Housing Demand and Neighborhood Choice with Housing Vouchers

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Abstract

One goal of the U.S. housing voucher program, as an alternative to public housing subsidies, is to help participants gain access to decent neighborhoods. I find that in a typical implementation of the program, participants in the housing voucher program live in better neighborhoods than public housing residents, but in lower-quality neighborhoods compared to unsubsidized households eligible for the program. I propose and estimate a new model of residential choice and housing demand that respects different budget constraints induced by various housing policies. The model is used to study several possible rental assistance schemes. With respect to crime rates and public school quality, a rental rebate program and a requirement to live in low-poverty neighborhoods would be most effective at improving neighborhood selection. The former would significantly lower program costs, while the later would have to be offset with high levels of compensation including relocation assistance.

1 Introduction

The goal of this paper is to understand how housing subsidies affect neighborhood choice, and how to design housing subsidies that facilitate access to neighborhoods with low crime rates and adequately performing schools. To begin, I review the current housing outcomes of the U.S. Housing Choice Voucher Program participants. I propose and estimate a model of neighborhood choice and housing demand using the revealed preferences of voucher recipients, as well as the revealed preferences of unsubsidized households. With the estimated choice model, I simulate alternative policy schemes to examine how voucher recipients' choices might change as a result of changes to the voucher program. The findings indicate that the policy change most effective at moving residents to improved neighborhoods would be to offer rental rebates instead of a vouchers and to impose a requirement that households live in neighborhoods with poverty rates below 30%.

Low-income households and the housing subsidy opportunities they face have not, until now, been addressed in equilibrium models of residential sorting. The low-income population tends to rent rather than own property, and is arguably more mobile. Most residential sorting models are estimated using data on home purchases and thus do not reflect the rental population. In addition, many of the theory-based outcomes of household sorting models, such as the joint stratification of income and public good provision, were made possible only by abstracting away from the small segment of the population receiving housing subsidies.[1] However, over 4.3 million households receive, and millions more are eligible for,

[1]For example Epple and Sieg (1999), Epple Romer Sieg (2001), Sieg et al (2004), Ferreyra (2007), and Walsh (2007) specify and estimate locational equilibrium models that include the endogenous creation of public goods through political processes. Other studies employ a discrete neighborhood choice framework. Bayer McMillan Reuben (2004), Bayer McMillan (2005), Bayer Ferreira McMillan (2007) and Ioannides and Zabel (2008) explore the effects of income inequality, racial sorting, sorting based on education, and neighbors' effect on housing consumption. From this previous work, we might hypothesize that housing subsidies disrupt the stratification of income and neighborhood amenity preferences, that minority subsidy

rental subsidies that alter their budget for housing by introducing non-convexities in the housing demand choice set (HUD, 2011). Thus to analyze low-income households' housing demand and neighborhood choices, I propose a new equilibrium sorting model that models the choices of the full population with, and without, housing subsidies. The model is easily generalizable to the inclusion of additional groups with other housing subsidy types.

Most of the recent analysis of U.S. housing vouchers stems from random experiments where participants were recruited from public housing and often the experimental group received relocation counseling or was required to choose a neighborhood with a low poverty rate.[2] The work presented here complements previous voucher program evaluation efforts in two respects. First, I analyze a different but more typical voucher program implementation: participants are not offered relocation counseling, participants do not face requirements to locate to neighborhoods above some minimum quality standard, and most participants were not previously public housing residents. I use a unique, restricted-use dataset describing the income, census tract location, voucher amount, and several demographic details of the 4,341 voucher recipients in Pittsburgh, Pennsylvania, in the year 2006. By focusing on a single city, a detailed specification of neighborhood amenities and housing price decomposition is available. I construct a neighborhood-level data set that includes, for example, violent crime rates, mean standardized test scores, and measures of the availability of voucher-friendly rental opportunities.

The second way in which my paper complements existing housing voucher program evaluation research is that I analyze the expected program outcomes that would result from

recipients face higher implicit housing prices, and that renters wish to consume a level of housing services similar to their neighbors', respectfully.

[2]The literature review of this paper reviews the Gautreaux and MTO studies (Turner, 1998), (Kling, Liebman, & Katz, 2007).

program implementation with alternative housing voucher schemes. This normative focus is a natural extension of the previous work on whether moving to better neighborhoods improves mental, physical, and employment outcomes; the normative focus also informs the possible design of new field experiments. The U.S. Department of Housing and Urban Development (HUD) has two main goals for its voucher program, which are to provide adequate, affordable housing to those currently without, and to ensure that the program does not restrict mobility across neighborhoods and thus result in exacerbating the socio-economic segregation of very-low income households. Program evaluation of mental, physical and employment outcomes is central to evaluating the benefits of the program, while normative analysis of the policy itself is central to understanding how best to achieve the stated goals of the federal program.

The choice model proposed here adapts elements of Dubin and McFadden's (1984) discrete-continuous choice model to a framework that includes kinked budget constraints induced by program participation, as in, for example, Hausman & Wise (1980), Hausman (1985), Moffitt (1999), Gordon & Blinder (1980), and McCarty (1990). In particular, a voucher household may obtain a fixed maximum level of housing subsidy in exchange for a fixed portion of its income. Non-voucher households face a regular budget constraint. The model views households as making a simultaneous discrete choice of which neighborhood to live in, and a continuous choice of how many units of housing services to purchase. The continuity of housing demand is an important feature for studying important variations in housing consumption that result from policy changes. The discretization of the neighborhood selection problem facilitates the parameterization of heterogeneous tastes for multiple neighborhood characteristics including crime, school quality, and racial composition.

I show that the parameters of the model can be estimated using a new GMM estima-

tor. The estimator allows for a combination of aggregate data and micro-level data, as I supplement the voucher data with Census data on the general low-income population. My estimator imposes that the model match the share of households, by demographic group, in each of 114 neighborhoods in Pittsburgh. Simultaneously, the estimator imposes that observed housing demand match predicted housing demand for each demographic group. The identification strategy requires an appropriate selection of instruments to account for endogenous variables including neighborhood price and neighborhood demographics. The specification and identification strategy combine to generate plausible estimates such as a negative utility for crime and a positive preference for school equality, i.e. preferences that are otherwise difficult to uncover in a demographic that tends to select neighborhoods with higher crime and poorer schools than average.

The estimation reveals that crime levels, commute times, public school quality, public open space, and racial composition impact households' preferences for specific neighborhoods. In addition, the availability of public open space serves as a substitute for housing services while public school quality and housing services are complements. The estimation suggests that the price elasticity of housing demand ranges from -.44 to -.83 , which is slightly lower than other estimates published in the literature, but reasonable given the focus on only poor households that typically consumes subsistence levels of housing, food, clothing, and childcare.[3] The model allows for the possibility of non-separable preferences for the discrete and continuous choices through co-varying parameters. Although I find significant covariation of non-separable preferences, I find that resulting bias correction of the housing demand equation generally accounts for less than 0.05% of the housing demand.

Finally, I consider the question of optimal voucher policy design. I compare the cost of

[3]Friedman and Weinberg (1982) offer a detailed overview, finding that estimates of price elasticity generally range from -0.6 to -1.7.

policy changes to the expected benefit as estimated by households' compensating variation, but I do not include potential neighborhood spillover effects. Average welfare improves with a 20% increase in the voucher, a voucher maximum that varied by census tract rather than metropolitan area, or the replacement of the voucher with a rental rebate. In terms of the average participant's neighborhood crime rate and school quality, a policy that allowed the maximum voucher amount to vary based on census tract would be twice as effective as, and 63% less expensive than, a policy that increased the current maximum voucher amount by 20%. Replacing the voucher with a rental rebate would significantly decrease total program costs and lead to neighborhood selection similar to the scheme introducing a voucher maximum that varies on the census tract level. A program restriction to reside in a neighborhood with a poverty level less than 30% would reduce the neighborhood choice set by 22% and yield significant improvements in most weighted mean neighborhood amenities, for example the newly optimized mean neighborhood choice would have a -20% lower violent crime rate (-10% for whites) and a 2.45% higher school quality index (1.3% increase for whites).

2 Background and Literature Review

The current recession and housing crisis has led to the highest absolute (7.1 million) and percentage-wise (22 percent) level, on record, of very low-income renters paying more than half of their income for housing or living in severely inadequate housing (HUD 2011). To assist some of these households, the government offers a variety of programs. The Housing Choice Voucher Program is the largest component of the general Section 8 voucher program which also includes project-based housing vouchers (i.e. site-specific vouchers). In 2009 the Housing Choice Voucher Program served roughly 2.1 million households. By contrast,

2.3 million households lived in public housing.

Housing vouchers were first introduced by HUD in 1970 in the form of an experimental housing allowance program commissioned by Congress. As a result of the success of that program, in 1974 Congress created the Section 8 voucher program and in the first five years the program expanded to 624,604 households (HUD 2000). As congressional studies continued to show that housing vouchers were more cost-effective than maintaining the country's public housing stock, the program grew to its current size of 2.1 million households (HUD, 2011), (Olsen, 2003). The program's most lauded features are its allowance for residential choice and mobility, the portability of a voucher across all national housing authorities, and its flexible contract options for the tenant and landlord.

All local housing authorities receive direction from HUD on how to shape their voucher programs. HUD stipulates income eligibility limits, maximum levels of subsidy amounts, and a minimum acceptable level of housing services ($h_{\min}$). Income eligibility levels and maximum subsidy amounts vary across metropolitan areas, taking local housing markets and income levels into account. Maximum subsidy amounts are often expressed in terms of Fair Market Rent (FMR) and are adjusted based on the number of bedrooms required by each household.[4] Generally HUD sets the FMR at the 40th percentile of local rental rates, based on the Census and the American Housing Survey data on contract rents and inflated using the local CPI index.[5] Generally, households participating in the housing voucher program must contribute 30% of their income towards housing expenses;[6] the

[4]For example, a parent with two daughters would qualify for a two bedroom while a parent with one daughter and one son would qualified for a three bedroom. Several households enjoy more bedrooms than they qualify for, perhaps because of lagged variables- for example, "empty-nesters".

[5]Where local CPI indices are not available, HUD uses data from its own regional Random Digital Dialing Survey.

