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RENT VOUCHERS AND THE PRICE OF LOW-INCOME HOUSING

By

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Rent Vouchers and the Price of Low-Income Housing

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Abstract

Since the early 1980s, low-income housing subsidies have increasingly shifted towards vouchers which allow recipients to rent in the private market. By 1993, vouchers subsidized as many households as lived in traditional housing projects, although most low-income households did not receive any subsidies. This study investigates whether this policy has raised rents for *unsubsidized* poor households, as many analysts predicted when the program was conceived. The main finding is that low-income households in metropolitan areas with more vouchers have experienced faster rent increases than those where vouchers are less abundant. In the 90 biggest metropolitan areas, vouchers have raised rents by 16 percent on average, a large effect consistent with a low supply elasticity in the low quality rental housing market. Considered as a transfer program, this result implies that vouchers have caused a \$8.2 billion increase in the total rent paid by low-income non-recipients, while only providing a subsidy of \$5.8 billion to recipients, resulting in a net loss of \$2.4 billion to low-income households.

Keywords: Subsidized Housing; Rent Vouchers

JEL classification: H23; I38; R31

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1 Introduction

1.1 Overview

Since its origins in 1937, subsidized housing has traditionally consisted of government funded construction known as public housing projects. However, since the Reagan administration, there has been a dramatic shift in the allocation of housing subsidies. New federal dollars no longer subsidize much new construction. In recent years, two thirds[1] of new subsidized housing units for the poor have been funded by vouchers (also called "certificates"), which are used to rent in the private market.[2] By 1993, over 1.3 million households received vouchers, about the same number as lived in traditional public housing projects.

Recent proposals could dramatically expand the use of vouchers. The Clinton administration has put forth plans which would essentially privatize traditional housing projects. All subsidies currently going to projects would be turned into vouchers, which the tenants would be free to spend elsewhere (Yeager 1996). Although this proposal has not become law, the Department of Housing and Urban Development (HUD) has begun to demolish housing projects, giving vouchers to the displaced tenants. From 1993-1998, the demolition of 76,000 units were authorized, about six percent of the stock (HUD, 1999).

However, there are some reasons for being cautious about privatizing or leveling housing projects. This paper investigates one possible side effect of vouchers: their potential to bid up market rents. The reasoning here is simple. Subsidies to tenants shift the demand curve up, as the subsidized choose more expensive housing. Further, since housing assistance is not an entitlement, but is instead rationed via a waiting list, subsidized renters compete with a large group of income-eligible non-recipients. In fact, about 70 percent of those with incomes low enough to be eligible do not receive vouchers, live in housing projects, or receive any other housing subsidy. These non-recipients will be hurt by vouchers if the increased demand raises market rents.[3]

The main finding of this study is that the voucher program has already caused a large

[1] This figure is for 1990-1996 from the Green Book (1998), and includes newly constructed units funded by programs that mostly serve the poor. It excludes units that are subsidized solely through the Low Income Housing Tax Credit, since LIHTC units are occupied by families that are considerably wealthier than those living in housing projects or receiving rent vouchers.

[2] There are two major demand-side subsidy programs, called the Section 8 Voucher program and the Section 8 Certificate program. As discussed below, the rules differ somewhat between the two programs. However, this paper will refer generically to both the programs simply as "vouchers."

[3] Apgar (1990) argues forcefully for supply-side subsidies on these grounds.

increase in the price of housing for the poor in the 90 metropolitan areas examined here. The most robust estimate presented here suggests that the voucher program has raised the rent paid by unsubsidized poor households in the average metropolitan area by 16 percent. These are first-difference estimates, which control for metropolitan area effects which are fixed over long periods of time. Given the size of the program, this is a large effect, consistent with a low supply elasticity in the low-income rental housing market. It also suggests considerable insulation between lower and higher income markets, since the ability to move easily between markets, or substitute towards higher-quality housing, should mitigate the price rise. Consistent with expectations, the first-difference specification implies that vouchers have very little effect on the middle- or upper-income groups. This sensible pattern of results should increase confidence that there are not important variables omitted from the equation, at least not ones that affect lower and higher income housing markets similarly.

An upward sloping supply curve also has the familiar implication that vouchers are not simply a transfer to those who receive them, but also to landlords. Considered as a transfer program, the estimated 16 percent increase in rent implies that vouchers have caused a $8.2 billion increase in the total rent paid by low-income non-recipients, while only providing a subsidy of $5.8 billion to recipients, resulting in a net loss of $2.4 billion to low-income households.

1.2 The Section 8 Program

There are actually two programs with different subsidy schemes: Section 8 Vouchers and Section 8 Certificates. The Certificate program, which is far larger, subsidizes rent in privately provided units, requiring tenants to pay no more than 30 percent of their income. Tenants must rent units that have been approved by local public housing authorities as meeting minimum habitability standards, and that rent for less than the "Fair Market Rent" (FMR). Fair Market Rent is defined as the 45th percentile of rents in an MSA.[4] However, the calculation is done only for units occupied by recent movers, that also meet minimum quality standards. So the standard is closer to the median rent, and is sometimes above it (HUD, 1995a). Tenants have no incentive to find units that rent for less than the FMR, since they do not keep the savings.

The main difference between the voucher and certificate programs is that vouchers allow

[4]FMRs are adjusted for the number of bedrooms. For voucher recipients, household size determines the number of bedrooms that they are entitled to.

tenants to keep the savings if they rent units that are cheaper than the FMR. Voucher recipients can also choose to rent units that are more expensive. Thus, vouchers are basically a lump-sum income transfer (for tenants of apartments renting for more than 30 percent of the recipient's income). The important exception to this, however, is that the units rented by voucher recipients must also meet HUD's quality standards.

In fact, the programs may not be as different as the rules seem to suggest. A careful study commissioned by HUD found, surprisingly, that the average rent paid by both voucher and certificate recipients was almost the same, and very close to the Fair Market Rent (Leger and Kennedy 1990).[5] On paper, the voucher program is a lump sum income transfer, which we would not expect to result in much of an increase in housing consumption (so the HASE experiments found, for example). It may be that the quality standards are enforced rigorously enough to be binding.

Leger and Kennedy found that 39 percent of recipients were not able to find a unit that met HUD's standards within the two to four months allowed for search. These vouchers are returned to the local public housing authority and are "recycled." Since a voucher is large enough to pay for half the units in an MSA, it is pretty surprising that so many people had to return their subsidy checks. Of course, there's no reason to expect that every landlord will be interested in, or capable of, being certified as meeting HUD's standards. Still, this seems like a hundred dollar bill lying on the street. It may imply that the quality standards are binding, and also suggests a slow supply adjustment in low-income rental markets.

This study will treat both vouchers and certificates as if they were simply an order to pay the FMR for an apartment. This is a fairly accurate description of the certificate program, which is by far the larger program.[6] In practice, if not on paper, the voucher program (which has grown faster in recent years) appears to be quite similar. Also, I will continue to use the term "vouchers" generically, to refer to both programs.

1.3 The Size of the Voucher Program

The demand increase induced by vouchers depends on the size of the population served (relative to the size of the market), the amount of the subsidy received by each household,

[5] Certificate rent were tightly clustered around the FMR, while the variance of voucher rents was much higher.

[6] In 1989, the mix was 12 percent vouchers and 88 percent certificates (Bartsch 1990). By 1995, certificates' share had fallen to 77 percent (HUD, 1995b).

and the extent to which the subsidy is spent on housing. The amount of the subsidy is easiest to evaluate: housing subsidies are fairly generous, as we might expect from a program that provides welfare recipients and other very low-income households with the median rental housing available. For example, the 1997 Fair Market Rent for a two bedroom apartment in the Oakland MSA is $794, which is about equal to welfare and food stamps benefits combined.[7] A 1989 General Accounting Office report describes units available to Section 8 recipients in the Houston area: "Most complexes had swimming pools...one had tennis courts, and a few had covered parking for tenant vehicles." Houston was not typical, it was chosen because the GAO thought that the FMRs were likely to be too high, but it may not have been that unusual.

Leger and Kennedy compared the rents paid by voucher recipients before and after they received vouchers. They found that tenants increased their housing expenditure by an average of 59 percent (from $274 to $437) after receiving certificates. This figure is a lower bound on the long run increase in rent expenditures, since in the long run all tenants have the opportunity to move (two thirds of tenants moved immediately).

The before and after comparison will be flawed if recipients' previous housing expenditures reflected a temporary situation. Simple cross-section comparisons, however, suggest that this is not a severe problem. Cage (1994) studied 1988-1990 Consumer Expenditure Survey data. He found that voucher recipients lived in units that rented for $527 a month, on average. Income eligible non-recipients paid only $337. However this 56 percent difference is probably understated, since the comparison group (of eligible non-recipients) are generally better off. Voucher recipients have 20 percent less income, for example. Another simple estimate can be calculated by assuming that voucher recipients would have spent 42 percent of their income on rent, as the unsubsidized group does. This suggests that vouchers caused recipients to spend $527 a month rather than $270, which is a 95 percent increase.[8]

To qualify for a voucher, households must meet HUD's "very low income" eligibility standard. Families earning less than 50 percent of the median income in a metropolitan area (MSA) are defined as very low income. However, housing assistance is not an entitlement; instead, vouchers are rationed through a waiting list and a system of preferences.[9] In 1995,

[7]In 1997, the maximum available TANF and food stamps benefits for a three person, single parent family amounted to a total of $826/month in California. (Green Book, 1998).

[8]These figures are unadjusted means. Cage also regresses out-of-pocket rent expenditures on demographics and dwelling characteristics. His results suggest that vouchers raise total rent expenditures by well over 100 percent, but are flawed by the inclusion of endogenous variables such as the number of bedrooms.

[9]Waiting times average about 18 months (Painter 1996). Priority is given to the homeless, those in

about 1.3 million households received a rent voucher, about the same number as lived in public housing projects. Compared to all 97.7 million U.S. households, this is quite a small number. For this to be a reasonable comparison, however, assumes that all homes are close substitutes, that low-income households can easily switch between owning and renting, or between poorer and wealthier neighborhoods. Compared to the 14.7 million poor households or the 8.7 million poor renter households, vouchers loom somewhat larger.[10] Table 1 shows the distribution of vouchers across the 90 large metropolitan areas studied in this paper. For the median MSA in the data, there are enough vouchers for 11 percent of poor households, for 16 percent of poor renter households, or for 3.6 percent of all renter households.

There are some theoretical and empirical reasons to think that housing markets are segmented into higher and lower quality portions (discussed below). For now, though, note the voucher program is quite small relative to a broad definition of a housing market, and is of moderate size relative to a narrower, and probably more reasonable, definition. In general, evidence that vouchers have a substantial effect on rents is also evidence that housing markets are quite segmented.

1.4 Literature Review

Most of what we know today about low-income housing markets is a result of the housing allowance experiments, which generated a large, but now somewhat dated, literature in the 1970s. One of these studies, the Housing Assistance Supply Experiment, is often cited as finding little effect on market rents. HASE, conducted from 1975 to 1980, was something of a trial run for the current Section 8 voucher program. In two small Midwestern cities, all residents who met income standards were eligible for voucher-based subsidies.

HASE analysts reported that rents in the two experimental sites increased by about the same amount as rents nationwide, and as landlord's costs (Lowry 1983, Rydell, Neels and Barnett 1982). However, the Housing Allowance experiments only raised recipients' rental housing expenditures by about 8 percent (Lowry 1983, p. 154), probably because the subsidies were very close to being lump-sum transfers, with minimal habitability standards. Since there was little increase in demand, the experiments ultimately didn't tell us much

substandard housing, and those with rent burdens (rent as a percentage of income) of 50 percent and higher (Nelson and Khadduri 1992).

[10] These figures are from the *American Housing Survey for the United States in 1995* except for the voucher figure which is from tabulations included in the *Picture of Subsidized Housing* documentation.

about the elasticity of supply. Also, the experiment was not well designed to capture small effects. Only two cities were studied, and there was no natural comparison group of cities. Finally, analysts were mainly concerned with effects on the whole local housing market, not merely the low-income submarket.[11]

The housing allowance experiments also funded the development of an elaborate housing market model by the Urban Institute (de Leeuw and Struyk 1975). de Leeuw and Struyk used the model to simulate a full scale voucher program that serves many times more people than does the actual program, but that induced much smaller increases in demand for each household. They warned that housing prices could increase by 40 percent in the worst case scenario.[12]

Vouchers will drive up rents if they fail to stimulate a supply response: inducing construction, reducing demolition, or increasing maintenance. It has not generally been recognized that without a supply response, housing subsidies cannot improve the housing conditions of the poor.[13] If the effect on supply is small, vouchers will mainly redistribute the stock of housing from one group to another. In the extreme case, where the stock of housing is fixed, voucher recipients will trade places with the unsubsidized, and there will be no net benefit from the program. In fact, the results presented below suggest that the elasticity of supply is very close to zero, that vouchers do very little to increase the size or quality of the low-income housing stock.

