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Abstract

This paper examines the determinants of the decision of low-income renters to move out of their current dwelling. Maximum score estimation is shown t be superior to ordinary discrete choice estimation techniques (probit, logit) for this problem, ad for similar discrete choices that require revering a previously optimal decision. The estimation reveals psychological costs f moving for typical low income renters of at least 8% of their income; these costs are even higher for older, longer tenure, or minority households. Policies that displace low income renters will have large social costs. In addition, the estimation results are used to calculate implicit household willingness to pay (WTP) for neighborhood amenities. This WTP based on mobility behavior is much greater than WTP estimates derived using hedonic methods, and is argued to be ore accurate.

Maximum Score Estimates of the Determinants of Residential Mobility: Implications for the Value of Residential Attachment and Neighborhood Amenities

This paper uses a semiparametric empirical technique to estimate the determinants of the decision of low-income renters to move out of their dwelling. These estimates show that low-income residents highly value remaining in their dwelling. In addition, these estimates are used to illustrate an alternative method to measure willingness to pay for neighborhood amenities.

Moving decisions are usually examined with standard discrete choice models such as probit or logit (e.g., Venti and Wise (1984), or Weinberg, Friedman, and Mayo (1981). But the moving decision presents econometric difficulties for standard discrete choice models. As will be explained in section 1, because the household decision about moving is conditional on having previously preferred the original location, the disturbance term in mobility models is unlikely to follow the simple distributional forms required for probit or logit estimation.

Maximum score estimation is an alternative estimation technique for discrete choice models that is robust to unusual distributions of the disturbance term. Although the theoretical properties of maximum score estimation have been well-explored (see Manski (1975,1985)), our paper presents one of the first empirical applications of maximum score techniques. Maximum score estimation of our residential mobility model yields similar parameter estimates to probit estimation, but much smaller standard errors. This advantage of greater precision may prove attractive to other researchers.

We use our estimates of the residential mobility model to calculate the value to households of remaining at their current dwelling rather than being forced to move out. We use the household's mobility response to rent changes to infer a monetary value of remaining in the current dwelling. Our calculations indicate that the typical low-income renter household is willing to pay at least 8% of its annual income to avoid being forced out of its current dwelling. These "psychological moving costs" increase greatly for older or longer tenure households.

Large "psychological moving costs" have important implications for public policy towards low-income neighborhoods. Neighborhood improvement policies or private market forces may displace low-income renters. If the losses suffered by low-income renters due to being forced out of their current dwelling unit are significant, as indicated in this paper, then it is important to include these losses in any evaluation of the net benefits of a neighborhood improvement program. In addition, policy makers might want to consider policies to prevent or compensate for privately-induced displacement. Estimates of the monetary value of low-income renters' psychological moving costs are important to determining the effects of these policies, and deciding appropriate compensation.

Finally, this paper uses the residential mobility estimates to infer the willingness t pay (WTP) of low-income renters for neighborhood amenities such as the physical condition of the neighborhood, neighborhood school quality, and the safety of the neighborhood from crime. The relative responsiveness of household mobility to changes in these neighborhood amenities, versus changes in rents, implicitly reveals households' monetary valuations of these amenities. The more common approach to measuring household WTP for neighborhood amenities is the hedonic price approach, which relies n the equilibrium relationship between housing prices and amenities. The calculations in this paper suggest that mobility-based WTP estimates for amenities may often be greater than hedonic based estimates of WTP, We consider which approach is more accurate.

Section 1 of the paper presents our econometrics, specification, and data. Section 2 presents the results. Section 3 is the conclusion.

1. Outline of Model and Data

1.1 Econometric Issues

This paper's model assumes that a household will move out of its current dwelling over some time interval if the change in its utility from moving, minus the change in utility from staying, exceeds the household's initial surplus from its dwelling. This initial surplus is the difference, just prior to the time interval over which we are analyzing the household's moving behavior, between the household's utility from its current dwelling, and the utility it would receive, net of moving costs, from its next best alternative. This initial surplus must be non-negative, because the household initially chooses that dwelling rather than alternatives.

These assumptions can be summarized in the following equation:

(1) $\Pr(\text{Household i moving between t-1 and t}) = \Pr(M_{it} = 1) = \Pr(\Delta\ U_{imt} - \Delta\ U_{ist} - D_{it-1} \geq 0)$,

where M_{it} is a dummy variable for whether the household moves between t-1 and t, $\Delta\ u_{imt}$ is the change between t-1 and t in the maximum utility the household would get from living elsewhere than the household's dwelling of residence as of time t-1, ΔU_{ist} is the change between t-1 and t in the maximum utility the household can get from its time t-1 dwelling and D_{it-1} is the difference at time t-1, including all relevant costs and benefits, between the household's utility from its time t-1 dwelling, and the maximum utility from its next best alternative. D_{it-1} must be non-negative, or some other dwelling would have been chosen at time t-1.

For low-income renters, this surplus form the household's chosen dwelling, compared to its best alternative, would be close to zero if the household had recently moved into that dwelling. In a large housing market, any dwelling will closely resemble many other dwellings in its objectively measurable attributes. At the time of choosing this dwelling, the household would be close to indifference between the chosen dwelling and the alternatives. Just after choosing this dwelling, the household avoids additional financial moving costs from staying in this dwelling rather than being forced to move to similar alternative dwellings. But for low-income renters, financial moving costs would be small.[1]

Over time, the surplus a household gets from its current dwelling will evolve in a complex manner. If the surplus becomes negative, the household moves out. Households that stay will become accustomed to the particular features of that dwelling, and the familiar places and people nearby. This increasing familiarity creates a "psychological moving cost" from moving to another dwelling, even one with similar objective features, and thus will tend to increase the surplus the household receives from its current dwelling. Psychological moving costs could be particularly large for older households, who place a greater value on familiarity and spend more time near their homes. Psychological moving costs might also be large for families with children, who have more frequent interactions with nearby households.

