outcomes between the waves, controlling for the time-varying covariates in the model – age, marital status, and income – as well as all other time-invariant covariates, including child's sex, mother's education, nativity, and race/ethnicity. The results using the single year measure of housing crowding are inconsistent and insignificant. We regain the expected direction of the crowding effect on all five wellbeing outcomes when we use average crowding.[29] Although most of the effects are not significant, we find that a unit increase in average crowding between the waves significantly increases external behavior problems by 4.2 percent between the waves ($p=.044$). We also find a marginally statistically significant effect of average crowding on physical health. A unit increase in average crowding between the waves decreases health between the waves by .082 on the 1 to 5 scale ($p=.063$).

[29] There is some variation in the single year housing crowding between waves I and II, but there is more variation between the waves when we use four year average crowding, making average crowding a better estimator for this fixed effects model.

In summary, living in crowded housing conditions has an independent negative effect on all the child wellbeing outcomes in LAFANS and all but the behavioral problems in PSID-CDS cross-sectional analyses after controlling for demographic and socioeconomic characteristics. Constructing a four year average value of housing crowding gives us a better sense of the duration that children are experiencing crowded housing conditions, and shows a larger magnitude for the crowding coefficient on academic achievement and physical health.

Pooling the two waves of the PSID-CDS gives us more precise estimates and stronger statistical power. Single year and average crowding are again significant in predicting math and reading scores, but not behavioral problems or physical health. Average crowding in the pooled OLS analysis has larger negative effects on all child wellbeing indicators. The fixed effects estimates of average crowding negatively affect all the child outcomes. We find significant effects of average crowding on external behavior problems and marginally significant effects on health. Although the PSID-CDS are panel data, we still may not have enough variability in the difference between waves I and II, which could result in the statistically insignificant results.

Dimensionality of Child Wellbeing

The five child outcomes discussed thus far represent different aspects of child wellbeing. We seek to determine whether or not housing crowding independently harms children. The analyses thus far have shown that housing crowding does have negative effects on children for each of the outcomes in LAFANS, independent of socioeconomic and demographic factors. Because a focal social concern is on the overall wellbeing of children, we utilize a MIMIC model to determine if we can investigate all five child outcomes in a single model. We use the LAFANS sample to test this latent variable hypothesis because all wellbeing outcomes consistently exhibit significant crowding effects.

We estimate a MIMIC model in which housing crowding, demographic variables and SES variables predict a single latent variable representing child wellbeing.[30] MIMIC Model 1 reveals that housing crowding has a significant negative effect on child wellbeing. An additional person per room decreases overall child wellbeing by a unit of 2.63. According to the fit statistics, however, the model does not fit the data well (chi-square=1185.24, 49 degrees of freedom (*df*), and p= .000).

It is possible that the five child outcomes indicate different processes of wellbeing. We investigate a second MIMIC model with two latent variables, one representing the cognitive performance of the child, based on math and reading scores, and the other representing health wellbeing of the child, based on internal and external behavior problems and physical health. This MIMIC Model 2 with two latent variables fits the data better, although it would still be rejected at conventional levels of significance (chi-square=351.485, 38 *df*, and p=.000).[31]

We present the estimates from the two factor model in Table 6a. Housing crowding has statistically significant negative effects on children's cognitive performance. An additional unit of housing crowding decreases a child's cognitive wellbeing by 2.13 units net of demographic and SES. One can also compare the estimated effect of crowding relative to other variables (see Table 6b). An increase in one person

[30] We use Mplus software to estimate the MIMIC models. The direction of the logged internal and external behavior outcomes were changed such that an increase communicates improved child wellbeing, matching the direction of the other outcomes.
[31] The error variance for the Internal Behavior Problems score was very small and negative, implying a perfect prediction. We fixed the error variance for this variable at zero. We were unsuccessful in estimating an interpretable MIMIC model more complex than the two factor model, yet more parsimonious than the saturated model.

per room is over one third as damaging to a child's cognitive performance as living in a never-married, single-parent household versus a two-parent household. The negative effect of an additional person per room on children's cognitive performance is comparable to reducing mother's educational attainment by one and a half years and a reduction of almost $30,000 in family income.

A second process through which crowded housing conditions affects children is their health, both behavioral and physical. An additional person per room decreases health wellbeing by 2.47 units and is statistically significant. In comparison with other variables, the negative effect of an additional person per room on behavioral and physical health is equivalent to one quarter the damage of living in a never-married, single-parent home versus a two-parent home, to a reduction in mother's educational attainment by three years, and to a reduction of family income by almost $80,000.

Mechanisms

Given that housing crowding generally has persisting negative effects on children's wellbeing even after controlling for SES, we now seek to understand the mechanisms through with this process operates. The PSID-CDS offers an interviewer assessed measure of noise inside the house in 2002. Noise is measured on a 5 point scale, from (1) not at all noisy to (3) somewhat noisy to (5) very noisy. Interviewers were instructed to think about noise as noise from "television, shouts of children, radio." Noise within the household can serve as a distraction for a child that is attempting to focus on homework or reading. Persons in the household making noise can make it difficult for children to get the proper amount and continuity of sleep that would allow children to be alert during the day while at school and while interacting with peers. The lack of sleep can also weaken children's immune systems and make them more vulnerable to illness and poorer health.

In order to determine whether noise inside the house is a mechanism through which crowding affects child wellbeing, we add noise to our 2002 full model, Model 3, and inspect the change in the effect and significance of the crowding coefficient. Table 7 shows the crowding coefficient without noise in the model, and the crowding and noise coefficients for this elaborated Model 3 using the wave II sample.[32] We find that adding noise to the model reduces the crowding coefficients predicting math scores, reading scores, and physical health as well as their significance level. The crowding coefficients predicting math and reading drop by 48 and 31 percent, respectively, when we add noise to the model. The crowding coefficient predicting physical health drops by 42 percent when we add noise to the model.

Unfortunately, the crowding coefficient in this more restricted sample is never significant for any child outcome even before we include noise to the model. We can see, however, that noise inside the house has a significant negative effect on academic and behavioral wellbeing ($p<.05$). The results suggest that increases in noise negatively affect a child's physical health, though this is statistically insignificant ($p=.185$). In summary, the data suggest that noise inside the home may be a mechanism explaining the negative effect of housing crowding on child wellbeing.

Discussion

The reported results should be interpreted with some caution. The LAFANS and

[32] The samples are based off of those used in prior PSID-CDS analyses but with the additional constraint that they also have non-missing values for noise inside the house in 2002.