[6]If households wish, they may choose to spend an additional 10% of their income towards rent to cover the difference between FMR and a rent that exceeds FMR. However, total household housing expenses may not exceed 40%.

difference between actual housing expenses and a household's contribution is subsidized by the housing authority in the form of a voucher, with a maximum subsidy of FMR. So long as the participant identifies an amenable landlord and the rental property meets a minimum quality level, the voucher is as flexible as a full-paying tenant's offer. In most regions including Pittsburgh, the relevant housing authorities direct the voucher to the landlords so the voucher household do not have a chance to use it as a general income subsidy. Vouchers offer the possibility that recipients can not only consume a reasonable quality of housing services, but also find housing in decent, safe neighborhoods.

The author is aware of no study that examines voucher recipients' choices of housing services versus neighborhood quality, although several studies examine relocations. Using a comparison group, Carlson et al (2009) finds that the receipt of a voucher substantially increases the chances of a household's relocation to a different neighborhood. Feins and Patterson (2005) note that, nationally, only 14.5% of households receiving vouchers move within the first two years after initial voucher receipt; 45.3% after five years; 60.8% after eight years; African Americans are the most likely to move, with 75% moving after their current lease expires. Also, Feins and Patterson (2005) find that the fewer the adults, the younger the children and adults, and the higher the income, the more likely a voucher recipient household will relocate.[7]

For relatively few housing voucher initiatives, some voucher recipients receive special assistance in their relocation decisions. These neighborhood counseling programs have demonstrated that counseling has a substantial effect on neighborhood choice (Turner, 1998) (Kling et al., 2007). For example, the Gautreaux Program offered minority families

[7]The higher relocation rates in the recent Moving To Opportunities studies are due to several factors; families had a deadline of 4-6 months to move in order to receive the voucher, and families had to volunteer to be in the study, (Kling et al., 2007).

vouchers for use only in predominantly white neighborhoods. In the Moving to Opportunities studies, families in the experimental group receiving a voucher were offered relocation assistance and were required to live in a neighborhood with a poverty rate of less than 10 percent. In another example of relocation decision assistance, several metropolitan areas have seen litigation regarding racial discrimination in public housing that has led to victims' compensation with vouchers coupled with relocation assistance. Still, relocation counseling is not a primary feature of most voucher programs. For this majority of voucher programs, it is important to understand how households exercise the joint decision of housing services choice and neighborhood choice.

One goal of the voucher program, to increase participants' mobility, stems from the understanding that well-being is impacted by neighborhood quality.[8] To study this hypothesis, the Moving to Opportunities study randomly assigned vouchers to families in public housing that were interested in the voucher program. In the program evaluation, Kling et al. (2007) found that adults in the treatment groups that received vouchers, compared to the control groups who did not receive vouchers, showed increases in exercise, nutrition, sleep and calmness; and decreases in obesity, distress, depression and anxiety. Recent research indicates that economic self-sufficiency is less impacted. Kling et al (2007) found no significant affect on earnings and welfare participation. In another randomized experiment, Jacob and Ludwig (2008) found that voucher recipients worked and earned less than those who did not receive a voucher. This finding is consistent with descriptive statistics indicating lower earnings for voucher recipients(Olsen, Tyler, King, & Carillo, 2005). Using comparison groups, Susin (2008) found vouchers appear to reduce earnings by 15%. Carlson et al (2009) found a positive effect on employment but negative effect on earnings.

[8]Spatial mismatch, suggesting diminished employment prospects for those living in distressed areas, is a topic explored in economics, for example Kain (1968) and Gobillon, Selod, & Zenou (2007). There is a large literature on this topic in sociology; classics include Wilson (1987) and Kozol (1996).

3 Data

3.1 Voucher Households

In Pittsburgh, PA, housing subsidies are managed through the HACP. For this research the HACP provided data on the residential location of households with vouchers in 2006. The data set contains the households' census tract, number of bedrooms, household income, and total rent due to the landlord (the sum of the household's contribution and the authority's contribution). Aggregate data on the voucher households' joint distribution of race and presence of children by census tract were provided by the Allegheny Department of Human Services. At the city level, aggregate data on tenure, income sources and age were obtained from the 2004-2007 Picture of Subsidized Households, a dataset published by HUD. Eliminating the observations with missing values, the HACP data includes 4341 households. The majority (79%) of voucher households in the HACP program are black, 2% are minority but not black, and only 1% of all households are Hispanic. 86% of voucher households with children are non-white, while 71% of voucher households without children are non-white. The majority of households are headed by females (85%) and half of the households include only one adult. Wages or net self-employment revenue is the main income source for only 30% of households; 17% of households obtain the majority of their income from welfare (TANF, Government Assistance, or Public Assistance); the remaining 53% of households receive income from other sources, for example Disability, Social Security, charitable handouts, food stamps, or no source at all. On average, households have been in the program for 49 months. Most heads of household (62%) are between the ages of 25 and 50; 14% of heads of household are under age 25, 24% are over age 50, and 12%, are over age 61.

Table 1 shows the HACP's voucher program income limits for 2006, the income levels for which the program prioritized entry into the voucher program, and the mean income of the households in the study. HUD requires that the local housing authorities serve a population where at least 75% of households earn an income below the "priority" limit. This requirement addresses the incentive of the housing authorities to minimize expenses by recruiting higher income households. Table 1 also shows the FMR, by number of bedrooms, for 2006. The voucher amount is directed towards both rent and utilities. For the housing authority in this study (the HACP), the voucher was directly paid to the landlord and thus could not be exercised as a general income subsidy. Also, not every household received the full voucher amount; rather, the voucher amount depended on the rent level chosen by the participating landlord.

Table 1: Income Limits and Program Benefits, HACP 2006

	Number of Bedrooms			
	1	2	3	4
Fair Market Rent*	$625	$755	$940	$1047
Income Limit	$20,100	$22,950	$25,850	$28,700
Priority Limit†	$12,050	$13,750	$15,500	$17,200
Observed Mean Income	$12,043	$13,586	$16,474	$19,774

*Maximum voucher amount.

† 75% of participating households must have income below this limit

After gaining entry to the HACP program, a prospective tenant initiates a dialogue with a potential landlord. If the landlord agrees to follow-through, the tenant approaches the housing authority with a description of the property and the rental contract specifics. The housing authority then meets with the landlord to inspect the property and review the rent. The HACP considers the FMR as a sum of a maximum allowable rent and the expected utility cost for the unit, where HACP holds a schedule of expected utility payments (m_{ph}) for each number of bedrooms and apartment types (apartment, town house, or single fam-

ily home). A household is expected to pay 30% of its income towards housing; the first portion will go towards utility bills and any left over will go towards the contract rent.[9] If a household desires an apartment that exceeds $FMR - m_{ph}$, the housing authority will allow it to spend an additional 10 percent of its income to pay for the higher rent. However, the household's resulting cost burden must not exceed 40% of its income. Not exceeding FMR, the housing authority computes the voucher amount by subtracting the difference between 30% of the household income minus expected utilities from the contract rent, as in equation (1).

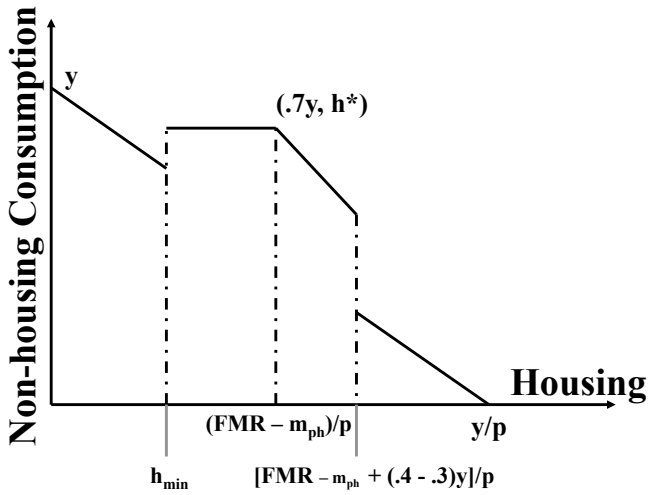
$$\text{Voucher} \quad = \quad \text{Contract Rent} - (.3 * \text{Income} - \text{Expected Utilities}) \tag{1}$$

Figure 1 illustrates this budget constraint for a household with income level y and a local housing services price of p_j. If a household desires housing services lower than $h_{\min}$, or desires to spend more than 40% of its income towards housing, it cannot participate in the voucher program. Between those values, however, the household has a discontinuous budget constraint induced by program participation. In the voucher program, the vast majority of households choose $h_j^* = (FMR - m_{ph})/p_j$ in housing services and contribute 30% of their income. Taking the expected utilities expense schedule into account, 50% of households included in this paper's data set secure an apartment for a rental amount within $15 of the maximum allowable rent; 75% secure an apartment within $90 of the maximum allowable rent. A reasonable conclusion is that the vast majority of the program participants are able

[9]There are several interesting economic implications. First, in the Pittsburgh Metropolitan Area the HUD-determined FMR results in lower voucher benefits the larger the family size. This inequality results because utility costs differences between an efficiency unit and a four bedroom unit (for example) exceed the differences in the FMR for these units. Second, households might be directed towards certain types of housing units and leases in order to exchange more square footage for lower utility costs. For example, a household in this study might choose a 3 bedroom apartment with water and garbage included over a 3 bedroom townhouse where the tenant pays for water and garbage removal in order to purchase $144 in housing services rather than spend that amount in utilities.

to maximize their program benefit, and observed deviations may be the result of optimization error or measurement error. In further analyses, I simplify the voucher household's general utility optimization problem to solely the discrete choice of a neighborhood j in which to enjoy h_j^*.[10]

Figure 1: Voucher Households' Budget Constraint



The voucher households' kinked budget constraint differs from the continuous housing budget constraint of low-income households who do not benefit from a housing subsidy. It is simply $y = ph + b$, where b represents non-housing consumption. The next section describes the data on these unsubsidized households.

[10]This simplification is not required to estimate the model. The model can easily be extended to the more complex case.

3.2 Households Without Vouchers

Voucher households are compared to low-income households in Pittsburgh, PA, using the 2000 Census Summary Level 3 files which provide a coarse joint income and rent distribution at the census tract level.[11] The census data is adjusted by subtracting the number of voucher households in each income category, by census tract.[12] Table 3.2 explains the size of population sub-groups in the eligible population and the population in the housing voucher program: whites/blacks and households residing/not residing with own children under the age of 18. The housing voucher's income limit for a family of four was $28,700; due to the coarse income distribution, I consider all households described in the 2000 Census as having an income of less than $35,000. 52% (about 74,000) of all households in Pittsburgh have a household income level of less than $35,000. Of the households, 7.5% received Public Assistance payments, 53% are black (79% of voucher recipients are black), less than 0.8% are Hispanic, 53% are female-headed households with no husband present (84% of voucher households are female-headed), 34% are age 65 and over, 14% are households headed by persons under the age of 25.

