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Poverty Concentration and Public Housing Programs

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ABSTRACT

This paper investigates the relationship between neighborhood poverty and public housing. Using 1990 and 2000 geo-coded census data and HUD (Department of Housing and Urban Development) data, I estimate the effect on neighborhood poverty rates of existence of public housing and explore its geographical variation in five large American cities. First, I find the positive effect of presence of fixed public housing and voucher and certificate (VC) program in census tracts on neighborhood poverty rates after controlling for time-lagged neighborhood poverty rate. The effect of VC is smaller than that of fixed housing. Second, I find geographical variations in this effect. The effect of public housing on poverty rates are stronger in Chicago and New York, more racially segregated than the other three cities (Baltimore, Boston and Los Angeles). This is consistent with the idea that racial segregation contributes to poverty concentration. The implications and limitations are discussed.

INTRODUCTION AND BACKGROUND

This research investigates the relationship between poverty concentration and public housing policy. The concentration of poverty concentration in large cities has been a significant concern of policy makers and social scientists for several decades. Residential segregation, either racial (Massey & Denton 1993) or economic (Jargowski 1997), aggravates poverty concentration. Public housing projects have contributed to residential segregation and as a result, worsened poverty concentration. Massey & Kanaiaupuni (1993: 114 – 117) showed that the construction of public housing increased the neighborhood poverty rate in Chicago during the 1960s and 1970s. According to Levitt & Venkatesh (2001), young males who grew up in public housing units in inner city Chicago are highly likely to experience educational failure and poor labor market outcomes and to be involved in gang activities.

These undesirable outcomes pushed policy makers to shift from funding housing projects to a tenant-based voucher and certificate (VC) program. The rationale behind this shift is to diversify the geographical location of government-assisted households and to weaken poverty concentration. More than 80 percent of new assisted households subsidized were subsidized by in the 1980s. However, most VC users stayed in distressed neighborhoods, which made it difficult to evaluate the net effects of this policy change (Pendall 2000: 881). In order to evaluate the effects of housing subsidies, a new experimental program, the Moving to Opportunity (MTO) project was developed. The MTO project, launched in 5 large cities (Baltimore, Boston, Chicago, Los Angeles, and New York) in 1994, randomly assigned assisted households into one of three groups: no treatment (fixed public housing), VC, and MTO. While VC users could choose their residence without restriction, MTO users had to move to neighborhoods with poverty rates of less than 10 percent. Comparison of outcomes among the three groups shows that MTO users are better off in terms of exposure to crime and neighborhood socio-demographic composition such

as racial composition (Rosenbaum & Harris 2001).

A PROBLEM IN PAST RESEARCH AND RESEARCH QUESTIONS

Past research on public housing has overlooked an important aspect of public housing projects, which I attempt to address in this research. Most research focuses on the effects of housing programs on individual outcomes (e.g., health, education, and occupational success). An important assumption underlying the VC and MTO programs is that dispersing assisted households would reduce poverty concentration and improve the life chances of participating groups. However, with a few exceptions (see Massey & Kanaiaupuni 1993), there has been little interest in the impact on neighborhoods that receive program participants. The effects of inflow of VC or MTO users into a certain neighborhood on neighborhood composition of the inflow of VC or MTO users into a certain neighborhood have not been carefully investigated.

While neighborhood characteristics affect individual's outcomes, individual residential choices affect these neighborhood characteristics as well (Bruch & Mare 2005). For example, out-migration of middle class African Americans from inner-city Chicago to its suburbs resulted in the deterioration of many neighborhoods from which people moved (Wilson 1987). In white-dominant receiving communities, the in-migration of black's was offset by the out-migration of white's, which resulted in persistent racial segregation (Quillian 2002 & 1999). In the context of public housing, VC users tend not to move away from distressed neighborhoods (Pendall 2000). Even though VC users move away from their original residence, they tend to concentrated once again in a few suburban neighborhoods (Hartung & Henig 1997). Therefore, I expect that public housing programs will affect neighborhood composition as well as individual outcomes. This research focuses on the following question: How does public housing (fixed or VC units) affect

neighborhood poverty? I estimate the effects of fixed housing and VC programs on neighborhood poverty, using regression analysis.

In addition, I estimate the effects of demographic characteristics of program participants on neighborhood poverty. This allows me to explore the mechanism through which public housing contributes to increasing the neighborhood poverty. According to Quillian (1995), the percentage of young black males residing in a neighborhood is a stronger predictor of whites' out-migration than is the real poverty rate because 'perceived' rather than 'actual' threats are influential in determining residential choice. The same logic can be applied to the relationship between the neighborhood poverty rate and the demographic composition of publicly assisted households in a given neighborhood. I speculate that the presence of disadvantaged groups participating in public housing programs in a neighborhood may intensify poor perception of the neighborhood and cause the out-migration of higher-come individuals and families, which in turn could result in higher neighborhood poverty rates. Therefore, I also investigate a second research question: How does the socio-demographic composition of publicly assisted households influence neighborhood poverty rates?