1997 and 2002 PSID-CDS OLS regression analyses are based on cross sectional data and, because persons living in crowded housing conditions tend to be more likely to suffer other forms of social deprivation, it is possible that our findings may be an artifact of failing to control for other aspects of children's environments that are correlated with crowding. While pooling the two PSID-CDS waves offers increased statistical power due to larger sample sizes, it does not control for unobserved heterogeneity. The fixed effects estimation allows us to control for all time-invariant parameters, but there may not offer enough variability to conclusively determine whether or not housing crowding effects are still present.[33] In future work, we will use the latest LAFANS and PSID-CDS waves to gain more precision and accuracy in our analyses. Nonetheless, our results are consistent with the conclusion that the effects of housing crowding on children are large and pervasive, spanning cognitive, behavioral, and health outcomes.

In Los Angeles, there are clear and significant negative effects of crowding on all indicators of child wellbeing. These data show mixed results on housing crowding effects on child wellbeing for the nation. Although not all results are significant, they suggest a negative relationship between crowding and child wellbeing. It is striking that there are still some significant effects of crowding at the national level that persist once controlling for all time-constant factors. We learn more about the effects of crowding at the national level by pooling the data and looking at a four-year average crowding measure. Averaging housing crowding levels over time offers more variability and a better sense of the effect of living in crowded housing for a longer duration on the outcomes. The fixed-

[33] Specifically, the fixed-effects model is limited in that differencing can greatly reduce variation in the explanatory variables, and less variability makes it difficult to attain significant results. The lack of significance in our crowding effects may be masked by limited variability across the five year time-span. Also, fixed-effects models are more stringent than a cross-sectional or pooled model, but may be too stringent and control for more factors than we would like.

effects model enabled us to control for all factors that remained constant between 1997 and 2002 that we could not capture in our cross-sectional analyses.

Ultimately, housing crowding is significantly associated with multiple aspects of child wellbeing, even after controlling for several dimensions of socioeconomic status. The inclusion of socioeconomic controls in the models reduces the effect of housing crowding on child wellbeing, however, there remains a significant harmful effect on each area of child wellbeing in the LAFANS, academic achievement for the pooled OLS in the PSID-CDS, and external behavior problems and physical health with average crowding for the fixed effects estimation in the PSID-CDS. The MIMIC models suggest that these five child outcomes operate through two dimensions of child wellbeing — cognitive performance and health. Noise inside the home plays a strong role in explaining how housing crowding can harm children's wellbeing, though we need more research to understand this process and continue to explore other possible mechanisms. Poor housing conditions have small but significant effects on different aspects of a child's life. These negative effects during childhood can persist throughout life, ultimately affecting their future socioeconomic status and adult wellbeing.

It is important to identify aspects of a child's living environment that may prove harmful in order that they may be prevented. Housing programs, informed on the manner in which housing crowding operates, can be designed to mitigate the effects of crowding and form standards of the appropriate unit size for households. Communities can better inform housing development with awareness of household sizes and the detriment of crowding. The living environment, net of socioeconomic status, is another area that can contribute to the intergenerational transmission of social inequality.

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Table 1a. Percent Household-Level Crowding, Census and LAFANS

Crowding (Persons/Room)	1990 Census- LA County	2000 Census- LA County	LAFANS (2000) (N=3,086)	2000 Census – United States
1.0 or less	80.7%	77.0%	73.8%	81.4%
1.01 – 1.50	6.8	7.9	12.4	10.1
1.51 or more	12.5	15	13.8	8.5

Note: We present the Census estimates from the 5% sample of persons per room at the household level to offer a longitudinal assessment and a national comparison. Census groups total rooms at nine or more. For the purposes of this comparison, we group LAFANS data on rooms at nine or more, and assign that group the mean rooms.

Table 1b. Percent Child-Level Crowding, Census and LAFANS

Crowding (Persons/Room)	1990 Census - LA County	2000 Census - LA County	LAFANS (2000) (N=2,500)	2000 Census – United States
1.0 or less	53.9%	47.7%	44.8%	81.6%
1.01 – 1.50	16.3	16.2	21.9	10.1
1.51 or more	29.8	36.1	33.3	8.3

Note: We present the Census estimates from the 5% sample of persons per room at the child level. For the purposes of this comparison, we group LAFANS data on rooms at nine or more, and assign that group the mean rooms.

Table 1c. Percent Child-Level Crowding, PSID-CDS

Crowding (Persons/Room)	1997	2001
1.0 or less	76.96%	81.08%
1.01 – 1.50	13.88	10.82
1.51 or more	9.16	8.1

Table 2a. Means, Standard Deviations, and Correlations for Children aged 3-17, LAFANS 2000 (N=2,301)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Math Score	1															
2. Reading Score	.582	1														
3.Internal Behavior (log)	-.230	-.185	1													
4.External Behavior (log)	-.169	-.163	.668	1												
5. Health	.169	.121	-.237	-.124	1											
6. Crowding	**-.230**	**-.187**	**.216**	**.122**	**-.178**	**1**										
7. Male	.073	-.112	-.005	.079	-.007	**.018**	1									
8. Age	-.159	-.186	-.075	-.067	-.026	**-.087**	.002	1								
9. Native Born	-.058	-.061	-.010	.013	-.114	**-.044**	-.010	.087	1							
10.Divorce/ Separated	-.138	-.182	.169	.115	-.073	**.133**	-.020	-.076	-.204	1						
11. Not Married	.123	.034	-.206	.040	.162	**-.317**	-.008	-.020	.104	.027	1					
12. Mom education	.366	.291	-.266	-.105	.282	**-.403**	.026	.010	-.012	-.154	.393	1				
13. Income(1000s)	.311	.268	-.218	-.062	.212	**-.319**	.031	.064	-.138	-.208	.269	.446	1			
14. Latino/other	-.285	-.200	.240	.046	-.258	**.411**	-.001	-.019	-.083	.124	-.513	-.589	-.324	1		
15. Black	-.060	-.076	-.046	.023	-.020	**-.062**	.010	-.016	.178	.192	.353	.145	-.055	-.379	1	
16. Asian	.181	.146	-.089	-.098	.143	**-.134**	.004	.024	-.038	-.137	-.221	.284	.105	-.356	-.119	1
Mean	53.4	50.1	2.00	2.32	4.203	**1.48**	.505	9.65	.167	.181	.441	12.1	53.1	.548	.111	.094
Standard Deviation	30.1	30.1	.343	.478	0.923	**1.01**	.500	4.22	.373	.385	.497	4.28	61.9	.498	.314	.292