Table 2: Sample Size

Source	Demographic			
	Black, Kid	Black, No	White, Kid	White, No
2000 Census	9,693	6,326	15,890	15,201
HACP Voucher 2006	1,694	1,218	256	521

Table 3 compares demographic characteristics of the HACP voucher households to the population without vouchers. Blacks, adults between the age of 25 and 61, and households

[11] Income levels and housing prices from the 2000 Census are adjusted for inflation based on the housing CPI statistics from the Bureau of Labor Statistics.

[12] No adjustment in the demographic distribution is considered for the fact that the voucher data are from 2006 instead of 2000. Overall, the population of Pittsburgh was slightly declining over that time period, mostly due to population aging.

with children are overrepresented in the voucher program in comparison to the general low-income population. Seniors are underrepresented in the voucher program.[13] The 75th percentile of the income distribution is higher in the general low-income population than in the voucher program population. While the 25th percentile of the income distribution appears lower in the general low-income population than in the voucher program population, this estimate (of $0 annual income) is likely underestimated due to reporting/measurement error. Moreover, the housing authority minimizes program cost by recruiting higher-income participants. The percentile of the income distribution for low-income households without a voucher was calculated using the publicly available Census Micro-Level data.[14]

Table 3: Comparison of Demographic Characteristics

	HACP	Census*, <$35K
% black	79%	53%
% of white with kids	38%	18%
% of black with kids	60%	34%
% under age 25	14%	14%
% over age 61, 65	12%	34%
25th %-tile inc	$10,400	$0
50th %-tile inc	$13,120	$12,115
75th %-tile inc	$17,040	$22,380

*Census minus HACP voucher program population.

Table 4 shows the inflation-adjusted mean gross rent of rental households by income. Table 4 also shows the mean budget share of housing for each income group. The mean unsubsidized household in the income category of $10-20K is spending 47% of its income on housing expenses to pay a rent of $590. If the mean unsubsidized household where to

[13]In the HACP data, seniors are identified as those over 61 years of age. In the coarse income and age distribution in the Census Summary 3 Files, I identify seniors as those 65 and over.

[14]In the model estimation, aggregate data from the joint income and rent distribution are used, as the Census Summary Level 3 data provides finer geographic detail. To be best representative and to avoid an income of zero, the income level used to calculate estimates is the average of upper and lower bounds of the income category.

receive a voucher for a two-bedroom apartment, its housing budget would drop to 30% of its income and it could seek an apartment with a rental price of $755. Thus, the majority of low-income households has a clear budget incentive to participate in the housing voucher program.

Table 4: Mean Rent and Rent-Equivalent of All Households in the City of Pittsburgh, by Income

	<$10K	$10-20K	$20-35K	$35-50K	$50-75K
Rent of Rental Households	490	590	686	756	846
Budget Share of Housing	0.735	0.472	0.299	0.213	0.162

3.3 Neighborhood Characteristics

In addition to housing consumption, this research also focuses on neighborhood choice. For the purposes of this study, the Pittsburgh neighborhoods are defined as census tracts. The density of Pittsburgh, its small neighborhoods resulting from hilly topology, and the wide variety in neighborhood quality across small geographic areas make census tracts a reasonable boundary.[15] Census tracts where less than 15% of households rent their home are excluded. After excluding additional census tracts with insufficient data, I estimate the model on 114 census tracts, or neighborhoods, within the city. The lowest number of voucher households in an included neighborhood is 0 (3 neighborhoods), the highest number of voucher households is 212, the mean number of voucher households in each neighborhood is 33.5. Similarly, the minimum, maximum, and mean number of low-income households in each neighborhood are 8, 517, and 135.7 respectfully.

This study employs several data sources to describe each neighborhood. The most en-

[15]For the most part, these census tract boundaries are the same as the boundaries describing the Bureau of Police's 90 distinct neighborhoods.

compassing source is the 2000 U.S. Census, from which I use information on neighborhood demographics, the percent of commuters who use public transit, the average public transit commute time, and measures of human capital, for example, the percent with a college degree and the percent employed. For a more detailed picture, I turn to local data sources described in the following paragraphs.

As a proxy for the availability of voucher-friendly apartments, I collected six months of apartment listings from the Allegheny County Housing Authority (ACHA) and HACP websites from January 2010 to July 2010.[16] Apartments were listed on these websites if landlords were amenable to accepting vouchers as partial payments and if the landlord contacted the ACHA or the HACP to list the apartment. In Pittsburgh, there were 409 apartment listings across 121 census tracts (about 50 apartments were excluded because of insufficient information to geocode their addresses).[17] In the estimation, I exclude neighborhoods that do not host a voucher household and do not contain a listing of an apartment available to voucher recipients and do not border a census tract that contains a voucher listing (only 2 census tracts were excluded for those reasons).

The dataset includes geographic data, in particular the percent of land that is dedicated as a park or recreation area for public use, and the number of street intersections per square mile. These data were obtained from the U.S. Geological Survey. Park land might substitute for housing services as people may substitute private lawns and gardens for public ones. Street intersection density is one measure of street-connectedness; some studies find that street connectedness is correlated with substitution away from motor vehicles (Frank, Sallis, Conway, Chapman, Saelens, & Bachman, 2006).

[16] Ideally I would have listings from 2006, but those were not available

[17] A proxy for low-income housing availability could be the a priori measure of low-income households in a neighborhood. For a discussion on income heterogeneity in U.S. urban places, see Hardman & Ioannides (2004).

Current and detailed information on school quality and crime statistics were obtained for neighborhoods in Pittsburgh. School quality is measured by 2006 state-standardized test scores, measured at the individual level but aggregated into census tract means.[18] The Pennsylvania System of School Assessment (PSSA) exams are a series of tests administered at all Pennsylvanian schools at the third through eighth grade, as well as eleventh grade. I use the sum of the mathematics and reading scores for eighth graders to measure school quality.

The number of violent and property crimes in each census tract were obtained from the 2007 Annual Report of the City of Pittsburgh Bureau of Police. Violent crime includes homicide, rape, robbery, and aggravated assault; property crime includes burglary, theft, motor vehicle theft, and arson. To normalize, I use violent crime rates per capita.

Finally, I employ data on the availability of public housing in each neighborhood (and its immediate neighbors, as a proximity measure) to allow for a comparison of vouchers to publicly managed housing. Data on public housing, occupancy rates, and whether it is publicly or privately managed is obtained from the ACHA and the HACP.[19]

Housing vouchers may be desirable since they provide recipients with greater residential and neighborhood choice than supply-side subsidies such as public housing. Since the 1990s, HACP has been increasing the number of households in its housing voucher program while reducing its stock of public housing properties. The map in Figure 2 compares the density of housing vouchers in each census tract to the locations of HACP's public housing structures. The map illustrates that vouchers clearly obtain a different residential

[18]These data stem from a CMU-RAND study, funded by the Institute of Education Sciences (Davis, Engberg, Epple, Sieg, & Zimmer, 2010).

[19]The public housing data is taken from Epple Geyer and Sieg (2011) and also Epple et al (2010), who employ panel data on public housing households in their study of mobility of low-income households. In Pittsburgh there are 34 public housing communities located in 28 different census tracts, varying in size from 4 housing units to over 600 housing units per community.

sorting outcome than public housing. However, voucher use is highest in areas neighboring public housing structures.

Figure 2: Housing Voucher Density and Public Housing Locations in Pittsburgh, 2006

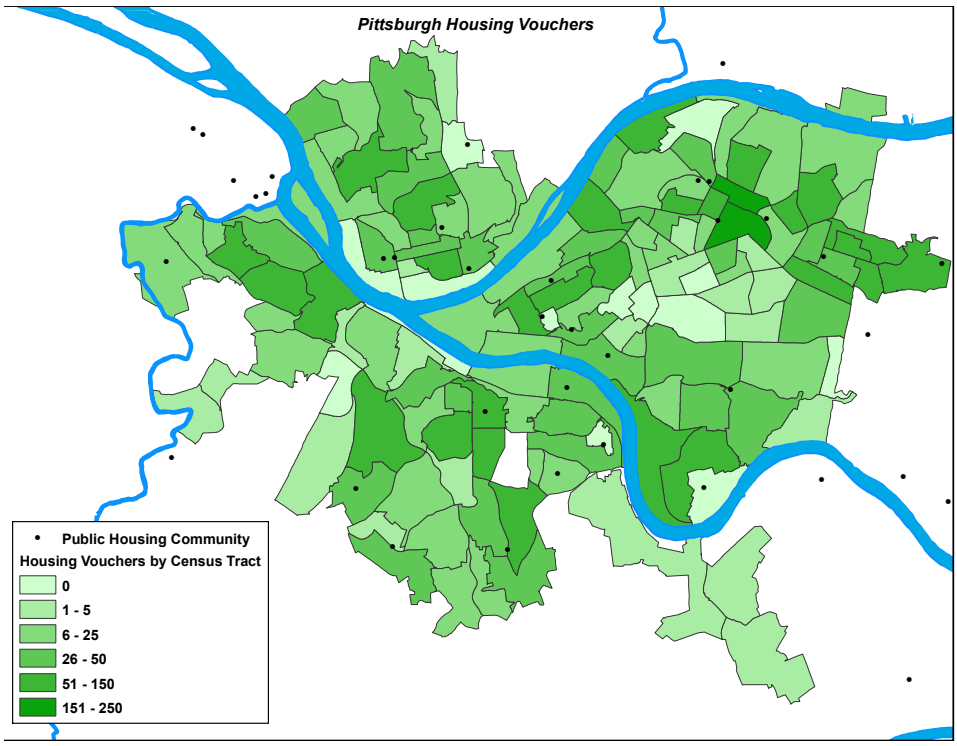


Table 5 compares the mean census tract attributes weighted by HACP public housing households, HACP households with vouchers, and all Pittsburgh households eligible for vouchers, and the full Pittsburgh population. On average, the voucher households live in more desirable neighborhoods than households in Pittsburgh's public housing. For example, voucher households tend to live in neighborhoods with lower crime, better schools, and less poverty than households in public housing. However, by most measures voucher households do not live in neighborhoods that are better than the typical neighborhood of a household eligible for a housing voucher. Compared to the eligible population, house-

holds with vouchers live in neighborhoods with higher crime, lower test scores, and more poverty.