Methodological Challenges: Simultaneity and Endogeneity Problems

Since most participants in public housing programs are poor, the existence or the percent of public housing units (either fixed or VC) is endogenously associated with high poverty rates. This association poses two important methodological challenges for this (see Duncan & Raudenbush 1998). First, the increase in the number of publicly assisted households in the neighborhood could be a cause or a result of the increase in neighborhood poverty rate. For example, increasingly poor neighborhoods may attract individuals and families with VCs because they want to reside near friends and relatives who tend to be poor, which will increase the

neighborhood poverty rate. This simultaneity problem makes it difficult to estimate the net effect of public housing on poverty. Second, there is a possibility that some common unobserved characteristics influence both the poverty rate and participation in public housing programs. This endogeneity has the potential to bias regression estimates. One solution to these methodological challenges, with some limitations, is the use of time-lagged variables seems. Compare the following two equations.

$$pov_{t1} = f(+fix_{t1}, +VC_{t1}, \ control_{t1}) \quad \cdots\cdots(1)$$

$$pov_{t2} = f(+pov_{t1}, +fix_{t1}, +VC_{t1}, \ control_{t1}) \quad \cdots\cdots(2)$$

where

pov_{t2} : time 2 poverty rate

pov_{t1} : time 1 poverty rate

fix_{t1} : percent living in fixed public housing units at time 1

VC_{t1} : percent living in VC units at time 1

$control_{t1}$: other factors affecting poverty rate, measure at time 1

The sign indicates the hypothesized direction of effects. The equation (1) states that the poverty rate at time 1 is a function of the percentage living in fixed public housing and VC at time 1 after controlling for other factors (i.e., racial composition, economic conditions, etc). This equation in particular suffers from the simultaneity problem since its estimates should confound the effects of public housing on poverty with the effects of poverty on public housing. If we assume a positive association between poverty and participation in public housing, the effects should be overestimated. Equation (2) is an improvement over equation (1) in terms of addressing the simultaneity problem since the poverty rate at time 2 cannot influence the percentage living in fixed or VC units at time 1. Furthermore, since we control for the poverty rate at time 1, the estimated effects seem to purge the effects of poverty on public housing. However, this approach also has limitations. We cannot interpret its results as the net effects. Consider a simple diagram.

$$fix_{t1} \rightarrow pov_{t2} \rightarrow fix_{t3} \rightarrow pov_{t4}$$

In this diagram, the percent living in fixed public housing (fix) at time 1 influences the poverty rate at time 2. In turn, the poverty rate at time 2 affects fix at time 3. Fix at time 3 again affects the poverty rate at time 4. If we estimate the effects of fix at time 1 on poverty rate at time 4 without information on poverty at time 2 and fix at time 3, the estimate may confound the interaction between poverty and public housing over time. Since Equation (2) only uses two time points and time can be divided infinitely, the estimated effects from Equation (2) can be interpreted not as the net effect but as the "total effects" of public housing at time 1 on poverty rate at time 2. It is important to note that neither Equation (1) and nor Equation (2) address the unobserved common factor problem. If some unobserved factor influences both the dependent and independent variables, the regression equations may not yield the net effects of independent variables. With recognition of its limitations, I will analyze the data using a model specification similar to Equation (2).[1]

In sum, this paper asks two questions. First, does a greater presence of public housing programs users, either fixed or VC, cause high neighborhood poverty rate after controlling for time-lagged neighborhood poverty rates? Second, does socio-demographic composition of publicly assisted households influence the neighborhood poverty rate?

[1] The use of a change score model is another alternative to tackle these methodological problems. In particular, when the errors in time 1 and time 2 variables are correlated each other, the change score model is an attractive alternative. I also estimated such models, but there is no substantive difference in the result between two model specifications. Since the model using time-lagged dependent variables is easy to understand, I only present the results using this model.

HYPOTHESES

Percentage public housings and poverty rate

Hypothesis 1: The proportion of people living in fixed public housing in 1995 in a given neighborhood is positively associated with neighborhood poverty in 1999 after controlling for the poverty rate in 1989.

Hypothesis 2: The proportion of people subsidized by voucher and certificate in 1995 in a given neighborhood is positively associated with neighborhood poverty in 1999 after controlling for the neighborhood poverty rate in 1989. However, I expect this association to be weaker than the association between poverty and fixed public housing.

The percentage of people living in fixed public housing is expected to be positively associated with the neighborhood poverty rate after controlling for the time-lagged poverty rate. There are possible two explanations for this association. First, this association can be explained by the fact that residents in fixed public housings themselves are poor. Therefore, more fixed public housing units necessarily imply a higher poverty rate. Second, a high percentage of fixed public housing units in a neighborhood can be an indicator of the deterioration of neighborhood conditions, which make them an undesirable place for higher-income people to live in. If this is the case, a high percentage of fixed public housing units increases the neighborhood poverty rate in addition to the fact that fixed unit users themselves are intrinsically poor. I also expect a positive but weaker association between poverty rates and the percentage of VC units. The shift to a tenant based public housing policy is aimed at ameliorating the problem of poverty concentration. If the program has succeeded in reaching its goal to some degree, the association between poverty rates and the percentage of VC units should have a weaker, though still positive, association than that of poverty and fixed public housing. If hypothesis 2 can be supported by the

data, we confirm the effectiveness of the VC programs in regard to reducing neighborhood poverty.