Note: This sample is equivalent to the one used for the LAFANS model predicting physical health. Statistics may be slightly different in the samples for the other models. Observations are weighted

Table 2b. Means, Standard Deviations, and Correlations for Children aged 8-17, PSID-CDS 2002 (N=2084)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Math	1														
2. Reading	0.667	1													
3. Internal Behavior (log)	-0.106	-0.136	1												
4. External Behavior (log)	-0.212	-0.207	0.511	1											
5. Health	0.202	0.217	-0.147	-0.246	1										
6. Crowding	**-0.155**	**-0.175**	**0.054**	**-0.023**	**-0.128**	**1**									
7. Male	0.129	-0.056	0.119	0.055	0.015	**-0.031**	1								
8. Age	-0.148	-0.054	-0.075	-0.067	-0.030	**-0.064**	-0.027	1							
9. Divorce/Separated	-0.052	-0.064	0.097	0.085	-0.030	**-0.014**	0.003	0.016	1						
10. Never Married	-0.168	-0.160	0.064	0.104	-0.184	**0.109**	-0.023	-0.013	-0.141	1					
11. Immigrant	-0.099	-0.112	-0.033	-0.087	-0.129	**0.437**	-0.045	-0.006	-0.064	0.064	1				
12. Mom Education	0.383	0.370	-0.077	-0.060	0.253	**-0.384**	0.021	-0.046	-0.046	-0.203	-0.439	1			
13. Income (1000's)	0.187	0.168	-0.035	-0.051	0.105	**-0.151**	0.032	0.025	-0.140	-0.114	-0.108	0.272	1		
14. Latino/Other	-0.140	-0.143	0.001	-0.015	-0.133	**0.435**	-0.047	-0.034	-0.021	0.082	0.775	-0.431	-0.117	1	
15. Black	-0.270	-0.267	0.029	0.074	-0.119	**0.034**	0.054	0.041	0.123	0.370	-0.153	-0.104	-0.125	-0.224	1
Mean	105.5	105.1	2.29	2.28	4.38	**0.94**	0.50	12.53	0.17	0.09	0.16	12.90	73.28	0.20	0.16
Stnd. Dev	16.8	17.9	0.37	0.40	0.82	**0.66**	0.50	2.80	0.38	0.29	0.37	2.76	105.78	0.40	0.36

Note : This sample is equivalent to the one used for the PSID-CDS model predicting physical health. Statistics may be slightly different in the samples for the other models. Observations are weighted.

Table 3. Average Household Crowding Level and Percentages for Independent Variables

	LAFANS			1997 CDS			2002 CDS		
	Mean Crowding	Stnd. Dev	%	Mean Crowding	Stnd. Dev	%	Mean Crowding	Stnd. Dev	%
Gender									
Male	1.49	1.05	50	0.93	0.51	50	0.91	0.70	50
Female	1.46	0.973	50	1.00	0.69	50	0.96	0.62	50
Total			100			100			100
Age									
3-5	1.60	1.14	21	1.01	0.68	31	na	na	0
6-12	1.51	1.02	50	0.94	0.57	69	0.98	0.74	50
13-17	1.33	0.88	30	na	na	0	0.89	0.57	50
Total			101			100			100
Marital Status									
Married	1.41	0.99	65	0.96	0.60	74	0.92	0.65	74
Divorced/Separated	1.37	1.05	17	0.90	0.56	9	0.90	0.70	17
Never Married	1.80	1.02	18	1.13	0.73	17	1.14	0.70	9
Total			100			100			100
Nativity									
Native	1.11	0.61	44	0.84	0.40	85	0.81	0.45	84
Immigrant	1.77	1.16	56	1.69	0.98	15	1.59	1.09	16
Total			100			100			100
Mother's Education									
<high school	1.95	1.22	37	1.35	0.69	15	1.48	0.99	15
high school grad	1.52	0.92	20	0.96	0.51	37	0.95	0.63	37
some college	1.18	0.66	21	0.86	0.45	26	0.78	0.37	26
college grad	1.02	0.47	5	0.73	0.38	15	0.69	0.34	15
>college	0.90	0.46	17	0.70	0.45	7	0.70	0.50	7
Total			100			100			100
Income									
<20k	1.86	1.02	27	1.23	0.70	18	1.25	0.76	11
20-<45k	1.67	1.21	36	1.01	0.67	27	1.03	0.71	24
45k+	1.01	0.49	37	0.85	0.50	54	0.85	0.61	65
Total			100			99			100
Race									
White	0.89	0.40	25	0.78	0.30	65	0.74	0.32	64
Latino/other	1.85	1.17	55	1.52	0.96	19	1.51	1.07	20
Black	1.27	0.59	11	1.05	0.58	16	1.00	0.57	16
Asian	1.07	0.45	9	na	na	0	na	na	0
Total			100			100			100

Note: Percentage totals may not add to 100 due to rounding error. This sample is equivalent to the one used for the model predicting physical health. Statistics may be slightly different in the samples for the other models. Observations are weighted.

Table 4. Household crowding Coefficients for Weighted Models Predicting individual observed Child Outcomes, LAFANS and PSID-CDS

	Model 1 (OLS)			Model 2 (OLS)			Model 3 (OLS)		
	LAFANS	1997 CDS	2002 CDS	LAFANS	1997 CDS	2002 CDS	LAFANS	1997 CDS	2002 CDS
Dependent Variables	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE
Mathematics Score	-7.55	-11.29	-6.15	-6.275	-10.46	-5.78	-2.068	-5.33	-1.64
	1.26	1.37	1.33	1.17	1.47	1.24	0.94	1.24	1.01
Reading Score	-5.887	-11.79	-11.8	-5.699	-10.45	-10.94	-2.042	-4.58	-4.211
	1.16	1.75	2.38	1.29	1.77	2.55	1.20	1.57	2.13
Internal Behavior Score (log)	0.072	0.035	0.028	0.046	0.052	0.019	0.026	0.041	-0.003
	0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.02	0.02
External Behavior Score (log)	0.056	0.015	-0.012	0.055	0.016	0.006	0.044	0.020	-0.018
	0.01	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02
Health	-0.179	-0.178	-0.16	-0.132	-0.131	-0.099	-0.044	-0.072	-0.026
	0.03	0.05	0.04	0.03	0.05	0.04	0.02	0.05	0.04

Note: T-statistics in the OLS models are calculated from robust standard errors. OLS Model 1 includes crowding effects only. OLS Model 2 includes effects of crowding, child's sex and age, and mother's marital and immigration statuses. OLS Model 3 include all effects included in OLS Model 2 plus effects of educational attainment of child's primary caregiver, family income, and race. For details of how variables are measured, see text. All coefficients for the three Model 3's are available in Appendix A.

