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Jens Ludwig
Helen F. Ladd

February 1998 #1

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Draft date: February 26, 1998

HELEN F. LADD
Sanford Institute of Public Policy
Duke University
Box 90245, Durham, NC 27708-0245
hladd@pps.duke.edu

JENS LUDWIG
Northwestern University / University of Chicago Joint Center for Poverty Research and Georgetown University
2046 Sheridan Road, Evanston, IL 60208
ludwigj@nwu.edu

Word Count for Abstract: 115
Word Count for Text: 9,348

This paper was written in part while Ludwig was a National Academy of Education / Spencer Foundation Postdoctoral Fellow in Education, and was also supported by grants from the U.S. Department of Housing and Urban Development, the Spencer Foundation, the Georgetown University Graduate School of Arts and Sciences, and the Mellon Foundation (Ludwig). Thanks to Gary Brager, Rohit Burman, Robert Crain, Joe Darden, Dick Doran, Judie Feins, Bob Gajdys, Janice Gentry, Martin Gould, Joseph Hawkins, Rebecca Hawkins, Paul Hirschfield, Laura Hodges, Matthew Kazcmierzak, Jeff Kling, Debbi Magri-McInnis, Juan Carlos Mendoza, Carter Nicely, Terence Trader, Kerry Whitacre, Amy Yost, and Philip Walsh for valuable assistance. Special thanks to Ruth Crystal, Greg Duncan, John Goering, Jennifer Hochschild, Christopher Jencks, Shazia Miller, James Peterson, Steve Pischke, Jim Rosenbaum, Julie Wilson, and seminar participants at the November 1997 HUD MTO Conference and the University of Chicago for helpful comments. The views expressed here reflect those of the authors alone.

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Abstract

This chapter focuses on the effects of the MTO demonstration in Baltimore on the educational opportunities of participating children. Our analysis of the distribution of affordable housing in the Baltimore area suggests that children in experimental group families who relocate will attend better schools, though this is less clearly the case for comparison group families, most of whom are expected to stay within Baltimore City. We find that, relative to the control group, children in comparison and experimental group families attend schools with higher average pass rates on standardized achievement tests, though these differences seem to be due primarily to higher resources and more advantaged student populations rather than differences in the effectiveness of schools.

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I. Introduction

The problems with education in our urban areas are well known. In major cities throughout the country, student test scores are extremely low and drop out rates are high. Given the increasing importance of education to a student's future success in the labor market, these abysmal educational outcomes mean that large groups of children, many of whom are from minority and economically disadvantaged backgrounds, are not getting the skills they need to compete effectively for future jobs. Addressing these problems has become increasingly urgent, as the earnings of workers with low skills have decreased both absolutely and relative to those with higher skills (Murnane, Willett and Levy, 1995, Murnane and Levy, 1996, Blank, 1997).

Because education can be viewed as the outcome of a process that involves family, neighborhood, and school inputs (Clotfelter, 1993), the educational challenges faced by many urban children are daunting. First, many of them have poor parents, who have themselves not gone far in school. As is well known, family background, especially the education level of the child's mother, has a big impact on the performance of students (Mayer, 1997). Second, low-income urban children may live in neighborhoods that have few role models to demonstrate the relationship of education to future labor market performance or are otherwise not conducive to educational achievement (Wilson, 1987, Ludwig, forthcoming, Turner and Ellen, 1997). Third, the schools they attend may be of low quality either because of insufficient resources or because they are poorly structured to deal with the multiple challenges they face.

Strategies to improve educational outcomes for disadvantaged youth include restructuring urban schools to make them more effective, augmenting resources, integrating schools through bussing and other methods, and more recently, as in Milwaukee and Cleveland, providing vouchers to children who wish to attend private schools. While some of these programs appear to be effective in some schools, mechanisms for improving the effectiveness of schools on a large scale remain elusive. Moreover, these strategies focus on the school inputs alone and do little to change the other contributors to educational outcomes, including the family and neighborhood influences that affect the child.

Another potential strategy for improving the educational opportunities of poor inner city children is residential relocation, an idea that is attracting attention in part because of the shift in U.S. housing policy away from public housing in favor of private housing for low-income households. The possibilities of residential relocation are highlighted by the Gautreaux program in Chicago. Under this program, which resulted from a court case in the mid-1970's, families in inner city housing projects in Chicago were given the opportunity to move to more racially mixed neighborhoods, including areas in the Chicago suburbs. Programs such as Gautreaux offer the opportunity to improve not only the quality of the publicly provided school inputs available to children, but also the household’s privately provided inputs (for example by improving the labor market or educational opportunities for parents) and the quality of the neighborhood.

Evaluators of that program have concluded that the educational outcomes of children in families moving to suburban areas were improved relative to those of city movers (Rosenbaum, 1995). However, because families under Gautreaux were not randomly assigned to cities or suburbs, questions remain about the effects of relocation on educational outcomes. Of primary concern is that difficult-to-measure family characteristics that are associated with choices about residential location are also associated with children’s outcomes, thereby confounding attempts to isolate the effects of relocation (and neighborhoods more generally) on schooling.

Such questions can now be addressed with data emerging from the Moving to Opportunity (MTO) demonstration, which is designed to move families out of high-poverty housing projects to areas with lower rates of poverty. The experimental design of the MTO demonstration provides a unique opportunity to examine the effects of residential relocation programs: random assignment breaks the link between family preferences and residential location decisions. The purpose of this chapter is to use information from the MTO demonstration in Baltimore to measure the effects of residential relocation programs on the educational opportunities of children.

II. Conceptual Framework

Three steps are required for generating improved educational outcomes through residential relocation programs such as MTO. Since none of these steps is assured, careful empirical research is required to determine the overall effects of such programs on educational opportunities and outcomes. The brief discussion of these three steps in this section puts into perspective the empirical work reported in this chapter, which focuses on educational opportunities at the school level.

Step 1: Successful Relocation For the MTO program to change school, neighborhood and potentially even home inputs into children’s educational processes, families in the experimental group must first successfully identify and obtain private-market housing in a census tract with a low poverty rate. Further, the children themselves must accompany the family to the new neighborhood. Neither of these steps need occur.

Despite the assistance provided to members of the experimental group in Baltimore by the local nonprofit Community Assistance Network (CAN), not all families will successfully relocate. For a variety of reasons, including the federal requirements for the Section 8 program, many landlords are reluctant to accept Section 8 tenants.[1] The combination of the standards for Section 8 payments together with the requirement that a family move to a low-poverty tract reduces the set of available private apartments, a point that we document below. Moreover, many of the experimental group families lack automobiles, and many have networks of friends and family within their old neighborhoods. When directly faced with the tradeoffs involved in relocating to a low-poverty neighborhood, some of these families may choose not to move --particularly those families with strong social networks in their original neighborhoods.

Even if a parent successfully leases a suitable rental unit in a low-poverty area, she may sometimes have trouble convincing her children to move with her. As with adults in the experimental group, children, especially those in their teens, are likely to have networks of friends in their old neighborhoods from whom they are reluctant to part. In some cases, friends and family in the old neighborhood may provide alternative housing options for children not wanting to accompany their families to the new neighborhood.

Step 2: Improvements in Educational Opportunities It is a well known fact that student performance, as measured by test scores, is typically much higher in affluent suburban schools than in urban schools serving large fractions of poor students (Clewell et al, 1995). This observation alone may lead many observers to conclude that the MTO program will lead to substantial improvements in the educational opportunities of participating children. However, several considerations complicate the picture.

First, high average student outcomes within a school need not be a good measure of how effectively the school contributes to the learning of its students. Such outcomes may instead largely reflect the socioeconomic backgrounds of the school's students. Moreover, to the extent that some schools are more effective than others in educating students from particular

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1. Among the Section 8 requirements that landlords may wish to avoid are annual inspections of housing units. In addition, Section 8 paperwork may delay payments, and other tenants may react negatively to Section 8 families.

backgrounds, a school with high average test scores need not be a good school for a specific student. Consequently, the value that MTO children would receive from attending different schools throughout the metropolitan area may not be directly aligned with the average test scores of those schools. However, working in the other direction is the potential for positive spillover effects from the presence of motivated, high achieving students. Thus, the characteristics of a school's population may itself be viewed as an input into the educational process to the extent that students seek to emulate their more motivated and high achieving peers (Jencks and Mayer, 1990). In addition, to the extent that high average outcomes reflect the availability of above-average resources, all students would presumably benefit from those resources.

Limitations on the residential mobility of the MTO families provide a second complication. The success of the MTO program in inducing changes in the school and neighborhood contexts of children may be limited by the fact that participating families are restricted to areas where they can find affordable housing.