Table 5: Mean Census Tract Statistics, Weighted by Number of Households (Pittsburgh, PA)

	Public Housing	Voucher	Eligible	All†
Violent Crimes per 1000	30.35*	25.94	21.02*	19.91*
Mean Test Score (in 100s)	24.10*	25.18	26.14*	26.23*
% Black	0.73*	0.45	0.32*	0.28*
% Single Mother Households	0.32*	0.13	0.12	0.10*
% Living in Poverty	0.49*	0.24	0.22	0.21*
Mean Pub Trans Time in Minutes	61*	86	100*	103*
% Commute by Pub Trans	0.43*	0.28	0.24	0.22*
Mean Str Intersections per Acre	0.42*	0.54	0.48*	0.47*
Park Land per Acre	0.03*	0.06	0.07*	0.07*
% Female, Completed College	0.09*	0.17	0.22*	.24*
% Male, Completed College	0.11*	0.20	0.26*	.28*
% Male Employed	0.40*	0.54	0.57	0.56
% Households That Rent	0.78*	0.52	0.49	.47*
Median Rent	225*	364	393*	407*
Median Income	31,471*	33,255	32,826	33,085

*Indicates significantly different from vouchers ($p < .01$).

†Full population, all income levels.

4 The Model

A priori, households have decided to live within a specific metropolitan area. Within the metropolitan area there is a finite number of neighborhoods J. I model households' simultaneous choice of one of these neighborhoods ($j \in J$) to live in, a level of housing services h, and a private composite good b representing non-housing expenses. The levels of housing services and the composite good are continuous, homogeneous variables. Choices are constrained by budgets governed by household income, housing prices, minimum accept-

able housing standards, and - if applicable - terms of a housing subsidy. Each neighborhood offers a bundle of predetermined public amenities and households can move freely between the neighborhoods. A neighborhood ($j \in J$) is characterized by public amenities observed by the econometrician (Z_j), unobserved public amenity ξ_j, and the price of housing p_j.

I begin with a direct utility function which yields different indirect utility functions with respect to various budget constraints. Household i has utility u_{ij} for neighborhood j described in equation (2).

$$u_{i,j} = \gamma Z_j + \gamma_i X_i Z_j + \xi_j + \alpha \log(h - H) + (1 - \alpha) \log(b - B_{ij}) + \epsilon_{ij} \quad (2)$$

$$B_{ij} = \beta X_i Z_j + \nu_i \quad (3)$$

The utility function allows for unobserved heterogeneity so that households with the same income may make different choices. Unobserved heterogeneity is modeled as the tuple $(\gamma_i, \nu_i, \boldsymbol{\epsilon}_i)$. Variations in household characteristic γ_i describe tastes for public services. In addition to allowing variation, the γ_i is interacted with household type X_i so that different households may have different mean utility for certain neighborhood characteristics, for example households with children might have a strong preference for neighborhoods with good schools. The parameter ν_i describes variation in private consumption patterns. The vector $\boldsymbol{\epsilon}_i$ represents household-neighborhood specific preferences.

As some previous work in residential choice has found significant nonseparable preferences for neighborhood and housing choice,[20] the model allows for non-separable pref-

[20]Rapaport (1997) and Ioaniddes and Zabel (2008) employ discrete-continuous choice models to study housing. Rapaport (1997) finds that allowing for nonseparability increases the price elasticity of demand and reduces the differential between price elasticities of white and comparable nonwhite households. Ioannides & Zabel (2008) find that nonseparable preferences are statistically significant and increase the estimate of the

erences for housing services and neighborhood attributes. In particular, the model allows variation in tastes for public amenities (γ_i) and private consumption (ν_i) to be correlated. For example, families with children might require more housing services and have a stronger preference for public school quality. Dubin and McFadden (1984) presented the first work on a model with non-separable preferences of a simultaneous discrete-continuous choice. Their model allows the unobserved component of the continuous good's demand elasticity to covary with the vector $\boldsymbol{\epsilon}_i$. While I permit unobservables γ_i and ν_i to be correlated with each other, I assume them to be independent of $\boldsymbol{\epsilon}_i$. This independence assumption simplifies estimation while permitting application of the results beyond the specific neighborhoods employed in estimating the model. The correlated unobserved preferences will also allow the model to predict more realistic substitution patterns between similar neighborhoods.

Households have utility for composite good b and housing services h. The specification allows the possibility for minimum consumption requirements, which may best describe the choices of low-income households. Specifically, there is a minimum housing consumption level H that is constant across all households. H can be interpreted as a minimum level of shelter required for survival, or minimum standard of residential zoning compliance; in this instance, the former interpretation is more applicable because H is constant across all neighborhood choices.[21] Non-housing consumption is augmented by the implicit value of consumption of neighborhood amenities, which can be negative in some neighborhoods and positive in others because of publicly available amenities. Transportation costs and school costs are two examples that might vary by location.

elasticity of housing demand with respect to mean neighbors' demand by 17 percent.

[21] In the model and its estimation, it is feasible for H to be interacted with household composition or other observables. However, random or unobserved components of H would create residuals in the housing demand that are correlated to price.

For the utility function to be well behaved, parameter α must lie in the interval $(0, 1)$. This condition is satisfied by my estimates. In estimation, parameter H is constrained to satisfy $(h - H) > 0$ for all households, and the random component of B_{ij} is truncated to satisfy the requirement $(b - B_{ij}) > 0$ for all households.[22]

For the estimation, there are two types of households: households without a voucher and households with a voucher.[23] Households without a voucher optimize their decision constrained by their income y and face the typical linear budget constraint $y = p_j\ h + b$. The housing expenditure function resulting from utility optimization is given by equation (4).[24]

$$hp_j \quad = \quad \alpha y + H(1-\alpha)p_j - \alpha\beta X_i Z_j - \alpha\nu_i \tag{4}$$

Given this specification, the housing price elasticity in equation (5) is a function of price, income, and neighborhood attributes.

$$E_{h,p_j} \quad = \quad \frac{\alpha(\beta X_i Z_j + \nu_i - y)}{\alpha(y - \beta X_i Z_j - \nu_i) + Hp_j(\alpha - 1)} \tag{5}$$

Now suppose a household receives a housing voucher. As discussed in the Background and Literature Review of this paper, voucher households optimize their housing consumption in any neighborhood by consuming the maximum allowable voucher amount, $h_j^* = \frac{FMR - m_{ph}}{p_j}$. Their decision problem is therefore simplified to a discrete choice over neighborhoods J.[25] The indirect utility function for a household with a housing voucher is

[22] For all households, I set the truncation point of B_{ij} to be equal to $min_{j,x}(y_m in - Hp - \beta_{j,x})$.

[23] The model could easily be extended to include any finite number of household types.

[24] For low-income rental households, Friedman and Weinberg found that a log-log housing demand function and a linear housing demand function yielded comparable price and income elasticities. See Sieg, Smith, Banzhaf, & Walsh (2002) for a general discussion on the estimation of housing prices.

[25] The literature on piecewise budget constraints proposed several issues in modeling demand, for example

equation (6).

$$v_{i,j} = \gamma Z_j + \gamma_i X_i Z_j + \xi_j + \alpha \log(\frac{FMR - m_{ph}}{p_j}) + (1-\alpha)\log(.7y - B_{ij}) + \epsilon_{ij} \quad (6)$$

The paucity of information about the applicant pool and wait list does not permit modeling endogenous participation.[26] While there is clearly some potential for selection effects arising from household participation decisions, this potential is limited due to the limited number of vouchers available and the mechanism for allocating vouchers. The HACP offers its limited number of vouchers in a first-in-first-out queue with some discretion, for example higher priorities for homeless families and veterans. The waitlist for HACP housing vouchers is often long enough that it is closed to new applicants for months, up to two years, at a time. Hence, there is a large element of randomness in access to the wait list. Frequent changes of address by school children from low-income households tell a story of frequent relocation by low-income households (Davis et al., 2010). Many households may fail to update their address with the HACP. Hence, they may not receive notice when a voucher becomes available, adding a substantial element of randomness in take-up of vouchers when the wait list clears.[27]

Also, I do not consider the possible endogeneity of income, for example by including

Hausman & Wise (1980) Moffitt (1986) Hausman (1985). In the current application, the data suggest that almost all voucher participants are exercising the full amount of the voucher but not choosing to pay any additional, allowable, rent above FMR; for this reason, there is no demand equation to estimate for voucher participants. There is also no measurement error in assigning which budget constraint they are facing. The possible endogeneity of the program participation decision is discussed in the next paragraph.

[26] In practice, households apply to the local housing authority, are assessed for eligibility, and put on a first-in first-out waitlist for an available voucher. In some periods, the demand for vouchers may be so high that housing authorities close the wait list. New vouchers become available when a participating household leaves the program or the housing authority receives additional funding.

[27] Lack of information may also contribute an element of randomness in voucher take-up. Studying food stamps, Daponte Sanders and Taylor (1999) found that eligible households elected not to enroll in the subsidy program for reasons consistent both with lack of information and choice theory. In almost half of the cases, households enrolled in the program after they received detailed information about the program.

employment decisions or any income generating process. There are several studies suggesting that housing program participation slightly reduces expectations of participants' employment and earnings.[28] In terms of policy analysis, this paper focuses on interesting nominal analyses of policies involving incremental change in the voucher program that would likely not significantly change voucher participants' employment incentives.

4.1 Housing Prices

Variation in prices for housing services across neighborhoods is important in explaining sorting patterns. Prices for housing services are obtained by estimating a hedonic regression model, equation (7), p_j is the price of a unit of housing services in neighborhood j.[29]

$$\ln h_{jn} = \ln p_j + \kappa \ln f_n + \upsilon_{jn} \tag{7}$$

The regression model is estimated using micro-level data on $93,415$ residences with attributes f_n, including the number of bedrooms, number of bathrooms, air conditioning, heating type, presence of central air, architectural style, furnished living area, lot square footage, overall condition, etc. There is significant variation in housing prices across all neighborhoods. The price in the least expensive community is normalized to equal one (a log price of zero). I estimate the maximum in the price range to be 3.78 ($p<0.001$, testing the hypothesis that its log is equal to zero).