On the other hand, the longer a household stays at a particular dwelling, the more likely are large changes in household circumstances or neighborhood characteristics. Such changes will make the dwelling a worse fit for the household's needs compared to its next best alternative. But if these changes make the household's surplus negative, the household will move out. Hence, for households who stay, we would expect some increase in the household surplus with length of tenure.

Thus, we assume that the household's surplus from its dwelling at time t-1 will depend on a number of characteristics of the household, including the household's length of tenure at the dwelling, the age of the household head, and the number of children.[2] These assumptions can be expressed in the following equation:

(2) $D_{it-1} = \underline{A}'\underline{X}_{it-1} + e_{idt-1}$,

where $\underline{X}$ is lengthh of tenure at the current dwelling and other household characteristics, and e_{idt-1} is the distrubance term.

The change from t-1 to t in the household's utility from moving to the next best alternative to its t-1 dwelling, minus the change in the household's utility from staying at that dwelling, will depend on changes inteh overall metropolitan housing market, changes in the t-1 dwelling and its

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[1]For example, Weinbert Friedman, and Mayo (1981) report that out-of-pocket moving costs for low-income renter households were \$12.59 in Phoenix, and \$54.06 in Pittsburgh, for the households surveyed as part of the Housing Allowance Demand Experiment.

[2]This surplus may also depend on how the characteristics of the current dwelling unit compare with the household's optimal dwelling. But in the presence of unobservable household and dwelling unit characteristics, any difference between dwelling unit characteristics and the household's optimal dwelling are difficult to measure. Furthermore, the presence of household optimizing behavior means that even a dwelling that appears ill-suited for the household may not be. At pointed out above regardless of the characteristics of the household and dwelling unit, the household's surplus just after moving in will be a small positive amount. In any event, the assumption made here is simply that the surplus can be regarded as some function of household characteristics and length of tenure alone. Other variables affecting the surplus will be part of the disturbance.

neighborhood, and changes in the household's characteristics. These relationships can be summarized by the following equation:

(3) $\Delta U_{imt} - \Delta U_{ist} = \underline{B}'\Delta\,\underline{Z}_{it} + e_{ict}$,

where $\Delta\underline{Z}$ represents changes in all variables that could affect moving or staying utiity (changeing rental preices, changing neighborhoods, changeing househod income, etc.), and e_{ict} is the disturbance term.

Combining equations (1), (2), and (3), we obtain the following:

(4) $\Pr(M_{it}=1) = \Pr(\underline{B}'\Delta\,\underline{Z}_{it} - \underline{A}'\underline{X}_{it-1} + e_{ict} - e_{idt-1} > 0 \mid e_{idt-1} \geq -\underline{A}'\underline{X}_{it-1})$.

The problem with equation (4) is that the conditioning on the initial surplus being non-negative implies that the disturbance can not follow a regular normal or logistic distribution. For example, if the unconditional distribution of the e_{idt-1} portion of the disturbance was normal, the conditional distribution of the e_{idt-1} portion of the disturbance would be truncated normal. Although in theory maximum likelihood estimation is possible with such a complex distribution of the disturbance, in practice this approach to estimation will be infeasible. In the present case, we were unable to get maximum likelihood estimates of equation (4) to converge when we assumed that the e_{idt} disturbance term was normal, and the e_{idt-1} disturbance term was truncated normal.[3] Maximum likelihood estimation that assumes a standard normal or logistic form for the disturbance term will in general yield inconsistent estimates.[4] The exception is that standard discrete choice models yield consistent estimates if the e_{idt-1} disturbance term is zero; this assumption, however, is untestable within the standard discrete choice framework.

We cannot reformulate the model in equation (4) to avoid these problems with maximum likelihood estimation. The decision to move is inherently made conditional on having preferred

[3]It might appear that a two-stage estimation procedure would work, with the selection equation ($D>0$) estimated first, allowing a selection bias correction term to be added to equation (4). But in the present case, all observed households are necessarily "selected": that is, households can only move out of the dwelling unit they originally lived in. In theory, such a truncated selection model is estimable; as pointed out by Maddala (1983, pp. 281-282), in practice researchers have found it very difficult to estimate such models.

[4]The problem here differs from the usual selection bias problem. If we actually observed the net utility gain from moving out at time t, rather than only observing an indicator of the sign of the net utility gain, we could consistently estimate how the different variables affect the net utility gain, conditional on the initial surplus being positive. Because we are attempting to explain moving behavior, and moving behavior is by definition conditional on having preferred to live at some particular dwelling initially, this conditioning is not a problem. Hence, the problem here is not the usual selection bias problem of wanting unconditional estimates for the entire population but only being able to obtain conditional estimates for a selected population. But probit orlogit estimation requires more stringent assumptions than regression estimation, and hence will not even yield consistent conditional estimates in this case. Even if the disturbance term is mean independent of $\Delta\underline{Z}$ and $\underline{X}$, conditional on $D > 0$, it will clearly not be normal or logistic or even independent of $\underline{X}$. Hence, "selection" in this case causes bias not because we want unconditional estimates, but because the selection alters the distribution of the disturbance term in a quite complex manner.

the initial dwelling prior to the move. This conditioning implies a complex distribution of the disturbance.[5]

Our solution is to use the maximum score estimation technique, which requires far weaker assumptions than standard discrete choice estimation procedures. Specifically, the maximum score approach only requires than the median of the disturbance term be zero. In the present case, we must assume that $\text{med}(e_{ict}\text{-}e_{idt-1} \mid \underline{Z}_{it}, \underline{X}_{it-1}, D > 0) = 0$.