Third, enrollment in a school with more favorable average characteristics and student outcomes may or may not lead to an improvement in the specific educational opportunities available to children. For example, MTO children might be placed in classrooms that are less demanding, more populated by low-income or minority students, or staffed by less able teachers than the average classroom within the school. Similarly, MTO children may either choose or be relegated to peer groups within the school or neighborhood that are disproportionately composed of other low-income, minority children. In this case, improvements for MTO children in the quality of schooling as measured by average school characteristics and student outcomes could overstate the improvements in their educational opportunities.

Step 3: Reaction of Families to New Neighborhoods and Schools Finally, for educational outcomes to improve, MTO children must respond positively to the changes in their neighborhoods and schools. Assuming that the average student performance in the new school is higher than in the old school, one possibility is that MTO children will lower their assessments of their own abilities and therefore reduce their effort or possibly drop out of the system. Alternatively, children may respond to the different school and neighborhood norms by increasing their own efforts and raising their educational aspirations (Jencks and Mayer, 1990).
Similarly, MTO parents may respond to more demanding schools and more affluent neighbors by increasing their own time and material inputs into their children's educational processes.

Alternatively, MTO parents may become less confident in their own abilities to assist their children with schoolwork or to effectively participate in school activities, or otherwise react negatively to their new neighborhoods.

Equally important is the decision of MTO families to remain in their new neighborhoods. It is not clear how families will weigh the possible long-term benefits of remaining in their new neighborhoods against any initial difficulties that they experience after moving. Some families may elect to return to areas close to their original neighborhoods.

III. Data

The data used in this paper come from two main sources: survey data collected by Abt Associates at the time of application to MTO (which we refer to interchangeably as "pre-program," "Abt" or "baseline" data); and school-level data on student performance, mobility, and socioeconomic characteristics for every school in Maryland obtained from the Maryland State Department of Education, supplemented by data from the U.S. Department of Education's Common Core of Data, ("school data"). In subsequent work, we plan to examine follow-up, post-intervention surveys that we have conducted for parents and one randomly selected child in each family in each of the three MTO experimental groups in Baltimore ("follow-up surveys"). In this chapter, we limit our attention to information drawn from the follow-up surveys about the schools that MTO children attend.

Abt Baseline Surveys Householders applying to participate in MTO completed a baseline survey questionnaire designed by Abt Associates containing questions about the characteristics of household members (including education and employment information for all adults, and for children, the most recent grade completed, participation in gifted or special education programs, and supervision during the day and evenings), reasons for applying to MTO, feelings about their current housing conditions, services in the current neighborhood (such as travel times to work and to church), recent experiences with crime, social interactions with and assistance from neighbors, and parental involvement with the child's school. A baseline survey is available for each family in the program.

School Data Our school level data come primarily from the Maryland Department of Education. The dataset provides information for 1,287 public schools for the 1992-93, 1993-94, and 1994-95 academic years.[2]

Our dataset contains information on the socioeconomic characteristics of students (such as percent eligible for free or reduced price lunch programs[3]), the proportion of students who are minorities, withdrawals and entries during each school year, dropout rates, the proportion of graduating students who go on to two- and four-year colleges, the percent of students who are absent less than 5 days and more than 20 days. We also have data for student pass rates on the standardized reading and math tests that are part of the Maryland School Performance Assessment Program (MSPAP).[4] Finally, we have data from the Maryland Department of Education for school resources measured at the school-district (county) level.

Sample of Children's Schools Central to the analysis in this chapter is the set of schools that the MTO children attend. We used two methods to identify the schools that children attend:

1. *School records*: For the Baltimore County and City school districts (the residence of most of the MTO families), school officials were able to identify for us the schools attended by 370 of the 1,319 MTO children. The return rate for the City was low because student identification numbers do not correspond to social security numbers, and the district had difficulty identifying children by name. The return rate was higher, but still only 50 percent, in Baltimore County, which uses social security numbers as student identifiers. Several additional schools were identified by the Anne Arundel and Montgomery school districts.

2. *Follow-up surveys*: The other main source of information on schools is our follow-up surveys. Since we included questions about school names only on the child surveys (and not on the parent surveys), we obtained school names only for the randomly-selected school-aged child from the

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2. We deleted 24 of these schools because they report no student population; we believe about half of these schools are evening schools. In addition, we deleted another 7 schools that report only marginal information because they are "Home and Hospital" schools, kindergartens, or "alternative centers."

3. This provides a more accurate measure of economic disadvantage for elementary school students than for high school students since for various reasons, many high school students who otherwise would be eligible do not sign up for subsidized lunches.

4. Average standardized test scores within a school would be preferable to pass rates, but they are not available.

families that we surveyed.5 Some of these schools overlap with those identified from district records. Others represent schools in counties that did not respond to our request for school information.

This strategy generated school matches for 605 of the MTO children. Because the school districts sometimes identified school information for multiple children from the same family, the number of families from which our sample is drawn (396) is less than the number of children in the sample. For a number of reasons, this set of MTO children may not be representative of the overall school-aged population in the MTO program. However, along most dimensions, the children in our subsample are similar to the other children in the MTO program. Analysis in Appendix A shows that they differ only in that they are somewhat older and tend to come from smaller families (which largely reflects our sampling strategy).

IV. Effects of the MTO Program on Potential Opportunities.

By facilitating the move out of public housing, the MTO program changes the set of residential choices available to families with low incomes and, consequently, also the schooling opportunities for their children. The magnitude and significance of the resulting changes are constrained in two ways. First, because relocators in the MTO program have low income and use section 8 subsidies, they are restricted to areas with affordable rental housing. Second, the families in the experimental group must move to census tracts with poverty rates less than 10 percent. We begin by examining the effects of these constraints on the potential location decisions of MTO families and on the quality of schools to which they have access. We reserve to Section V an analysis of the actual locations and schools that the MTO families chose.

Housing Market and Program Constraints The first question is where within the metropolitan area the rental housing units that participants in the MTO program can afford are located. The rent that participants can afford depends in part on whether they receive Section 8 housing certificates or vouchers. Because the variation in utility allowances for housing support through certificates makes it difficult to specify an affordable rent for that type of support, we focused on

5. For those children living in Baltimore City, or Anne Arundel, Baltimore or Montgomery counties, in some cases the schools reported on the follow-up surveys were different from the schools reported by the school districts. Our default was to use the school names reported by the school districts, though we replicate all of our analysis using the school names listed on the follow-up surveys in such cases as well. The results are generally not sensitive to these decisions.

the maximum rent participants could afford with vouchers. Families receiving Section 8 vouchers receive a subsidy based on the Federally-defined Fair Market Rent (FMR), which varies by county and housing unit size. Families receive a subsidy equal to this payment standard minus 30 percent of the family's income. Families are allowed to lease units with rents that exceed the voucher payment standard, though CAN strongly discouraged families in the Baltimore MTO demonstration from spending more than 40 percent of their income on rent plus utilities. Given the incomes of most MTO families, this is equivalent to discouraging them from leasing units with rents that exceeded the FMR by more than $100 per month.

In the following analysis, we identify housing that is affordable to MTO families as the voucher standard in each jurisdiction augmented by $100 (appropriately deflated to make the figures comparable to the rents in the 1990 census). Based on these rents, we use data from the 1990 Census to calculate the number of rental units affordable to MTO participants in each census tract, expressed as a share of the total number of affordable rental units in the Baltimore metropolitan area.[6,7] These calculations account for the fact that the Section 8 voucher payment standards vary by county and housing unit size.[8] Since many landlords are reluctant to accept vouchers or certificates in lieu of cash, our estimates are likely to overstate the access of MTO families to the private housing market.

Table 1 reports our estimates for the distribution of affordable rental housing throughout the Baltimore metropolitan area (defined as Baltimore City, Baltimore County, Anne Arundel

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6. We first calculate (p_{ij}), the number of housing units in tract (j) of size (i) that had rent levels below the Section 8 payment standard plus $100, divided by the total number of affordable housing units of size (i) in the entire Baltimore metropolitan area. We then calculate the fraction of the Baltimore area's affordable rental housing located in tract (j) as $p_j=\sum_i (p_{ij})$, and the fraction of the area's affordable rental housing in each county by summing across both housing unit sizes and census tracts within the county, or $p_c=\sum_j\sum_i (p_{ij})$.

7. CAN staff informed us that no families rented single-bedroom units because families with children are typically eligible for units with at least two bedrooms. As a result, we did not count any one- or no-bedroom units as "affordable" in our calculations, regardless of the rent prices for these apartments. The maximum voucher payment for a five-bedroom apartment was equal to the four-bedroom payment adjusted upwards by 15 percent, per Federal regulations.