There has been a fair amount of study of the supply of newly constructed housing (see DiPasquale (1999) for a review). However, there has been very little examination of the housing supply mechanisms that are probably most relevant to the market served by vouchers, such as demolition or the maintenance of rental housing. Rydell (1982), the more recent of the two studies of maintenance cited in Dipasquale's survey, found that the elasticity of repair expenditures with respect to rent is quite low (about 0.2).[14]

Because little is known about the supply response to vouchers, little can be said about their cost-effectiveness. Vouchers have lower budgetary costs, and are often promoted as a

[11]Rosen (1985) offers a similar analysis.

[12]Barnett (1979) discusses a number of similar predictions.

[13]An exception is Galster (1997) who argues for vouchers on the grounds that they induce a supply response. Although such a response is possible, it has not been documented.

[14]But see the strong criticisms of Rydell in Olsen (1987). O'Flaherty (1996) examined demolitions, and Weicher and Thibodeau (1988) studied the stock of substandard housing, but neither directly examine the effect of demand or prices on a measure of the quantity of existing housing.

cheaper solution than construction subsidies.[15] Knowing that a voucher costs the government, say, \$400 a month while subsidizing construction costs \$600 a month tells nothing about how many new (or better) units are supplied by the subsidies. Although vouchers may induce landlords to maintain their buildings better, and stave off demolition, it is quite possible that construction subsidies, which target the marginal unit of the housing stock, are a more efficient way of supplying new housing. Ultimately, this is an empirical issue. Construction subsidies may increase the size of the housing stock, or they may simply crowd out private construction.[16] By the same token, vouchers may induce new construction, or they may simply bid up rents and redistribute the existing housing stock.

2 Model

2.1 Theoretical Model

The model assumes that each market has a supply and demand curve for housing services, with constant elasticities. Think of a market as an MSA/income class combination, such as the low-income housing market in the Oakland MSA. Formally:

$$\ln Q_{ij}^{D} = X_{ij} - \varepsilon_j^{D} \ln P_{ij} + \eta_{ij}^{d} \quad \textit{constant elasticity housing demand} \tag{1}$$

$$\ln Q_{ij}^{S} = Z_{ij} + \varepsilon_j^{S} \ln P_{ij} + \eta_{ij}^{s} \quad \textit{constant elasticity housing supply} \tag{2}$$

Here, Q_{ij}^D and Q_{ij}^S are the quantity of housing demanded and supplied in a market; P_{ij} is the price; Z_{ij} is an index of supply shifters; and X_{ij} is an index of demand shifters. The elasticity of demand is denoted ε_j^D, and the elasticity of supply is ε_j^S. The error terms, assumed to be uncorrelated with X_{ij} and Z_{ij}, are denoted η_{ij}^d and η_{ij}^s. MSAs are subscripted by i, and income categories (low, middle, and high) are subscripted by j. In all the equations below, both these housing market subscripts will be suppressed.

[15] Building a new unit costs 58 percent more than a voucher on an annualized basis according to Apgar (1990). Such costs figure prominently in policy debates. See, for example, Burman (1992).

[16] Murray (1999) finds that low-income public housing has not crowded out private construction, but that moderate-income subsidies have.

In the long run, $Q^D = Q^S$, so the equations can be solved to generate the reduced form:

$$\ln P^* \quad = \quad \frac{X - Z}{\varepsilon^S + \varepsilon^D} + \eta_p \tag{3}$$

where the error term (η_p) is a combination of η^s, η^d, ε^S, and ε^D. With some modifications, equation 3 will be the equation estimated in this paper.

Now we need to determine the the appropriate measure of voucher-induced demand to be included in X. To derive this, consider the demand curve for an unsubsidized family:

$$\ln q_i = x_i - \varepsilon^D \ln P.$$

In a market without vouchers, market demand equals the sum of the individual demands:

$$Q^D = \sum_{i \in N} q_i,$$

where N indicates the number of households in a market (and the analogous set). In a market with vouchers, market demand can be written as the sum of the demand without vouchers plus the change due to vouchers:

$$Q^D = \sum_{i \in N} q_i + \sum_{i \in N^V} (q_i^v - q_i^b),$$

where N^V indicates the number of (set of) subsidized households (i.e. with a voucher). The quantity demanded by a voucher recipient is denoted q_i^v, while the quantity demanded by a voucher recipient before receiving the subsidy is denoted q_i^b. Taking logs and making a first-order Taylor series approximation about the first term yields

$$\ln Q^D = \ln(Nq) + \frac{N^v}{N} \frac{q^v - q^b}{q},$$

where the suppressed index indicates the average; for example, q indicates the average of q_i. Take $\frac{q^v - q^b}{q}$, the subsidy generosity, to be a constant, denoted θ. For example, if voucher recipients spend \$200 a month before receiving a voucher and \$400 after, while the average tenant in the market spends \$300, then $\theta = 2/3$ and a voucher will induce demand equal to an extra 2/3 of an average person. This is a substantive assumption, discussed below.

Substituting θ, and rearranging, yields the extended demand equation

$$\ln Q^D = \ln q + \ln N + \theta \frac{N^v}{N} = X - \varepsilon^D \ln P + \ln N + \theta \frac{N^v}{N}, \tag{4}$$

where $X = \frac{1}{N} \sum_{i \in N} \exp(x_i)$. That is, X is the average of some demand shifter, for example, average family income. Equation 4 shows that the appropriate measure of the demand induced by vouchers is the fraction of housholds with a voucher, N^v/N, multiplied by the generosity of each voucher.

Combining this with supply equation 2 yields the reduced form

$$\ln P^* = \frac{1}{\varepsilon^S + \varepsilon^D} [X + \ln N + \theta V - Z] \tag{5}$$

where $V = N^v/N$. This is the equation estimated in the paper, and so we have an interpretation of the estimated voucher coefficient. The regression coefficient on V will be $\theta/(\varepsilon^S + \varepsilon^D)$. Vouchers will cause a large increase in price when the subsidy generosity is high, and when the supply and demand curves are inelastic.

The main assumption here is that vouchers don't change the demand elasticity. In fact, assuming that θ is a constant is equivalent to assuming that vouchers act by shifting the intercept, but not twisting the demand curve. This is not as strong an assumption as it seems. Recall that voucher recipients' housing expenditures are determined by the Fair Market Rent (FMR), which in turn is simply set to allow recipients to buy approximately the median quality housing. This can be written: $q^v = q^m$, where q^m is the housing demanded by a median household. Then, $\ln q^v = x^m - \varepsilon^D \ln P^m$, which shows that HUD's process for determining the FMR forces voucher recipients to spend as if they were the median household.[17]

To see this, consider two MSAs, one with rent in the median market 10 percent higher than the other. If the demand elasticity is, say, 0.6, then the unsubsidized will consume 6

[17] The result that θ is a constant depends on two assumptions. First, assume that the ratio of the voucher recipients' housing expenditures to the housing expenditures of the average person is a constant. Write this as $q = k_1 q^b$, for some constant k_1. Further, assume that $q^v = k_2 q^b$, for some constant k_2. This says that vouchers shift only the intercept of the demand curve, but don't change the elasticity. To see this, take logs, yielding $\ln q^v = \ln k_2 + \ln q^b = \ln k_2 + x^b - \varepsilon^D \ln P$. These two assumptions imply

$$\frac{q^v - q^b}{q} = \frac{k_2 - 1}{k_1},$$

which is a constant.

percent less housing in the more expensive city. HUD observes the median rent and adjusts the FMR so that the subsidized households also consume 6 percent less housing. That is, HUD raises the FMR, but not by enough to fully offset the price increase. Thus, by setting the FMR based on the housing consumption of the unsubsidized, voucher households are forced to behave as if they had the same demand elasticity.

In general, voucher recipients may not face the median price, since they may well end up renting in the low-income market. However, if the low- and middle-income prices move together, then the result that the demand elasticity is unchanged still holds. Some price shocks are market-wide (changes in construction costs may be an example), but this assumption should be regarded as an approximation.[18]

Although the model to be estimated is a reduced form, the voucher coefficient has a direct interpretation that suffices to answer the main question. It reveals how much a percentage point increase in the voucher stock increases the price of housing. In addition, if some of the parameters are assumed to be known from past research, then the supply elasticity can be backed out. This is of interest in itself, and provides a useful check on the results.

2.2 Relationship to Filtering Models

The model treats the bottom, middle, and top income categories as separate markets. It might be regarded a simple version of a more complex model with a continuum of income

[18]To see when subsidy rules which provide voucher recipients with the median quality housing will result in an unchanged demand elasticity, consider three cases. First, recall that the demand curve for an unsubsidized household (such as a voucher recipient before receiving a voucher) is $\ln q^b = x^b - \varepsilon^D \ln P$.

A voucher recipient will consume the median quality housing, so $q^v = q^m$. This implies that $\ln q^v = x^m - \varepsilon^D \ln P^m$. If voucher recipients were in the median market before receiving a subsidy, then $P^m = P$, and the demand elasticity will be unchanged.

Now suppose that voucher recipients were in another market (presumably a lower one), but prices in the two markets move together, so that $P^m = \gamma P$. Then $\ln q^v = x^m - \varepsilon^D \ln P + \varepsilon^D \ln \gamma$. Again the demand elasticity is unchanged, since $d \ln q^v / d \ln P = -\varepsilon^D$. Here, we also have to assume that unsubsidized households in both markets have the same demand elasticity.

An alternative possibility is prices in the low- and middle-income markets don't move together, so that HUD doesn't adjust the Fair Market Rent in response to a price shock to the low income market. In this case, the demand elasticity may actually become larger than than of unsubsidized households. If the FMR is fixed, then voucher recipients will consume $q^v = \text{FMR}/P$, which implies that $\ln q^v = \ln\text{FMR} - \ln P$, which is simply a demand curve with an elasticity of one. However, I do not make this assumption for several reasons. First, past research suggests that low-income renters have demand elasticities less than one (Hanushek and Quigley 1980). Thus, assuming that vouchers recipients have unit demand elasticities amounts to assuming that vouchers raise the demand elasticity, which seems implausible. Instead, it seems more likely that vouchers may lower the demand elasticity (perhaps because recipients searching for housing are limited to units that accept vouchers). In addition, allowing voucher recipients to have a different demand elasticity would lead to a much less tractable model.

types and housing qualities. It is worthwhile briefly discussing the more complex model.

"Filtering" models are the natural candidate for consideration.[19] Filtering models assume a range of housing qualities, with the poorer consumers occupying the lower quality housing. The production function for houses exhibits diminishing returns to quality, but constant returns to scale. Once built, houses deteriorate unless maintained. If construction costs rise more rapidly with quality than do maintenance costs, then above a certain point homes will be built and maintained forever. Since the production function has constant returns to scale, the supply of higher quality housing is infinitely elastic. At lower levels of quality, however, it is cheaper to build medium quality homes for middle income people and allow them to deteriorate until they are affordable by the poor (call this the "build-and-deteriorate" level of quality). Thus a crucial determinant of the supply of low-income housing is the ratio of middle income people to the poor. More middle income people in a city means more new housing, housing that will eventually "filter down" to the poor.[20]

In a filtering model, there are three cases where vouchers can end up raising the price of low income housing. First, vouchers can move people from very low in the quality distribution to some point near the middle, but below the new construction level. This is the case that most closely corresponds to an increase in demand for low-income housing. Second, vouchers can could induce doubled-up households to separate.[21] If the number of poor households increases, the price of low-income housing should rise (since new construction only responds to an increase in the middle class). Third, since by law vouchers can only be used in well-maintained units, they could interfere with the filtering process. Vouchers could remove some apartments from the filtering chain, causing them to be maintained forever at higher qualities.

Vouchers could also lower the price of low-income housing. If vouchers are generous enough, they move voucher recipients to the high-income, build-and-maintain-forever interval. The price of housing for the rich won't change, but the price of low-quality housing will fall since there are now effectively fewer poor people for each middle-income person. Slightly less generous vouchers could move recipients to new construction at the build-and-deteriorate quality. This will lower rent for the poor for the same reason, and for an additional one: they

[19] This section closely follows the analysis in O'Flaherty (1995).