The maximum score approach requires some reinterpretation of our estimated parameters. The maximum score parameter estimates yield "vest median predictors". For each observed household with given characteristics, we choose $\underline{B}$ and $\underline{A}$ so that the calculated "moving index" is accurate for the median household with those characteristics (that is, half the households would be expected to have higher values of the index, and half lower, if we examined a large number of households with those characteristics). In contrast, regression and maximum likelihood procedures try to create best mean predictors; parameters are chosen to predict the mean value of the left hand side variable for a household with given characteristics (that is, if we observed a large number of households with those characteristics, the mean value of the left-hand side variable would b expected to be equal to our prediction). Hence, maximum score estimates reveal the behavior of the typical household, while ordinary regression and maximum likelihood estimates reveal the average behavior of all households.

The median and mean are both defensible measures of the central tendency in a distribution. The median is less sensitive to the overall shape f the distribution of a variable, which is both a disadvantage (the median throws away information) and an advantage (the estimates are less sensitive to outlier observations).

Maximum score estimation was introduced by Manski (1975), who has also done the most work on it subsequently. Following the original presentation, Manski (1985) proved the consistency of the maximum score estimator.

Obtaining maximum score estimates of the parameters in a discrete choice model is straightforward. The estimated parameters are chosen to maximize the number of correct predictions.[6] In the model outlined above, a correct prediction would occur if $M_{it}=1$ and $(\underline{B}'\Delta\underline{Z}_{it}\text{-}\underline{A}'\underline{X}_{it-1}) > 0$, or Mit = 0 and $(\underline{B}'\Delta\underline{Z}_{it} - \underline{A}'\underline{X}_{it-1}) < 0$.

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[5]For example, we might reformulate the choice to move as depending on thelevel of the $\underline{Z}$ variables at time t, or $\Pr(M_{it} = 1) = \Pr(\underline{C}'\underline{Z}_{it} + w_{it} > 0)$, as was done by Venti and Wise (1984). But all observed households must have had levels of $\underline{Z}$ variables at time t-1, together with disturbance terms at t-1, that would cause the household to prefer its initial dwelling that is , we know that $\underline{C}'\underline{Z}_{it-1} + w_{t-1} < 0$. Because the w disturbance is probable correlated over time, the disturbance term in this "levels" model cannot follow a simple normal or logistic distribution. Standard discrete models will yield inconsistent estimates even if we are just interested n conditional inference.

[6]We thank Manski for use of his computer software program that provides a good algorithm to solve this problem.

Estimating the variances of these parameters estimates is difficult. There are no formulas for the variances of maximum score parameter estimates is difficult. There are no formulas for the variances of maximum score parameter estimates. Variances must be obtained by resampling techniques.[7] Given a size n sample, we select 100 random sub-samples, with replacement, of size n, and base our confidence intervals on the range of parameter estimates obtained.[8]

1.2 Functional Form of the Estimating Equation

To derive our estimating equation, we assume Cobb-Douglas utility, $U = B_1 1nH + B_2 1nN$, where H is housing consumption and N is the non-housing numeraire. The Cobb-Douglas function is chosen because it is the only utility function yielding a linear form for both direct and indirect utility functions.[9] An indirect utility function represents household utility if it moves, allowing optimal adjustment of housing consumption to market opportunities. But if the household stays, housing consumption cannot be optimally adjusted, and the direct utility function is appropriate.

Under these assumptions, the change from t-1 to t in the household's utility if it moves, and the change in the household's utility if it stays, can be written as:

$$(5) \qquad \Delta U_{imt} = B_{mt} - B_1 \Delta \ln P_{imt} + (B_1 + B_2) \Delta \ln Y_{it} + \underline{B}_m \Delta \underline{Z}_{it} + e_{imt};$$

$$(6) \qquad \Delta U_{ist} = B_{st} + B_1 \Delta \ln H_{ist} + B_2 \Delta \ln N_{ist} + \underline{B}_s \Delta \underline{Z}_{it} + e_{ist};$$

where $\Delta \ln P$ is the logarithmic change in the quality-adjusted price per unit of housing that prevails in the metropolitan area for new residents of rental units,[10] $\Delta \ln Y$ is the logarithmic change in real income,[11] and constant terms, changes in control variables $\underline{Z}$, and disturbance terms are added to equatins (5) and (6) to reflect other factors affecting utility.

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[7]Efron (1982) provides a guide to various resampling techniques.

[8]This resampling approach treats the original sample as representative of the larger population. Selecting 100 random sub-samples with replacement is the same as taking all the original observations replicating each one M times, where M is very large, and then obtaining 100 samples of size n with replacement from this very large artificial population. This approach approximates the distribution of parameter estimates for this artificially created population, which should closely resemble the original population.

[9]A linear form for the level of utility is needed to allow for a simple linear form for the changes in utility that enter equation (4).

[10]This is a change in a relative price; the price of non-housing consumption is taken to be one. Note that the rent generally charged for new residents for a particular quality housing unit may differ from the rent charged a long-term tenant, due to both long-term tenure discounts, and idiosyncracies of the landlord or the landlord-tenant relationship.

[11]Defined in terms of the non-housing numeraire commodity.