8. We also experimented with adjusting for the rental vacancy rate within census tracts. With this adjustment we found no statistically significant relationships between any of the housing accessibility measures and school quality. This could reflect the effects of at least two sources of measurement error with the vacancy variable. First, the 1990 vacancy rate within an area's rental market will be at best a rough approximation of the area's vacancy rate when MTO families entered the market during 1994 and 1995. Second, the 1990 Census does not provide vacancy rates separately for units in different rent categories, so we are only able to calculate the overall vacancy rate for all rental units within a tract.

County, and Howard County). It shows that over half of all of the rental units within the Baltimore metropolitan area that are affordable to MTO families are located in Baltimore City. Given the transportation advantages and access to friends and family obtained by relocating within the city, together with the possibility of racial discrimination in the suburbs, this pattern suggests that families in the comparison group of the MTO program are much more likely to move to other parts of the city than to move to the suburbs.

The prediction differs for families in the experimental group because members of that group are required to move to census tracts with low rates of poverty. We estimate that almost four-fifths of all of the affordable rental units in low-poverty tracts in the Baltimore area are located outside the city. Thus, we predict that a much larger proportion of the experimental group than of the comparison group families are likely to move outside the city. However, the exodus from the city is not likely to be dramatic given other forces such as availability of public transportation and support groups that may keep these families in the city.

School Quality in Areas Available to MTO Families

Of particular interest is how the constraints imposed both by the rental housing market and the program requirement of low-poverty census tracts affect the educational opportunities available to MTO children as measured by the resources of the schools, the challenges they face, and student outcomes.

The resources available to specific schools results reflect a variety of considerations such as the ability and willingness of the school district to raise local property tax revenue for schools, the formula by which state education aid is distributed among school districts, the mechanism by which the district distributes resources to schools within the district, and the amount of federal aid available through the Chapter 1 program and other programs to meet the special needs of disadvantaged students.

Unfortunately, no information on resources is available at the school level. Hence, we must rely on district-level data, some of which is presented in Table 2. With only $124,290 in property wealth per pupil, the City of Baltimore has less than one half of the wealth of the other school districts in the Baltimore area and, hence, is significantly less able to raise revenue through the property tax for local schools. Some of this disparity in wealth is offset by federal and state aid, which combine to make it possible for the city to spend about 90 percent of what schools in Baltimore County can spend on education. However, given the greater educational needs faced by the children in the city, the remaining difference in spending presumably translates into an even greater difference in the level of services provided.

Table 3 describes the characteristics of students within Baltimore area public schools by four categories that are relevant for the MTO program. The categories include the 65 MTO baseline schools, attended by the children of MTO enrollees at the time they signed up; the 114 other public schools in Baltimore City which represent the set available to most of the comparison group children; the 328 schools in the Baltimore suburbs, some of which are available to the children in the experimental group; and, for purposes of comparison, all 1,256 public schools in the state. All of the averages are weighted by school enrollment so that they refer to the school of the typical student in each category.

Table 3 shows that the challenges facing city schools -- whether MTO baseline or other schools -- are much greater than those facing suburban schools. The city schools have much higher proportions of poor children (as measured by participation in subsidized lunch programs), children who are absent more than 20 days per year, and much higher rates of student mobility as measured by the percentage of students leaving the school in any year. Thus the city schools are serving a large group of students who are likely to be less well prepared to learn than students from more advantaged backgrounds. In addition, these students may create negative spillovers on the learning of other students, which exacerbates the task of educating all students in the school (Jencks and Mayer, 1990). It is hard for schools to provide a coherent education either to the absent and mobile students or to the students who are continuously enrolled (for example, see the evidence in Ferguson and Ladd, 1996).

Thus, the schools attended by children who move out of public housing projects to other parts of the city (as would be the ca se for most of the comparison families and some of the experimental families) are likely to end up in schools facing many of the same challenges faced by the schools that the students were in before their move. Although the non-baseline city schools face somewhat smaller challenges than the baseline schools in terms of rates of absenteeism and mobility, significant challenges remain in the city schools. In contrast, a move out of the city to the larger Baltimore area could, in principle, put a child in a school with a significantly more advantaged student body. However, given the constraints of the housing market, such an outcome is not guaranteed.

Student outcomes can be measured by the rates at which high school students drop out of school or graduates continue on to college, or by student performance on tests. Drop out rates in city schools are typically far higher than those in the suburbs or the state as a whole. In 1994-95, drop out rates in the baseline schools were 13.1 percent, in the rest of the city 9.5 percent, and in the suburbs only 2.8 percent. Similarly, the percentage of high school graduates continuing on to college was much lower in the city than in the suburbs. These patterns are similar to the patterns of test results in the lower grades which is what we focus on here.

Table 4 reports information on student outcomes for fifth grade students on the Maryland School Performance Assessment Program (MSPAP). The entries in the first four rows are the average percentages of the students who scored satisfactory or above on the test. These averages reflect not only the effects of the schools themselves but also the effects of the factors such as family background and neighborhood characteristics that also affect student outcomes.

The patterns are striking. The rates of satisfactory performance for all fifth graders are extremely low in the MTO baseline and city schools relative to schools in the Baltimore area and the rest of the state, although rates in those areas are fairly low as well. The low rates of satisfactory performance in the city schools are cause for concern. Whether because of the greater challenges of educating students in an urban setting, insufficient resources, or inefficiencies in the system, schools in Baltimore City schools are having difficulty preparing their students for labor markets that are placing an increasing value on education.

Because most of the children in the MTO program are African American, it is instructive to look at the comparisons for black students alone as in rows 3 and 4.[9] Those results are similar to those reported for all students: typically test results are the weakest for the MTO baseline schools and are only slightly better for the group of all city schools. Results for schools in the larger Baltimore area are quite a bit better, as are those in the state as a whole.

From the perspective of a typical student, schools with higher average student outcomes are preferable to those with lower student outcomes to the extent that high-performing peers generate positive spillover effects, an outcome that is plausible but not convincingly documented (Jencks

9. Note that our average test results for blacks should be viewed as only approximate. Although we have test results disaggregated by race and gender, we do not have from the Maryland Department of Education the numbers of students in each racial and gender group taking the test. The figures in the table assume that 50 percent of the students are male and 50 percent are female. Further, these weighted results are based on 1993 data on the number of black children by school from the NCES Common Core of Data.

and Mayer, 1990, Evans, Oates and Schwab, 1992) or to the extent that the schools enjoy greater resources. However, because high average outcomes may largely reflect the socioeconomic backgrounds of a schools' students rather than the effectiveness of the school itself, we would prefer to measure a school's effectiveness by its value added, that is, the contribution of the school to the learning of its students after adjusting for the effects of student characteristics and their prior performance. Our value-added measures are calculated as the actual 5th grade pass rate on the state reading and math tests that we observe within a school minus the pass rates that we would predict for the school given the socioeconomic characteristics and 3rd grade pass rates for the school's students. (See Appendix B for additional discussion of these value-added measures).

The bottom of Table 4 reports the medians of value-added measures across the schools in each category. Because the approach is subject to some error for individual schools, we prefer the median to the mean as a measure of the average value added by type of school. The more negative is the entry, the less effective is the category of schools. A school could emerge as ineffective by this measure for any one of the following reasons: it has too few resources, it uses those resources ineffectively toward the goal of student learning, or concentrations of disadvantaged children generate negative spillover effects. The pattern of results at the bottom of Table 4 indicate that by our measure of value added, schools in the city appear to be less effective that the schools in the suburbs or in the state.

By adding to the value-added equation dichotomous indicator variables for the affordability of the housing stock, we can examine the relative effectiveness of the public schools that are located in the census tracts that are most accessible to MTO comparison group families. (In the absence of information about school catchment areas, we must assume that each school serves students in the census tract within which the school is located). To construct the accessibility measures we first rank the schools in the Baltimore area by the percentage of the area's housing stock that is affordable and accessible under Section 8 standards and then divide them into quartiles, which allows for a nonlinear relationship between rental housing and school quality. Schools in the lowest quartile are those with the lowest proportion of housing units affordable to MTO families, and serve as our base category. A separate variable is included to indicate those schools in Maryland that are outside of the Baltimore area.

The results are presented in Table 5. The schools that are likely to be most accessible to families with Section 8 vouchers (that is, are located within census tracts with the highest proportions of housing units that are rental and affordable) appear to be significantly less effective in mathematics than the schools that are located in census tracts with fewer affordable rental units. The quartile 3 and 4 coefficients of -0.27 and -0.16 translate into differences of 16 and 7 percent in pass rates in the most accessible areas compared to the least accessible areas. We produce qualitatively similar findings using alternative value-added model specifications, such as a model that controls for student body SES but not third grade pass rates.