The composition of public housings and poverty rate

Hypothesis 3: The more female-headed households in public housing in a given neighborhood in 1995, either fixed or VC, the higher neighborhood poverty rates will be in 1999.

Hypothesis 4: The more welfare dependent households in public housing in a given neighborhood in 1995, either fixed or VC, the higher neighborhood poverty rates will be in 1999.

Hypothesis 5: The more minorities in public housing in a neighborhood in 1995, either fixed or VC, the higher neighborhood poverty rates will be in 1999.

Hypothesis 6: The more racially segregated public housing programs are in 1995, the higher the neighborhood poverty rates will be in 1999.

Hypothesis 7: The more new users in public housing in a neighborhood in 1995, the lower neighborhood poverty rates will be in 1999.

In general, single-parent families tend to be poorer than conventional two-parent families (see Ellwood & Jencks 2004), welfare dependents are more likely to poor than those who are not dependent on welfare, racial segregation increases poverty concentration (Massey & Denton 1993) and minorities are disproportionately poor (Iceland 2003). These characteristics are perceived as being associated with poverty status and the prevalence of people with these characteristics may push higher-income individuals and families out of neighborhoods. Combined with the fact that people with such characteristics in public housing are also likely to be poor, the prevalence of people with these characteristics in public housing in a neighborhood will increase the poverty rate. I also expect the percent of newly entering public housing users to

have a negative effect on poverty rate. Since a longer stay in public housing certainly implies persistent poverty, the existence of or a high proportion of longer stayers will be positively related with neighborhood poverty.

Geographical variation

Hypothesis 8: The effects posited in hypothesis 1 –2 vary across cities. The more racially- and economically-segregated are cities, the stronger the impacts of public housing on poverty rates.

Each city has a distinctive context, which should result in different outcomes regarding neighborhood poverty and neighborhoods composition. I expect racial and economic segregation in a city to increase the effects of public housing on neighborhood poverty. In particular, the association between neighborhood poverty and the proportion of people living in the fixed public housing will be strong in cities where there is strong racial segregation because racial segregation aggravates poverty concentration (Massey and Denton 1993) and fixed units in general are concentrated in poor neighborhoods, which in turn strengthens the effects of public housing on poverty rates.

Control variables

In the regression analysis, I control for several factors that presumably affect neighborhood poverty. For the census data, I control for time-lagged poverty rate (poverty rate in 1989), racial composition, percentage young people (age 20 – 39), and percentage employed. I expect a positive effect of the time-lagged poverty rate and the proportion of black, Hispanic, and young people on neighborhood poverty. Among these variables, time-lagged poverty rate will be the strongest predictor. The percentage of the employed is expected to be negatively associated with

the neighborhood poverty since employment certainly reduces poverty. In terms of neighborhood poverty and the percent of the young, according to Moller et al. (2003), the size of the youth population is positively associated with the poverty rate in countries since it may depress incomes at the bottom of the distribution. The same logic can be applied to the neighborhood level since job instability is high for the young.

DATA, MEASUREMENT, AND METHODS

This analysis is based on data sets from the U.S. census (1990 and 2000) and HUD (U.S. Department of Housing and Urban Development, 1995) data.[2] The unit of analysis is census tract, which approximates neighborhood. Most variables are measured as percentage in census tract. HUD data provide information on public housing units and all other information comes from the census. I include five cities (Baltimore, Boston, Chicago, Los Angeles, and New York) in this analysis. Inclusion of these five cities will allow me to compare the results in the current research with those using MTO data at a later point.

One problem with the data is that many census tracts have on public housing units. In addition, some census tracts have both fixed and VC units while some have one or the other. Not all of those census tracts that contain public housing units provide information on demographic characteristics of people living in the public housing. Therefore, I use three different samples. The first sample (sample 1) is composed of all of the census tracts in the five cities. Since some tracts do not have public housing units, I cannot perform regression analysis with this sample fully incorporating the information on public housing units. Therefore, I estimate the effect of the

[2] I cannot use the MTO data in this paper for data access problem. HUD allows only a few research teams to access the MTO data because of the highly confidential nature of the data. I contacted a HUD personnel who is charge of the data access, but the response was negative.

existence of and the percent of public housing units on poverty rate, controlling for the variables from census data in the sample 1. Definitions of variables are given in Appendix A, and descriptive statistics for sample 1 are given in Table 1. Two patterns are of note in the descriptive statistics. First, census tracts without public housing units are the least poor and those with fixed housing units are the poorest. Those tracts with VC units lie between these two extreme. Second, census tracts with some type of public housing, either fixed or VC, experienced an increase in poverty rate between the decennial censuses while poverty rate in census tracts without public housing unit decreased. This implies the existence of public housing in census tract is positively associated with neighborhood poverty. The estimates using this sample are generalizable to the five cities. Table 2 provides correlation coefficients among variables in sample 1.