Using equations (5) and (6) in the general moving behavior equation results in the following:

(7) $\Pr(m_{it}=1) = \Pr((B_1+B_2)\Delta\ln Y_{it} - B_1\,\Delta\ln P_{imt} - B_2\Delta\ln N_{ist} - B_1\,\Delta\ln H_{ist} + (\underline{B}'_{mt} - \underline{B}'_{st})\Delta\underline{Z}_{it} - \underline{A}'\underline{X}_{it-1} + e_{ict} - e_{idt-1} > 0 \mid D \geq 0)$,

where the constant terms are absorbed intothe constant term in $\underline{A}$, and the distrubances in (5) and (6) are absorbed into the original disturbance.

A key advantage of explicity utility functions istheir allowance for sensible patterns in how changes in income and prices affect mobility. Consider the effect of income change on mobility. Let G be the latent variable indicating the net gain from moving out at time t (i.e., the left-hand side of the moving behavior equation). The derivative of this utility gain with respect to income Y_{it} at time t is

(8) $\partial G/\partial Y_{it} = B_1 + B_2(Y_{it}/N_{ist})$.

This net utility gain from moving, and hence the probability of moving, will increase as income increases if $N/Y > B_2/(B_1 + B_2)$, and will otherwise decrease with income. $B_2/(B_1 + B_2)$ is the optimal expenditure share for the non-housing numeraire. Thus, if the household at its original dwelling would at time t be spending "too little" on housing compared to its optimal expenditure share (and hence too much on non-housing goods), greater income promotes mobility. If the household is spending "too much" on housing, greater income retards mobility. This pattern makes sense because an income increase moves the household away from equilibrium at its original dwelling if the household is underconsuming housing, and towards equilibrium if the household is overconsuming housing. But most ad hoc specifications of the moving behavior equation would incorrectly constrain income changes to affect mobility always in the same direction.

The assumption of Cobb-Douglas utility may seem overly restrictive, but this paper estimates the parameters of a utility function, not a demand function. Cobb-Douglas utility is a first-order approximation to an arbitrary housing demand function.

1.3 Data

The data come from the Demand Experiment f the Experimental Housing Allowance Program. This experiment was conducted by the U.S. Department of Housing and Urban Development from 1973 to 1976 in Pittsburgh and Phoenix.

The households included in the Demand Experiment were low-income renters. As part of the Experiment, households were randomly assigned to several treatment groups. This paper uses data on households in treatment groups in which various percentages of rent were subsidized, households who received unrestricted income transfers, and control households. The experimental nature of the data is helpful statistically because it provides a great deal of exogenous variation in housing prices.

The dependent variable in our empirical analysis is whether the household moved out of its original dwelling during the first two years of the experiment. The independent variables are listed in Table 1.

Some variables in Table 1 require further explanation. Housing quantity change at the original location is proxied by changes in three variables measuring the quality of that location's neighborhood. Changes in the size or physical quality of the original dwelling cannot be measured for movers in these data because households were followed, not dwellings; one would suspect that these changes are small. The three neighborhood variables, neighborhood physical condition, school quality, and crime, are each linear characteristics.

For households who move, one cannot observe the rent they would have paid if they had stayed. This rent is predicted using estimated hedonic rent functions for each city that include neighborhood dummy variables.

The variation in housing prices is largely due to the rent subsidy treatments. But this paper also measures market changes in housing prices over two years in Pittsburgh and Phoenix by estimating separate hedonic rent functions for each city and period.

Finally, the independent variables used to predict moving costs (the $\underline{X}$ variables) include the constant, minority status, marital status, the number of children, a dummy variable for Phoenix, age of eh household head and tenure at the current dwelling unit. The variables causing changes in moving or staying utility (the $\Delta\underline{Z}$ variables) include dummies for changes in marital status, and the change in the number of children.

2. Results

2.1 Probit and Maximum Score Estimates

Tables 2, 3, and 4 present probit and maximum score estimates of the moving behavior model for Pittsburgh, Phoenix, and the two cities pooled. For the maximum score estimates, t-statistics can not be provided due to the lack of an asymptotic distribution theory for these estimates. Instead, we report 95% confidence intervals and the root mean square error of the maximum score estimates based on the results from taking 100 random samples and reestimating the model.

In general, it is striking how similar the coefficient estimates are in the probit and maximum score approaches. The greatest dissimilarity occurs in some of the "$\underline{X}$" variables that explain the initial disequilibrium (particularly age, and length of tenure).

A surprising result is that the maximum score approach yields much more precise estimates than the probit approach. We attribute this greater precision to two causes. First, Monte Carlo studies by Manski and Thompson (1986) suggest that maximum score estimates will have a smaller variance than estimation methods based on distributional assumptions when those distributional assumptions are incorrect. In the present case, the probit assumption of an independent normal disturbance is incorrect.

Second, maximum score estimates explain the behavior of the median household. Hence, maximum score estimates will be less sensitive to the characteristics of "outlier" observations than is true of maximum likelihood estimates. This provides the maximum score estimates with greater precision, but at a cost: the estimates describe the behavior of the median household, rather than average behavior for all households. We regard this cot as minor.

The coefficients on the change in income variable, change in housing price variable, and change in non-housing expenditure variable are remarkable close to those predicted by the Cobb-Douglas functional specification, particularly for Pittsburgh.[12] According to the Cobb-Douglas specification, the non-housing expenditure and housing price coefficients should be negative, and should sum to minus the income change coefficient. Furthermore, the ratio of the housing price coefficient to the income coefficient should equal the share of income spent on housing (an average of 34% in this sample), and the ratio of the non-housing expenditure coefficient to the income coefficient should equal the non-housing expenditure share (66%). These restrictions come close to being satisfied in Pittsburgh, although the estimates are so precise that the restrictions are statistically rejected in the probit model. The coefficients do not so closely match prediction in Phoenix, but they are at least in the ball park.