Table 5. Comparing Single Year and 4-Year Average Crowding for Model 3 - 1997, 2002, Pooled, and Fixed-Effects, PSID-CDS

	1997		2002		Pooled		Fixed Effects	
	Single Yr	Average	Single Yr	Average	Single Yr	Average	Single Yr	Average
Dependent Variables	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE	Coeff. SE
Mathematics Score	-5.326	-7.908	-1.644	-2.424	-3.304	-4.307	-0.128	-1.108
(N=1447)	1.238	2.003	1.012	1.902	0.887	1.569	0.696	1.168
Reading Score	-4.583	-6.104	-4.211	-5.987	-4.656	-6.714	0.617	-0.085
(N=998)	1.565	2.571	2.131	2.738	1.390	2.092	0.807	1.314
Internal Behavior	0.041	0.050	0.003	0.014	0.017	0.026	-0.004	0.001
Score (log) (N=2023)	0.020	0.025	0.020	0.029	0.015	0.020	0.013	0.020
External Behavior	0.020	0.031	-0.018	-0.007	0.008	0.030	0.016	0.042
Score (log) (N=2053)	0.017	0.022	0.021	0.031	0.016	0.020	0.014	0.021
Health (N=2084)	-0.072	-0.095	-0.026	-0.003	-0.049	-0.052	-0.030	-0.082
	0.162	0.067	0.044	0.064	0.034	0.048	0.029	0.044

Note : The pooled and fixed-effects models have a wide data structure and, therefore, double the sample size (N*2). We report robust standard errors for the 1997, 2002, and pooled OLS estimates.

Table 6a. Estimates for MIMIC Model 2 for Crowding and Other Effects on Child Wellbeing, LAFANS (N = 2,454)

	Latent Variable for Child Wellbeing			
	Cognitive Performance		Health	
	Coeff.	Coeff./S.E.	Coeff.	Coeff./S.E.
Effects of Exogenous Variables on Latent Variables for Wellbeing				
Crowding	-2.132	-2.29	-2.466	-2.45
Male	-0.564	-0.31	0.985	0.72
Age	-0.718	-3.77	0.362	1.81
Divorce/Separated (vs. Married)	-0.459	-0.19	-1.864	-0.66
Never Married (vs. Married)	-5.335	-2.82	-10.060	-3.73
Native Born (vs. Immigrant)	-5.027	-2.33	5.941	1.57
Caregiver's Education	1.457	6.58	0.878	3.60
Income (in 1000s)	0.073	6.40	0.032	2.23
Latino/other (vs. White)	-9.560	-3.92	-2.254	-0.76
Black (vs. White)	-8.050	-2.07	0.806	0.20
Asian (vs. White)	-0.988	-0.33	3.209	0.57
Effects of Wellbeing Latent Variables on Indicators				
Mathematics	1.000			
Reading	0.910	11.15		
External Behavior (log)			1.000	
Internal Behavior (log)			1.060	32.56
Health			0.695	8.24
Intercepts of Wellbeing Indicators				
Mathematics	51.928	9.51		
Reading	48.395	9.02		
External Behavior (log)			114.293	118.37
Internal Behavior (log)			108.344	17.23
Health			410.337	76.39
Correlation of Latent Variables	88.413	3.83		

Note: Due to the small scale size of the behavioral and physical health variables, the independent variables showed small coefficients. We multiply the three indicators by 100 and present the estimates.

Table 6b. Equivalence of Crowded Housing Effects on Wellbeing, MIMIC 2, LAFANS

	Cognitive	Health
Mom Education Level (yrs)	-1.5	-3
Family Income	-$30,000	-$80,000
Never Married Parent (v. 2-Parent)*	1/3	1/4

Note: * These values refer to the fraction of the Never Married coefficient, in reference to two-parent households, on wellbeing.

Table 7. The Effect of Noise Inside the House on the Relationship between Crowding and Child Wellbeing, 2002

Dependent Variable	Crowding (without Noise)		Crowding (with Noise)		Noise Inside the House	
	Coef.	p	Coef.	p	Coef.	p
Math (N=1360)	-1.7836	0.107	-0.9261	0.411	-1.6425	0.002
Reading (N=941)	-4.3595	0.063	-3.0108	0.212	-2.1591	0.007
Internal Behavior Problems (N=1765)	-0.0252	0.278	-0.0366	0.108	0.0524	0.000
External Behavior Problems (N=1824)	-0.0031	0.885	-0.0104	0.618	0.0325	0.004
Health (N=1832)	-0.0201	0.669	-0.0117	0.801	-0.0363	0.185

Note: Each model is based on Model 3, using robust standard errors. The sample is based on the sample used in all prior PSID-CDS analyses, but with the added restriction that there must be a non-missing value for noise inside the house. Coefficients of other variables are available upon request.