<Table 1> and <Table 2> about here

The second sample (sample 2) is composed of census tracts which contain VC units, and the third sample (sample 3) is composed of census tracts with fixed housing units. Sample 2 and 3 are used to estimate the effects on poverty rate of socio-demographic composition of households living in public housing. Of course, the estimates are not generalizable to the entire geographic area within the five cities. However, the exclusion of tracts without public housing is not problematic given my interest in the effects of the characteristics of public housing units. Definitions of the variables in samples 2 and 3 are given in Appendix A. Descriptive statistics and correlation coefficients among variables are given in Tables 3 and 4. With two exceptions, the residents in fixed and VC units are socio-demographically similar to each other. Most of recipients of either type of public housing assistance lived in female-head households (82% for VC units, and 71% for fixed units); racial composition and segregation are similar; about 20

percent of people in these census tracts are poor; and about 10 percent of the assisted households have been subsidized for less than 1 year. However, the average number of assisted units in fixed programs is much higher than that in VC programs, and more VC users rely on welfare as their main source of income.

<Table 3> and <Table 4> about here

Several points should be mentioned with regard to the measures from HUD data. First, variables from HUD are measured in 1995. Since I use 1990 and 2000 census data, I use variables measured at three different time points: 1989, 1995, and 1999. Using these data, I estimate the following equation for sample 1.

Pov99 = f (+pov89, +black89, +hisp89, -young89, -empl89, +p_fix95, +p_VC95) – (3)
(where the definitions of variables are given in Appendix 1 and signs indicate the hypothesized direction of effects).

This equation has some weaknesses. First, the estimates cannot be interpreted as net effects. As I mentioned earlier, the estimated effects of percent black in 1989, for example, may be confounded with the interaction between racial composition and poverty rate between 1989 and 1999. Thus, the estimates from this equation should be interpreted as "total effects" of the percent black in 1989 on the poverty rate in 1999. Second, an even more critical weakness for the estimates for p_fix95 and p_VC95 concerns simultaneity, which is problematic because p_fix95 and p_VC95 may reflect any changes in poverty between 1989 and 1999 that actually occurred

prior to 1995. Since I do not have any comparable HUD data prior to 1989, this research cannot resolve this issue. This issue limits causal interpretation of results.

Third, since variables from HUD are measured in 1995, the denominator for percent people living in VC units in tracts (p_VC95) and percent people living in fixed units in tracts (p_fix95) should be measured in 1995. Since I have information in 1989 and 1999 from the decennial census, the mean of 1989 and 1999 census tract population is used as a denominator for p_VC95 and p_fix95.

Finally, HUD data provide information on VC units and all assisted units at the census tracts level, but not on fixed units at the census tract level. Therefore, the figures for fixed units are obtained by manipulating the VC and all assisted housing.[3]

RESULT

Public housings and poverty rate

<Table 5> about here

Table 5 reports robust regression results for sample 1. As shown in the bottom of Table 5, there is significant heteroskedasticity, which makes the estimates inefficient. Other models also suffer from heteroskedasticity, so all regression coefficients presented below are estimated using robust regression. Census tract poverty rate in 1999 is regressed on poverty rate in 1989, percentage

[3] The number of units in fixed public housing (units_fix) is obtained by subtracting the number of VC units in the tracts (units_vc) from the number of all assisted housing units (units_all). In the case of percentage measures, the relationship is more complicated. For example, mover_fix = (units_all*mover_all - units_cv*mover_cv)/units_fix. (where mover_all is the percentage of mover among the units_all).

black, Hispanic, aged 20 – 39, and employed in 1989 and the presence or percentage of public housing users. Model 1 uses a dummy variable for public housing. The reference category of the dummy variable is no public housing, so the difference in poverty rate between the reference category and each tract type is reported, controlling for other covariates is reported. Model 2 uses the percent living in fixed public housing units (p_fix95) and the percent of VC users (p_VC95) as measures of public housing. These two models yield very similar coefficients for control variables but somewhat different results for the effects of public housing on poverty rate. I first describe the results from Model 1 first.

As expected, poverty rate in 1989 is a strong predictor. A one percent difference in the 1989 poverty rate is expected to make a .53% difference in the poverty rate in 1999, holding other factors constant. Other results are also consistent with my expectation. A high proportion of minority and young people is positively associated with the poverty rate while employment rate is negatively associated. Coefficients of the dummy variable 'tract type' clearly show that the existence of public housing increases the poverty rate. The poverty rate in census tracts with VC units but no fixed units is on average 2.2 percent higher than that in tracts with no public housing units, and the difference between tracts with fixed units but no VC units and those with no public housing units is 3.7 percent after the control of other covariates. This result supports hypothesis 1 (positive effects of fixed units) and hypothesis 2 (positive but weaker effects of VC units). The effects of VC programs are much smaller than those of fixed units. It strongly suggests the tracts with fixed public housing units are poorer than those with VC units. Based on this result, it can be argued that VC programs are at least better than fixed public housing in terms of reducing the poverty rate even though VC is still positively associated with poverty rate.