Property values from 2004 are obtained from the Allegheny County Office of Property

[28] For example, see Jacob & Ludwig (2008) Susin (2005) and Olsen et al. (2005).

[29] Sieg, Smith, Banzhaf, and Walsh (2002) discuss and evaluate this approach, finding it an appropriate method for constructing price indices for a model with separable preferences for housing and community services.

Assessments.[30] Both the most recent sale values and the assessed values are available, I use the assessed property values. Of all properties, I estimate housing prices from residential one-, two-, three- , and four-family homes over 100 square feet; this leaves 93,415 residences. I assume that the ratios of the price indices of assessed properties are equivalent to the ratios of price indices in unobserved lease contracts.[31]

5 Estimation

The paper develops a new simulated method of moments estimator for the parameters of the model that accounts for the endogeneity of housing prices and selection of households into communities.[32] There are three types of moment conditions that are used in the estimation. The first moment condition is the unobserved neighborhood amenity ξ_j, which is simply the difference between the mean neighborhood quality δ_j and its observable components γZ_j. The second set of moments is the difference between the observed and expected percent of the population in each neighborhood; this calculation is done for population subgroups, separated by subsidy type (voucher or non-voucher), race (white and nonwhite) and presence of children, for a total of eight moments. The third set of moments stems from estimation of the housing demand of the non-voucher households and corrects for the endogeneity of neighborhood choice while instrumenting for the endogeneity of price, which enters linearly into the demand equation.[33]

[30] The data were made available to me by Michael Peress and Brett Gordon and were also used in Epple, Peress, Sieg (2010)

[31] This assumption is consistent with a model where home price-rent ratios vary by macroeconomic variables that uniformly affect all neighborhoods within the metropolitan area. See, for example (Sommer, Sullivan, & Verbrugge, 2011).

[32] See, for example, Pakes & Pollard (1989) for a discussion of the asymptotics of optimization estimators with simulation.

[33] An estimation procedure similar to the one used here is also described in Fullerton, Gan, & Hattori (2005) who use aggregate data to estimate a Dubin McFadden choice model for vehicle usage and emissions, with

The housing demand parameters, $(\alpha, \beta, \text{stdev}(\nu), H)$ are identified from variation in housing consumption of unsubsidized households and from the use of appropriate instruments for price. The household-specific preference in housing elasticity is not identified from the voucher households alone, as they do not optimize over a continuous budget constraint. The 2000 Census provides the joint distribution of income and rent for each census tract as well as the budget share of housing for each income group.[34] For each census tract, the estimation employs three housing demand observations: specifically, the estimation utilizes the housing budget share of the first three income categories (less than $10,000, $10,000 - $19,999, $20,000 - $34,999). This exclusion means that only households with annual incomes of less than $35,000 are represented, providing an adequate comparison population to the low-income households in the voucher program. The simulated method of moments estimation minimizes the distance of the two sides of equation (8), with respect to instruments for price.

$$E[hp_j|d_j = 1] \quad = \quad \alpha y + H(1-\alpha)p_j - \alpha\beta X_i Z_j - \alpha E[\nu_i|I\{d_j = 1\}] \tag{8}$$

For the housing demand equations, the endogeneity of neighborhood choice is accounted for by using the conditional expectation of individual-specific housing budget share variation, as in equation (8).[35] The conditional expectation correction for ν_i is ob-

the addition of random coefficients. Imbens & Lancaster (1994) review the issues of accuracy, efficiency, and compatibility in estimating economic models with a combination of micro and macro data. Also, see Sieg, Smith, Banzhaf, & Walsh (2004) for estimation matching different moment conditions of a sorting equilibrium.

[34]Unfortunately, in the public data this joint distribution is not conditional on household characteristics such as race or presence of children. To work around this, I weight the bins of this distribution according to the joint income, race, presence of children, and housing tenure distributions that are publicly available.

[35]Dubin and McFadden (1984) compared the conditional expectation correction usage to other approaches, and found that the conditional expectation correction led to the least biased estimates in the presence of

tained using a Monte Carlo simulation and Bayes' rule.[36]

The housing demand is estimated simultaneously with the remainder of the model parameters (namely γ_i and ξ_j), which are identified by matching predicted and estimated neighborhood choice shares (s_j and $\hat{s}_j$, respectfully) using the method proposed by Berry (1994) and Berry, Levinsohn, and Pakes (1995).[37] The identification requires instruments for the endogenous neighborhood variables. I also introduce restrictions on some of the variance parameters governing γ_i, i.e. only preferences for a subset of neighborhood characteristics co-vary.

Let the indicator variable $d^m_{i,j}$ equal one if a household in housing program m chooses neighborhood j, otherwise it is equal to zero. For this exposition, let $m = 0$ if a household is not in the voucher program, and thus faces the indirect utility obtained by substituting the housing demand in equation 8 and the continuous budget constraint into the direct demand in equation 2. Also, let $m = 1$ if a household participates in the voucher program and faces the indirect utility specified in equation 6. Neighborhood choices are mutually exclusive and hence:

$$\sum_{j \in J} d^m_{i,j}(y, X_i, \gamma_i, \nu_i, \boldsymbol{\epsilon}_i; \theta) = 1 \tag{9}$$

The share of households in neighborhood j is the integral of the decision variable $d_{i,j}$ over

nonzero covariance of non-separable preferences.

[36] I use simulation methods to compute the expectation of ν_i conditional on the probability of choosing neighborhood j.

[37] Berry and Haile (2010) discuss the identification criteria for BLP. The model in this paper meets the criteria set by Berry and Haile, namely, that $v_{i,j}$ is monotonic in mean neighborhood utility δ_j (equation (11)), the indirect utility is quasi-linear in elements of Z_j, there is perfect substitutability of Z_j for neighborhood unobservable ξ_j and the location of ξ_j is normalized. Identification also rests on the quality of the instruments W[(Berry & Haile, 2010), (Newey & Powell, 2003)].

the distribution of the random preference parameters , equation (10).

$$\hat{s}_j(X|\theta) \quad = \quad \sum_{m\in\{0,1\}} \frac{N_m}{N_{m=0}+N_{m=1}} \int d_{ij}^m(y, X, \gamma_i, \nu_i, \boldsymbol{\epsilon}_i|\theta)\ P(\gamma_i, \nu_i, \boldsymbol{\epsilon}_i)\ f(y|X)\ \partial y \partial\gamma_i \partial\nu_i \partial\boldsymbol{\epsilon}_i \tag{10}$$

Berry, Levinsohn, and Pakes (1995) ("BLP") show there is a contraction mapping that computes the best estimates of neighborhood unobservables ξ_j as a function of the remaining parameters in the model. Let:

$$\delta_j = \gamma Z_j + \xi_j \tag{11}$$

The BLP contraction mapping $T(\delta_j)$ defined by

$$T(\delta_j^{n+1}) \quad = \quad \delta_j^n + \ln s_j - \ln \int \hat{s}_j(X|\theta) f(X) dX \tag{12}$$

is applied until convergence, where s_j is the actual share of households in neighborhood j and $\hat{s}_j(X|\theta)$ is the estimated share described in equation (10). The vector $\boldsymbol{\xi_j}$ is the set of residuals from $\delta_j(\theta, s_j) - \gamma Z_j$. To normalize, the lowest-priced neighborhood quality is fixed at $\delta_0 = 0$ and the utility function of the choice $j = 0$ is simplified to equation 13.

$$u_0 = \alpha \log(y) \tag{13}$$

As in typical discrete choice models, the household-neighborhood specific random preferences ϵ_{ij} are assumed independent and identically distributed according to the Extreme Value Type 1 distribution (McFadden, 1974). The random coefficients (ν_i, γ_i) are assumed to vary according to a truncated multivariate normal distribution with covariance Σ. I assume the ν_i are mean zero, but the means of γ_i are nonzero and depend on household

demographics, for example blacks may have a preference for living in a neighborhood with a large minority presence. I integrate over this multivariate distribution using a simulated integral to obtain the estimated share of households in each neighborhood.[38]

To summarize, the moments are listed in equation (14):

$$
g_j(\Theta) = \left\{ \begin{array}{c}
\delta_j(\theta, s_j) - \gamma Z_j \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=0}(Z_j, \hat{\xi}_j, p_j|\theta, \text{white, kids}) - s_j^{m=0}(\cdot|\text{white, kids}) \right| \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=0}(Z_j, \hat{\xi}_j, p_j|\theta, \text{white, no kids}) - s_j^{m=0}(\cdot|\text{white, no kids}) \right| \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=0}(Z_j, \hat{\xi}_j, p_j|\theta, \text{black, kids}) - s_j^{m=0}(\cdot|\text{black, kids}) \right| \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=0}(Z_j, \hat{\xi}_j, p_j|\theta, \text{black, no kids}) - s_j^{m=0}(\cdot|\text{black, no kids}) \right| \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=1}(Z_j, \hat{\xi}_j, p_j|\theta, \text{white, kids}) - s_j^{m=1}(\cdot|\text{white, kids}) \right| \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=1}(Z_j, \hat{\xi}_j, p_j|\theta, \text{white, no kids}) - s_j^{m=1}(\cdot|\text{white, no kids}) \right| \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=1}(Z_j, \hat{\xi}_j, p_j|\theta, \text{black, kids}) - s_j^{m=1}(\cdot|\text{black, kids}) \right| \\
\sum_{j=1}^{J} \left| \hat{s}_j^{m=1}(Z_j, \hat{\xi}_j, p_j|\theta, \text{black, no kids}) - s_j^{m=1}(\cdot|\text{black, no kids}) \right| \\
h_{q=1} p_j - \hat{\alpha} y_{q=1} - \hat{H}(1-\hat{\alpha}) p_j + \hat{\alpha}\hat{\beta} X_{kids} Z_j + \hat{\alpha} E[\nu_i | I\{d_{j,q=1,kid} = 1\}] \\
h_{q=2} p_j - \hat{\alpha} y_{q=2} - \hat{H}(1-\hat{\alpha}) p_j + \hat{\alpha}\hat{\beta} X_{kids} Z_j + \hat{\alpha} E[\nu_i | I\{d_{j,q=2,kid} = 1\}] \\
h_{q=3} p_j - \hat{\alpha} y_{q=3} - \hat{H}(1-\hat{\alpha}) p_j + \hat{\alpha}\hat{\beta} X_{kids} Z_j + \hat{\alpha} E[\nu_i | I\{d_{j,q=3,kid} = 1\}] \\
h_{q=1} p_j - \hat{\alpha} y_{q=1} - \hat{H}(1-\hat{\alpha}) p_j + \hat{\alpha}\hat{\beta} X_{nok} Z_j + \hat{\alpha} E[\nu_i | I\{d_{j,q=1,nkid} = 1\}] \\
h_{q=2} p_j - \hat{\alpha} y_{q=2} - \hat{H}(1-\hat{\alpha}) p_j + \hat{\alpha}\hat{\beta} X_{nok} Z_j + \hat{\alpha} E[\nu_i | I\{d_{j,q=2,nkid} = 1\}] \\
h_{q=3} p_j - \hat{\alpha} y_{q=3} - \hat{H}(1-\hat{\alpha}) p_j + \hat{\alpha}\hat{\beta} X_{nok} Z_j + \hat{\alpha} E[\nu_i | I\{d_{j,q=3,nkid} = 1\}]
\end{array} \right\} \quad (14)
$$

[38] For the pure frequency simulation, I use the Marsaglia method to generate standard normal variables and I multiply them by the estimates the lower diagonal of the Cholesky decomposition matrix for Σ.