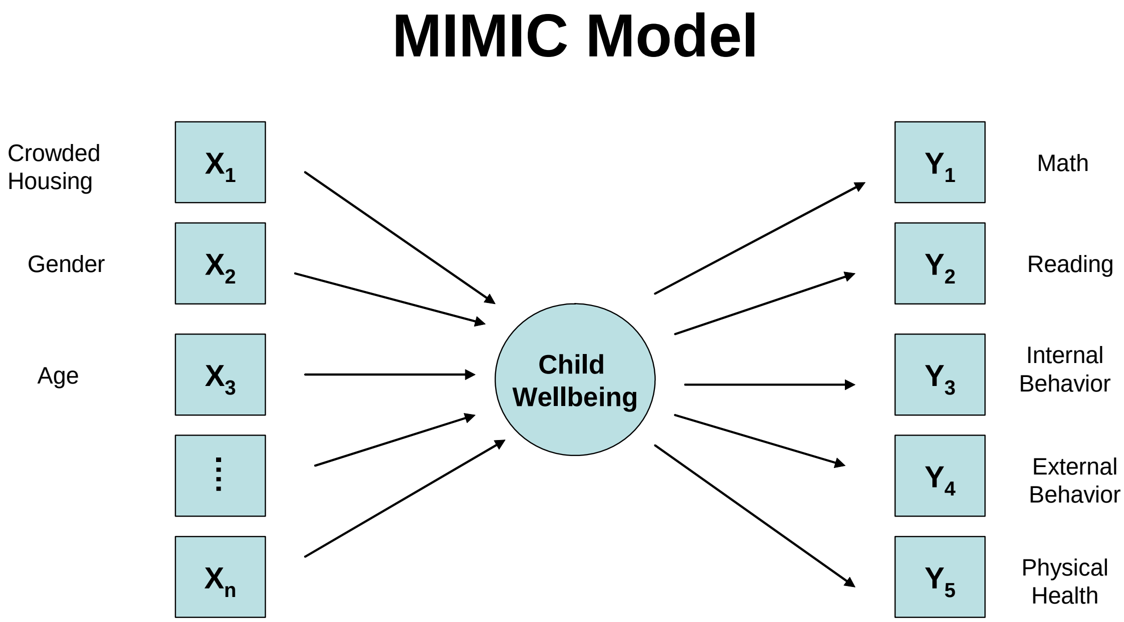


Figure 1a. Multiple Indicators, Multiple Causes model with one latent variable

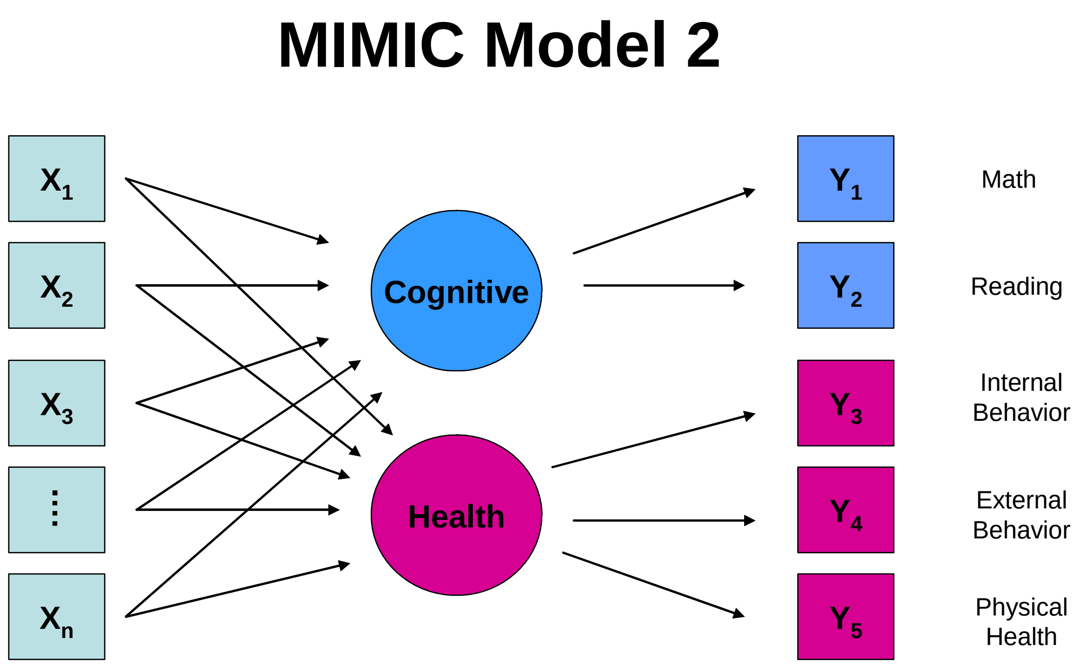
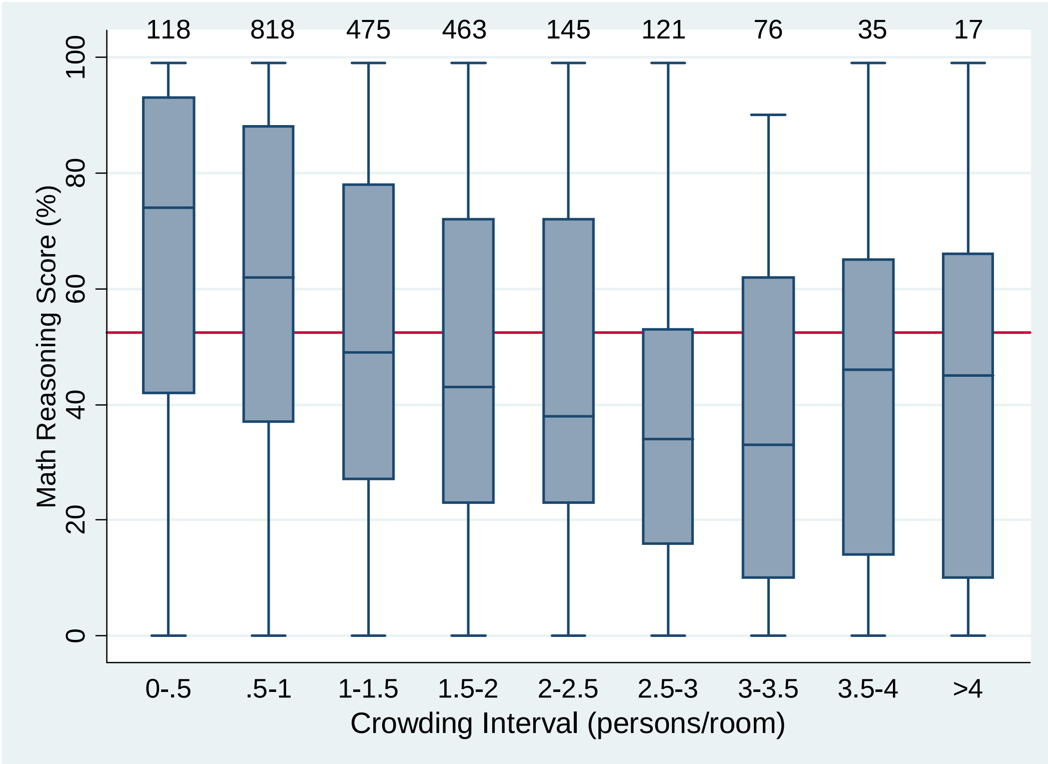


Figure 1b. Multiple Indicators, Multiple Causes model with two latent variables – cognitive and health wellbeing