[20] The lower, middle, and upper treciles used in this paper may loosely correspond to the three ranges of a filtering model, or they may not. Just where the new construction interval begins is an empirical question beyond the scope of this paper.

[21] One third of voucher recipients were doubled-up before receiving a voucher (Leger and Kennedy 1990).

will increase the amount of new housing being built that will filter down. The supply and demand model with segmented markets should be flexible enough to capture any of these possibilities. It allows the estimation of the effects of vouchers on different market segments without imposing too many assumptions on the data.

3 Data

The model can be estimated in the following manner. First, using data on individual households, estimate a hedonic regression in order to obtain the price of low-income housing in each MSA. That is, regress (log) rent on dwelling characteristics (e.g. the number of bedrooms) and a set of dummy variables for each metropolitan area/income group interaction. The coefficient on, for example, the Oakland/low-income dummy will be interpreted as "the price of housing for the poor in Oakland," and is labeled $\ln P^*$ in equation (5). Now take the prices and regress them on population, population growth, median income, and the percent subsidized in each MSA.

No supply shifters enter the model because in practice it is very hard to identify ones which are reasonably well measured. Construction costs are an obvious possibility. However, a large component of construction costs are wages, which affect both demand and supply: high wages attract migrants, which is demand. Most studies of housing supply have found no effect of costs on the volume of construction, probably because costs are measured so poorly (DiPasquale 1999). Somerville (1999) has documented numerous deficiencies in the commonly used Boeckh and RS Means construction cost indexes.[22] Excluding supply shifters will result in bias if construction costs, for example, are correlated with V. However, there is no obvious reason why voucher allocations should depend on construction costs, or vice versa.

The main dataset is the American Housing Survey (AHS) national file, which will be used to estimate the price of low-, middle-, and high-income housing in each MSA. Conducted every two years, the AHS contains detailed information on dwelling units and their occupants. Crucially, it includes information on subsidy status. The sample used for the hedonic regression consists of unsubsidized renter households only, since the goal is to estimate the effect of vouchers on the private-market rent for the poor. Since subsidized households, such

[22]For example, both indexes rely on union wage rates to measure construction wages, even thought residential construction is predominantly non-union.

as residents of housing projects, are insulated from market forces, they are not included in the analysis.[23] In addition, observations with imputed rent, or who paid rent only once or twice a year were dropped.[24]

The year 1993 is chosen because few new vouchers have been issued since then, making any effects harder to detect. The 1993 AHS contains usable observations on 6,526 households occupying rental housing in 108 MSAs. The main drawback of this dataset is that the number of observations in each MSA is not large, with the median MSA having 33 observations.[25] This doesn't bias the results, and weighted least squares will insure the small MSAs get the appropriate amount of weight. However, these sample sizes limit the precision of the estimates. In addition, 1974 Annual Housing Survey data is used to calculate similar price variables in the year that the voucher program began.[26] Finally, rents in the AHS are topcoded at \$1000 in 1993, at approximately the 95^{th} percentile of my sample. Based on the distribution of 1974 rents, which are not topcoded, I recoded the 1993 rents from \$1000 to \$1147.[27]

The AHS also contains a "neighbor sample," which is used in certain auxiliary results. For a subset of AHS sample members, the AHS questionnaire was administered to the ten closest neighboring households. There are usable clusters of 608 neighbors in the 1993 AHS data, containing a total of 4,396 observations (including both renters and owners). If the neighbor sample were big enough, it could be used to directly estimate a hedonic equation that includes dummy variables indicating the average income of each sample member's neigh-

[23] Arguably, voucher households should be included in the analysis, since they are presumably renting in the private market. This is done in the sensitivity analysis, but not in the body of the paper.

[24] Most households that reported paying rent once a year in 1993 paid extremely low rents. When I examined rents for the same units in 1991, I found that most of the households had reported paying reasonable rents, on a monthly basis. Typically, the 1991 rent was about 12 times as high as the 1993 rent. For example, a household might have reported paying \$400 a month in 1991, but \$400 a year for the same unit in 1993. Very likely, the 1993 data is a result of a data entry clerk entering a "1," meaning "once a year," rather than "12," meaning "12 times a year."

[25] MSAs with fewer than 10 observations are excluded from the sample, and the maximum is 670.

[26] The Annual Housing Survey was renamed the American Housing Survey in 1985, and a new panel of housing units was drawn. The sample size used in the 1974 hedonic regressions is 8,476.

[27] This figure (1147) is an estimate of E(Rent | Rent $\geq$ 1000). This was calculated by regressing the 94 non-topcoded centiles of 1993 log rents on the lower 94 centiles of 1974 log rents and a constant. The regression procedure relates mean and variance of the two distributions as $E(R_{93}) = a + bE(R_{74})$ and $V(R_{93}) = b^2V(R_{74})$. Then I extended the estimated regression line and calculated the expected value of topcoded rents as $E(R_{93} \mid R_{93} > R_{93}^{(94ile)}) = a + bE(R_{74} \mid R_{74} > R_{74}^{(94ile)})$. Graphing the quantiles of two distributions is a graphical method of assessing their equality or relationship (Wilk and Gnanadesikan 1968, Gerson 1975). The first 94 centiles of the two distributions appeared to be well-described by a linear relationship (the R^2 of the regression is .994). In addition, the sensitivity analysis, below, shows that alternative corrections for topcoding make little difference.

bors. The neighbor sample is too small and clustered to allow this. However, the neighbor sample can be used to develop an index that relates the income of households to the average incomes of their neighborhoods. As discussed below, this index plays an important role in the hedonic estimates of housing prices. In addition, it can be used to examine the the type of neighborhoods that voucher recipients live in.[28]

MSA characteristics, such as median family income and population, are needed in the second stage regressions. These come from various years of the decennial census. The percent subsidized is calculated using the HUD administrative data released in the Picture of Subsidized Housing dataset. Vouchers are mostly administered by several thousand local public housing authorities (PHAs), which typically cover a city (e.g., the Berkeley PHA). Counting vouchers in each MSA required the creation of a PHA to MSA concordance, a time-consuming task which took many weeks. Some vouchers are administered by state agencies. Fortunately, the PSH dataset also contains detailed information on the location of state agency voucher households, and so a complete count of vouchers in each MSA can be constructed.[29]

4 Neighborhoods of Voucher Recipients

A general conclusion that can be drawn from a filtering model is that if voucher recipients are able to move to high enough quality markets, they won't be competing with the poor, and vouchers will not raise the rent that the unsubsidized poor pay. Since the fair market rent is set around the median, a natural assumption is that voucher recipients move into the middle housing market. On the other hand, if there is a stigma attached to vouchers, or if voucher recipients are considered undesirable tenants, then voucher recipients may find themselves trapped in lower trecile neighborhoods. Table 2 provide some basic information about the kinds of neighborhoods that voucher recipients live in, as measured by the characteristics of their eight closest private-market neighbors.[30] The 30 % of voucher recipients without

[28] I restrict the AHS neighbor sample to the set of MSAs used in the national sample.

[29] An exception is the state of Michigan, where many vouchers are administered by state agencies, but the PSH lacks geographic information on most of these vouchers. For this reason, no Michigan MSAs are used in this study.

[30] Table 2 compares the characteristics of the neighbors of voucher recipients and the neighbors of lower, middle, and upper trecile renters. For example, in a cluster of eight neighbors, four of whom are renters, I calculate the average income of the other seven households in the cluster for each of the four renters. The table then reports the average neighbors' income of the sample members. Another way to think about this is to view the unit of observation as the neighborhood. Each neighborhood is then weighted by the number

private-market neighbors, living in "section 8 ghettoes," are excluded from this table. Hence, the figures in Table 2 probably exaggerate the quality of voucher recipients neighborhoods.[31]

The figures in Table 2 indicate that voucher recipients tend to rent in the lowest trecile market. Recipients' private-market neighbors have an average income of $24,215, which is quite close to the incomes in neighborhoods where lower trecile renters live. This figure will be misleading if voucher recipients are concentrated in MSAs with low (or high) incomes. A crude adjustment is to compute the average neighborhood income relative to the average household income in the whole MSA. This adjustment strengthens the conclusion that voucher recipients live in lower trecile neighborhoods.

Private market neighbors of voucher recipients pay $467 a month in rent, which is a fairly close to the $442 average rent in lower-trecile neighborhoods (Table 2). The voucher recipients themselves, however, pay $512 (not reported in the table). A natural interpretation of these results is that stigma confines voucher recipients to low-income neighborhoods, but vouchers are generous enough to allow them to rent high-quality (perhaps spacious) housing in those neighborhoods. Again, these estimates are likely to be conservative, to overstate the average neighborhood quality of recipients, since some of the lowest income voucher recipients (with no private market neighbors) are excluded from the sample. There is some evidence, then, that we live in a world where the voucher program is likely to bid up rent for the unsubsidized poor.

5 Measuring "The Price of Low-Income Housing"

Ultimately, a measure of "the price of housing for the poor" is needed for each MSA. The first step is to define "poor," which is a little more complicated than it seems. Once three dummies for the lower, middle, and upper treciles have been created, a hedonic regression can be estimated with dummies for each MSA/income level interaction. The dummy coefficients will be interpreted as the price of low- (middle-, and high-) income housing.

Why should there be one price of housing for the poor, and another for the rich? To

of voucher recipients (or lower trecile renters, etc.) who live there, so that the neighborhoods are roughly representative of the neighborhoods that the typical household lives in.

[31] The fact that the excluded voucher recipients have no private-market neighbors is itself an indication that they live in lower-quality neighborhoods. In addition, voucher recipients in section 8 ghettoes have less income and are more likely to be African-American. They have about $3,600 less annual income than recipients with private-market neighbors ($5,769 vs. $9,410). 39 percent of black voucher recipients have no private market neighbors, compared to only 26 percent of white recipients.

answer this requires defining the price of housing. Define $R_{ij} = P_j Q_{ij}$, which says that observed rent for individual i in market j is equal to the (unobserved) market price times quantity. This is, two neighbors face the same price of housing (P_j). But the neighbor with the bigger apartment and a better view receives more housing services (Q_{ij}), and will pay a higher rent (R_{ij}).[32] Replace Q_{ij} with an index of housing quantity, $Q_{ij} = \exp[(X_{ij}\beta)]$, implying

$$\ln R_{ij} = \ln P_j + X_{ij}\beta.$$

X is a vector of characteristics of the housing unit, the neighborhood, and perhaps conditions of the rent contract (such as whether utilities are included in the rent), while β is a vector of characteristic prices (or simply weights). The X_{ij}'s should *not* include individual characteristics, unless there is price discrimination.[33] In general, though, different people will be charged the same price, just as grocery stores charge both the rich and the poor the same price for apples. In practice, though, individual income does affect rent, even when a long list of dwelling characteristics is included on the right hand side. The reason for this is straightforward: in real data, there will always be some omitted variables. Call the unobserved variables Z, and the equation to be estimated becomes:

$$\ln R_{ij} = \ln P_j + X_{ij}\beta + Z_{ij}\gamma.$$

If income is correlated with $Z_{ij}\gamma$ (unobserved housing quality), then income will be significant in the regression. If unobserved housing quality is a normal good, income will enter positively. So income will serve as a proxy for any omitted variables in the hedonic. The interpretation of the income coefficient, then, will depend crucially on precisely which variables are included in the regression, and which are excluded. The AHS data contains a long (though still incomplete) list of characteristics of the unit itself (like the number of bedrooms), but a very short list of neighborhood characteristics. So the income dummies will primarily serve as proxies for neighborhood quality.

In general, the filtering model provides some theoretical justification for this procedure. In

[32] Quigley (1995), among many others, uses a similar setup (interpreting time dummy variable coefficients as the price of housing at a particular time). An alternate interpretation, which changes nothing of substance, would call the P_j's, "The price of neighborhood amenity service flows."