I am using the two-step optimal GMM estimator defined as:

$$\hat{\Theta} = \underset{\hat{\Theta}\in\Theta}{\arg\min} \left\{ \frac{1}{J} \sum_{j=1}^{J} w_j g_j(\Theta) \right\}' \hat{\Lambda}^{-1} \left\{ \frac{1}{J} \sum_{j=1}^{J} w_j g_j(\Theta) \right\} \tag{15}$$

with the weighting matrix $\hat{\Lambda}^{-1}$ as the inverse of the covariance of the moments of the first stage estimator.[39]

While there are only fifteen moments in equation (14), there are at most 18 parameters to estimate. To identify them, I employ 8 instruments. The set of instruments w_j is chosen with the goal of a nonzero correlation with endogenous variables but independence of error in the model as estimated by $g_j(\Theta)$. There are three types of error: the estimates of the joint income and housing expenditure distribution from the cross section reported in the Summary Level 3 Census Data, error from the Monte Carlo integration methods, and unobserved household and neighborhood attributes.

Several observable neighborhood variables in the model specification are assumed to be endogenous: price, percent black, percent of women who are college graduates, and the percent of males who are employed. The set of instruments w_j identifies the mean and variance of preferences for the endogenous neighborhood characteristics, and identifies the parameters embedded in the price coefficient of the housing demand equation (α and H). Following Bayer, McMillan and Reuben (2005), the main instrument for price is constructed based on housing prices in similar neighborhoods. This method recognizes that the price of housing services in similar but distant neighborhoods contain information about price variation attributable to exogenous features across similar neighborhoods. I construct the instrument by clustering the neighborhoods and computing the mean hous-

[39]The first stage employed the identity matrix (basic model) or the weighting matrix from the estimates of the corresponding baseline model.

ing prices of neighborhoods within each cluster, excluding the neighborhood for which the instrument is being computed.[40] For additional instruments, I assume the following characteristics are exogenous: the percent of housing units that are owner-occupied in similar neighborhoods, the ratio of the HACP voucher-friendly apartment listings to the number of rental units in similar neighborhoods, the median age of rental properties, the average commute time of commuters using public transit, the number of violent crimes per capita, the percent of acres that are designated park land, and mean test scores[41].

I test several specifications of the model, even the largest (with eighteen parameters) has several restrictions. For the Z_j neighborhood characteristics directly affecting housing demand, I include the percent of land area that is designated as a public park, the average commute time using public transit, and school quality multiplied by a dummy variable indicating whether a household has children. Households experience direct utility (γ_i) from a wider set of neighborhood services Z_j, specifically the number of violent crimes per capita, school quality multiplied by the with-children indicator, the percent of land area that is designated park land, intersection density, the average commute time of persons using public transit to get to their job, the percent of females that completed a college degree, and the percent of adult males that are employed. I include these variable choices as they are possible neighborhood attributes that affect outcomes such as physical and mental health, employment, and education measured by other studies such as the Moving To Opportunities study. All other neighborhood characteristics are absorbed in the estimated neighborhood-specific effect ξ_j. I also estimate a racial preference parameter for the percent of households that are black, interacted with householders' own race. Preference for

[40] To compute the clusters, I use the k-means algorithm on the observed neighborhood attributes, with 25 clusters across the 114 neighborhoods.

[41] Test scores are also used as exogenous variables in other residential choice models, for example Bayer, McMillan, & Rueben (2004).

school is interacted with presence of children. In some models I allow variation in the preference for school quality, average length of commute by public transit, and/or race, and I estimate their covariance with variation around mean zero for randomness in housing demand ν_i. Preferences for the remaining observable neighborhood attributes are constant across all households.

The 2-stage optimal GMM optimization routine is based on a simplex algorithm with simulated annealing. The three-dimensional integral of ν_i and the γ_i coefficients is estimated using 4000 sets of randomly, independently generated standard uniform variables multiplied by estimates of the covariance matrix Σ's Cholesky decomposition, with the ν_i truncated.[42]

6 Estimation Results

The parameter estimates of several specifications are displayed in Table 6. The Table 7 displays the resulting mean price elasticity of housing demand and the neighborhood-attribute elasticity of housing demand. Model 1 does not include random coefficients and maintains constant price elasticity across neighborhoods and it is a useful baseline model to compare the remaining models. Models 2 and 4 relax the price elasticity restrictions and attempt different inclusions of neighborhood amenities; model 4 is useful because it adds human capital variables that could influence program participants' labor market outcomes. Models 3 and 5 offer different specifications of random coefficients and thus allow for nonseparability between the housing and neighborhood choice. The standard errors of parameter

[42] I re-draw a set of variables if the ν_i component exceeds the truncation value. The truncation value is endogenously determined by estimates of the minimum survivable consumption levels H and B_j.

estimates were generated by bootstrapping.[43]

Table 6: Parameter Estimates (and Standard Errors)

Parameter	Variable	Model 1	Model 2	Model 3	Model 4	Model 5
α		.13* (.02)	0.13* (.04)	0.10* (.01)	.17* (.02)	.12* (.02)
H		2.10* (.17)	1.17* (.33)	1.36* (.20)	1.40* (.29)	1.59* (.26)
β	const	-2.76* (.13)	-16.04* (.40)	-15.97* (2.07)	-15.84* (2.00)	-16.14* (2.32)
	parks		2.03* (.17)	2.13* (.40)	1.33* (.43)	2.12* (.34)
	educ X_{kid}		-21.23* (.29)	-21.24* (3.97)	-19.89* (2.56)	-21.25* (4.33)
	bus		-2.61* (.28)	-2.55* (.51)	-2.71* (1.31)	-2.58* (.36)
σ_{ν_i}				2.71* (.575)		0.03 (.125)
γ	crime	-14.90* (1.00)	-3.80* (1.87)	-3.37 (1.88)	-6.69* (3.24)	-3.34* (1.37)
	educ X_{kid}	2.88* (1.09)	4.78 (2.88)	5.41* (1.38)	2.61* (1.16)	4.70* (1.50)
	race X_{blck}	4.51* (.68)	4.63* (.32)	4.52* (.96)	5.64* (.67)	3.71* (1.12)
	bus	.33* (.17)	.01 (.18)	-.20 (.50)	-.16 (.41)	.03 (.68)
	strts	-.20 (.44)	-1.04 (.55)	-.86 (.77)	-1.01 (1.07)	-1.44 (.93)
	parks	0.60 (.70)	-.70 (.83)	0.29 (1.32)	-1.11 (.71)	.57 (1.26)
	college				.18 (.63)	
	work				.50 (.73)	
σ_{γ_i}	race X_{blck}			3.40* (.56)		2.73* (.40)
σ_{γ_i}	educ X_{kid}			3.11* (.47)		
σ_{γ_i}	bus					.15 (.10)
ρ_{γ_i,ν_i}	race X_{blck}, ν_i			-.96* (.04)		.08 (.90)
ρ_{γ_i,ν_i}	educ X_{kid}, ν_i			-.97* (.02)		
ρ_{γ_i,γ_i}	race X_{blck}, educ X_{kid}			.99* (.02)		
ρ_{γ_i,ν_i}	bus, ν_i					.08 (.65)
ρ_{γ_i,γ_i}	race X_{blck}, bus					.99* (.25)

*Indicates significant at .05% level

parks, educ, bus, strts, college, work, race are percent of acreage designated as public land, mean standardized test scores, mean public transit commute time, number of street intersections per acre, percent of females that have a college degree, percent of males who are employed, and percent of the population that is black.

Most specifications imply that positive neighborhood attributes are lower crime rates and lower street grid density, although the parameters for street density were not significant. All models suggest that households with children have a high preference for neighborhoods with high eighth grade test scores, blacks have a high preference for living in neighborhoods with other blacks. Average public transit commute times and acreage of

[43]To bootstrap, the model was re-estimated 25 times, each time excluding a different random set of 30% of the neighborhoods.

Table 7: Elasticities of Demand

	Model 1	Model 2	Model 3	Model 4	Model 5
price	-0.440	-0.760	-0.659	-.784	-.830
educ X_{kid}		.165	.141	.163	.147
parks		-.002	-.002	-.001	-.002
bus		.045	.038	.049	.039

educ, parks, bus are neighborhood mean standardized test scores, percent of acreage designated as public land, and mean public transit commute time.

public parks were not found to be significant in neighborhood choice, although each of these attributes were found to significantly affect housing demand. Model 4 suggests that households value living in neighborhoods where a higher percentage of females graduated college and a higher percentage of males are currently employed, however these estimates were not statistically significant. To illustrate the relative magnitudes of these estimates, consider a black household with children weighing options according to model 3: a one standard deviation decrease in violent crime per capita (a decrease of 0.3 violent crimes per 1000 people), a .62 standard deviation increase in mean eighth grade test scores (3.5 score points), and a .02 percentage point increase in the percent of blacks in the neighborhood.