However, Model 2 seems to indicate the opposite effect. The coefficient of VC (.378) is much bigger than that of fix (.118). In this model, percent VC seems to have a larger effect than

fix, which undermines hypothesis 2. However, a direct comparison between fix and VC is not a good strategy since the variance in p_VC95 is much smaller than that of p_fix95. Therefore, comparing the change in poverty rate caused by one standard deviation change in p_VC95 and p_fix95 may be fair. A one standard deviation increase in p_fix95 increases the poverty rate by 1.44 (=12.23*.118) percent while a one standard deviation increase in p_VC95 increases the poverty rate by 1.17 (=3.10*.378) percent. While this difference seems small, it is evident that the effect of p_VC95 is not larger than that of p_fix95. Combined with the results in Model 1, we can conclude that the effect of fixed public housing on the poverty rate is larger than that of VC program even though we cannot completely exclude the possibility of the opposite effect.

Geographical variation

<Table 6> and <Table 7> about here

Table 6 presents dissimilarity indices (poor vs. nonpoor, white vs. black, and white vs. Hispanic) for each city. The index of dissimilarity is given by $\Delta = \frac{\Sigma | P_i - Q_i |}{2}$, where P_i is the percentage of cases in the *i*th category of the first distribution and Q_i is the percentage in the *i*th category of the second distribution. This index shows the percentage of cases in one distribution that would have to be shifted among categories in order to make the two distributions identical: 0 means no segregation while 100 means perfect segregation (Treiman 2006).

The results indicate that there is some variation across cities. In particular, we can see that segregation of white and black is higher in Chicago and New York than in other cities. This implies that the effects of public housing on the poverty rate would be stronger in these cities.

Separate regression analysis by cities, using Model 1 in Table 5, confirms this idea. In Chicago and New York, the effects of public housing are statistically significant while there is no such effect in Boston and Los Angeles. In particular, the poverty rate of tracts with fixed units but no VC units in New York is 11.6 percent higher than those with no public housing unit. Since Chicago and New York are more racially segregated cities, the larger effects in Chicago and New York support the hypothesis 8 (the more segregation, the stronger public housing effects). However, more rigorous testing of this idea would require multi-level modeling with more city-level observations, which would allow estimation of contextual effects (Raudenbush & Bryk 2002).

The estimates for census variables are similar to those reported in Table 5 with some exceptions. The effects of percentage Hispanic and young people are not significant in Baltimore, and percentage black is insignificant in Boston.

The composition of public housing and the poverty rate

<Table 8> about here

Table 8 reports determinants of census tracts poverty rates where information on the demographic compositions of the VC users are available (sample 2). The dependent variable here is $100 \times \frac{(poor\ \ in\ \ census\ \ tract\ \ -\ \ people\ in\ VC\ \ units)}{people\ in\ the\ census\ tract}$. Subtracting the number of people in VC units makes the dependent variable cleaner via removing the portion of the poverty population associated with poverty program variables. Some hypotheses with regard to VC are supported by the data while others are not. First, the percentage of VC is positively associated with poverty

rate. A ten percent increase in VC users in the census tracts will result in a 2.1 percent increase in the poverty rate. Second, the percent of female-headed households in VC units has a negative effect on the poverty rate. Therefore, hypothesis 3 is not supported. The more female-headed households in the VC units, the less poor the neighborhood. According to Ellwood & Jencks (2004), single-parent families tend to be poorer than conventional two-parent families. Since female-headed households are important components of single-parents families, this result is quite surprising. This result might be related to the high percentage of female-headed households in VC units (mean = 82%). In other words, most VC users live in female-headed households. It implies that VC users who live in male-headed households might be very unusual. Taking into account men's advantage in workplace and their lower participation in public housing programs, male-headed households who are VC users might lack economic motivation or ability. If this is the case, the negative effects on the poverty rate of percent of female-headed households is understandable. Third, the effects of racial composition variables in HUD are not statistically significant, which does not support the hypothesis 5. Since bivariate correlations between racial composition in HUD data and the poverty rate (see Table 3) are positive and statistically significant, these insignificant effects imply that other variables mediate these effects. In other words, they affect poverty rate only indirectly. In contrast, the effects of racial composition measured in the census data are highly significant. This implies that racial composition in VC units explain little variance in neighborhood poverty rate after controlling for the overall racial composition in the neighborhood. Fourth, racial segregation within the VC programs has a significant positive effect. Therefore, hypothesis 6 is supported. Considering the geographical variation between the poverty rate and public housing reported in the previous section (the more segregation, the stronger effects of public housing), this result implies that racial segregation matters in public housing programs as well as cities. Fifth, there exists a significant negative

association between the poverty rate and the percent of newcomers to the VC program. This significant negative effect of percentage new-comers to the VC program supports hypothesis 7. It implies that longer stay in the VC housing program is positively associated with persistent poverty. Finally, the proportion of welfare dependence among the VC users is positively associated with the poverty rate, as expected (hypothesis 4).