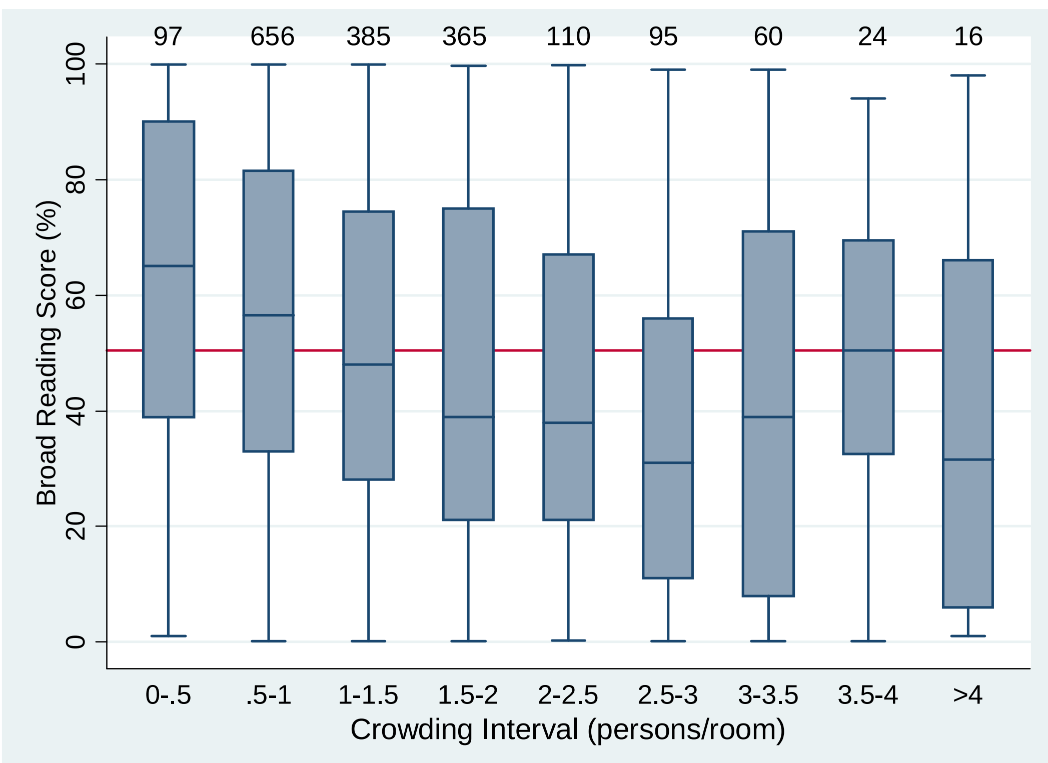
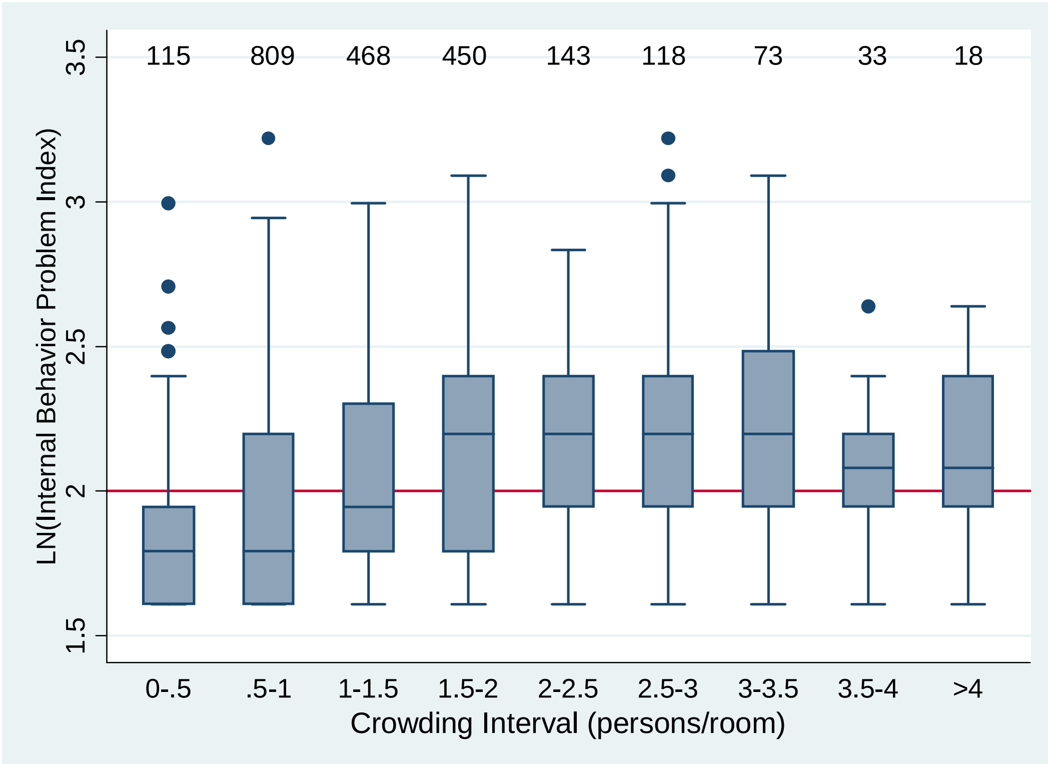


Figure 2a. Boxplots for Associations Between Math and Reading Scores and Household Crowding