[33] Of course, racial discrimination is an obvious possibility. For this reason, the X_{ij}'s used in the hedonic will include race.

a recent study, Goetzmann and Spiegel (1997) provide some important empirical justification. Goetzmann and Spiegel studied the pattern of housing price movements among different neighborhoods (defined by zip codes) in a large metropolitan area. They found that housing prices in neighborhoods with similar income levels (or similar demographics) tend to move together. This result holds even for widely separated neighborhoods. In fact, they found very little spatial correlation in price movements. This suggests that a patchwork of low-income neighborhoods spread out across an MSA may form a single housing market. Demand or supply shocks in one poor neighborhood seem to affect the price of housing for the poor in the whole MSA.[34]

This procedure constrains the characteristic prices (β) to be the same in all neighborhoods, using a shift in the intercept to model the price of housing in a different markets. An alternative method relaxes this constraint and estimates separate regressions for each market. Several authors have compared the two methods, and found that the less constrained method does little to improve the resulting price indexes. Schnare and Struyk (1976), using data for a metropolitan area, estimated a hedonic regression that includes only dwelling characteristics, a single location dummy variable, and average neighborhood income (intended to proxy for neighborhood service flows). They compared this model to a procedure that estimated separate regressions for each of several neighborhoods (for example, the low-income tracts in the outer suburbs). They found that price indexes calculated from the unconstrained model had only a marginally tighter fit, and endorsed the single-regression model. Rothenberg et al. (1991) estimated a hedonic price index with national data using dwelling characteristics and MSA dummies. They found that estimating separate models for each MSA did not lead to a statistically significant improvement in fit (i.e. in the price indexes). Thus, a pooled regression appears to be an adequate model.

5.1 Measuring "Low-Income" – The Neighborhood Poverty Index

The obvious method of creating the income dummies simply splits the sample into treciles based on the poverty level (that is, household income as a percent of the poverty line).

[34] There is also a long tradition of using ad-hoc procedures to split up the housing market into quality tiers. Some authors have used a single hedonic equation to calculate the predicted price of two or three housing bundles (Poterba 1991, Thibodeau 1995, Thibodeau 1989, Gyourko and Linneman 1993). Others have examined housing price quantiles (Mayer 1993, Case and Shiller 1994), or some combination of the two (Pollakowski, Stegman and Rohe 1991, de Leeuw and Ekanem 1971, Rothenberg, Galster, Butler and Pitkin 1991). Jencks (1994) has estimated hedonic price indexes for low-income households.

However, a concern is that those with low income in a given year may be only temporarily poor, perhaps suffering a spell of unemployment, starting a business, or simply failing to report some source of income to the surveyor. This concern is exacerbated by the fact that the hedonic regression sample consists of unsubsidized renters only. Thus, a large group of the long-term poor has been dropped from the sample.

Table 3 shows the characteristics of the sample split into treciles based on the poverty level. Rent sharply increases with income, suggesting that this probably would be a workable method of categorizing the sample, in spite of the problems noted above.[35] However, the lower trecile has 11.6 years of education, and 20 percent receive some kind of income from capital, indicating that many in this trecile may not be the long-term poor.

Instead of simply using income, the sample will be classified using an index based on household income, education, and indicators for the receipt of welfare or capital income. The idea is that a high-school drop-out on welfare is poorer (at least in the long run) than a college graduate with a job, even if they have the same income in a particular year. More specifically, the drop-out will presumably be living in a worse neighborhood than someone who is temporarily poor. Housing decisions, after all, are more closely related to permanent income than to income in any one year. The AHS neighbor sample is used to construct the weights for each element of this index by regressing neighborhood income on the individual characteristics listed in the bottom panel of Table 3.

Table 3 shows the characteristics of the AHS national sample sample when split into treciles using the index, labeled "neighborhood poverty treciles." Compared to the simple poverty treciles, the lower trecile has 40 percent higher income on average, a year less education, and is half as likely to receive income from capital. The other changes are less dramatic. Rent does become more dispersed (the lower trecile pays less, and the upper pays more), as expected, but the change is slight.

5.2 Hedonic Regression

"The price of low-income housing" is measured using a hedonic regression of the log of rent on a long list of housing characteristics, and the 108x3 MSA/neighborhood poverty dummies. Except for these dummies, the specification follows (with some slight modification)

[35] In fact, the sensitivity analysis reported below shows that this measure yields similar conclusions about the effect of vouchers on rents.

Thibodeau (1995).[36] The key point to note is which variables are included, or excluded, in the regression.

The AHS data contains a long list of dwelling characteristics (ranging from the number of bedrooms and the frequency of equipment breakdowns), race, two contract conditions (crowding and length of tenure), and a short list of neighborhood characteristics. The neighborhood characteristics are very limited, including only a few opinion questions[37] , and one objective measure: the presence of nearby abandoned buildings. The opinion questions don't matter much. None are statistically significant at the five percent level and the most precisely measured one (about crime) lowers rent by only 2.4 percent (with a t-statistic of 1.94). The presence of abandoned buildings does lower rent by 12 percent, however (with a t-statistic of 6.95).

Conspicuously absent are many other important locational characteristics like educational quality, good measures of crime rates, access to transportation and employment, and local amenities such as parks. Since neighborhood quality is presumably a normal good, individual income should proxy for it. More generally, the income trecile dummies will proxy for any housing quality variables that are omitted from the regression. Although neighborhood characteristics are probably the most important, other potentially relevant variables are omitted from the equation as well. Although a number of measures of dwelling size are included, square feet is not. Although dummies indicate whether the dwelling is detached, or part of an apartment complex, no specific information about a lawn is included. In the end, though, just what the omitted variables are isn't very important, as long as we keep in mind that the hedonic measures the price of housing for the poor, holding the included variables constant.

The coefficients on the MSA/income dummies will be interpreted as estimates of the price of low- (middle-, and high-) income housing services in each MSA. A desirable property of these estimates is that the top trecile rent should be higher than the bottom trecile. To check this, the difference between upper and lower trecile rent was calculated for each MSA. The method does reasonably well on this criterion, but is hardly perfect. In the median MSA, upper trecile rent is 24 percent higher than the the lower, using the neighborhood

[36] Complete regression results are available from the author upon request. I added extra categories (i.e. dummy variables) to two measures: bathrooms (0 bathrooms added) and respondents' opinion of neighborhood ("no neighborhood" added). I also changed the built "1940 or before" dummy to "built 1920 or before."

[37] These are: (1) overall quality of neighborhood on a 1-10 scale, and (2) whether crime or street noise is so bad that the respondent would like to move.

poverty index to split the sample. When the simply poverty level is used, the difference is only 17 percent. In 5-10 percent of the MSAs the bottom trecile rent is higher than the top. The neighborhood poverty index (used in the main results) does somewhat better than the simple poverty measure, but not spectacularly so.

6 Empirical Results

6.1 Identification

Simply regressing price on vouchers will lead to biased estimates if HUD targets high-rent MSAs when allocating vouchers. To the extent that vouchers are sent to "needy" areas, identifying the causal effect of vouchers on rents is difficult: do vouchers raise rents or do high rents lead to voucher allocations? Fortunately, a good deal is known about the methods HUD used to allocate vouchers.

A substantial portion of vouchers are allocated using a formula. For each HUD "allocation area" in the country (usually an MSA), the formula determines what percentage of new vouchers will go to that area. For example, the Oakland MSA is an allocation area which receives 1.2 percent of all vouchers allocated by formula in any given year. In recent years, vouchers have come with a five year funding commitment from HUD. However, expiring vouchers have always been renewed, so it's reasonable to assume that once a voucher is handed out, it's handed out forever. The voucher allocation formula is based on 1980 census data, even as late as 1993.[38] This census data is used to calculate a weighted average of six factors such as the percent of the nation's poor renters that are in a particular metropolitan area. Full details are given in Appendix B.[39]

From 1988-1992, 65 percent of all vouchers were allocated using the formula. Although figures for earlier years are not available, an examination of federal regulations governing the voucher program (discussed in Appendix B) suggests that the magnitude must have been roughly similar.[40] The correlation between the fraction of the poor with a voucher in each

[38] See Belsky (1992) and Apgar and Herbert (1994) for some cogent criticism of this practice.

[39] The six formula factors are (1) households, (2) poor households, (3) poor households in old housing, (4) crowded households, (5) households with high rent burdens, and (6) two measures of the vacancy shortage. All formula elements refer to renter households only. A similar formula was used from the beginning of the program in 1974 until the 1980 census data became available (Conversation with HUD Economist Ray Kahn, (March 6, 1997). See the *Code of Federal Regulations* (24 CFR 791.402, 1995) for the legal definition of the formula, and Apgar and Herbert (1994) for a detailed explanation.

[40] These figures have only been published since 1990. The figures for 1988 and 1989 are from unpublished

MSA and the fraction with a formula-allocated voucher is 0.68.

So formula allocation is quite important in determining how many vouchers go to each MSA. One cause for concern is that the formula appears to favor older cities on the coasts, which tend to have high rents. Probably the most serious concern is that all the formula elements are calculated for renter-occupied housing only. Thus, the formula favors cities with low ownership rates, since cities with a large percentage of renters also have a large percentage of poor renters, renters living in crowded housing, and so on. Holding income constant, low ownership rates are associated with higher rents. For this reason, it is important to control for the formula, in a manner that will be discussed below. In addition, metropolitan fixed effects should help to reduce any bias, since the formula is itself fixed over time.

In 1993, but not for earlier years, a detailed breakdown of allocation methods is available. Approximately 47,000 new vouchers were given out in 1993, of which 61 percent were allocated by formula, and the rest were allocated on a discretionary basis. The discretionary vouchers include 26 percent which were allocated on a competitive basis akin to applying for a grant (often for demonstration projects), 7 percent which were given to families displaced by rehabilitation or demolition of government projects, 5 percent which were used for disaster relief, and a small number were allocated by direct congressional mandate.[41]

If 1993 is typical, then most discretionary (non-formula) vouchers went to housing authorities who successfully competed for them. If a "housing crisis" prompted local authorities to apply, then the results could be biased. Note, though, that a temporary housing crisis won't necessarily bias the results, since the vouchers stick after the crisis is over. Disaster relief vouchers should not present a problem, since they are only funded temporarily, and will therefore make up a very small percentage of the voucher stock.

Vouchers allocated to families displaced by renovation or demolition are potentially worrisome, since they are associated with a change in the housing stock. However, during the period covered by the data, demolition of subsidized housing was very rare. The policy of "vouchering-out" severely distressed housing projects began only around 1993. Previously, regulations required that demolished public housing be replaced one-for-one with newly constructed units.[42] Prior to 1993, renovation was much more common. Since housing stock is

tabulations supplied by HUD.

[41] These figures are from the *Federal Register* (58 FR 38813 and 58 FR 36808). In theory, old vouchers can also be reallocated among MSAs, if housing authorities aren't able to use them, or if recipients move. I suspect both factors are minor, but there is little information available.

[42] HUD could waive one-for-one replacement in some circumstances, but rarely did. "Only under certain limited conditions, may public housing units be replaced with demand-oriented subsidies...At present, virtu-

only temporarily lost during a renovation, this situation is much less worrisome.

So, although neither the discretionary nor the formula allocation methods are as clean as a random, experimental, allocation method would be, the discretionary method approaches this ideal more closely. It is not obvious that local public housing authorities are much concerned with local housing market conditions when they apply for extra vouchers. Even if they are, the conditions that led PHAs to apply may have long vanished by 1993, the main year examined here, while the vouchers are likely to have remained.

With these considerations in mind, a useful diagnostic would be to estimate

$$\ln P = Xa + b_D V_D + b_F V_F + \eta, \tag{6}$$

where V_F indicates vouchers allocated by formula (as a percentage of poor households) and V_D indicates discretionary vouchers. "Formula vouchers" and "discretionary vouchers" are identical from the point of view of recipients, differing only in the method of allocation to metropolitan areas. Hence, they should have the same effect on housing markets. Testing $b_D = b_F$, therefore, is a test of whether allocation is endogenous, whether vouchers chase rents.

Equation 6 cannot be directly estimated, since V_F is observed only up to a constant. For example, the data indicate that Oakland received 1.2 percent of all formula vouchers, but not the total number.[43] So V_F is calculated by assuming that one million formula vouchers have been allocated, multiplying by each MSA's share, and then dividing by the number of households in poverty.[44] In addition, the total number of vouchers in each MSA is observed ($V = V_D + V_F$), while V_D is not observed directly. This turns out to be enough information to estimate b_D, and to test $b_D = b_F$. Equation 6 can be rewritten in terms of observables by noting that

$$\ln P = Xa + b_D(V_D + V_F) + (b_F - b_D)V_F + \eta$$

which implies

$$\ln P = Xa + b_D V + \frac{b_F - b_D}{\alpha}\alpha V_F + \eta, \tag{7}$$

ally no replacement housing plans have been approved that consist primarily of demand-oriented subsidies" (Schill 1993, pp. 541-542).

[43]Since the formula remained constant until 1993, the formula percentages can be calculated using census data. I have obtained the unpublished 1980 Census tabulations HUD used to calculate the formula from Professor Apgar of Harvard University.