The signs on the other coefficient estimates in general seem reasonable, particularly in the Pittsburgh model. The Pittsburgh estimates suggest lesser mobility for minorities, married couples, households with children, older households, and longer tenure households; these effects seem plausible.[13] Changes in marital status also increase mobility. The estimates also suggest that mobility declines if the original neighborhood improves its physical condition or schools, or becomes safer from crime, holding non-housing expenditure constant.

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[12] Note that the fact that these utility function parameters are close to Cobb-Douglas predictions does not imply that income elasticities of housing demand are close t one, and housing demand price elasticities are close to one. We are attempting to develop an index of the change in utility due to percentage shocks in the different variables, and <u>any</u> utility function should yield ratios of the appropriate coefficients that are close to expenditure shares. This is similar to the finding that changes in price indicies yield good first order approximations to a household's change in real income from a price change for one component of a consumption bundle; such a finding does not imply that households do not substitute among commodities in response to this relative price change. From the perspective of utility functions, the amount of adjustment among different commodities is a second order effect. Obviously, in predicting demand behavior, such adjustments are first-order in importance.

[13] Minority households would be expected to be less mobile because discrimination will increasetheir search costs for finding a new residence; in addition, minority households may have greater attachment to ethnic neighborhoods.

Some Phoenix results are harder to explain. For example, households that get married are less mobile. Neighborhood improvements are associated with increased mobility. Most other Phoenix coefficients match expectations more closely.

The puzzling results for some Phoenix coefficients may be due to Phoenix's extraordinarily high mobility rates. 56% of Phoenix households in our sample moved during the 2-year period we consider, compared to 36% in Pittsburgh. These extremely high mobility rates in Phoenix are not artifacts of the Demand Experiment sample; even higher mobility rates for Phoenix renters are found in the 1970 Census of Housing (57% one-year mobility rate), and for Panel Survey of Income Dynamics renter households who live in the West Census region (60) one-year rate) (MacMillan, 1980, pp.29-30). These huge mobility rates may indicated disequilibrium in Western housing markets during the early 1970s. Western cities such as Phoenix were rapidly growing, with many new housing developments. Further evidence for disequilibrium in the Phoenix housing market is a 14% rental vacancy rate in 1974, compared to 5% in Pittsburgh (MacMillan, p. 30).

Table 5 reports the numbers of correct and incorrect predictions of moving behavior in the various models. The maximum score model does the best job of prediction, which is not surprising given that this approach seeks to maximize correct predictions.

2.2 The Magnitude of Moving Costs

The estimates in Tables 2, 3, and 4 allow"moving costs" to be calculated, in the following sense. Consider a "typical" household; based on the overall means of the sample, this would be a non-minority household, with no spouse present, 2 children, and a head age 44, which has been at its current residence for 48 months. We can calculate, holding observed variables constant, what reduction in this household's available resources, at its current location (the non-housing expenditure variable) would cause a household with these average characteristics, and a median value of the disturbance term, to move out of its dwelling between the initial and two-year interview.[14] Because all other variables, including income and overall housing prices, are held constant, this reduction in resources must be caused by a differential rent increase at the household's current dwelling. This rent increase is equal to the increase needed for us to predict at 50% probability of moving, that is, an increase that will cause the left-hand side of the moving equation to equal zero.

[14]Note that only observed variables can be held constant. Any changes in unobserved variables that for the typical household tend to increase or reduce mobility will be absorbed into the constant term (as noted in discussion above of equation (7), the constant-terms in equation (5) and (6) -- the change in moving and staying utility equations -- can not be separated from constant factors affecting the household's initial surplus). Hence, our measure of moving costs captures the household's surplus at time t, from the dwelling chosen at time t-1, if no observed variables had occurred. thus, it is possible for this moving cost measure to have a negative value for a typical household.

This calculation yields a flow measure of the monetary value to the typical household of its current dwelling versus its next best alternative. But moving costs should properly be thought of as a stock rather than flow value. To convert flow values to stock values requires assumptions about household discount rates, and how long houseolds expect to apply this rent increase. We adopt conservative assumptions that almost surely provide a lower bound to the stock value of moving costs. We assume: the flow rent increase started just before the household was interviewed at the 2-year interview; households move out at observed city mobility rates during the subsequent year; at the end of one year, no further rent increases are expected to persist, either because households will have moved out or landlords will have eliminated these rent differentials; household real discount rates are 20% per year, or 1.5% per month. We believe these assumptions are conservative because: many households will have been paying these rent differentials for some time before the 2-year interview; some households will stay at the current location for more than one year, and some rent differentials will persist for more than one year; for any household that signs an annual lease, the rent differential will persist fully for one year; a 20% real discount rate is relatively high.

Table 6 presents those flow values and stock values of moving costs. We consider an average household, a household 10 years older (age 54), a household with 5 years more tenure in its current residence (total tenure of 108 months or 9 years), and a minority household. We state "moving costs" as a percentage of household income.