Experimental group families will be similarly constrained to apartments with rents below the Section 8 payment standards. However, the MTO requirement that such families move to census tracts with low poverty rates eliminates from consideration much of the housing in the Baltimore area. The questions of interest are whether housing market constraints push experimental families into the least effective schools within the low-poverty areas of Baltimore, and whether these schools are in fact better than those found in areas with more poverty. In Table 6, we have constructed a separate category for all the schools located in census tracts in the Baltimore area with poverty rates of 10 percent or more, and then have classified the remaining schools by quartiles based on the availability of affordable housing. Schools in low-poverty areas with the smallest proportions of affordable rental housing serve as the comparison group, and a separate indicator variable is included for Maryland schools outside of the Baltimore area.

The table shows first, and most clearly, that housing programs that do not require families to move to areas of low poverty may condemn the children of such families to the schools that are least effective. This conclusion emerges from the coefficient of -0.64 for reading and -0.66 for math which translate into differences of 46 percent and 32 percent in pass rates for students in high poverty compared to low poverty areas. Within the set of low-poverty census tracts, we find some evidence to suggest that the schools in low-poverty areas with relatively large numbers of affordable rental units are less effective in math than those schools few affordable rental units, though this finding is somewhat sensitive to the specification for the value-added model.

V. School and Neighborhood Outcomes for MTO Participants

The previous section focused on how the market and program constraints implicit in the MTO demonstration might affect the educational opportunities of the MTO children. This section shifts the focus to the decisions actually made by program participants.

Program Population

The participants in the MTO program reflect the census tracts from which they came, ones in which the average poverty rate was 67 percent in 1990. When the program was initiated, the tracts had four low-rise and four high-rise public housing projects which housed 3,807 families, with an average income of $6,880. Virtually all (99.6 percent) of the families were African American (Goering, 1996). Information from the baseline surveys (Table 7) indicates that families who apply for MTO are almost exclusively African American, were headed by a female, and had very low incomes.

The average MTO household in Baltimore had 2.6 children and four out of five of the families contained at least one school-aged child at the time they applied. The educational experiences of the MTO children at the time of the baseline surveys varied greatly, with some doing well and others having problems. About one of five MTO families had a child who has received services for learning problems. At the same time, about one out of six had a child who receives services for gifted or advanced education. The baseline surveys also showed that parents were involved in their children's schools. The majority attended a meeting or event at the child's school in the past year, and nearly half volunteered at the school in some capacity. These figures compare favorably with national samples of African-American and white parents (Cook and Ludwig, 1997).

With random assignment of families to the three treatment groups (experimental, comparison, and control), the characteristics of MTO families should differ across groups only by chance. This appears to be the case. Based on the averages by group in Table 7, we use multivariate analysis of variance to test the null hypothesis that the sets of means are equal across each of the three MTO groups (See Johnson and Wichern, 1992). The relevant test statistic implies families in the three groups are not different with respect to these variables.10

Relocation Patterns

We present the relocation results for experimental and comparison group families in Baltimore in Table 8. Of the 273 families who were randomly assigned to the experimental group, 146 successfully relocated to a low-poverty area. The 53 percent lease-up rate for the Baltimore experimental group is substantially higher than the 25 percent rate experienced by Gautreaux families in Chicago (Goering, 1996), though lower than the 77 percent relocation rate among the

10. The value of Wilks' Lambda for the full set of means presented across Tables 9 and 10 is equal to 0.735, with an F-statistic equal to 0.97 and probability value of 0.57.

Baltimore MTO comparison group. We return to the question of which families are more likely to relocate than others below.

Of the 146 experimental group relocators, 59 percent relocated to Baltimore City, while the rest relocated primarily in Baltimore and Howard counties (24 and 13 percent, respectively). Although the program required that experimental group relocators move to census tracts with 1990 poverty rates below 10 percent, there was some slippage, with around 9 percent of relocators moving to areas with poverty rates between 10 and 20 percent. In contrast, the vast majority of comparison group families who relocated moved to other parts of Baltimore City (88.5 percent). Of the comparison group relocators, around one in seven moved to tracts with poverty rates with less than 10 percent, while over a third moved to tracts with poverty rates of at least 30 percent.

Comparisons of the Characteristics and Quality of the Schools Attended by Children in the Three Groups

We begin by estimating the effect of randomly assigning families to particular groups within MTO, also known as the "intent-to-treat" effect (Manski, 1996). The results shown in Table 9 indicate that MTO has successfully moved children in both the comparison and experimental group into schools with greater resources and more favorable student characteristics. Less clear is whether MTO moves children into schools that are actually more effective. (The methods used to calculate these results are discussed further in Appendix C).

Compared with children in control group families, children in the experimental group end up in schools that have fewer poor students as measured by the percent of students on free and reduced price lunch (18 percentage points below the control group) or in Chapter 1 programs (17 percentage points below) and lower withdrawal rates (by 4 percentage points). These schools also have more resources, with around $34,000 more wealth per pupil and $200 more in annual per pupil expenditures (equal to 27 and 4 percent of the Baltimore City averages, respectively). Thus, the challenges faced by these schools are lower than those faced by the schools serving children in the control group.

Not surprisingly, these schools also have higher test scores. Their average fifth grade pass rates on the Maryland standardized reading and math tests exceed those of the schools serving the control group children by about 6 percentage points in both subjects. These differences are sizable compared with the average Baltimore City 5th grade pass rates of 8.4 and 16.2 percent for reading and math. At the eighth grade level we observe similarly large differences of 8 and 12 percentage points between the experimentals and the controls in the average pass rates in reading and math.

The results differ quite markedly when we use as the dependent variable our best estimates of each school's value added -- the residuals from the value added regressions. For both the experimental and control groups the value-added residuals are negative in both reading and math, suggesting that these schools underperform relative to what we would have expected given the socioeconomic characteristics of their students. The differences in the value-added residuals are not statistically significant. Hence, being assigned to the experimental group apparently does not substantially improve the average effectiveness of the schools that the children attend. Stated differently, the larger pass rates observed in those schools appears to reflect the higher proportion of children from economically advantaged backgrounds rather than the pure contribution of the school to student learning.

Turning now to the results for children in the comparison group, we find that the estimated effects of random assignment to this group on schooling opportunities are generally favorable and statistically significant, although they are generally between one-quarter and one-half the magnitude of the effects for the experimental group. For example, assignment to the comparison group reduces by 4 percentage points the proportion of students on free and reduced prices lunch (compared to an 18 percent reduction for experimental group); expenditures per student are $60 higher (compared to $202 for the experimental group); and average pass rates in reading are 2 percentage points higher (compared to 6 percentage points for the experimental group). When the outcome variable is our value-added measure of school effectiveness, we find that the schools serving comparison group students appear to be no more effective than schools serving children in the control group.

Because the value-added results are somewhat surprising, we explored the sensitivity of our findings to the specification of the value-added model. We find that our results are fairly robust to different model specifications.11

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11. When we use value-added outcome measures that are kept in log-odds form (rather than converted back into pass rates), the results are qualitatively similar to those presented in Table 9. More parsimonious specifications that control for either previous pass rates or student socioeconomic characteristics, but not both simultaneously, also produce results that are quite similar to those presented in Table 9. The only change is that the estimated effects of assignment to the comparison group on schools' effectiveness in mathematics become slightly larger (by one-half

A potential complication arises because the Department of Housing and Urban Development funded the demolition of several high rise housing projects in Baltimore through the Hope VI program at the same time that MTO was operating. All of the estimates discussed so far treat the movement of control group families occasioned by the Hope VI project as part of the relevant counterfactual, that is, as part of what might have happened to families in the absence of the MTO program. Alternatively, we could view the Hope VI project as an aberrant event that confounds our analysis of the MTO program. Because about 18 percent of all families in the Baltimore MTO demonstration had a baseline address in one of the buildings affected by Hope VI, our conclusions could potentially be sensitive to our treatment of the Hope VI demolitions. Fortunately, they do not appear to be, as we produce generally similar results when we estimate separate intent-to-treat effects for MTO families who reported baseline addresses in one of the buildings affected by Hope VI.

Effects of Relocating to Low-Poverty Areas on School Characteristics and Quality.

As we documented earlier, for a variety of reasons not all the families in the MTO experimental and comparison groups were able to lease-up private-market housing. Moreover, even though they received no relocation assistance through the MTO program, some families in the control group did in fact relocate, and a few (under 3 percent) relocated to low-poverty areas. Some of this movement may simply reflect the typical movement of low-income families. In addition, for a variety of reasons, children in the control group may not remain in their baseline schools; some parents may work creatively to send their children to schools outside of the local catchment area, others may rotate children among relatives living in different catchment areas, or their children may be expelled from a school. Moreover, the movement of families in the control group may be higher in Baltimore than in other MTO sites because of HUD's Hope VI program.