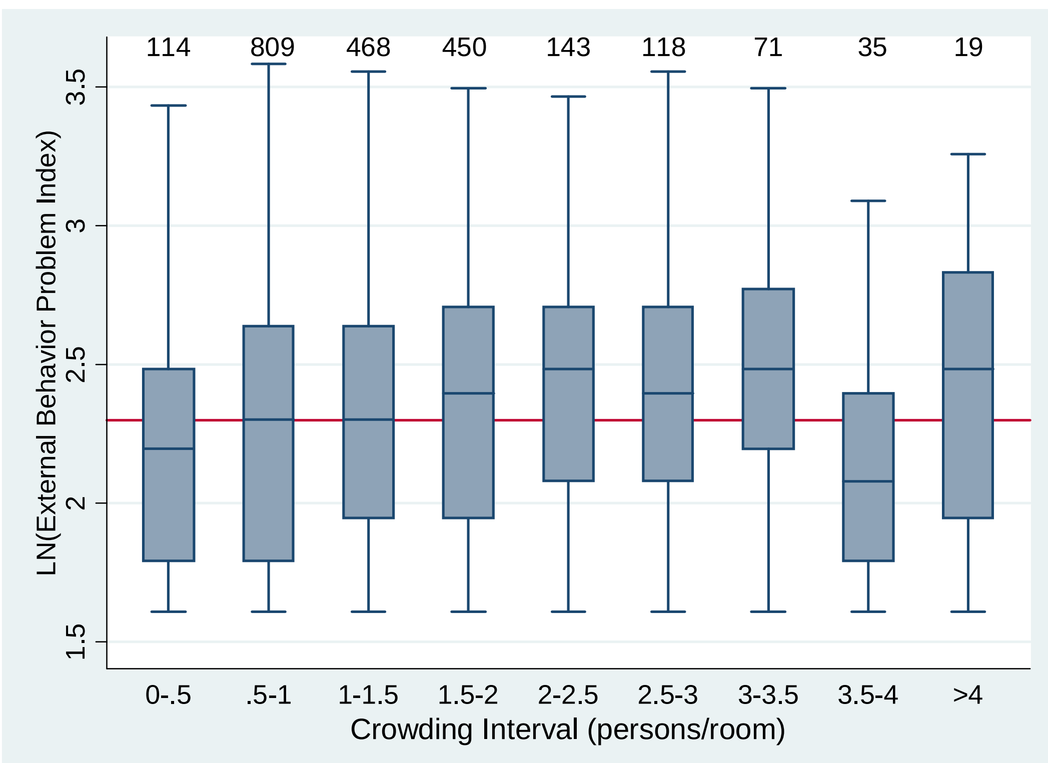


Figure 2b. Boxplots for Associations Between Behavioral Problems and Household Crowding

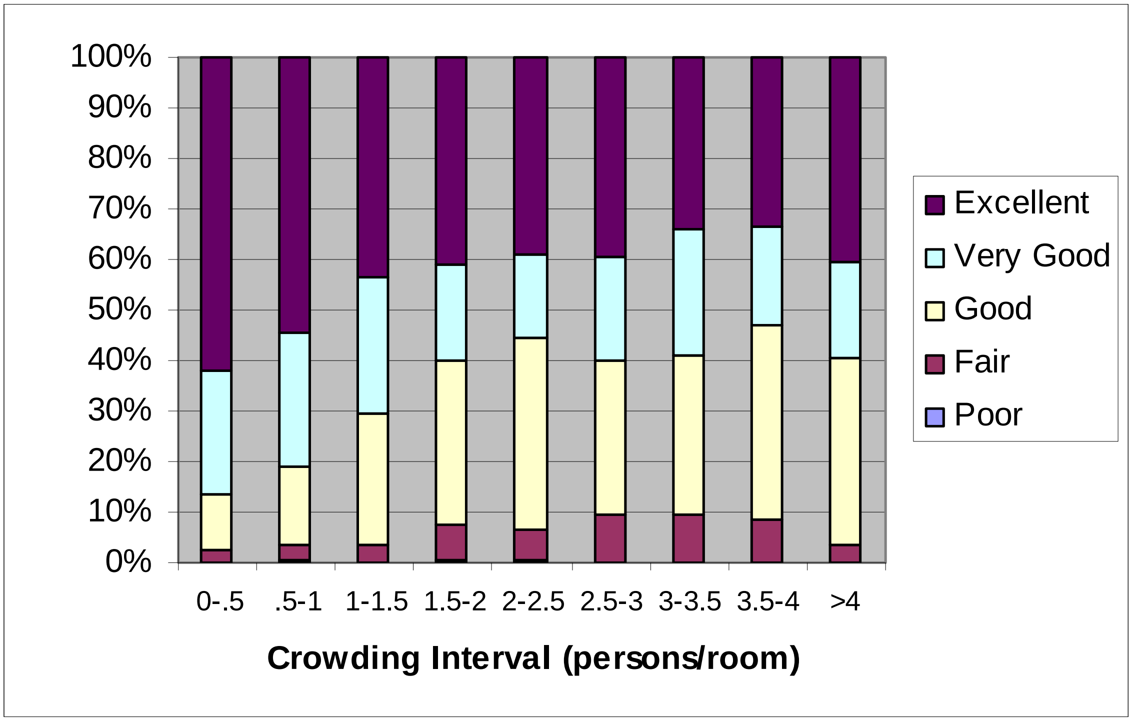


Figure 2c. Association Between Child Health and Household Crowding

Appendix A.

Table A1. Model 3 measuring Mathematics Score, Rating Score, Internal Behavior Problem Score, External Behavior Problem Score and Health Rating, LAFANS 2000

Independent Variables	Math (N=2265)		Reading (N=1806)		Internal Behavior (log) (N=2224)		External Behavior (log) (N=2223)		Health (N=2301)	
	Coeff.	p	Coeff.	p	Coeff.	p	Coeff.	p	Coeff.	p
Crowding	-2.068 (.943)	.031	-2.042 (1.203)	.093	.026 (.010)	.016	.044 (.016)	.006	-.044 (.021)	.038
Male	3.209 (1.695)	.062	-7.250 (1.856)	.000	-.007 (.014)	.598	.068 (.019)	.001	-.046 (.038)	.236
Age	-.450 (.178)	.013	-1.918 (.230)	.000	-.004 (.002)	.055	-.009 (.003)	.003	-.006 (.006)	.346
Divorce/Separated (vs. Married)	-.718 (2.353)	.761	-1.886 (3.009)	.532	.010 (.030)	.729	.031 (.035)	.380	-.223 (.082)	.008
Never Married (vs. Married)	-4.101 (2.241)	.071	-8.634 (2.383)	.000	.111 (.029)	.000	.130 (.039)	.001	-.023 (.078)	.766
Native Born (vs. Immigrant)	-2.738 (2.332)	.244	-7.429 (2.577)	.005	-.063 (.041)	.134	.078 (.047)	.102	.160 (.072)	.028
Mom Education	1.458 (.214)	.000	1.399 (.304)	.000	-.009 (.003)	.002	-.008 (.004)	.003	.035 (.008)	.000
Income (in 1000s)	.071 (.014)	.000	.074 (.010)	.000	-.0003 (.0001)	.020	-.000 (.000)	.895	.0003 (.0003)	.325
Latino/other (vs. White)	-9.629 (2.634)	.000	-6.094 (3.155)	.057	.023 (.030)	.446	-.021 (.049)	.668	-.277 (.079)	.001
Black (vs. White)	-8.742 (3.918)	.028	-7.544 (4.977)	.133	-.017 (.044)	.691	-.037 (.049)	.606	-.445 (.145)	.003
Asian (vs. White)	.728 (3.196)	.820	-1.608 (4.019)	.690	-.039 (.063)	.538	-.083 (.077)	.288	.095 (.099)	.338
Intercept	45.989 (5.126)	.000	66.376 (7.070)	.000	2.132 (.062)	.000	2.368 (.083)	.000	4.071 (.142)	.000
R-square	.2005		.2114		.1099		.0516		.1423	