We regard the figures in Table 6 as surprisingly large. Households re willing to pay sizable shares of their annual income to stay where they are. These moving costs are much too large to be attributed solely to financial moving costs. Other data from the Demand Experiment indicate out-of-pocket moving expenses of $54 in Pittsburgh and $13 in Phoenix, or about 1% of annual income in Pittsburgh and 0.25% of annual income in Phoenix (Weinberg, Friedman, and Mayo (1981). An additional financial cost of moving is that the household forgoes rent discounts attributable to long-term tenure: these rent discounts for a household with 4 years of residence amount to about 2% of income in Pittsburgh and 4% of income in Phoenix. It seems clear to us that a substantial component of household moving costs must be attributed to psychological factors: that is , to the household's attachment to its current dwelling and neighborhood.[15]

The flow measures of moving costs estimated here, averaging between 10 and 20% of income, are similar in magnitude to the flow measures estimated in Dunn (1979), Venti and Wise (1984), and Weinberg, Friedman and May (1981), using different methodologies, and in the case

[15]If one redoes these calculations for a "typical" Pittsburgh household, but with zero tenure, estimated moving costs are very close to zero, as predicted by the model if there are not unobserved variables changing moving versus staying utility. For Phoenix, median "zero tenure" households are estimated to have negative moving costs. This implies that unobserved changes in the housing market over the two-year period are artificially boosting Phoenix households' mobility. As mentioned previously in the text, Phoenix households in general appear to be hypermobile, possibly due to the rapid growth and consequent housing market disequilibrium of this city during the 1970s.

of Dunn, a totally different data base.[16] This consistency increases our confidence in the results obtained here.

One clear policy implication of these results is that public programs or private market forces that displace low-income renters impose major costs on these households. The needed compensation to "hold harmless" these renter households would be larger than the figures in Table 6, as compensating variation will exceed the equivalent variation figures in Table 6. The required compensation would be much greater than amounts typically paid under government relocation programs.

A second policy implication is that the costs imposed by displacement vary a great deal with household characteristics. As shown in Table 6, moving costs are much higher for minorities, older, or longer-tenure households.

These displacement costs should be included as part of the benefit cost analysis of public programs that intervene in urban neighborhoods, such as urban renewal type programs, neighborhood improvement programs, and major urban construction projects. Whether these displacement costs justify government intervention in neighborhood improvements caused by private market forces is a more difficult issue. It has been shown (Bartik, 1986) that t he gain to property owners from the improvement of neighborhood quality must exceed the net loss to displaced tenants. From an efficiency perspective, government intervention is not justified. But government intervention might be justified on distributional grounds.

2.3 The Value of Neighborhood Amenities

The mobility estimates in Tables 2, 3, and 4 also allow calculation of the households' valuations of neighborhood amenities. Given these parameter estimates, we can calculate how much of a reduction in non-housing resources would be needed to offset an improvement in a neighborhood amenity, leaving moving probabilities unchanged. This calculation estimates the household's WTP for that amenity.

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[16]Dunn reported results of a survey of 200 workers in a rural Southern community who had recently lost their jobs due to the closing of the town's textile mill. She reports that the average worker stated a willingness to accept 14% lower wages to remain in the home community. The stock measures of moving costs in our paper are much lower than Dunn's stock measure because Dunn assumes no depreciation over time of this 14% flow measure, and annual discount rates of only 6-8%.

Venti and Wise used the Demand Experiment data, and the observed housing choices of mover households, to infer the potential gains that stayer households are willing to forego. Venti and Wise estimate that the average stayer household is willing to forego gains from moving to a new home that are equivalent to 14% of household income.

Weinberg, Friedman, and Mayo (1981) also used the Demand Experiment data, but did not report their calculations of moving costs. However, if we calculate the dollar change in their experimentally induced disequilibrium variable that is needed, based on their Model I coefficients and sample means, to increase a Pittsburgh household's moving probability to .50, we obtain \$60, or 13.9% of monthly household income of \$432. Their other dollar measures of benefits and costs imply quite different moving cost estimates, but the experimentally-induced disequilibrium variable seems most likely to be exogenous and uncorrelated with household characteristics affecting mobility.

WTP calculations of this sort are presented in Table 7. Calculations were only done for Pittsburgh because neighborhood amenities in Phoenix had unexpected signs.

For comparison, Table 7 also presents estimates of the average effect on rent, as a percentage of household income, of these amenities. These calculations are based o estimated hedonic price functions for Pittsburgh (Bartik, 1982). Table 7 also presents estimates of household WTP for neighborhood physical condition, derived from hedonic estimated using procedures described elsewhere (Bartik, 1986, 1987).

A key point of interest in Table 7 is that mobility-based WTP estimates are inconsistent with the rent effects of these amenities. The "average" household, living in an average house, should be willing to pay less than the required hedonic rent increase for an improvement in amenities beyond the level originally chosen. Otherwise, the original house, with its level of amenities, could not be the optimal choice. But the average WTP estimates from the mobility model are considerable greater than the average effects of the amenities on rent.

This inconsistency suggests that either the mobility WTP estimates are biased upwards, or the hedonic rent figures are biased downwards. We believe the latter. Hedonic rent coefficients reflect the household's valuation about a dwelling's amenities before living there. Mobility-based WTP measures reflect the household's information about a dwelling's amenities after having lived there for some time. Household information about amenities is probably worse before the household moves in that after it moves in. The lack of good information will bias downwards estimates of household WTP. The estimates presented here suggest that this bias can be substantial.

This conclusion is important because hedonic-based WTP estimates are widely used to assess the benefits and costs of environmental and health and safety regulations. The hedonic benefit estimation approach has always been hampered by econometric difficulties in untangling the willingness t pay functions of households from the hedonic price function (Bartik and Smith 1987) review this research literature). If hedonic price approaches frequently underestimate households' WTP because of imperfect information, hedonic-based benefit estimates should be used with caution, and other benefit estimation approaches should receive greater emphasis.

3. Conclusion

This paper suggests that maximum score estimates of discrete choice models can be more precise than standard estimation approaches, that low-income renters' moving costs are large, and that hedonic-based WTP estimates may be downward biased. In addition, this research has two important broader implications.