Thus, many MTO families did not receive the "treatment" prescribed for their random-assignment group. Consequently the effects reported in Table 9 of being assigned to each of the different "treatment groups" will understate the effects of relocating to a low-poverty area. In this section, we focus specifically on the effects of relocating to an area of low poverty. That is, we examine the differences between the schools of the families who successfully relocated to areas of

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and one-third percentage points, respectively) and are now statistically significant at the 10 percent level.

low-poverty and the schools of other families. Because successful relocation may be nonrandom, we cannot simply compare the schools of relocators with nonrelocators. Instead, we need to use the outcome of the random assignment process as an instrumental variable in the estimation process. (This method is discussed further in Appendix C).

We begin by examining who relocates. As shown in Table 10, compared with families in the control group, families in the experimental group are 51 percentage points more likely to relocate to a low-poverty area, while those in the comparison group are 6 points more likely to do so. Families with more children are less likely to relocate to a low-poverty area, perhaps reflecting the difficulty of finding suitably large quarters within those communities. Families with higher incomes are also less likely to relocate, which is consistent with the idea that families with relatively greater labor market success in their current neighborhoods may perceive fewer gains from relocating.12 Householders with at least a high school degree or its equivalent were more likely to relocate to a low-poverty area, which could reflect either that more educated participants are more inclined or able to complete the CAN workshop sequence and navigate the challenges of finding and leasing an apartment, or that more educated householders are more eager or able to take advantage of improved employment or schooling opportunities in low-poverty areas.

Table 11 reports the differences in school quality measures between families who have and have not relocated, making use of the results in Table 10 to adjust for the fact that relocation is not random (see Appendix C). The table shows that relocating to a low-poverty area moves MTO children to schools with more favorable characteristics. As would be expected given the 50 percent relocation rates for families in the experimental group, the effects of relocating on school characteristics such as SES of the student body, resources, and average math and reading pass rates are nearly twice as large as the estimated effects associated with being randomly assigned to the experimental group. In contrast, relocating to a low-poverty area apparently does not put the children in schools that are more effective as measured by our value-added variables. Alternative specifications of the value added model do not alter this conclusion. Substituting a probit model for the linear probability model in the first stage also does not significantly change our estimates of the effects of relocating.

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12. Rosenbaum and Popkin (1991) find that suburban relocators in the Gautreaux program in Chicago had higher employment rates, but not higher hourly wages, than those who relocated to other parts of the city of Chicago. In this case, we might expect the greatest benefits of relocation to accrue to unemployed participants in MTO.

Actual vs. Predicted Changes in School Quality.

How do the schools that children of MTO relocators (both in the experimental and in the comparison group) attend compare to the schools that we predicted for them based on the distribution of affordable rental housing within the Baltimore area? Table 12 answers that question.[13] We find that the schools attended by comparison and experimental group relocators have fewer resources, more poor students, lower test scores, and are less effective than what we had predicted from our analysis of the housing stock in the Baltimore area.[14]

Most of the discrepancies between the actual and predicted choices appear to reflect the fact that the MTO families were more attracted to rental units within Baltimore City than to those in the suburbs. To adjust for this preference, we recalculated the predictions taking account of the actual split between suburban and city locations. For example, since 59 percent of the experimental group families chose to stay in the city, we predicted school characteristics assuming that 59 percent were distributed in the city in line with the availability of affordable housing stock in low-poverty areas in the city, and assuming that the other 41 percent were distributed in a similar way in the suburbs. We followed a similar approach for the families in the comparison group. The results indicate that the schools actually serving children in experimental or comparison group families who relocated still have lower pass rates in reading and math than what we predicted based on the distribution of affordable housing throughout the Baltimore area. Yet along most of the other measures of school quality, including our value-added measures, the schools that experimental and comparison group families chose appear to be quite similar to the predicted measures.

Section VI. Discussion and conclusions

How has MTO changed the educational opportunities of children in Baltimore, and how will these changes translate into future educational outcomes? In this section, we review our

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13. We predict the school quality for experimental and comparison group relocators by calculating the weighted average of school characteristics for schools in the Baltimore metropolitan area, with each school weighted by the relevant experimental and comparison housing accessibility measure as discussed in section IV.

14. Note that the results for the experimental and comparison group relocators shown in Table 12 do not exactly correspond to those shown in Table 13. This is because Table 13 presents the actual outcomes for relocating families, while Table 12 presents the predicted outcomes for relocating families as estimated from the instrumental variables regression described in Appendix C.

empirical evidence on the first question, and then discuss the implications of our results for the second question.

Consider first the families in the comparison group. Assuming such families relocated to areas in line with the availability of housing that was affordable under the Section 8 guidelines, a disproportionate share of those families would have stayed in Baltimore City and their children would have attended schools that were quite similar to those they left behind in the original neighborhoods. For experimental families, the additional constraint that they move to Census tracts with low rates of poverty would make them more likely to move to the suburbs. However, this requirement could also make it more difficult for them to relocate successfully. Assuming that families moved successfully, our analysis indicated that children in the experimental families would end up attending better schools, regardless of whether school quality is measured by the socioeconomic composition of the student body, the resources available to the school, average student pass rates on standardized tests, or "value-added" measures of school effectiveness.

The neighborhoods and schools actually chosen by MTO families largely but not fully conform to these predictions. As expected, a smaller proportion of the families in the experimental group successfully relocated compared to families in the comparison group, and among those who did relocate, a larger proportion of them left Baltimore City. Moreover, assignment to the experimental group helped move children into schools that had more resources, more affluent students, and higher pass rates on standardized reading and math tests. The surprising finding, and one that deserves further investigation, is that the schools attended by the children in the experimental group appear to be no more effective in a value-added sense than the schools the children left behind.

The schools actually chosen by members of the comparison group turn out to differ from those of the control group by somewhat more than we predicted based on our housing market analysis. Nonetheless, the differences are still smaller than those for the families in the experimental group. Compared to the control group, the comparison group schools have somewhat lower proportions of students receiving subsidized lunches and higher pass rates on the Maryland tests. However, the schools do not appear to be any more effective than the control schools in terms of our value-added measure of school effectiveness. One explanation for the finding that children in the comparison group improve their schools by moving is that their families care about and were able to identify which of the schools within the neighborhoods to which they had access were the best. An alternative explanation is that their previous adverse experiences with crime led MTO comparison group families to seek areas with relatively low crime rates and that such areas happened to be served by schools with fewer poor children and higher average student performance.

We are relatively confident in our finding that the schools attended by the MTO children (in either the comparison or the experimental group) are better than the control group schools in terms of resources, SES of the student body, and average outcomes. We are less confident of our conclusion that the schools attended by the MTO children are no more effective than those attended by the control group children. That conclusion should be tempered by the empirical and conceptual uncertainties surrounding our value-added measures. First, our value-added measures rely on school- (rather than student-) level data, and make use of psuedo-cohorts to control for difficult-to-observe characteristics of a student population.15 In a separate analysis using student-level data from a different state, we found that the school-level value-added measures that we use in this paper are correlated, but imperfectly so, with "gold standard" value-added measures derived from the student data. Second, our value added measures represent the contribution of each school to student learning, controlling for the effects on learning of the socioeconomic characteristics of the students. Hence, this approach may mask some important differences in school effectiveness. For example, suppose that schools serving higher-SES students are more able to recruit and retain well-trained and talented teachers, who are in turn more able to implement effective instructional practices. If that is the case, our value-added measures will understate the difference in instructional effectiveness between schools serving low and high SES students.

Even if it is true that the MTO program does not put children in schools that are more effective as measured by our concept of value added, the program could still improve the educational outcomes of children. Because children in the experimental and comparison groups end up in schools serving more affluent students with higher pass rates compared to children in the control group, they may benefit from positive spillover effects. Variation in educational environments within a given school also means that the educational opportunities experienced by MTO children could change even if schools did not differ from each other in terms of their average

15. That is, we control for difficult-to-measure characteristics of each group of 5th graders in 1995 by using the pass rates for 3rd graders two years earlier, rather than matching each individual 5th grader in 1995 with her own pass rate in 3rd grade.

effectiveness. However the direction of that change is unclear. Working in one direction, the experiences of MTO children could be below the average experience of other children in the school. This outcome would occur if the MTO children were assigned to less-challenging educational tracks or to the least-effective teachers. Working in the other direction, MTO children could gain access to higher quality remedial and other services in their new schools than would have been available in their old school environments. Finally, the MTO moves may change the behavior of children and parents in ways that are unrelated to school quality but are still quite relevant to the educational outcomes of children. For example, if experimental and comparison group families now live in safer neighborhoods (a likely outcome given the lack of security in the baseline communities), both parents and children may become more engaged in schools, churches, or other activities that may help children's cognitive development.