Table A2. Model 3 measuring Mathematics Score, Reading Score, Internal Behavior Problem Score, External Behavior Problem Score and Health, PSID-CDS 1997

Independent Variables	Math (N=1447)		Reading (N=998)		Internal Behavior (log) (N=2023)		External Behavior (log) (N=2138)		Health (N=2084)	
	Coeff.	p	Coeff.	p	Coeff.	p	Coeff.	p	Coeff.	p
Crowding	-5.3264	0.000	-4.5829	0.003	0.0415	0.039	0.0198	0.253	-0.0719	0.162
Male	4.1359	0.000	-3.7830	0.003	0.0864	0.000	0.0111	0.518	-0.0660	0.133
Age	0.8878	0.000	0.7748	0.014	-0.0084	0.024	0.0241	0.000	0.0083	0.274
Divorce/Separated (vs. Married)	0.4784	0.743	3.4594	0.115	0.1321	0.000	0.1123	0.000	-0.0365	0.594
Never Married (vs. Married)	2.4470	0.444	0.3142	0.916	0.0907	0.012	0.0240	0.012	-0.0527	0.555
Immigrant (vs.Native Born)	2.1017	0.829	na		-0.1316	0.010	-0.0097	0.796	-0.1040	0.362
Mom Education	1.4254	0.000	1.6725	0.000	-0.0149	0.002	-0.0068	0.076	0.0491	0.000
Income (in 1000s)	0.0314	0.001	0.0342	0.021	-0.0001	0.397	0.0001	0.714	0.0000	0.976
Latino/other (vs. White)	-4.7030	0.272	-5.8572	0.167	0.0193	0.704	-0.0129	0.771	-0.0047	0.961
Black (vs. White)	-7.8449	0.000	-7.6467	0.000	-0.0474	0.101	-0.0862	0.000	-0.3675	0.000
Intercept	85.9847	0.000	83.7318	0.000	2.4562	0.000	1.8459	0.000	3.8276	0.000
R-square	0.21		0.22		0.06		0.072		0.089	

Note: Missing values were imputed for those with >5% missing. Those coefficients are not presented here. No Immigrants were given the Woodcock-Johnson reading tests in 1997.

Table A3. Model 3 measuring Mathematics Score, Reading Score, Internal Behavior Problem Score, External Behavior Problem Score and Health, PSID-CDS 2000

Independent Variables	Math (N=1447)		Reading (N=998)		Internal Behavior (log) (N=2023)		External Behavior (log) (N=2053)		Health (N=2084)	
	Coeff.	p	Coeff.	p	Coeff.	p	Coeff.	p	Coeff.	p
Crowding	-1.6442	0.104	-4.2114	0.048	0.0029	0.884	-0.0180	0.401	-0.0257	0.563
Male	4.4834	0.000	-2.9852	0.042	-0.0194	0.360	0.0431	0.053	-0.0044	0.924
Age	-0.9335	0.000	-0.2800	0.416	-0.0058	0.117	-0.0090	0.024	-0.0055	0.504
Divorce/Separated (vs. Married)	1.1711	0.460	2.4706	0.365	0.0708	0.023	0.0927	0.002	-0.0894	0.187
Never Married (vs. Married)	-1.6251	0.455	1.0112	0.804	0.0921	0.071	0.1431	0.002	-0.3115	0.004
Immigrant (vs.Native Born)	1.7079	0.767	(dropped)		-0.0877	0.147	-0.2489	0.000	-0.0320	0.793
Mom Education	1.7397	0.000	2.0639	0.000	-0.0136	0.008	-0.0165	0.002	0.0548	0.000
Income (in 1000s)	0.0075	0.149	0.0058	0.223	-0.0001	0.316	-0.0001	0.441	0.0002	0.233
Latino/other (vs. White)	-4.7841	0.168	-6.8928	0.207	0.0687	0.215	0.1125	0.027	-0.0605	0.461
Black (vs. White)	-10.4978	0.000	-11.7027	0.000	-0.0886	0.005	-0.0160	0.634	-0.1289	0.038
Intercept	95.2444	0.000	87.6211	0.000	2.3142	0.000	2.5914	0.000	3.8155	0.000
R-square	0.243		0.196		0.033		0.055		0.091	

Note: Missing values were imputed for those with >5% missing. Those coefficients are not presented here. The sample consists of those in 2002 whom have values in 1997. For this reason, there were no immigrants in the reading model sample.

Appendix B. Percent Occupied Housing Units with 1.01 or More Occupants Per Room

	Census 2000	AHS 2001	AHS 2003	ACS 2003	ACS 2004
LA County	22.9				12.7
CA	15.2			9.9	
US	5.7	2.5	2.4	3.8	

Note: There are other datasets aside from Census that offer crowding information. These include the American Housing Survey (AHS) and the American Community Survey (ACS). However, because these datasets do not offer time-trends, we did not include these figures in Table 1. Furthermore, the estimates offered by AHS and ACS do not correspond well to those offered by Census. The 2001 and 2003 American Housing Survey's (AHS) U.S. estimates and the 2004 American Community Survey (ACS) county and city-level estimates offer considerably lower percentages for occupied housing units greater than one person per room compared to Census national-, county-, and city-level estimates in general, including L.A. County. According to Census staff, there were underestimates of rooms and overestimates of household size in the Census, partly due to the nature of self-response surveys. They note that "self-response modes for a single question asking for the total number of rooms in the housing unit, where the definition of a room is subject to interpretation, is likely to produce a different estimate than a survey … conducted by interviewers, that asks a battery of questions on how many rooms of specific types are in the unit" (Chapin, Marie, Love, & Cresce 2006) The ACS uses experienced field representatives to clarify the questions on number of rooms for respondents, improving the accuracy of the measure; however there is no accurate longitudinal information available. The LAFANS gathers information on number of rooms through both a single item question, but it is asked by and also confirmed by an interviewer, which, by the above rationale, makes this figure more accurate than the Census figures. Though the estimates in AHS and ACS are consistently lower than Census, the comparisons between cities, counties, and the nation are consistent within datasets.