First, the maximum score model used here may also be applicable to other situations in which a discrete decision is inherently made conditional on having previously made a reverse decision. For example, our approach could be used to model labor force entry, the firm's decision to adopt a new technology, or make a large-scale investment, or a household's decision to buy a first home. Our results suggest that maximum score estimation will prove superior for modeling these types of "reversing" decisions, for which the usual probit or logit assumptions are incorrect.

Second, if psychological moving costs are so important for low-income renters -- and presumable even more important for middle and upper-income homeowners -- then moving costs deserve more emphasis in theoretical and empirical models of urban areas and housing markets. There have of course been some attempts to theorize about the phenomenon of residential attachment, such as Bolton's (1989) recent paper providing an economic interpretation of what geographer and planners mean by a "sense of place". Also, some empirical work has explicitly recognized the importance of moving costs, such as Dynarski's work (1985, 1986) on housing demand and residential attachment. But on the whole, it is fair to say that most urban economists have ignored moving costs in their modeling efforts. we would argue that greater attention to psychological moving costs can help improve both the positive and normative content of urban economic analysis.

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Table 1
Description of Variables

Variable	Description	Mean	Standard Deviation
Minority Household	= 1 if household head is black or Hispanic	.28	.45
Spouse Present	= 1 if spouse present as of initial interview	.28	.45
# of children	# of children as of initial interview	1.52	1.65
Age	Age of household head, in years	44.4	18.3
Tenure	Length of tenure at current dwelling, as of initial interview, in months	47.5	65.9
Change in Income	= $\ln(y_2)-\ln(y_0)$, where y_0 is real monthly income at initial interview, y_2 is real income at 2-year interview	-.03	.45
Change in Housing Prices	= $\ln(P_{im2})-\ln(P_{im0})$, where P_{im0} is real housing price index for household's city at initial interview, P_{im2} is real housing price index for household's city and treatment group at 2-year interview	-.32	.30
Change in Non-Housing Spending	= $\ln(N_{is2})-\ln(N_{is0})$, where N_{is0} is household's real monthly income minus monthly rent at initial interview, N_{is2} is household's monthly income minus predicted monthly rent at 2-year interview, if household had remained at original dwelling	.08	.72
Became married	= 1 if household head became married between initial and 2-year interview	.04	.19
Became divorced	= 1 if household became divorced between initial and 2-year interview	.06	.24
Change in # of Children	Change in # of children between initial and 2-year interview	-.06	.59

Table 1
(Continued)

Variable	Description	Mean	Standard Deviation
Improvement in Neighborhood Physical Condition	= PC_2 - PC_0, where 0 and 2 subscripts are interview times, and PC is average over all households in neighborhood of 1st principal component of 11 physical attributes of neighborhood, such as housing evaluator's rating of condition of neighborhood houses (see Bartik (1986) for details)	.21	.26
Improvement in School Quality	= SQ_2 - SQ_0, where SQ is average in neighborhood of households' ratings of elementary, junior high, and senior high quality	-.04	.17
Increases in Crime	= C_2 - C_0, where C is 1st principal component of a # of variables measuring crime rates in census tract. See Bartik (1982) for details	.01	.15
Phoenix	= 1 if household resides in Phoenix	.42	.49
Dependent Variable Move Out	= 1 if household moves between initial and 2-year interview	.45	.50

Table 2
Results for the Mobility Model for Pittsburgh

	Probit Results				
	Estimate of			95% Confidence Interval	
	Coefficient	Std. Error	t-value	Lower	Upper
Constant	.1748	.0635	2.76	.0505	.2992
Minority Household	-.0419	.0340	-1.23	-.1085	.0248
Spouse Present	-.0695	.0392	-1.77	-.1463	.0073
# of Children	-.0065	.0116	-.056	-.0292	.0162
Age	-.0046	.0011	-4.31	-.0067	-.0025
Tenure	-.0010	.0003	-3.24	-.0017	-.0004
Change in Income	.7390	.1506	4.91	.4439	1.0342
Change in Housing Price	-.2642	.0607	-4.35	-.3831	-.1452
Change in Non-Housing Spending	-.5594	.0179	-5.18	-.7709	-.3479
Became Married	.1007	.0962	1.05	-.0879	.2893
Became Divorced	.0852	.0644	1.32	-.0411	.2115
Change in # of Children	.0493	.0289	1.70	-.0074	.1060
Improvement in Neighborhood Physical Condition	-.0653	.0627	-1.04	-.1882	.0577
Improvement in School Quality	-.0803	.0721	-1.11	-.2217	.0611
Increase in Crime	.0576	.0947	0.61	-.1281	.2433

Log likelihood function = -353.771

Table 2
(Continued)

Maximum Score Results

	Estimate of Coefficient	Std. Error	t-value	95% Confidence Interval Lower	Upper
Constant	.1742	.0042		.1626	.1849
Minority Household	-.0414	.0042		-.0491	-.0261
Spouse Present	-.0697	.0060		-.0896	-.0578
# of Children	-.0074	.0063		-.0279	.0105
Age	-.0038	.0012		-.0056	-.0019
Tenure	-.0018	.0014		-.00550	.000005
Change in Income	.7394	.0037		.7295	.7499
Change in Housing Price	-.2633	.0036		-.2693	-.2526
Change in Non-Housing Spending	-.5594	.0045		-.5727	-.5481
Became Married	.1006	.0060		.0879	.1164
Became Divorced	.0851	.0035		.0778	.0968
Change in # of Children	.0489	.0045		.0363	.0618
Improvement in Neighborhood Physical Condition	-.0660	.0059		-.0884	-.0526
Improvement in School Quality	-.0799	.0057		-.0948	-.0649
Increase in Crime	.0577	.0049		.0470	.0728

Note: To make all parameter estimates comparable, all estimates are normalized so that the sum of the squares of all parameters is one. The lower 95% confidence bound for each parameter under maximum score is halfway between the 2nd and 3rd lowest parameter estimate from the 100 re-samples used. The upper bound is similarly defined.