In future research, we plan to use information from our follow-up surveys to learn more about the experiences of MTO children within their schools and about how parents and children react to their changes in schools and neighborhoods. We also plan to use standardized test score data obtained from the school district offices in Baltimore City and County to learn more about how MTO affects achievement. Finally, because parents' educational or labor market experiences may be relevant for the educational achievement of children, our future work will also examine program effects on employment, job-training and welfare, using information from our follow-up surveys as well as state administrative data on quarterly earnings and participation in social-service programs.

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Table 1
Population and Housing Market Characteristics for Baltimore

	Baltimore City	Baltimore Area*	Anne Arundel County	Baltimore County	Columbia, MD	Howard County**
% of pop in poverty	21.4	4.4	4.0	5.1	2.9	2.8
% of pop black	64.5	12.7	12.0	13.6	20.4	5.6
% housing units rental	46.8	29.3	25.7	32.1	30.8	22.5
Rental vacancy rate	8.4	7.4	5.6	7.8	12.7	7.6
Units that are rental & affordable (as share of total stock of rental, affordable units in Balt. metro area)	53.9	46.1	12.1	28.0	3.7	2.4
Vacant units that are rental & affordable (as share of total stock of vacant rental, affordable units in Balt. metro area)	53.4	46.6	8.8	29.4	6.1	2.3
Units that are rental, affordable & in low-poverty area (<10%) (as share of total stock of rental, affordable units in low-pov areas within Balt. metro area)	22.7	77.3	23.0	41.3	7.9	5.2
Vacant units that are rental, affordable & in low-poverty area (<10%) (as share of total stock of vacant rental, affordable units in low-pov areas within Balt. metro area)	22.0	78.0	17.8	41.5	13.7	5.0

NOTES: Affordable defined using the Section 8 voucher payment standards, as described in text. Low poverty tracts defined as those with poverty rates below 10 percent in 1990. Calculations from 1990 U.S. Census data.
* Baltimore area defined as Anne Arundel, Baltimore, and Howard counties.
** Excludes Columbia, Maryland.

Table 2
Resources of Selected School Districts
(1994-95 School Year)

	Baltimore City	Baltimore County	Anne Arundel County	Howard County	State total (Weighted)
Property wealth per pupil	$124,290	$269,442	$259,609	$282,594	$234,000
Spending per pupil	$5,566	$6,191	$6,144	$6,571	$6,106

Source: Maryland Department of Education.

Table 3
Student Characteristics

	MTO Baseline	City	Suburbs	Rest of State
(As a percent of all students)				
Free and reduced price lunch	66.8	70.6	17.8	30.4
Absent > 20 days	40.3	21.4	8.9	13.6
Withdrawals	25.8	20.5	10.4	12.6

Source: Maryland Department of Education.

Table 4
Student Outcomes*

Percent satisfactory	MTO Baseline	City[a.]	Suburbs[b.]	Rest of State
All students				
5th grade reading	8.4	9.7	35.7	29.8
5th grade math	16.2	17.2	54.8	45.2
Black students				
5th grade reading	7.9	8.1	18.5	14.0
5th grade math	15.6	15.0	29.8	22.3
Value added (All students, medians)				
5th grade reading	-3.07	-2.84	-0.66	-0.34
5th grade math	-3.29	-5.79	0.50	-0.21

Source: Maryland Department of Education. Value-added estimates by the authors based on Table C-1.
* Results by jurisdiction are weighted by school enrollments.
a. Baltimore public schools excluding those schools identified as serving MTO students at the time of baseline.
b. Baltimore County, Anne Arundel County, and Howard County.

Table 5 Selected coefficient estimates from value-added regressions for 5th grade reading and math in 1993 -- quartiles defined by % housing affordable and rental in tract

	Quartile 1 (lowest)	Quartile 2	Quartile 3	Quartile 4 (highest)	Rest of Maryland
Reading	Base	-0.13* (1.93)	-0.04 (0.48)	-0.07 (0.86)	0.18** (3.39)
Math	Base	-0.11 (1.26)	-0.27** (2.73)	-0.16* (1.70)	0.01 (0.12)

NOTES: t-statistics in parentheses. Cells contain coefficients estimated from a value-added model which includes student socioeconomic and mobility variables, along with each school's 3rd grade pass rate in 1993. ** = significant at 5 percent level. * = significant at 10 percent level.

Table 6 Selected coefficient estimates from value-added regressions for 5th grade reading and math pass rates in 1995 -- quartiles defined by the % housing affordable and rental within low-poverty census tracts.

	> 10% poverty	Quartile 1 (lowest)	Quartile 2	Quartile 3	Quartile 4 (highest)	Rest of Maryland
Reading	-0.64** (5.20)	Base	-0.10 (1.28)	-0.11 (1.45)	-0.03 (0.41)	0.11* (1.89)
Math	-0.66** (4.88)	Base	-0.06 (0.58)	-0.13 (1.33)	-0.21** (2.12)	-0.04 (0.60)

NOTES: t-statistics in parentheses. Cells contain coefficients estimated from value-added models which include student socioeconomic and mobility variables, as well as each school's 3rd grade pass rate in 1993. ** = significant at 5 percent level. * = significant at 10 percent level.

Table 7
Characteristics of Baltimore MTO Households and Children

	Total	Experimental	Comparison	Control
Families (N)	638	252	188	198
Householder age	35.1	35.8	34.3	34.8
African-American (%)	97.4	96.8	97.2	98.4
Female householder (%)	94.7	96.0	92.0	95.5
Receive AFDC at baseline (%)	80.3	79.3	81.6	80.4
Householder educ. (%)				
Has h.s. degree	41.7	44.1	45.8	34.8
Has G.E.D.	14.9	15.0	13.0	16.6
Number of children	2.62	2.57	2.75	2.55
HH has school-aged child (%)	80.7	83.4	77.8	80.1
Child in K-6	65.0	64.7	64.4	66.0
Child in grades 7/8	23.2	27.0	18.9	22.5
Child in high school	13.9	16.6	11.7	12.6
HHolder engagement w/ child's school (%)				
Attend meeting last 12 mos.	81.6	83.1	77.1	83.9
Attend event last 12 mos.	68.4	66.2	71.2	68.7
Volunteered last 12 mos.	47.5	50.2	50.3	41.4
HH has child who receives services for (%):				
gifted/advanced education	16.0	17.0	17.8	13.1
learning problems	21.2	19.5	25.6	19.4
behavioral/emotional problems (%)	12.7	13.7	12.8	11.5
HH has child who has physical, emotional or mental problem+ (%)	13.6	13.7	15.0	12.0
as child who was suspended last 2 yrs (%)	24.5	26.6	23.3	23.0
HH has been called by school to discuss problems a child was having w/ school or behavior (%)	37.6	40.7	35.0	36.1

NOTES: + = defined as physical, emotional or mental problem for which child receives special medicine or equipment, or that makes it hard for child to get to school or play active games or sports.

Table 8
Relocation Outcomes for Experimental and Comparison Groups

	Experimental Group	Comparison Group
Total families randomly assigned	273	150
Number of families who relocated through MTO program	146 (*53 percent*)	115 (*77 percent*)
Destination of relocators (%):		
Baltimore City	59	88.5
Anne Arundel County	1.4	0
Baltimore County	24	7.7
Harford County	0.7	0
Howard County	13	3.8
Montgomery County	0.7	0
(*Number for whom we have relocation info*)	*(146)*	*(130)*
Percent minority in destination census tract (%):*		
0- 9.9	10.7	1.6
10-19.9	11.4	10.9
20-29.9	20.0	3.1
30-39.9	10.0	10.9
40-49.9	8.6	9.3
50 plus	38.6	63.6
Percent poor in destination census tract (%):*		
0- 9.9	90.0	15.5
10-19.9	9.3	27.1
20-29.9	0.0	19.4
30-39.9	0.0	27.1
40-49.9	0.0	8.5
50 plus	0.0	1.6

NOTE: * = Calculations taken from Abt Associates (1997). Column does not add to 100 percent because one family in each group relocated outside of Baltimore PMSA, for whom Abt did not calculate census tract characteristics.