The neighborhood amenities affect housing demand by the contribution ($-\alpha\beta$). The β contribution to the housing demand suggests that average public transit commute time is a complement to housing demand (.038 - .049 elasticity of demand) while parks are a (small) substitute (-.002 elasticity of demand). For households with children, school quality is a complement to housing demand (.141 to .165 elasticity of demand). The estimation suggests that the price elasticity of housing demand ranges from -.44 to -.83 , which is slightly lower than other estimates published in the literature which generally range from -0.6 to -1.7, but reasonable given the fact that we focus only on poor households eligible for housing subsidies.[44]

[44]See Friedman & Weinberg (1982) for an overview, literature summary, and elasticity estimates from the

The ability to include random preferences for neighborhood attributes is important, as the model identified significant taste variation for school quality (model 3 and model 5) and racial mix (model 3). Model 3, but not model 5, also identified significant taste variation for housing consumption. Model 3 also found significant correlation between neighborhood attributes and housing consumption; namely, race and education were positively correlated with each other and negatively correlated with housing services consumption. These directions are plausible for urban, very low income groups because very-low-income households with children, and thus interest in public schools, tend to be racial minorities.

Although the parameters for the random preferences are statistically significant, the random preferences for neighborhood amenities only have a small effect on the endogenous housing demand, with the expectation corrections in the housing demand equation contributing up to a maximum of 0.05 percent of the housing demand. Previous literature (see Section 3) has found important homogeneities of the joint housing consumption and neighborhood selection decision, which partly motivated the model selection for this work. There are some significant differences between this study and previous ones. In the present study, the narrow focus on the very-low income population might be a limitation in estimating taste variation across the whole population. In addition, I do not use micro-level data on housing consumption for unsubsidized households. Moreover, the specification of the my model allows for correlation for preferences of observed neighborhood attributes with housing demand, whereas the previous studies focused on the correlation between household-specific random preferences for neighborhood unobservables (the vector $\boldsymbol{\epsilon_{ij}}$) with housing demand.

For the nominal analysis described in the next section of this paper, model 3 is the

1974 Housing Demand Experiment.

preferred specification because it contains coefficients allowing for nonseparability that are estimated to be significant. Also, model 3 identifies a plausibly negative correlation between race (black) and housing consumption whereas model 5 finds a positive correlation.

Tables 8 and 9 show how well a simulation of model 3 fits the data. The simulation takes as input only income, race, and presence of children, and simulates both neighborhood choice and housing services demand for each sub-population. Starred values indicate the outcomes of χ^2 tests of goodness of fit where we do not reject the null hypothesis that simulated values equal observed values, with a significance level of 0.05. Table 8 compares the simulated and observed choices of the voucher program participants. For the voucher population, most outcomes are replicated reliably by the model: for example, households with children consume more housing than those without children; blacks consume more housing services than whites; and blacks live in more violent neighborhoods. The model correctly replicates that blacks with children live in neighborhoods with higher test scores than those that do not have children, but the model misses this relationship for the white voucher holders, perhaps because of the population of whites is not as large. The main difference between the actual choices of voucher participants and the simulated choices is that racial preferences are slightly exaggerated. This issue is not a problem that appears in comparing the unsubsidized population; there appears to be less racial sorting among voucher households than one would suspect by estimated the model only based on unsubsidized households.

Table 9 compares the simulated and observed choices of the unsubsidized low-income households. Relative neighborhood outcomes between sub-populations in the simulated model remain true to the relative outcomes in the observed data; the strength of this fit is probably driven by the fact that unsubsidized households accounted for the largest por-

Table 8: Simulated and Observed Choices of Voucher Program Participants

	Black, Kids	Black, No Kids	White, Kids	White, No kids
	Sim (Obs)	Sim (Obs)	Sim (Obs)	Sim (Obs)
h	3.42* (3.53)	3.33* (3.29)	2.74* (2.95)	2.69 (2.59)
b	$8.36^{n/a}$ (8.36)	$8.26^{n/a}$ (8.26)	$8.23^{n/a}$ (8.23)	$8.28^{n/a}$ (8.28)
Violent	26.11* (25.97)	26.66* (28.70)	18.72* (19.14)	19.73* (22.75)
Educ	24.96* (24.80)	24.81* (24.65)	26.73 (26.13)	26.34 (27.15)
Black	0.59 (0.50)	0.61* (0.55)	0.17* (0.15)	0.20* (0.16)
PubTransTime	0.82* (0.87)	0.81* (0.78)	1.10* (1.08)	1.09 (0.94)
Intersection	0.50* (0.53)	0.50 (0.56)	0.49* (0.53)	0.50* (0.53)
Parks	0.05* (0.06)	0.05* (0.05)	0.08* (0.06)	0.07* (0.11)
FemaleCollege	0.16 (0.14)	0.15 (0.17)	0.24 (0.16)	0.21 (0.25)
MaleEmployed	0.50 (0.53)	0.49* (0.52)	0.61* (0.61)	0.60* (0.60)
PercentRent	0.57 (0.48)	0.57* (0.59)	0.45 (0.39)	0.45 (0.52)
MQrent	331 (348)	326 (361)	414 (385)	402 (417)
MedianInc	32.97* (32.28)	32.96 (34.66)	32.63* (30.41)	32.58* (34.54)
SingleFKid	0.18 (0.14)	0.19 (0.14)	0.08* (0.08)	0.09 (0.07)
MaleCollege	0.18* (0.17)	0.17 (0.20)	0.28 (0.19)	0.25 (0.30)
Poverty	0.30* (0.25)	0.31* (0.27)	0.17* (0.17)	0.18 (0.19)

*Indicates do not reject the hypothesis of equality, $p < .05$

Violent in the violent crime rate 1000, *Educ* is mean eighth grade standardized test score in 100s, *Black* is the percent of the population that is black, *PubTransTime* is the mean public transit commute time in minutes, *Intersection* is the number of street intersections per acre, *Parks* is the percent of acreage designated as public park land, *FemaleCollege* is the percent of females that completed college, *MaleEmployed* is the percent of males that is employed, *PercentRent* is the percent of households that rent their dwelling, *MQrent* is the median rent, *MedianInc* is the median income in 1000s, *SingleFKid* is the percent of households headed by a single mother, *MaleCollege* is the percent of males that completed college, and *Poverty* is the percent living below the poverty level.

tion of neighborhood shares, thus having a large influence on the estimation of the mean neighborhood utility δ_j in the BLP contraction mapping step.

Table 9: Simulated and Observed Choices of Unsubsidized Households

	Black, Kids	Black, No Kids	White, Kids	White, No kids)
	Sim (Obs)	Sim (Obs)	Sim (Obs)	Sim (Obs)
h	3.94* (3.60)	3.91* (3.60)	3.46* (3.45)	3.44* (3.38)
b	11.22* (12.07)	15.59* (16.38)	10.66* (10.57)	15.13* (14.81)
Violent	25.65* (27.33)	26.34* (28.74)	18.07* (15.60)	19.20* (19.43)
Grd8Alone	25.07* (24.47)	24.89* (24.38)	26.89* (27.01)	26.52* (27.01)
Black	0.57 (0.68)	0.60 (0.74)	0.16* (0.12)	0.19* (0.13)
PubTransTime	0.83* (0.76)	0.81 (0.69)	1.11* (1.20)	1.09* (1.09)
Intersection	0.49* (0.49)	0.49* (0.51)	0.47* (0.47)	0.49* (0.48)
Parks	0.06* (0.05)	0.05* (0.04)	0.08* (0.08)	0.07* (0.08)
FemaleCollege	0.17* (0.14)	0.16* (0.14)	0.27* (0.26)	0.24* (0.28)
MaleEmployed	0.50* (0.48)	0.50* (0.44)	0.61* (0.63)	0.60* (0.61)
PercentRent	0.56* (0.59)	0.57* (0.62)	0.45* (0.40)	0.46* (0.48)
MQrent	339* (311)	333* (305)	429* (435)	419* (438)
MedianInc	33.019* (33.77)	33.03* (33.77)	32.80* (31.99)	32.75* (32.70)
SingleFKid	0.18* (0.22)	0.18* (0.20)	0.08* (0.07)	0.08* (0.06)
MaleCollege	0.19* (0.15)	0.18* (0.15)	0.31* (0.30)	0.28* (0.33)
Poverty	0.29* (0.33)	0.30* (0.35)	0.17* (0.15)	0.18* (0.17)

*Indicates do not reject the hypothesis of equality, $p < .05$

Violent in the violent crime rate 1000, *Educ* is mean eighth grade standardized test score in 100s, *Black* is the percent of the population that is black, *PubTransTime* is the mean public transit commute time in minutes, *Intersection* is the number of street intersections per acre, *Parks* is the percent of acreage designated as public park land, *FemaleCollege* is the percent of females that completed college, *MaleEmployed* is the percent of males that is employed, *PercentRent* is the percent of households that rent their dwelling, *MQrent* is the median rent, *MedianInc* is the median income in 1000s, *SingleFKid* is the percent of households headed by a single mother, *MaleCollege* is the percent of males that completed college, and *Poverty* is the percent living below the poverty level.

7 Policy Simulations

I consider the question of optimal voucher policy design and run several policy experiments to compare housing consumption, neighborhood, and program cost. I compare the cost of policy changes to the expected benefit as estimated by households' compensating variation. It is well-known that this type of discrete choice models does not yield closed form solutions for compensating variations. I, therefore, follow McFadden (1989, 1995) and adopt a simulation based approach. There are some limitations to this analysis. First, I assume households act with full information, i.e. that the choices I observe in the data reflect full information of benefits or disadvantages they would derive from neighborhood and housing outcomes. Second, participants' willingness to pay is of course limited by their already very-low incomes. Finally, potential neighborhood spillover effects are not included.

The policy simulations are motivated by the proposed voucher policies tested in the Housing Allowance Demand experiments (Friedman & Weinberg, 1982), the Gautreaux Program (Rosenbaum, 1994), and the Moving To Opportunities experiment (Kling et al., 2007). I compare all policies to the model's simulation of the current housing voucher policy: participant contribution of 30% of income, an FMR of about 40% of local median rents, and a minimum housing standard.[45] Table 10 compares neighborhood characteristics, housing consumption, income remaining for non-housing expenses, and program costs under the proposed policies to the choices predicted by the baseline model.