<Table 9> about here

Table 9 reports determinants of census tract poverty rates where information on the demographic composition of fixed housing is available (sample 3). The dependent variable here is $100 \times \frac{(poor\ \ in\ \ census\ \ tract\ \ -\ \ people\ in\ \ fixed\ \ units)}{people\ in\ the\ census\ tract}$. The reason for this transformation is explained in above. First of all, the percentage of people living in fixed public housing in a census tract has a positive impact on the neighborhood poverty rate, which supports hypothesis.[4] Second, mover_fix95 has no effect, which does not support hypothesis 7. This result implies that a longer stay in fixed public housing may not be related to persistent poverty, which is contradictory to my expectation. However, this result also implies there is no difference between those who stay in fixed public housing for a long time and newcomers to fixed public housing. This selection process may be an important mechanism for explaining the relationship between neighborhood poverty rate and public housing, but is outside of the scope of this study. Third, the effects of racial composition are mixed. The racial composition in neighborhood has significant positive effects on the poverty rate. However, percent black in fixed public housing has no effect

[4] In this case, we cannot compare the magnitude of the effects of fixed public housing and those of VC program since the samples are different.

and percent Hispanic in fixed public housing has a negative effect on the poverty rate. These unexpected results are hard to explain. Finally, racial segregation in fixed public housing has no effect. This may reflect an already high level of racial segregation in the census tracts which contain fixed public housing units, which is not tested in this study.

SUMMARY, LIMITATIONS AND FURTHER RESEARCH AGENDAS

This research produced mixed results. First, I found positive effects on poverty rate of fixed and VC programs after controlling for time-lagged poverty rate and other covariates. The effect of VC programs is smaller than that of fixed units, which suggest that VC programs are more effective with regard to reducing the poverty rate. Second, I failed to find some expected effects of demographic characteristics of public housing units. Percent of female-headed households in public housing is negatively associated with the poverty rate, which contradicts my expectation; racial segregation within public housing programs does not affect poverty rates; and the percentage of newcomers to fixed public housing does not affect the poverty rate. Negative effects of female-headed households and insignificant effects of newcomers to fixed public housing imply the possibility of selection bias. However, due to the lack of information on residential mobility and difference between female-headed households and male-headed ones, I cannot determine which the case is. Third, I found some geographical variations with regard to the relationship between poverty rate and public housing programs. Chicago and New York, which are more racially segregated than the other cities in this study, show a stronger effect of public housing on poverty rate. This is consistent with the idea that racial segregation contributes to poverty concentration.

This research leaves some important issues unanswered, which should be addressed by future research. First, since the data used here have no precise information on migration of public housing users, the mechanisms governing the relationship between the poverty rate and public housings could not be examined in this study. Analysis with more sophisticated data like MTO data may resolve some of these issues, which would be the next step of this research. Second, this research could not resolve the simultaneity and endogeneity issues completely. Using an instrumental variable would be a good approach to these issues. Ramsey reset test for omitted variables, which is reported at the bottom of Tables, 5, 7, 8, and 9, suggests that the model I use in this study suffers from omitted variables. Some of these omitted variables should be unobservable. If I can identify a variable that is associated with participation in public housing but not with poverty rate, using this variable as an instrumental variable may yield an unbiased estimate of the net effects of public housing on poverty rate (Angrist & Krueger 2001; Wooldridg 2000). Third, examining spatial externality may help to provide more consistent and efficient estimates of the effects of public housing on poverty. Neighborhoods are interdependent each other, which makes the assumption of independence among observation problematic. In particular, from the previous research (i.e., Wilson 1987, Massey & Denton 1993), we know poverty is geographically concentrated. While the exact mechanism governing poverty concentration is still under investigation, using spatial data analysis (Anselin & Bera 1998) will certainly reduce inconsistency or inefficiency of estimates.

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Table 1 Descriptive Statistics from Census by Tract Types

Variables	No public housing (N = 1,016)	VC only (N = 4,033)	Fixed units Only (N = 124)	Both (N = 1,751)
		Mean		
pov_99	8.72	13.82	23.48	23.59
pov_89	9.08	11.93	25.67	22.15
black_89	8.49	18.72	27.24	34.02
hisp_89	11.79	18.10	13.22	24.43
empl_89	48.57	48.49	43.28	42.95
young_89	32.25	34.67	34.90	36.03
fix	-	-	29.74	13.88
VC	-	1.76	-	2.98
		Standard Deviation		
pov_99	12.81	11.11	22.26	14.70
pov_89	15.38	11.33	26.84	15.52
black_89	20.54	30.58	35.39	35.64
hisp_89	20.35	22.19	21.31	26.72
empl_89	13.62	9.61	19.47	12.11
young_89	11.81	7.13	12.17	7.33
fix	-	-	35.42	17.88
VC	-	3.23	-	3.23