[44]One million is a convenient number, which puts V and V_F in the same scale, since it turns out that this is almost exactly the same as assuming that all vouchers were allocated using the formula.

where α is an unknown constant, and αV_F is observed. Thus, $\frac{\widehat{b_F - b_D}}{\alpha} = 0$ tests $\hat{b_D} = \hat{b_F}$ with observables. If the results suggest the $b_D = b_F$, this is reassuring, since this can only occur if the allocation method is not biased, or if both allocation methods are biased in exactly the same way. In the preferred estimate below, the hypothesis that $b_D = b_F$ cannot be rejected by the data.

The case where $b_D \neq b_F$, is also worth discussing, since this occurs in the specification tests. In this case, it is likely that b_F is not a valid estimate, because the formula reflects housing market conditions, such as the ownership rate, while b_D, which is only loosely tied to market conditions, would appear to be a more plausible estimate.

Further, it can be shown that, under certain circumstances, bias in b_F will not be transmitted to b_D, even under the rather pessimistic assumption that V_F is correlated with the error term. This result requires, first of all, that V_D could be used as a valid instrument for V, if it were observed (i.e. that V_D is not correlated with the error term). V_D is not observed, but including V and V_F in the regression produces the same coefficient on V as if V_D were observed and substituted for V. The cost of not observing V_D, however, is that the assumption that V_D and V_F are not correlated, conditional on X, is also necessary to insure a consistent estimate in this setting. In particular, Appendix A shows that if $\text{Cov}(V_D, \eta) = 0$ and $\text{Cov}(V_D, V_F \mid X) = 0$, then plim $\hat{b_D} = b_D$. One way in which these assumptions could be violated is if HUD uses discretionary vouchers to "compensate" for formula voucher allocations that are too small or too large. Some intuition for this result comes from partitioned regression. Recall that b_D can be estimated by first regressing V on V_F and X, taking the residuals, and then regressing $\ln P$ on those residuals. In creating the residuals, V_F, the endogenous part of V is stripped away.[45]

6.2 Empirical Model

The main regression results are presented in tables 5, 7, and 8. The means of the regression variables are reported in Table 4. The dependent variable in all the tables is the price of housing for the lower, middle, and upper treciles, as measured by the neighborhood poverty index, from the first stage hedonic. Henceforth, this will be called simply lower (middle, and upper) trecile rent. The rents for each MSA are then regressed on vouchers and formula

[45] This conclusion is closely related to the result that bias due to measurement error is not transmitted to variables that are uncorrelated with the error-ridden variable (Griliches 1986, p. 1479)

vouchers per household in poverty, as well as the log of population, 10-year population growth, median family income, and, in some specifications, a set of regional dummies.[46]

Note that the number of households in poverty (both renters and owners) is chosen for the denominator of the voucher variables, rather than one third of unsubsidized renters, which would match the dependent variable, and which would seem more appropriate in light of the theoretical model. This choice was made because the homeownership rate is correlated with rents and it seemed unwise to confound the fraction with vouchers with the fraction of renters. Of course, the chosen measure still confounds the fraction with vouchers with the fraction of poor households, and poverty rates are also correlated with rents. Including poverty in the denominator was thought to be the lesser of two evils, because income is also included in the regression. These issues are explored in the sensitivity analysis below.

Since the number of individual observations in each housing market is not constant in the first stage hedonic, the second stage error term will be extremely heteroskedastic. To correct for this, the second stage estimation technique is weighted least squares, with the inverse of the standard errors from the first stage hedonic price dummies used as weights.[47] This model could be estimated using a one-step procedure by replacing the MSA/income group interactions in the first stage with a series of MSA/income group/MSA characteristic interactions. However, the two-step procedure greatly facilitates analysis since the appropriate conceptual unit here is the housing market, not the individual.

One way to address concerns about the voucher allocation process is to estimate the model in difference form (i.e. the change in price, rather than simply the price). Differencing the

[46]The regional dummies represent the nine Census Divisions. They should not be confused with the four Census Regions, which are never used in this paper.

[47]Card and Krueger (1992) and Hanushek, Rivkin and Taylor (1996) estimate such two stage models and discuss the econometric issues involved. The simplest WLS model assumes that the variance of the error term in the second stage is inversely proportional to the sample size in each housing market: $\sigma_m^2 = \delta(1/N_m)$. There are no covariance terms to consider, since the hedonic price dummies are orthogonal by definition. A better model assumes that $\sigma_m^2 = \delta\xi_m^2$, where ξ_m^2 is the variance of the prices in each market, estimated in the first stage regression. This is the model estimated here.

I considered the model $\sigma_m^2 = \kappa^2 + \delta\xi_m^2$, where κ^2 is the variance that would remain if N_m were large. κ^2 might be thought of as the "substantive" variance due to omitted MSA characteristics, while ξ_m^2 is the sampling variance due to varying numbers of observations in different markets (Dickens 1990, Hanushek et al. 1996). This variance components model could be estimated using GLS. I ran some tests to determine if the WLS model is adequate (i.e. if the weighting had transformed the model to homoskedasticity). In every case, I was unable to reject the null hypothesis of homoskedasticity at anything approaching conventional levels of significance. In addition, estimates of κ^2 were extremely imprecise, suggesting that a less constrained GLS model could well be worse. In general, WLS will be an adequate model when the sample size (of individuals in each housing market) is small, and varies significantly between markets. That is certainly the case here.

data controls for any unobserved "metropolitan effects." Since the formula was fixed for over a decade, and since its elements change only slowly, controlling for MSA fixed effects should go a long way towards alleviating concerns about the endogeneity of allocation. The difficulty with differencing the data is that only one year of voucher stock data is available, so the change in vouchers can't be calculated. Even if time series data were available, it seems unlikely that there's much within-MSA variance in vouchers over time, given the fact that voucher allocations are cumulative. However, since the voucher stock was zero in 1974, when the program was started, the model can be estimated using twenty year price changes.

The first difference results will only be reasonable if there are MSA characteristics that are fixed over the course of twenty years. Although this is a long time, many underlying conditions are essentially permanent. San Francisco's stock of developable land has been constrained by the Pacific Ocean for a long time and its climate has always been foggy, for example. Figure 1 plots the 1993 lower trecile rent index against the equivalent for 1974. Clearly, there is a high correlation, even across two decades. In general, MSAs with the highest rents in 1974 still had the highest rents in 1993. The R^2 from the regression of the 1993 index on the 1974 index is 0.53 (implying a correlation coefficient of 0.73). This is consistent with fixed effects. It doesn't rule out MSA-specific time trends, but it does suggest such time trends cannot be too large.[48]

Another way to address these concerns about the endogeneity of allocation is to estimate a series of specification tests. A classic test from the training literature is applicable to the cross-section results. Evaluations of job training programs frequently test for an effect on *pre*-program earnings. If the trained had higher wages *before* they underwent training, then the estimation method is likely biased (due to omitted variables or selection on unobservables). Similarly, if vouchers are found to raise rents in 1974, the year before the program began, then voucher allocations aren't exogenous. Failing this specification test suggests that voucher allocations are determined by some fixed (or at least slowly-evolving) effect that is omitted from the equation.

Another test examines the effect of vouchers on rent for the middle and upper treciles. The idea is that there should be decreasing pattern to the coefficients. Vouchers should affect wealthier housing markets less than they affect poor markets. If the specification test is failed, a natural assumption is that there is an omitted variable which is positively

[48]Poterba (1991) also notes this pattern in house prices, which are much more volatile than rents. Similar plots for the middle and upper treciles show higher correlations (of 0.79 and 0.80, respectively).

correlated with both vouchers and rents. Since this variable is unknown, a clear concern is that this variable enters both the equation for the lower and upper trecile, biasing both.[49]

A priori, to the extent that the lower trecile results are big, the middle and upper trecile results should be small. The issue hinges on the cross-price elasticities between the three markets. At one extreme, lower trecile tenants may be unable to move from one market to another. Then, vouchers will have a large effect on lower trecile rent, and none on the other treciles. At the other extreme, all three treciles may be perfect substitutes. In that case vouchers will have moderate effects on all markets. In between, vouchers will presumably have a larger effect on the lower trecile than on the middle, which will be larger than the effect on the upper trecile. A filtering model also leads to the same conclusion. If vouchers have a large effect on lower trecile rent, then it must be that few recipients are moving to the high-quality market, where rent is simply a function of construction cost.

6.3 Cross-section Results

Table 5 shows the effect of vouchers on all three rent treciles. The sample is restricted to include only MSAs where 1974 rent information is available. This sample is used for the rest of the results in the paper. All the regressions in this table include regional dummies, which were always jointly significant at the 1 percent level or better.

The lower trecile voucher coefficient is .762 (t-statistic 1.57). To interpret this figure, recall that, on average, there are enough vouchers for 12.4 percent of the poor (Table 4). This implies that eliminating the voucher program would lower rents by 9.4 percent (= $.124 \times .762$).[50] This is a fairly large effect, though not implausible. I return to this point below. The middle and upper trecile results are quite reasonable too, suggesting that vouchers raise rents by about 2 percent in the other two markets, which cannot be distinguished from zero. This calculation extrapolates beyond the range of the data, since there are no cities with less that than 4 percent subsidized (Table 1). A more conservative thought experiment considers halving the size of the program, which would reduce rents by 4.7 percent.

In all three specifications, the formula voucher coefficients are large and statistically significant. As discussed in the sensitivity analysis below (Table 9), if the formula variable is

[49]Note, though, that the omitted variable may only affect the upper trecile equation. An example of such a variable might be 75th percentile income.

[50]Besides representing a useful thought experiment, this figure is also the calculation of the elasticity of rent with respect to the fraction with vouchers. This elasticity is, therefore, .094 in this specification.

removed from the equation, the effect of vouchers more than doubles, and the specification test is failed, since the middle and upper trecile results also become large and statistically significant. Because the formula coefficient is greater than zero, the results imply that formula vouchers have larger effects than do discretionary vouchers. This can only happen if one of the allocation methods is endogenous, and determined in part by rents. Above, it was argued that the details of the formula allocation suggest that it is tied to long run trends in housing market conditions. The remaining discretionary vouchers, which identify the effect of the voucher coefficient, appear to be less tied to metropolitan conditions. Nonetheless, the results would be strengthened if a specification could be found where the formula coefficient were zero, and identification relied on fewer, hard to test, assumptions.

6.4 Pre-program Rents Specification Test

Another specification test asks if 1995 vouchers "affect" 1974 rents. Since the voucher program did not exist in 1974, finding significant effects suggests that vouchers were allocated to cities with high rents, rather than causing high rents. Table 6 reports the results. The middle and upper treciles pass the test, with point estimates that are fairly small and aren't statistically significant. The lower trecile estimate, however, is -.9 (t-statistic 1.49), which is much larger in absolute value than the results for the other treciles. Thus, more discretionary vouchers were allocated to metropolitan areas with low rents in 1974. The 1993 cross-section results, then, may be biased towards finding smaller effects on lower trecile rent than are actually caused by the voucher program.

This table also highlights the importance of including the formula in the equation. This table is an equally valid specification test for formula-allocated vouchers. In every specification, though, the formula coefficient is large and significantly different from zero, often at high levels of confidence. In addition, when the formula is omitted from the equation, only the lower trecile specification test is passed, and quite weakly, with a coefficient of .71 and a t-statistic of 1.35. It is quite clear, then, that the formula allocates vouchers endogenously. Thus, excluding the formula from the regression would certainly lead to biased results in a cross-section.

6.5 Results with Lagged Rent and 1974-1993 Differences

Table 7 reports results for cross-section regressions that include 1974 rent as an additional explanatory variable. Again, the regional effects are highly statistically significant, so results will only be reported that include them.[51] In all specifications, lagged rent is highly significant, with t-statistics ranging from 2.5 to 4. Adding lagged rent increases the lower trecile coefficient somewhat to .862 (t-statistic 1.83), and it becomes statistically significant at the ten percent level. The middle and upper trecile coefficients remain statistically insignificant and close to zero. All the formula coefficients fall as well, although they remain large and statistically significant. Overall, the results are similar to the cross-section results.