The first simple policy change would be to increase the amount of the voucher (column "Big" in Table 10). I simulate what the neighborhood outcomes might be if the HACP simply increased the voucher amount by 20%. The simulation suggests that most

[45] I do not compare models with and without a minimum housing requirement. It is difficult to calibrate the appropriate level of housing services h that corresponds to the HACP's list of housing requirements, which includes for example that electric stoves have a separate electric line, rather than be plugged into a wall outlet.

of the voucher increase would be dedicated to increased housing consumption. In addition, there are slight changes in mean neighborhood attributes that are generally positively correlated with price: -0.75% lower crime, .019% better schools, 4.2% more college-educated women. White households, on average, would benefit more from the increase in the voucher amount (-2.26% lower crime, .51% better schools, 10.5% more college-educated women), especially due to their willingness to move into areas with fewer minorities. Although average welfare increases, the program cost of increasing the voucher amount by 20% exceeds the sum of the compensating variations.[46]

Clearly there is great price variation within a metropolitan area and setting an FMR for an entire region may be too restrictive. "ConstH" compares current outcomes to outcomes expected if the HACP set housing services (h) constant but allowed the voucher amount to vary with neighborhood price variation, rather than regional price variation. This practice would require the housing authority to have a decent estimate of price variation across communities. As black households without children are often empty-nesters enjoying the larger space for which they previously qualified, on average they would experience a -13% decrease in their level of housing consumption. Whites, however, would experience an increase. All groups would experience significant neighborhood gains including -2.1% lower crime and 0.5% better schools (-4.8% and 1%, respectfully, for whites); these gains are generally more than 2 times greater than they would be under the program to increase the voucher amount by 20%. The estimates suggest that the cost of implementing a voucher that varies based on neighborhood price would be 63% less expensive than simply increasing the maximum voucher amount by 20%. Average welfare increases, for example the

[46]Not reported here, I also simulated expected outcomes if the HACP were to decrease the voucher amount by 20%. Most of the voucher decrease is felt in housing consumption, but there are also declines in mean utility from neighborhood attributes. The lower voucher results in residents living in poor neighborhoods with more crime and lower performing students, for example. The savings in program cost would be less than the cost of compensating program participants for the policy change.

mean black household with children is willing to pay $68/month for the program change.

I consider a rental rebate ("Rebate") program that was tested in the 1970 Housing Demand Experiments. This simulation compares outcomes if the HACP were to get rid of the income contribution requirement and the voucher maximum, but instead offered a 50% rebate for rental expenses, excluding utility payments. In general, the rebate program would result in increased consumption of housing (an increase of 60%) and lower amounts of non-housing private consumption (about -25%), especially for those with children. There are gains in mean neighborhood amenities as well, exceeding the gains expected from simply increasing the voucher amount. For example, black households would, on average, locate to neighborhoods with -1.3% less crime and 0.3% better schools, -4% and .7% respectfully for whites. However, the gains in mean neighborhood amenities are typically less than the gains expected under the policy of allowing FMR to vary based on local neighborhood prices ('ConstH'). The cost of the program is lower than the expected benefit as measured by the sum of households' willingness to pay for the change in policy. These results do not agree with those of Friedman & Weinberg (1982). Friedman and Weinberg found that the majority of participants in their rebate implementations continued to consume substandard or overcrowded housing after two years in the program. The simulations of my model do not include moving costs; perhaps moving costs were a factor that hindered participants in the Housing Demand Experiments. Also, the parameter estimates in my model did not yield a positive lower bound on minimum non-housing consumption (B_{ij}). As a result, the expected decrease in non-housing consumption predicted by the model under a rebate policy may not accurately reflect minimum survivable non-housing consumption.

Finally, I consider the paternalistic policies of the Gautreaux program and the experimental group in the Moving To Opportunities program. In both of these studies, the exper-

imental group with vouchers was required to move to a neighborhood with a low poverty level.[47] I consider a policy that requires voucher recipients to live in neighborhoods with less than a 30 percent poverty rate ("30% Req"). This requirement would yield significant improvements in most mean neighborhood amenities, for example the newly selected neighborhoods had an average -20% decrease in violent crime rates compared for the formerly selected neighborhoods (-10% for whites); a 2.45% increase in school quality (1.3% increase for whites); and a 35% increase in females who graduated from college (16% for whites). Mean housing consumption slightly increases, consistent with higher implicit prices for minorities due to racial sorting preferences (see, for example Bayer et al. (2004)) and the possibility that landlords traditionally serving voucher-friendly neighborhoods extract the largest rents possible from the HACP. However, the choice restriction reduces the number of qualifying neighborhood by 22 percent. Naturally, compensating variations are positive because recipients lose full range of choice, in particular with regard to race-specific preferences and the individual-neighborhood specific unobservables ϵ_{ij}. The expected compensating variation for black households is quite high owing to the large drop in the percent of blacks in the reduced set of neighborhoods; on average, black participants would locate to neighborhoods with -23% fewer blacks. Even if the parameter estimates I obtained for racial preference are unbiased, paternalistic policies such as this one are motivated by the belief that households do not have enough information to properly gauge the benefit of moving out of their preferred neighborhood. Despite the estimation's use of instruments, there could be bias in the parameter estimates for racial preference due to the confounding factor of racial discrimination against prospective tenants, a factor that is very difficult to observe or capture. If the parameter estimates for racial preference are biased in this regard, the compensating variation might be reduced if paired with assistance and

[47]The MTO studies had two experimental groups, one of which had this requirement.

advocacy for tenants in their apartment search, as well as mentoring and counseling programs after placement. The HACP's expenditure on landlord contracts would remain the same, but the simplified cost analysis presented in Table 10 might hide the additional need for housing counseling or relocation assistance.

Overall, the types of neighborhoods chosen by voucher participants is not greatly affected by changes to the budget constraint alone. The most effective policy change in achieving different neighborhood selection is to impose a requirement that households live in neighborhoods with poverty rates below some acceptable maximum, such as 30 percent. In analyzing the budget constraint, my analysis suggests that changing the structure of the program to be a rebate instead of a voucher would improve most participants' welfare, achieve neighborhood selection most similar to a program with an unrestricted voucher amount, and would significantly lower costs. While I present expected mean neighborhood outcomes, housing outcomes, and compensating variation, a concern with the rebate policy is that it might endanger the non-housing consumption of the poorest program participants because it rewards excessive consumption of housing.

8 Conclusions

This paper has analyzed the Housing Choice Voucher Program. I have shown that voucher recipients are able to achieve better housing consumption with a voucher than without, but that vouchers alone do not lead to an increase in households' access to better neighborhoods. Compared to several proposed policy specifications, a rental rebate scheme would reduce the cost of the program and serve most program participants better than the current scheme of a maximum voucher amount subject to contribution of a fixed portion of income.

Table 10: Policy Simulations

Expected Changes for Blacks with Children

Policy	Big	ConstH	Rebate	30% Req
Housing (h)	19.24%	3.28%	63.27%	12.63%
Non-Housing (b)	0.00%	0.00%	-24.42%	0.00%
Violent	-0.75%	-2.11%	-1.36%	-19.46%
School	0.19%	0.46%	0.31%	2.45%
Poverty	-0.52%	-1.36%	-0.90%	-39.70%
Black	0.29%	0.95%	0.68%	-23.11%
FemaleCollege	4.21%	9.13%	6.65%	35.55%
Household CV	-$111	-$68	-$72	$221

Expected Changes for Blacks with No Children

Policy	Big	ConstH	Rebate	30% Req
Housing (h)	19.18%	-12.92%	47.17%	12.81%
Non-Housing (b)	0.00%	0.00%	-18.10%	0.00%
Violent	-0.75%	-2.06%	-1.37%	-18.51%
School	0.20%	0.45%	0.31%	2.29%
Poverty	-0.56%	-1.32%	-0.83%	-40.15%
Black	0.28%	0.92%	0.70%	-22.44%
FemaleCollege	4.76%	9.92%	7.40%	36.72%
Household CV	-$93	$30	-$45	$242

Expected Changes for Whites with Children

Policy	Big	ConstH	Rebate	30% Req
Housing (h)	17.78%	28.78%	74.42%	14.82%
Non-Housing (b)	0.00%	0.00%	-29.15%	0.00%
Violent	-2.31%	-4.83%	-4.04%	-8.30%
School	0.45%	0.92%	0.70%	1.30%
Poverty	-1.31%	-2.90%	-2.07%	-14.06%
Black	0.12%	0.63%	0.61%	-25.53%
FemaleCollege	8.19%	15.99%	12.77%	12.79%
Household CV	-$146	-$229	-$140	$57

Expected Changes for Whites, No Children

Policy	Big	ConstH	Rebate	30% Req
Housing (h)	17.39%	7.84%	58.74%	13.60%
Non-Housing (b)	0.00%	0.00%	-20.70%	0.00%
Violent	-2.26%	-4.81%	-4.14%	-10.33%
School	0.51%	0.99%	0.77%	1.49%
Poverty	-1.55%	-3.34%	-2.47%	-16.56%
Black	0.09%	0.69%	0.62%	-29.33%
FemaleCollege	10.55%	19.91%	16.30%	16.23%
Household CV	-$122	-$105	-$123	$27

Expected Changes in Cost, Benefit

Policy	Big	ConstH	Rebate	30% Req
Δ Cost	$574,900	$210,600	-$827,850	$0
Δ Benefit	$402,368	$192,086	$276,824	-$697,823

A program requirement to live in a neighborhood where less than 30 percent of households live below the poverty level would relocate participants to neighborhoods with much lower crime levels and improved schools. This requirement would most negatively affect minority households that have a high regard for locating in neighborhoods with high minority concentrations; perhaps relocation assistance and counseling could overcome these issues.

The equilibrium residential sorting model proposed here offers a method to study the impact of housing policy on residential sorting, as it incorporates households with different budget constraints. With its direct utility specification the model can be used to study choices derived from housing policy, discontinuous borrowing constraints for residential mortgages, or other constraints on neighborhood or housing choice that impact residential sorting equilibria. In addition, the model offers several desirable features found to be important in the literature, including horizontal demand and nonseparable random preferences of the neighborhood public services and housing demand. The error structure proposed in the model allows the research to study the covariance of housing demand elasticity and preferences for specific observable public goods. In particular, this paper finds that a public parks are a substitute for housing services, while school quality and mean public transit commute time are complements. The generalized model presented here provides ample scope for studies on policy or borrowing practices that induce discontinuous budget constraints in households' joint discrete-continuous choice making.

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