Table 9
Effects of MTO Random Assignment on School Characteristics and Quality

	Experimental group[a]	Comparison group[a]	Control Group
School characteristics			
Percent free lunch (595)	66.82**	80.82*	84.82
Withdrawal rate (595)	6.94**	15.94	23.94
Percent special ed (604)	12.92	14.92	13.92
School enrollment (604)	697.34	717.82	731.59
School resources			
Wealth per pupil, $1,000s (596)	158.4**	135.5**	124.5
Expenditures per pupil, $'s (605)	5,593**	5,451**	5,391
Instructional staff per 1,000 students (596)	57.7**	56.9**	56.6
Outcomes (raw pass rates)			
Reading -- 5th grade (445)	11.84**	7.84**	5.84
Reading -- 8th grade (99)	12.27**	6.27	4.27
Math -- 5th grade (442)	18.40**	15.40*	12.40
Math -- 8th grade (99)	20.48**	12.48	8.48
Outcomes ("value-added")[b]			
Reading -- 5th grade (400)	-1.34	-2.34	-2.34
Math -- 5th grade (430)	-4.57	-0.57	-3.57

Notes: a=Experimental and comparison values are calculated as control group school quality plus effect of assignment to experimental or comparison group, as estimated from regression equation as discussed in Appendix A. b= Value-added outcome variables are measured as difference between school's 1995 5th grade pass rate and the 5th grade pass rate as predicted by 1995 student characteristics (free lunch and withdrawal rates) and school's 1993 3rd grade pass rates (see text). Negative values indicate that the school is "underperforming" relative to what we would have predicted given the socioeconomic composition of the school's student body. ** Difference between experimental or comparison group and control group is statistically significant at 5 percent level. * Difference between experimental and comparison group and control group is statistically significant at 10 percent level. Statistical tests calculated from regression of school quality measures against MTO treatment group assignment variables, using Huber/White standard errors that are adjusted for nonindependence of observations (see Appendix C). Resource variables measured at school district (county) level. All school characteristic and outcome variables measured in 1995; school resource variables are measured in 1994. In order to reduce standard errors for the experimental and comparison group variables, regression equations also include baseline survey covariates likely to be relevant for child's school quality.

Table 10
Effects of Random Assignment on Relocation to Low-Poverty Areas (<10%)

	Dependent variable: =1 if relocate to low-poverty rate (<10%), 0 otherwise	
	Full sample	*Experimental & Controls Only*
Explanatory variables:	(1)	(2)
Random assignment to group:		
Experimental	0.51 (0.03)**	0.52 (0.03)**
Comparison	0.06 (0.03)**	N/A
Householder has GED	0.09 (0.04)**	0.06 (0.05)
Householder has H.S. degree	0.05 (0.03)*	0.05 (0.04)
Number of children in HH	-0.02 (0.01)*	-0.02 (0.01)*
Total HH Income ($1,000s)	-0.01 (0.003)**	-0.01 (0.004)**
Householder married	-0.08 (0.07)	-0.10 (0.09)
Last 12 months, adult in HH has:		
Attended meeting at school	0.04 (0.04)	-0.004 (0.05)
Attended event at school	0.02 (0.03)	0.05 (0.04)
Volunteered at school	-0.04 (0.03)	-0.05 (0.04)
Child receives services for:		
Gifted/advanced education	-0.003 (0.05)	0.05 (0.06)
Learning problem	0.02 (0.05)	-0.01 (0.07)
Child has been suspended during last 2 years	-0.08 (0.05)*	-0.06 (0.06)
N	594	417
Adjusted R-squared	0.37	0.38

Notes: Model estimated using ordinary least squares regression. Huber/White standard errors in parentheses (adjusted for nonindependence of observations). ** significant at 5 percent cutoff * significant at 10 percent cutoff
(file: mkstata6)

Table 11
Effects of Relocation to Low-Poverty Areas (<10%) on School Characteristics and Quality

	Families who relocate to low-pov (<10%) area[a]	All non-relocators
School characteristics		
Percent free lunch (595/418)	49.87**	82.60
Withdrawal rate (595/418)	16.78**	23.61
Percent special ed (595/418)	11.80	14.32
School enrollment (595/418)	657.35	724.22
School resources		
Wealth per pupil, $1,000s (596/419)	190.2**	129.3
Expenditures per pupil, $'s (596/419)	5,754**	5,418
Instructional staff per 1,000 students (596/419)	58.5**	56.7
Outcomes (raw pass rates)		
Reading -- 5th grade (442/309)	16.87**	6.49
Reading -- 8th grade (99/72)	19.99**	5.38
Math -- 5th grade (442/309)	22.16**	13.22
Math -- 8th grade (99/72)	30.14**	10.23
Outcomes ("value-added")[b]		
Reading -- 5th grade (400/280)	-1.56	-2.42
Math -- 5th grade (427/301)	-4.89	-3.14

Notes: a= School quality for families who relocate calculated as school quality for experimental and control group families who do not relocate plus effect of relocation, as estimated from regression equations described in Appendix A. b= Value-added outcome variables are measured as difference between school's 1995 5th grade pass rate and the 5th grade pass rate as predicted by 1995 student characteristics (free lunch and withdrawal rates) and school's 1993 3rd grade pass rates (see text). Negative values indicate that the school is "underperforming" relative to what we would have predicted given the socioeconomic composition of the school's student body. ** = Difference between experimental group relocators and nonrelocators statistically significant at 5 percent level. * = Difference between experimental group relocators and nonrelocators statistically significant at 10 percent level. In order to reduce standard errors for the experimental and comparison group variables, regression equations also include baseline survey covariates likely to be relevant for child's school quality.

Table 12
Actual Changes in School Quality for MTO Families
Compared with Predictions From Affordable Housing Stock in Baltimore Area

	Experimental Group Relocators (<10% Pov Tract)			Comparison Group Relocators		
	Actual	Predicted[a]	Predicted[b] (Adjust for suburban-move rate)	Actual	Predicted[a]	Predicted[b] (Adjust for suburban-move rate)
School characteristics						
Percent free/reduced lunch	56.81	26.81	44.60	80.01	46.27	71.33
Withdrawal Rate	17.34	14.17	15.84	22.65	17.38	21.74
Percent special ed	12.62	14.29	14.68	15.30	16.32	17.66
School enrollment	656.09	651.42	645.92	682.99	615.68	594.01
School Resources						
Wealth per pupil ($1,000s)	192.8	237.7	184.0	141.2	200.9	141.3
Expenditure per pupil ($)	5,901	6,072	5,859	5,639	5,774	5,648
Instructional staff per 1,000 students	54.4	56.2	55.0	54.0	55.4	54.3
Outcomes (Raw pass rates)						
Reading, 5th grade	17.19	29.43	20.38	8.83	21.49	10.80
Math, 5th grade	25.58	45.01	31.66	16.53	35.09	21.00
Outcomes ("Value-added")						
Reading, 5th grade	-0.42	0.02	-1.57	-1.62	-0.61	-2.38
Math, 5th grade	-1.82	-0.53	-2.35	-0.91	0.27	-0.13

NOTES: a = Predicted school quality calculated as average school quality in Baltimore metropolitan area, using the housing accessibility measures for each school's census tracts (discussed in Section IV of the paper) as the school's weight.
b = We first calculate the quality of the schools that experimental and comparison children would attend if their families allocated themselves across suburban neighborhoods and schools in proportion to the availability of affordable rental housing. We then perform a similar calculation for the schools that families would attend if they distributed themselves throughout Baltimore City in proportion to the availability of affordable rental housing. The adjusted predicted school quality for the experimental group is then equal to the proportion of experimental group relocators who stay within the city (59 percent) times the predicted school quality for city relocation, plus the proportion of experimental group relocators who move to the suburbs (41 percent) times the predicted school quality for suburban relocation. This last step is repeated for the comparison group, using the proportion of comparison group families who move to the suburbs versus city.

Appendix A

Representativeness of School Sample for MTO Children

Despite our attempts to follow up the addresses and schools of MTO families using several different methods and datasources, address and school information are still missing for some families who have participated in the Baltimore demonstration. Conceivably there could be some systematic differences between those children for whom we could versus could not identify the schools they attend. To explore this possibility, we conducted a probit analysis using as our dependent variable an indicator equal to 1 if we had information about the post-intervention school that the child attended, equal to 0 otherwise, and a set of covariates related to family SES and child characteristics. The results are presented in Appendix Table A1.

Except along two dimensions -- age of the child and size of the families -- the children in our subsample appear to be very similar to the rest of the children in the MTO program. Compared to the other MTO children, the children for whom we have school data tend to be somewhat older and tend to come from smaller families.