Table 8 reports the first-difference results, with all variables defined as twenty-year differences. So the dependent variable is the 1974-1993 rent change, and the right hand side variables include the 1970-1990 change in median family income, and so on. The voucher measures are unchanged from the cross-section specifications. 1974 vouchers (and formula vouchers) were zero so these variables are already implicitly differenced. Since regional effects are differenced out, they are not included in these specifications. Also, tests for the joint significance of the regional effects do not reject zero in two out of the three treciles, confirming that the dummies don't belong in the first difference equation.[52]

The lower trecile voucher coefficient increases to 1.31 (t-statistic 2.41) in the differenced specification. The middle and upper trecile results remain close to zero. In this model, eliminating the voucher program (reducing the fraction with vouchers from .124 to zero) would lower rent for the poor by 16 percent, the middle by 3.2 percent, and the top by .08 percent, which is a very sensible pattern of results. Further, the null hypothesis that vouchers have no effect on rent for the middle and upper treciles can't be rejected. The fact that the middle and upper trecile coefficients are consistently close to zero is heartening. However, given the size of the standard errors, concern about the power of the specification test is quite sensible. Although zero can't be rejected, the 95 percent confidence interval for the upper trecile coefficient reaches .87, which is substantively large.

Another important result is that the formula coefficient falls almost to zero in the lower

[51] The results in tables 5 and 7 were reestimated without regional dummies. In every case the voucher coefficient became bigger, increasing to 1.16, .45, and .39 for the lower, middle, and upper treciles, respectively, in Table 5 and to increasing to similar values in Table 7.

[52] The P-values for the F-tests of the regional dummies were 0.35, 0.004, and 0.13 for the lower, middle, and upper treciles respectively. In specifications that include the regional dummies, the lower trecile voucher coefficient falls to 0.80 (with a t-statistic of 1.27). The other two voucher coefficients fall as well, becoming negative.

trecile results. This should reduce concerns about the endogeneity of allocation. In addition, omitting the formula from the equation has little effect on the lower trecile results (Table 9). The upper trecile results, however, are affected by the inclusion of the formula variable. The formula coefficient in the upper trecile results remains large, although they are smaller than those in earlier tables, and omitting the formula causes the specification test to be failed.

6.6 Sensitivity Analysis

To check for the robustness of the results, the cross-section and first difference results were replicated using different measures of rents, of vouchers, and of formula vouchers. The top panel of Table 9 reports the voucher coefficient from regressions with alternative measures of rent. For comparison, the baseline result from Tables 5 and 8 are in the first row. Recall that rents in the 1993 AHS are topcoded at $1,000, and the baseline results recode this to $1,147. The first row of this panel shows the voucher coefficient when topcoded rents are left at 1000. In the second row, a tobit is used instead of imputation. Unsurprisingly, topcoding has no effect at all on the lower and middle treciles. The upper trecile coefficient is slightly larger in the baseline specification compared to the specifications with no correction, and slightly smaller than the tobit specification. In no case, however, does the top-coding adjustment (or lack of one) change the overall conclusions.

The next row substitutes treciles based only on household income as a percent of the poverty line for the neighborhood poverty index, based on a longer list of income and wealth measures, used in the body of the paper. The poverty treciles have almost no effect in the cross section specifications. In the difference specification, somewhat surprisingly, the lower trecile voucher coefficient becomes bigger, and the upper and middle coefficients become smaller. The poverty treciles are likely to produce more classification errors than the more complete neighborhood income treciles (moving some of the truly rich into the poor category, and vice versa). This should have resulted in a compression of the coefficients, just as they compress the distribution of mean rents across treciles. However, although this result is surprising, it doesn't alter the main conclusion that vouchers increase rents for those in the lower trecile. It does offer some evidence that the effect may be bigger than the baseline results suggest.

Finally, the last row of the panel uses the baseline definition of rents, but includes voucher recipients in the sample. Voucher recipients were dropped from the main results because of suspicion about the accuracy of the rent data they report, and confidence in the hedonic to avoid sample selection bias. In this table, rent for voucher recipients is measured as the rent received by the landlords (rather than the rent paid by the tenant after the subsidy). Sample members who didn't report this information were dropped.[53] Adding voucher recipients has almost no effect on the voucher coefficient, although the standard errors become uniformly smaller, reflecting the larger sample size.

The bottom panel of Table 9 reports results when the formula, which is based on 1980 Census data, is updated using 1990 census data. Earlier drafts of this paper focussed on results using the updated formula. These results allow identification to come not only from discretionary vouchers, but also from "erroneous" formula vouchers. Because this specification uses more of the variation in vouchers, the standard errors are slightly smaller. Ultimately, however, the slight gain in precision was far outweighed by the added complication and greater difficulty of interpreting the updated formula results. Whether the actual or the updated formula is used, both sets of first difference results are quite similar, which is one reason to place the greatest confidence in this set of results. Using the updated formula, the first difference coefficient falls to 1.11, which is, if anything, a more plausible result than the baseline estimates. The cross section coefficients show the same general pattern as the baseline results, although they are all larger. When the updated formula is used, the lower trecile coefficient is quite close in size to the first difference coefficient, and is statistically significant. The middle and upper trecile results become larger as well, and only weakly pass the specification test.

One potential problem with the specification is the possibility that the results are driven by the poverty counts in the denominator of the voucher measures rather than the numerator. That is, it could be that poverty is negatively correlated with rents. Vouchers/poverty, then, would be positively associated with rents, even if there was no true effect of vouchers. To explore this, the equations were re-estimated using vouchers (and formula vouchers) per capita as instruments for vouchers (formula vouchers) per household in poverty. This had little effect on the results. Although the cross section lower trecile falls, the corresponding first difference coefficient is little affected.

The next row of the table removes formula vouchers from the equations entirely. As dis-

[53] I suspect that many of those who failed to report the amount received by the landlord were living in some other kind of subsidized housing, and weren't really receiving a voucher. In all, 329 voucher recipients were added to the 6,526 observations already in the 1993 hedonic regression.

cussed earlier, the voucher coefficients become bigger and specification tests are failed, when the total effect of vouchers is estimated. The one exception is the crucial lower trecile first difference coefficient, which is almost unchanged. The fourth row combines the previous two, removing formula vouchers from the model, and using vouchers per capita as an instrument for vouchers per poor household. The cross section results are no more plausible than the results in the previous row, which use neither formula voucher nor instruments. However, the first difference results are quite similar to the baseline, and the lower trecile coefficient is almost the same as the baseline. The middle and upper trecile coefficients follow a sensible decreasing pattern, although the middle trecile specification test is only weakly passed.

The last row of the table modifies the measure vouchers per household in poverty by replacing the denominator with one third of renters (i.e. the number of renters divided by three), which more closely matches the dependent variable, and the theoretical model. Just as vouchers per household in poverty confounds the fraction poor with the fraction with vouchers, so too does vouchers per lower trecile renter confound voucher availability with ownership rates. The table suggests that this issue is quite important in the cross section, causing the coefficients to become small for all three treciles.[54] However, the first difference results are much more robust, with the lower trecile coefficient almost unchanged. Presumably, differencing controls for the homeownership rate, which is fairly constant over time.[55]

Overall, none of the changes explored in the sensitivity analysis do much to alter the overall conclusions from the baseline results. Alternative measures of rents make very little difference to any of the results. Changes in the explanatory variables and estimation technique do make some difference in the cross-section model. The first difference results, however, are quite robust to changes in specification.

[54]This is to be expected, since high rents imply a large fraction of renters, which implies a low rate of vouchers to renters, which biases the coefficients downwards.

[55]It is reasonable to compare coefficients because the scale of the two variables is, coincidentally, about the same: the average city has enough vouchers for 11.1 percent of lower trecile renters and 12.4 of poor households (both figures from Table 1). However, it is not coincidence that the effect of vouchers on rent in the average city in the first difference specification is 15 percent ($= .111 \times 1.38$), which is almost the same as the baseline result. It is a substantive result that would remain the same if the voucher denominator were replaced with number of lower quartile renters or some other fraction.

7 Conclusion

Overall, the baseline results consistently show that the effect of formula vouchers on rent follow an implausible pattern, while the discretionary voucher results are much more reasonable. Formula vouchers were found to substantially raise rents not only for the lower trecile, but for the middle and upper groups as well. In addition, formula vouchers have large effects in 1974, before the voucher program began. The discretionary voucher results, however, pass all the specification tests. The point estimates in all specifications show almost no effect on middle and upper trecile rent. Nor are discretionary vouchers associated with higher 1974 rents. The only anomaly is the negative effect of vouchers on lower trecile rent in 1974 (t-statistics 1.5), which suggests that cross-section results may actually understate the effect of vouchers. In addition, in the difference specification, the hypothesis that formula and discretionary vouchers have the same effect on lower trecile rent cannot be rejected. This suggests that the difference specification is sufficient to control for the targeting of vouchers. Finally, the first difference results were found to be quite robust to changes in the rent and voucher measures.

7.1 Elasticity of Supply

The supply and demand model shows that the voucher coefficient equals $\theta/(\varepsilon^S + \varepsilon^D)$, where θ is the subsidy generosity and ε^S and ε^D are the elasticities of supply and demand. If vouchers allow the subsidized to purchase 75 percent more housing than they otherwise would (relative to non-recipients), so that $\theta = 0.75$, then a coefficient of 1.31 implies that $\varepsilon^S + \varepsilon^D = 0.57$.[56] This suggests quite small elasticities, but not out of the realm of possibility.

An estimate of the elasticity of demand can be found in Hanushek and Quigley (1980), who estimated it to be around 0.6 in the long run. This is a convenient estimate for my purposes, since they are estimated using experimental data from the Housing Allowance Demand Experiments, which tested a voucher style subsidy program for low-income renters[57]. If the elasticity of demand is 0.6, then the model implies that the elasticity of supply is -.03, i.e. just about zero.

[56] Calculation of θ uses figures from Cage (1994), who found that recipients spent \$527 a month in rent, while income eligible non-recipients spent \$337. Voucher recipients would have spend \$270 a month on rent, were they unsubsidized, assuming that they would have spent the same proportion of their income on rent (42 percent) that unsubsidized income-eligible households do. Then $\theta = (527 - 270)/337 = 0.76$.

[57] Hanushek and Quigley found that the short run elasticity of demand was about 0.15, and extrapolated using only two years of data. This is a drawback, but these are still the best available estimates

Now, all this is predicated on the point estimate of 1.31. The 95 percent confidence interval is (0.22, 2.40), and so we can not rule out larger supply elasticities. For example, if the true coefficient were 0.77 (one standard deviation below the point estimate), the elasticity of supply would be 0.38, which is still quite small. At the extremes of the 95 percent confidence interval, however, the supply elasticity runs from -.29 to 2.8.

7.2 Discussion

These calculations clarify two points. First, the small elasticity implied by the results suggests that, despite its moderate size, the effect of the voucher program on rents is surprisingly large. The calculations also imply considerable insulation between lower and higher income housing markets, since the ability to move easily between markets, or substitute towards higher quality housing, should mitigate the price rise. Since the lower trecile coefficient is about as big as could be expected from a theoretical analysis that assumes that movement between markets is impossible, it follows that the other coefficients must be small. Hence the data tell a consistent story, since the estimated effect of vouchers on middle and upper trecile rents is close to zero, as expected.

Another way to characterize the size of the results is to calculate the redistributive effect of vouchers; the "leakiness of the bucket," to borrow Arthur Okun's metaphor. Some simple calculations, reported in Table 10, suggest that vouchers do little to redistribute, in the aggregate. Specifically, vouchers cover about two thirds of recipients' rent, costing $5.8 billion dollars in total. There are about 9.6 million households in the lower third of the private rental market, whose rents have been increased by 16 percent as a result of the voucher program, according to the results presented here. In total, therefore, while vouchers transfer $5.8 billion to recipients, they cost similarly impoverished non-recipients $8.2 billion dollars. The net transfer is $2.4 billion, which goes from poor households to landlords.[58]

The conclusion that vouchers raise rents depends only on the correct specification of the reduced form empirical model. Given a number of strong assumptions, the theoretical model also allows us to extrapolate from the results that the elasticity of supply must close to zero. Although this study does not attempt to distinguish which particular feature of low-income housing markets inhibits their adjustment to demand shocks, it is worth thinking about what

[58]Note that a calculation of the welfare loss due to vouchers would be still more gloomy. The calculations in the text neglect the fact that in kind transfers are not valued at par by recipients, and the distortions imposed on taxpayers, low-income non-recipients, and landlords.

could cause these results.

First, the lack of free exit could cause low supply elasticities. An apartment building yielding low rents can not be removed from the market except though demolition. There may be many landlords in poor neighborhoods who are earning enough to cover their operating costs, and thus they do not abandon the building, but are not covering the fixed costs associated with creating new housing. Increased rents would then raise profits, but do nothing to increase entry (or decrease demolition). In the extreme case, when housing lasts forever without maintenance, there is a kink in the supply curve. Once housing is built, upward demand shocks will raise prices and increase construction. But the below the current quantity of housing, the supply curve will be vertical and downward shocks will lower prices without affecting the quantity supplied. Then, in neighborhoods that have suffered unanticipated falls in demand, landlords might find themselves on the vertical section of the supply curve.