Table 2 Correlation Matrix for Census Variables (N = 6,924)

Variables	pov_99	pov_89	black_89	hisp_89	empl_89	young_89	Fix_95	VC_95
pov_99	1							
pov_89	.83	1						
black_89	.49	.51	1					
hisp_89	.46	.43	-.09	1				
empl_89	-.65	-.71	-.47	-.34	1			
young_89	.06	.05	-.10	.17	.31	1		
p_fix95	.49	.49	.35	.09	-.38	-.04	1	
p_VC95	.37	.41	.33	.16	-.30	.01*	.30	1
Mean	15.61	14.46	21.24	18.70	47.01	34.66	5.00	1.78
S.D.	13.55	14.58	31.93	23.50	11.44	8.22	12.23	3.10

* These coefficients are not statistically significant at .05 level.

Table 3 Correlation Matrix for Tracts with Detailed Information on VC Units (N=2,742)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. pov_cv_99	1												
2. pov_89	.86	1											
3. black_89	.40	.43	1										
4. hisp_89	.43	.40	-.25	1									
5. empl_89	-.75	-.80	-.45	-.32	1								
6. young_89	-.12	-.12	-.31	.14	.50	1							
7. p_vc95	.40	.38	.27	.04	-.10	-.13	1						
8. fem_vc95	-.02*	.02	.36	-.02	-.35	-.08	-.02	1					
9. welf_vc95	.37	.32	.29	.34	-.32	-.03*	.17	.34	1				
10. black_vc95	.29	.30	.80	-.18	-.28	-.13	.17	.44	.39	1			
11. hisp_vc95	.14	./12	-.35	.70	-.07	.15	.-01	-.04*	.22	-.45	1		
12. dif_vc95	-.06	-.10	-.14	-.19	.03*	-.17	.03*	-.38	-.23	-.28	-.19	1	
13. mover_vc95	.11	.17	.23	-.04	-.15	-.03*	.03*	.07	.15	.21	-.04*	-.15	1
Mean	21.52	19.62	31.37	25.27	44.23	35.89	3.89	82.39	25.61	48.13	19.13	18.73	10.04
S. D	12.64	13.68	34.60	25.52	10.69	6.60	3.97	14.33	15.54	36.59	21.58	16.23	10.87

* These coefficients are not statistically significant at .05 level.

Table 4 Correlation Matrix for Tracts with Detailed Information on Fixed Public Housing Units (N = 1,120) – revised!

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. pov_fix_99	1												
2. pov_89	.88	1											
3. black_89	.48	.52	1										
4. hisp_89	.37	.30	-.32	1									
5. empl_89	-.81	-.86	-.56	-.27	1								
6. young_89	-.27	-.31	-.44	.09	.60	1							
7. p_fix95	.53	.56	.37	-.02*	-.52	-.31	1						
8. fem_fix95	.06*	.08	.27	-.18	-.13	-.19	.12	1					
9. welf_fix95	.26	.26	.23	.11	-.26	-.05*	.10	.24	1				
10. black_fix95	.35	.38	.81	-.30	-.40	-.30	.25	.32	.29	1			
11. hisp_fix95	.23	.21	-.23	.12	-.19	.03*	.06	-.19	.10	-.42	1		
12. dif_fix95	-.17	-.20	-.16	-.10	.16	.06	-.14	-.14	-.03*	-.17	-.02*	1	
13. mover_fix95	-.02*	-.02*	.03*	.02*	.01*	.02*	-.05*	-.03*	.07	.07	.01*	-.03*	1
Mean	26.09	25.69	38.98	27.60	40.94	36.02	15.84	70.96	14.93	44.72	25.45	17.41	9.45
S. D	14.04	16.00	35.41	26.62	12.06	6.83	19.45	17.88	17.07	36.42	28.71	15.26	12.05

* These coefficients are not statistically significant at .05 level.

Table 5 Determinants of Census Tract Poverty Rates (Robust Regression, N=6,924)

	Model 1		Model 2	
Variables	Coefficients	t-ratio	Coefficients	t-ratio
Intercept	7.112	6.88	7.380	7.33
pov_89	.527	19.52	.479	17.05
black_89	.062	10.66	.057	10.39
hisp_89	.097	11.99	.105	12.73
young_89	.075	2.66	.088	3.21
empl_89	-.150	-5.70	-.132	-4.95
Tract type (ref. = no public housing)				
only VC units	2.164	6.11		
only fixed units	3.731	4.01		
both VC and fixed units	3.365	6.95		
p_fix95			.118	8.31
p_VC95			.378	3.73
R^2 = .731	S.E.E. = 7.036		R^2 = .742	S.E.E. = 6.888
Breusch-Pagan test for heteroskedasticity		χ^2=4391.95, df=1 p<.000		χ^2=4118.86, df=1 p<.000
Ramsey reset test for omitted variables		F(3, 6912) = 115.35 p<.000		F(3, 6913) = 94.48 p<.000