Appendix Table A1
Probit Analysis for Child/School Matched Sample

Dependent variable: Equals 1 if school of attendance available for child, 0 otherwise	Full sample+ (1)	Experimental group sample+ (2)
Child's age++	$.5 \times 10^{-3}$ ($.3 \times 10^{-3}$)**	$.5 \times 10^{-3}$ ($.1 \times 10^{-3}$)**
Family receives AFDC	-0.22 (0.14)	-0.47 (0.25)*
Last 12 months, householder:		
Went to meeting at school	0.06 (0.14)	0.01 (0.22)
Went to event at school	-0.09 (0.11)	-0.20 (0.17)
Volunteered at school	-0.16 (0.09)*	-0.14 (0.16)
Female-headed household	0.11 (0.29)	0.47 (0.65)
Householder has GED	0.02 (0.12)	-0.07 (0.21)
Householder has h.s. degree	0.04 (0.10)	-0.22 (0.17)
Householder works f-time	0.05 (0.15)	-0.07 (0.24)
Householder married	-0.05 (0.22)	0.45 (0.42)
Householder separated	0.18 (0.14)	0.37 (0.21)*
Householder divorced	-0.13 (0.16)	0.39 (0.23)*
Householder widowed	0.02 (0.25)	0.32 (0.61)
Household income (1,000s)	-0.01 (0.01)	-0.02 (0.02)
Number of children in HH	-0.10 (0.03)**	-0.10 (0.06)*
Someone in HH victimized by crime last 6 months	-0.04 (0.09)	-0.06 (0.14)
Log likelihood	-576.3	-224.7
N	1,532	630

NOTES: Standard errors in parentheses. ** significant at 5 percent, * significant at 10 percent.
+ Samples restricted to those children ages 5 and older at the time of the baseline survey. ++ Coded as date of birth measures as number of days after January 1, 1960.

Appendix B
Estimating School "Value-Added"

Measures of each school's value added are most accurately estimated with longitudinally matched data at the student level (see Ladd, Roselius, and Walsh, 1997). Because such data are not available for Maryland, we rely instead on pseudo cohorts of students at the school level to estimate the contribution of each school to the learning of its students. The dependent variable in each equation is the log of the odds of each school's 5th grade pass rate on the state reading or math test. Explanatory variables include several measures of a school's student population, including socioeconomic characteristics and withdrawal rates. As a proxy for prior performance, we include pass rates for 3rd graders in the same school in 1993; the groups of students will differ somewhat because of student mobility, which is particularly high in city schools (where withdrawal rates exceed 20 percent).

We have experimented with many forms of a model to predict fifth grade test scores. The model that we are most comfortable with takes the following form:

(B1) $\text{Log}\ (P5)/(1\text{-}P5) = f(P3, P3^2, PS3, PS3^2, P3{*}PS3, C, W)$

Where

> P5 is a pass rate (more precisely, the fraction of students receiving a satisfactory grade or better) for a fifth grade subject such as reading, math, language arts or writing:
> P3 is a pass rate for that same subject for third graders two years earlier;16
> PS3 is the pass rate of third graders in a different subject;
> C is a vector of student characteristics at the school level, including the logarithm of the percentage of students receiving free or reduced price lunch, and the fractions of students in special education and chapter 1 programs; and
> W is the percentage of students leaving the school the school during the year.

For example, we predict a school's fifth grade pass rate in math as a function of the school's third grade pass rate in math two years before, its third grade pass rate in language arts and, to allow for nonlinearities, those two variables squared and interacted. In addition, we control for various characteristics of the student body, such as the percentage of students receiving subsidized lunches or with limited proficiency in English, and the mobility of students out of the school. We have written the dependent variable in the form of log of the odds of passing to assure that the predicted pass rates fall in the range of 0 to 1.

Because we are missing third grade pass rates for reading in 1993, we substituted the third grade pass rates in language arts in the fifth grade regression equation for reading.

As a measure of each school's value added, we simply use the difference between each school's actual pass rate (for fifth grade students) and the pass rate predicted by the equation. While this measure is imperfect, it is the best that we can do with the available data. Fortunately, the results generally seem reasonable. The main problem arises from the reliance on school-level aggregates (at the fifth grade level) rather than longitudinally matched student data. To examine the quality of our estimates, we used a data set on student test scores in North Carolina that were longitudinally matched by student over the period 1993-95. With this North Carolina data we were able to simulate school effectiveness measures for North Carolina schools using a method similar to the one we used for Maryland. We then compared these measures to the best measures of school effectiveness (at the fifth grade level) that could be estimated with that data. Those best measures, which are described in Ladd, Roselius, and Walsh (1997), are derived from equations that predict fifth grade scores for individual students using fourth grade scores as explanatory variables, with appropriate corrections for measurement error. The correlation between the gold plated measures and the measures using the methodology for Maryland is 0.55. If we do not make the correction for measurement error (which requires that we use the third grade test scores as an instrument for fourth grade scores), we can use the North Carolina data to estimate each school's value added between third and fifth grade which is more comparable to the approach we used in Maryland. The correlation between the 3rd to 5th grade school effectiveness measures based on the individual data and that based on school level data is 0.77.

Appendix C
Calculation of Program Effects

The results shown in Tables 9 and 11 come from estimating regression equations for both the effect of random assignment on school quality (the "intent-to-treat" effect) and the effects of relocation *per se*. Let y_i represent some dependent variable of interest for parent or child (i), for example, the pass rate within a school on a standardized reading or math test, or expenditures per pupil, or some other measure of either school inputs or outputs,[17] and let $z_i(n)$ represent the treatment intended for each family (i) where n signifies the group to which families were randomly assigned, with 0 for the control group, 1 for the comparison group, and 2 the experimental group. We assign the value 1 to $z_i(n)$ if family (i) is assigned to program "n," and the value 0 otherwise.

We determine the "intent-to-treat" effect by applying ordinary least squares (OLS) to equation (2), using the full sample of Baltimore MTO families.

(C1) $$y_i = \alpha_1 z_i(1) + \alpha_2 z_i(2) + ß\mathbf{x_i} + \varepsilon_i$$

The parameter α_1 represents the effects of being assigned to the experimental group, and α_2 the effects of assignment to the comparison group, compared with the counterfactual of what would have happened to low-income families in the targeted Baltimore census tracts in the absence of MTO (including mobility induced by Hope VI). We include a vector $\mathbf{x}_i$ of socioeconomic characteristics that may be relevant for outcome y_i in the equation to generate more efficient estimates of α_1 and α_2 (that is, to reduce the size of their standard errors). We present Huber/White standard errors to control for nonindependence of the error terms, since our dataset contains multiple children from some families.

The parameter α_1 estimated from equation (C1) is the product of the proportion of experimental group families who relocate to low-poverty areas (designated by r_1) and the effects of relocation to a low-poverty area on school characteristics, λ (see for example Rouse, 1997). Because r_1 will be less than one, the "intent to treat" effects estimated in the preceding section will understate the effects on school quality of relocating to a low-poverty area.

(C2) $$\alpha_1 = (r_1)*(\lambda)$$

In the future we will make use of the longitudinal structure of our dataset, for example from the overlap in questions on our follow-up surveys and the Abt baseline surveys, or the multiple periods of data that we have from state administrative records, to define the outcomes of interest as individual gains. This strategy may increase the power of our evaluation in light of previous findings that individual fixed-effects in the New Jersey NIT experiment were responsible for the majority of the variation in responses (Hausman and Wise, 1976, 1979).

Our goal is to estimate the effects of relocating to a low-poverty area on various school characteristics (y_i) as in the following equation:

(C3) $y_i = \lambda t_i(1) + ß\mathbf{x}_i + \varepsilon_i$

where $t_i(1)=1$ represents the "treatment" of relocating to a low-poverty area (with $t_i(1)=0$ otherwise) and $\mathbf{x}_i$ represents the same set of covariates as in equation (C1). If we were to estimate this equation by ordinary least squares we would obtain a biased estimate of λ, the treatment effect since a family's success at relocating is not a random event and may well be correlated with unobserved family characteristics that are captured by the error term, ε_i. The effects of relocating to a low-poverty area (λ) can be identified by using the outcome of the random-assignment process as an instrumental variable. This instrument is appropriate since the group to which each family is assigned [$z_i(1)=1$ for the experimental group and $z_i(2)=1$ for the comparison group] is exogenous (it is outside the family's control) and is highly correlated with the likelihood of relocating to a low-poverty area ($t_i(1)=1$). Hence we first predict the probability that a family relocates to an area with a low poverty rate using either a linear probability model or a probit model of the following form:

(C4) $t_i(1)=\delta_1 z_i(1) +\delta_2 z_i(2) + \gamma\mathbf{x}_i + v_i$

We then substitute the predicted probability of relocation to a low-poverty area for the actual probability of treatment in equation (4), that is, we estimate an equation of the form:

(C5) $y_i = \lambda \hat{t}_i(1) + ß\mathbf{x}_i + \varepsilon_i$

where $\hat{t}_i(1)$ represents the predicted probability of relocating to a low-poverty area.