Consider the Woodlawn neighborhood of Chicago discussed in Wilson (1996), which housed 80,000 people in 1960. By 1990, the population had fallen to 24,000, with one fifth of the decrease occurring over the 1980s. Much housing has been demolished over the years, and the neighborhood is now scarred by vacant lots. It seems quite possible that in such a neighborhood, vouchers could raise rents, but not by enough to induce landlords to repair the roof, or engage in other costly maintenance projects that would stave off decay.

Further, habitability laws, building codes, and zoning restrictions like minimum lot sizes may restrict with the creation of low-income housing.[59]. As filtering models emphasize, low quality housing isn't built; instead high quality housing is built, and over a number of years it depreciates ("filters down") and becomes lower quality. Laws preventing, for example, the conversion of single family housing into multiple occupancy units would then lower the elasticity of supply of low-income housing.

An important topic for future research are studies that distinguish among these various explanations for low elasticities. Low elasticities also have important implications for tax and subsidy policy. In particular, they suggest that construction subsidies may do more to improve the housing conditions of the poor than do demand side subsidies like vouchers.

[59]See, e.g., Downs (1991) and Advisory Commission on Regulatory Barriers to Affordable Housing, 1991.

Appendix A: Consistency Proof

This section shows that even if V_F is correlated with the error term, the bias will not be transmitted to b, the coefficient on V, if V_D and X are uncorrelated with the error term, and if V_D and V_F are uncorrelated, conditional on X. The proof is for the case with a single X variable, hence all the variables should be interpreted as deviations from means.

First, recall that

$$\ln P = aX + bV_D + cV_F + \eta,$$

which is a version of equation 6.

We are concerned that V_F is correlated with the error term. The bias can be written as:

$$\text{plim } \hat{\beta} = \beta + \text{plim } (Z'Z/N)^{-1} Z'\eta_/N,$$

where $Z = [V_D \ V_F \ X]$, β, the coefficient vector, is $\begin{bmatrix} a \\ b \\ c \end{bmatrix}$, and N is the sample size.

Examining the second part of this expression, we have,

$$\text{plim } Z'\eta/N = \text{plim } \begin{bmatrix} V_D'\eta/N \\ V_F'\eta/N \\ X'\eta/N \end{bmatrix} = \begin{bmatrix} 0 \\ \text{plim } V_F'\eta/N \\ 0 \end{bmatrix}$$

since η is uncorrelated with X and V_D.

Therefore, plim $\hat{b} = b +$ plim $z_{12}V_F'\eta/N$, where z_{ij} is the $(i,j)^{th}$ element of $(Z'Z)^{-1}$. Using the cofactor method to invert $(Z'Z)$ yields,

$$z_{12} = \frac{-1}{|Z'Z|} \begin{vmatrix} V_D'V_F & V_D'X \\ X'V_F & X'X \end{vmatrix},$$

where the vertical bars indicate the determinant.[60]

Taking the determinant and multiplying by N/N yields:

$$z_{12} = \frac{-1}{|Z'Z|/N}(V_D'V_F X'X - V_D'XX'V_F)/N.$$

Now, we assume we can decompose V_D into a part that is correlated with X and a part that isn't: $V_D = pX + e_D$. Similary, decompose V_F into $V_F = qX + r\eta + e_F$. Here, it is assumed that $\text{Cov}(V_D, \eta) = 0$ and therefore $\text{Cov}(V_D, V_F \mid X) = 0$. That is, conditional on X, V_D and V_F are uncorrelated.[61] Then

$$\begin{aligned} \text{plim } z_{12} &= [\text{Cov}(V_D, V_F)\text{Var}(X) - \text{Cov}(V_D, X)\text{Cov}(X, V_F)]\text{plim } \frac{-1}{|Z'Z|/N} \\ &= [pq\text{Var}(X)\text{Var}(X) - p\text{Var}(X)q\text{Var}(X)]\text{plim } \frac{-1}{|Z'Z|/N} \\ &= 0, \end{aligned}$$

[60] This is the only part of the proof where the assumption that X is a vector matters. If X were a matrix, we would need to use another method to invert $Z'Z$.

[61] Linearity is also assumed. This would not be a particularly restrictive assumption if the proof were generalized to the case of multiple Xs. We also need the technical assumption here that all the terms have finite variances in the limit.

since $\mathrm{Cov}(X, \eta) = 0$, and because e_D and e_F are uncorrelated with each other and all the other variables. Hence plim $\hat{b} = b$, and the coefficient on V_D is consistent.

Finally, recall the result from the text that the same $\hat{b}$ will be estimated when the equation is rewritten in terms of observables.

$$\ln P = aX + bV + (b + c)V_F + \eta \longleftrightarrow \ln P = aX + bV_D + cV_F + \eta$$

since $V = V_D + V_F$. Hence, the coefficient on V will also be consistent.

Appendix B: Formula Allocation of Housing Subsidies

HUD uses a formula to allocate vouchers to different areas of the country. Allocation areas are generally MSAs (although sometimes MSAs are split at state lines, and sometimes several MSAs are grouped together). In 1990, there were 151 allocation areas. Within an allocation area, local public housing authorities compete for the area's funds, though a process akin to applying for a grant. Since the unit of observation in this study is the MSA, the details of the competitive process aren't of much concern. A separate process is used to allocate vouchers to rural, non-MSA areas.[62]

The voucher allocation formula is based on 1980 census data, even as late as 1993. For each formula element, HUD calculates the percent of the metropolitan total in each MSA (in 1980). For example, 1.0 percent of the all the poor renter-occupied households in the metropolitan U.S. lived in the Oakland MSA in 1980. HUD then adds up these factors using the weights shown in Table B1. Using census data, these formula percentages can be calculated for all the MSAs in the sample.

Until 1989, the HUD was legally mandated to allocate 85 percent of new vouchers by formula, while HUD retained the rest in a "headquarters reserve fund."[63] In the wake of a series of scandals, the HUD Reform Act of 1989 lowered the reserve fund to 5 percent, in order to reduce the possibility of political manipulation. The HUD Reform Act also mandated that HUD provide increased documentation of the formula allocation process. Specifically, HUD was mandated to publish the allocations annually in the Federal Register. Table B2 displays the available information on formula allocations. Note that even in 1988 and 1989 3/4 and 2/3 of vouchers were allocated by formula, in spite of the 85 percent legal requirement. The reason is that the budget passed by congress every year often overrides the law, and sets aside a number of vouchers for a specific purpose. Since the HUD Reform Act, formula allocation has actually become less important. During the years covered by the table, 65 percent of the vouchers were allocated by formula.

[62] Legally, 20-25 percent of new vouchers must go to rural areas (24 CFR 791.403, 1995).

[63] See, e.g., 24 CFR 791.403, 1988.

Table B1: Formula Elements

Formula Measure (refers to renter-occupied housing)	Weight
Households	.2
Households in Poverty	.2
Poor households in Pre-1940 housing	.2
Crowded households (with more than one person per room)	.1
Households with high rent burdens (greater than 30 percent of income)	.2
The vacancy shortage and the long-term (2+ months) vacancy shortage (the number of vacancies required to raise the vacancy rates to 7.0 percent and 3.4 percent, respectively)	.05/.05

Table B2: Voucher Stocks and Flows

	Vouchers		Allocated	Allocated
	Stock	Flow	by Formula	by Formula
Year	(1000s)	(1000s)	(1000s)	(percent)
1988	956	65.3	48.0	74
1989	1,025	68.9	46.4	67
1990	1,090	61.3	49.4	81
1991	1,137	55.9	41.1	74
1992	1,166	62.6	18.9	30
Total	–	314	204	65

SOURCES: Voucher Stock and Flow: Green Book, 1994
Formula allocations:
1988, 1989: Unpublished HUD data supplied by Gerry Benoit
1990: Federal Register; 55 FR 23684
1991: Federal Register; 56 FR 2754 (also 56 FR 24290)
1992: Federal Register; 57 FR 60223 (also 57 FR 33606)

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Table 1: Vouchers relative to size of MSA housing market, 1995

	Representative Metropolitan Area	Vouchers per: Household in Poverty	Renter Hhd. in Poverty	Renter Household
Quantile				
min	Chattanooga, TN	0.043	0.070	0.018
5	Austin, TX	0.058	0.081	0.021
10	Wichita, KS	0.069	0.103	0.023
25	Kansas City, KS-MO	0.086	0.123	0.028
50	Las Vegas, NV	0.109	0.158	0.036
75	Newark, NJ	0.149	0.202	0.042
90	San Francisco, CA	0.220	0.294	0.051
95	Hartford, CT	0.243	0.316	0.060
max	Ventura County, CA	0.372	0.556	0.067
Mean		0.124	0.175	0.037

NOTE: The table reports the ratio of vouchers to various measures of the size of the MSA housing market. The representative MSAs have approximately the same fraction of vouchers per poor households as the indicated quantile. Since the quantiles are rounded (e.g. the median is the average of the 45th and 46th MSA), quantiles may not exactly match the actual MSA figures. The sample size is 90 MSAs.

Table 2: Characteristics of Private-Market Neighbors, by Market
AHS Neighbor Sample

	Voucher Recipients	Private Market Renters: Lower Trecile	Middle Trecile	Upper Trecile
Rent	467	442	511	631
Household income	24,215	24,303	30,527	41,233
HHd Income/poverty line	245	226	307	422
HHd income/MSA median	0.664	0.687	0.855	1.078
N (Core households)	92	612	517	513
N (Neighborhoods)	55	295	279	234
Hhds per neighborhood	5.7	6.4	7.0	7.4
Renters per neighborhood	3.5	4.0	4.6	4.6

SOURCE: Author's tabulations, 1993 American Housing Survey Neighbor File.

NOTE: See Table 3. For each group of "core households" (for example, lower trecile private-market renters), the table reports the characteristics of their neighbors, who may belong to any trecile, may own or rent, and may be subsidized or not.

Table 3: Renter Household Characteristics, by Trecile and Recipiency Status

	Income as % of Poverty Level			Neighborhood Pov. Trecile			Voucher
	<167%	167–347%	>347%	Lower	Middle	Upper	Recipients
Age of Hhd head	41.7	39.9	39.4	41.2	39.6	40.2	46.4
White	0.649	0.726	0.811	0.631	0.722	0.834	0.526
Black	0.229	0.190	0.124	0.259	0.188	0.096	0.398
Other	0.122	0.084	0.064	0.109	0.091	0.070	0.076
Hispanic	0.256	0.159	0.074	0.304	0.128	0.057	0.167
Married	0.310	0.348	0.304	0.356	0.312	0.294	0.134
Single Female	0.469	0.359	0.314	0.440	0.374	0.329	0.729
Rent	447	520	633	443	521	637	537
Household income	10,604	26,405	52,851	14,543	24,821	50,475	9,579
HHd income as % of poverty level	91	253	550	121	244	529	93
Education	11.6	13.0	14.6	10.5	13.4	15.3	11.2
Interest, dividend or rental income	0.202	0.366	0.563	0.089	0.355	0.687	0.103
AFDC, SSI or other Welfare income	0.208	0.036	0.008	0.246	0.006	0.001	0.471
Assets > $25K and Income < $25K	0.017	0.027	0.005	0.001	0.012	0.036	0.006
Sample size	2178	2173	2175	2175	2176	2175	329

SOURCE: Author's tabulations, 1993 American Housing Survey National File.

NOTE: Neigborhood poverty treciles are based on an index computed from household income as a fraction of the poverty line, education, and the receipt of welfare or capital income. See text. Subsidized households are included only in the last column.