Table 6 Racial and Economic Segregation by Cities

City	# Census Tracts	D_pn*	D_wb**
Baltimore	569	.43	.68
Boston	660	.38	.67
Chicago	1746	.44	.79
LA	1631	.34	.62
New York	2318	.36	.75

*D_pn: Dissimilarity index between poor & nonpoor
**D_wb: Dissimilarity index between white & black

Table 7 Determinants of Census Tract Poverty Rate by Cities, Robust Regression

Variables	Baltimore	Boston	Chicago	Los Angeles	New York
Intercept	.933	7.837	8.314	1.728	13.466
pov_89	.736	.647	.412	.771	.456
black_89	.040	.027**	.098	.047	.050
hisp_89	-.210**	.013**	.096	.053	.094
young_89	.023**	.195	.087**	.122	.029
empl_89	-.015**	-.217**	-.179	-.067**	-.214
Tract type (ref. = no public housing)					
only VC units	2.129	-1.106**	1.050	.452**	2.887
only fixed units	-1.423**	.883**	3.468	3.045**	11.643
both VC and fixed units	3.508	.040**	2.159	1.244**	4.599
R^2 (N)	.81 (569)	.79 (660)	.75 (1746)	.80 (1631)	.67 (2318)
Breusch-Pagan / test					
Ramsey reset test			p<.000		

** These coefficients are statistically insignificant at .05 level.

Table 8 Determinants of Census Tract Poverty Rate, where Detailed Information on VC Public Housing Units is Available, Robust Regression (N = 2,742), Robust Regression

Variables	Metric coefficients	Robust Standard error	t-ratio
Intercept	20.199	1.688	11.96
pov_89	.499	.024	20.88
black_89	.039	.007	5.76
hisp_89	.069	.009	7.61
young_89	.178	.043	4.10
empl_89	-.279	.037	-7.60
p_vc95	.214	.049	4.67
fem_vc95	-.099	.012	-8.42
welf_vc95	.060	.010	5.94
black_vc95	.010	.006	1.63
hisp_vc95	-.010	.009	-1.18
dif_vc95	.022	.008	2.73
mover_vc95	-.043	.013	-3.41
R^2 = .792	S.E.E. = 5.788		
Breusch-Pagan / test for heteroskedasticity		x^2=549.88, df=1	p<.000
Ramsey reset test for omitted variables		F(3, 2726) = 29.51	p<.000

Table 9 Determinants of Census Tract Poverty Rate, where Detailed Information on Fixed Public Housing Units are Available, Robust Regression (N = 1,120), Robust Regression

Variables	Metric coefficients	Robust Standard error	t-ratio
Intercept	13.388	2.582	5.19
pov_89	.447	.036	12.26
black_89	.072	.013	5.62
hisp_89	.125	.015	8.21
young_89	.236	.059	3.98
empl_89	-.297	.058	-5.10
p_fix95	.064	.015	4.17
fem_fix95	-.020	.014	-1.44
welf_fix95	.014	.012	1.17
black_fix95	-.013	.010	-1.28
hisp_fix95	-.038	.011	-3.47
dif_fix95	.021	.012	1.75
mover_fix95	.001	.020	.06
R^2 = .811	S.E.E. = 6.142		
Breusch-Pagan / test for heteroskedasticity		x^2=137.04, df=1	p<.000
Ramsey reset test for omitted variables		F(3, 1104) = 13.02	p<.000

Appendix A: Description of Variables

Census Variables

1. pov_99: Percent of the people in census tract whose income is below the poverty line in 1999

2. pov_89: Percent of the people in census tract whose income is below the poverty line in 1989

3. black_89: Percent of African American in census tract in 1989

4. hisp_89: Percent of Hispanic origin in census tract in 1989

5. empl_89: Percent of people employed in census tract in 1989

6. young_89: Percent of people aged 20 – 39 in census tract in 1989

HUD VC Variables

1. p_vc95: Percent of people assisted by voucher and certificate program in census tracts in 1995

2. fem_vc95: Percent of households among VC users lead by female head in census tract in 1995

3. welf_vc95: Percent of households among VC users whose main income comes from welfare in census tract in 1995

4. black_vc95: Percent of VC users who are African Americans in census tract in 1995

5. hisp_vc95: Percent of VC users who have Hispanic origin in census tract in 1995

6. dif_vc95: average percent minority among VC users minus average percent minority in census tract in 1995

7: mover_vc95: Percentage of VC households who stay in VC program less than 1 year in census tract in 1995

HUD Fix Variables

1. p_fix95: Percent of people living in fixed public housing in census tracts in 1995

2. fem_fix95: Percent of households lead by female head living in fixed public housing in census tracts in 1995

3. welf_fix95: Percent of households living in fixed public housing whose main income comes from welfare in 1995

4. black_fix95: Percent of households living in fixed public housing who are African Americans

5. hisp_fix95: Percent of households living in fixed public housing who have Hispanic origin

6. dif_fix95: average percent minority among living in fixed public housing minus average percent minority in census tract

7: mover_fix95: Percentage of households living in fixed public housing who stay less than 1 year