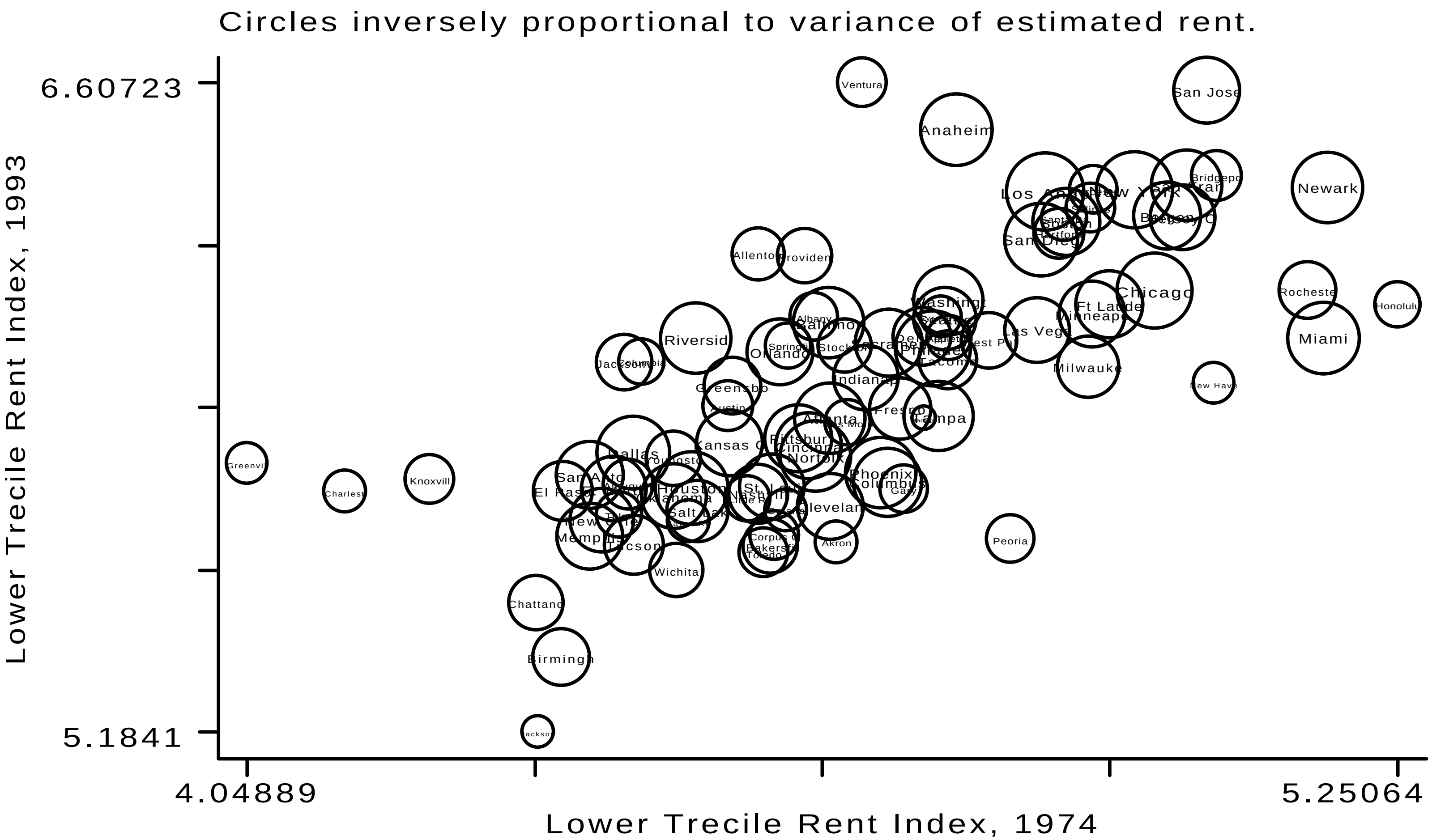

Figure 1: MSA Rent Over Two Decades

Table 4: Means of Regression Variables

	Mean	Std. Dev.
Rent, 1993		
Lower Trecile	5.94	0.286
Middle ”	6.07	0.262
Upper ”	6.18	0.257
Rent, 1974		
Lower Trecile	4.69	0.236
Middle ”	4.81	0.196
Upper ”	4.89	0.177
Median family income, 1990	3.62	0.156
Population, 1990	13.8	0.774
Population growth, 80-90	0.129	0.125
Median family income, 70-90 change	1.32	0.080
Population, 70-90 change	0.277	0.261
Decade's population growth, 70-90 change	-0.068	0.112
Vouchers, 1995	0.124	0.058
Updated formula vouchers	0.125	0.063
Formula vouchers	0.110	0.051
N	90	

NOTE: All variables are in logs, except for the voucher variables, which are expressed as a fraction of households in poverty. “Trecile” refers to the neighborhood poverty index treciles.

Table 5: WLS Cross Section Regressions

Effect of Vouchers on Rent Treciles

	Lower	Middle	Upper
Vouchers per poor household, 1995	0.762	0.200	0.142
	(0.486)	(0.404)	(0.410)
Median family income, 1990	0.0912	0.120	0.0857
	(0.158)	(0.142)	(0.146)
Population, 1990	0.0169	0.0275	0.0420
	(0.0206)	(0.0178)	(0.0180)
Population growth, 80-90	0.577	0.445	0.454
	(0.172)	(0.148)	(0.156)
Formula vouchers per poor hhd	2.77	3.14	3.31
	(0.579)	(0.513)	(0.525)
Regional dummies	Yes	Yes	Yes
R^2	0.837	0.858	0.860
N	90	90	88

NOTE: Dependent variable is a hedonic index of unsubsidized (log) rent for the lower, middle, and upper income treciles in 1993. Income and population are in logs. Both voucher measures indicate vouchers as a fraction of households in poverty. All regressions include a constant and dummies for the nine census divisions.

"Formula Vouchers" indicate the number of vouchers allocated using a formula based on census data. See text.

Coefficients are weighted least squares estimates, with the weights proportional to the inverse of the standard error of the first stage hedonic rent estimates. Standard errors in parentheses.

Table 6: Specification Test: Effect on 1974 Rent Treciles

	Lower Trecile		Middle Trecile		Upper Trecile	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Vouchers per poor household, 1995	-0.902 (0.605)	0.707 (0.525)	0.373 (0.460)	1.68 (0.418)	-0.287 (0.424)	1.06 (0.390)
Median family income, 1970	0.212 (0.258)	0.669 (0.260)	-0.126 (0.196)	0.270 (0.200)	-0.111 (0.177)	0.307 (0.182)
Population, 1970	-0.0139 (0.0235)	0.0170 (0.0248)	0.00463 (0.0182)	0.0321 (0.0195)	0.0149 (0.0164)	0.0432 (0.0179)
Population growth, 60-70	0.192 (0.182)	0.0403 (0.198)	0.198 (0.131)	0.101 (0.146)	0.141 (0.115)	0.0552 (0.132)
Formula vouchers per poor hhd	2.85 (0.666)		2.47 (0.520)		2.47 (0.476)	
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.657	0.574	0.700	0.612	0.745	0.653
N	90	90	90	90	88	88

NOTE: Dependent variable is a hedonic index of unsubsidized (log) rent for the lower, middle, and upper income treciles in 1974. Income and population are in logs. Both voucher measures indicate vouchers as a fraction of households in poverty. All regressions include a constant and dummies for the nine census divisions.

"Formula Vouchers" indicate the number of vouchers allocated using a formula based on census data. See text.

Coefficients are weighted least squares estimates, with the weights proportional to the inverse of the standard error of the first stage hedonic rent estimates. Standard errors in parentheses.

Table 7: Cross Section WLS Regression with Lagged Rent

Effect of Vouchers on Rent Treciles

	Lower	Middle	Upper
Vouchers per poor household, 1995	0.862	-0.0382	0.153
	(0.471)	(0.370)	(0.390)
Median family income, 1990	0.0898	0.136	0.157
	(0.152)	(0.128)	(0.141)
Population, 1990	0.0159	0.0240	0.0382
	(0.0199)	(0.0161)	(0.0171)
Population growth, 80-90	0.508	0.381	0.432
	(0.168)	(0.135)	(0.149)
Formula vouchers per poor hhd	2.12	2.26	2.36
	(0.615)	(0.508)	(0.592)
Hedonic Rent, 1974	0.223	0.375	0.351
	(0.0877)	(0.0886)	(0.118)
Regional dummies	Yes	Yes	Yes
R^2	0.850	0.885	0.875
N	90	90	88

NOTE: Dependent variable is a hedonic index of unsubsidized (log) rent for the lower, middle, and upper income treciles in 1993. Income and population are in logs. Both voucher measures indicate vouchers as a fraction of households in poverty. All regressions include a constant and dummies for the nine census divisions.

"Formula Vouchers" indicate the number of vouchers allocated using a formula based on census data. See text.

Coefficients are weighted least squares estimates, with the weights proportional to the inverse of the standard error of the first stage hedonic rent estimates. Standard errors in parentheses.

Table 8: First Difference WLS Regression

Effect of Vouchers on 74-93 Change in Rent Treciles

	Lower	Middle	Upper
Vouchers per poor	1.31	0.259	0.0655
household, 1995	(0.544)	(0.453)	(0.411)
Median family	0.766	0.0509	0.590
income, 70-90 change	(0.262)	(0.232)	(0.213)
Population, 70-90	0.0640	0.0674	0.130
change	(0.0785)	(0.0683)	(0.0620)
Decade's population	0.0959	0.203	0.137
growth, 70-90 change	(0.159)	(0.142)	(0.129)
Formula vouchers	-0.112	1.56	1.63
per poor hhd	(0.615)	(0.521)	(0.463)
Regional dummies	No	No	No
R^2	0.324	0.284	0.444
N	90	90	88

NOTE: Dependent variable is 1974-1993 change in a hedonic index of unsubsidized (log) rent for the lower, middle, and upper income treciles. Income and population are in logs. Both voucher measures indicate vouchers as a fraction of households in poverty. All regressions include a constant.

"Formula Vouchers" indicate the number of vouchers allocated using a formula based on census data. See text.

Coefficients are weighted least squares estimates, with the weights proportional to the inverse of the standard error of the first stage hedonic rent estimates. Standard errors in parentheses.

Table 9: Sensitivity Analysis

Voucher Coefficients from WLS Regressions

	Cross-Section			First Difference		
Rent Trecile	Lower	Middle	Upper	Lower	Middle	Upper
Baseline, from tables	0.762	0.200	0.142	1.31	0.259	0.0655
5 and 8	(0.486)	(0.404)	(0.410)	(0.544)	(0.453)	(0.411)
Alternate Rent Treciles						
No top-coding	0.757	0.180	0.0731	1.32	0.259	0.0126
correction	(0.482)	(0.390)	(0.401)	(0.542)	(0.446)	(0.403)
Tobit	0.761	0.214	0.207	1.31	0.275	0.144
	(0.487)	(0.407)	(0.419)	(0.544)	(0.454)	(0.420)
Simple poverty	0.704	0.218	0.162	1.55	0.204	-0.143
treciles	(0.497)	(0.399)	(0.383)	(0.595)	(0.434)	(0.378)
Voucher recipients	0.654	0.239	0.156	1.37	0.284	0.0314
in sample	(0.468)	(0.364)	(0.391)	(0.526)	(0.444)	(0.388)
Alternate Specifications						
Formula updated	1.19	0.615	0.724	1.11	0.200	0.246
from 1990 Census	(0.480)	(0.395)	(0.431)	(0.531)	(0.427)	(0.404)
Per capita variables	0.478	0.0520	0.0301	1.18	-0.144	-0.501
as instruments	(0.555)	(0.461)	(0.471)	(0.603)	(0.508)	(0.485)
No formula vouchers	1.85	1.28	1.26	1.24	1.19	1.06
	(0.486)	(0.441)	(0.456)	(0.385)	(0.346)	(0.318)
No formula vouchers	2.09	1.77	1.66	1.32	0.679	0.203
& Per capita IV	(0.616)	(0.566)	(0.589)	(0.530)	(0.481)	(0.476)
Vouchers per	0.276	-0.161	-0.178	1.38	-0.392	-0.636
renter/3	(0.630)	(0.529)	(0.555)	(0.708)	(0.639)	(0.564)
N	90	90	88	90	90	88

NOTE: Table entries are voucher coefficients from weighted least squares regression, with the weights proportional to the inverse of the standard error of the first stage hedonic rent estimates. Standard errors in parentheses.

Cross-section regressions follow the same specification as table 5. First difference regressions follow the same specification as table 8.

Table 10: How Leaky is the Bucket?

	Lower-income Unsubsidized Households	Voucher Recipients
Monthly Rent	$443	$537
Transfer/Rent	.16	.69
Households	9.6 million	1.3 million
Annual Total	$8.2 billion	$5.8 billion

SOURCE: Monthly Rent: Table 4. Transfer/Rent: .16 from text; .69 from author's tabulations, 1993 American Housing Survey. Households: 1/3 of unsubsidized renters from *American Housing Survey for the United States in 1995*, table 4-12, and Voucher recipients from *A Picture of Subsidized Housing*.