Table 3
Results for the Mobility Model for Phoenix

Probit Results

	Estimate of Coefficient	Std. Error	t-value	95% Confidence Interval Lower	95% Confidence Interval Upper
Constant	.6888	.1300	5.30	.4341	.9435
Minority Household	-.0570	.0614	-0.93	-.1774	.0633
Spouse Present	-.1013	.0715	-1.42	-.2414	.0387
# of Children	-.0145	.0175	-0.83	-.0488	.0197
Age	-.0131	.0020	-6.58	-.0170	-.0092
Tenure	-.0017	.0009	-1.89	-.0034	.00006
Change in Income	.3732	.2052	1.82	-.0291	.7754
Change in Housing Price	-.2815	.1035	-2.72	-.4844	-.0785
Change in Non-Housing Spending	-.2967	.1277	-2.32	-.5469	-.0465
Became Married	-.0955	.1229	-0.78	-.3363	.1454
Became Divorced	.0910	.1179	0.77	-.1402	.3221
Change in # of Children	-.0560	.0431	-1.30	-.1404	.0284
Improvement in Neighborhood Physical Condition	.0091	.1708	0.05	-.3257	.3439
Improvement in School Quality	.3434	.2506	1.37	-.1478	.8347
Increase in Crime	-.2581	.2609	-0.99	-.7695	.2532

Log likelihood function = -281.699

Maximum Score Results

	Estimate of Coefficient	Std. Error	t-value	95% Confidence Interval Lower	95% Confidence Interval Upper
Constant	.6886	.0066		.6690	.7112
Minority Household	-.0570	.0116		-.0852	-.0292
Spouse Present	-.1032	.0113		-.1422	-.0848
# of Children	-.0103	.0094		-.0223	.0179
Age	-.0127	.0012		-.0153	-.0107
Tenure	-.0041	.0016		-.0084	-.0011
Change in Income	.3736	.0087		.3592	.3907
Change in Housing Price	-.2802	.0083		-.2951	-.2481
Change in Non-Housing Spending	-.2975	.0084		-.3282	-.2801
Became Married	-.0951	.0085		-.1169	-.0691
Became Divorced	.0910	.0126		.0600	.1213
Change in # of Children	-.0559	.0099		-.0759	-.0244
Improvement in Neighborhood Physical Condition	.0098	.0103		-.0093	.0251
Improvement in School Quality	.3425	.0165		.3186	.3599
Increase in Crime	-.2564	.0110		-.2770	-.2247

Table 4
Results for Phoenix and Pittsburgh Pooled

Probit Results

	Estimate of Coefficient	Std. Error	t-value	95% Confidence Interval Lower	Upper
Constant	.3486	.0687	5.07	.2139	.4832
Minority Household	-.0461	.0363	-1.27	-.1172	.0250
Spouse Present	-.0976	.0431	-2.26	-.1820	-.0131
# of Children	-.0107	.0114	-.093	-.0330	.0117
Age	-.0091	.0012	-7.61	-.0115	-.0068
Tenure	-.0015	.0004	-3.61	-.0024	-.0007
Change in Income	.6804	.1572	4.33	.3723	.9885
Change in Housing Price	-.3017	.0687	-4.39	-.4364	-.1670
Change in Non-Housing Spending	-.5107	.1114	-4.58	-.7290	-.2923
Became Married	-.0007	.0919	-0.01	-.1808	.1794
Became Divorced	.1166	.0701	1.66	-.0209	.2540
Change in # of Children	.0039	.0292	0.13	-.0534	.0612
Improvement in Neighborhood Physical Condition	-.0263	.0747	-0.35	-.1728	.1202
Improvement in School Quality	-.0216	.0968	-0.22	-.2114	.1681
Increase in Crime	.0542	.1147	0.47	-.1706	.2789
Phoenix	.1849	.0414	4.46	.1036	.2661

Log-likelihood function = -652.956

Maximum Score Results

	Estimate of Coefficient	Std. Error	t-value	95% Confidence Interval Lower	Upper
Constant	.3483	.0032		.3383	.3549
Minority Household	-.0468	.0052		-.0578	-.0401
Spouse Present	-.0978	.0028		-.1074	-.0919
# of Children	-.0092	.0031		-.0126	.0010
Age	-.0091	.0006		-.0099	-.0070
Tenure	-.0023	.0011		-.0055	-.0013
Change in Income	.6806	.0033		.6727	.6864
Change in Housing Price	-.3018	.0030		-.3122	-.2961
Change in Non-Housing Spending	-.5104	.0029		-.5165	-.5028
Became Married	-.0009	.0038		-.0154	.0056
Became Divorced	.1173	.0023		.1137	.1261
Change in # of Children	.0038	.0034		-.0063	.0128
Improvement in Neighborhood Physical Condition	-.0259	.0023		-.0301	-.0171
Improvement in School Quality	-.0214	.0030		-.0283	-.0137
Increase in Crime	.0538	.0038		.0372	.0612
Phoenix	.1842	.0039		.1696	.1916

Table 5
Predicted and Actual Outcomes Under Various Models

No and Yes refer to staying and moving. A household whose estimated probability of moving is at least 0.50 is predicted to move.

Phoenix (490 households)

		Probit Model Predicted			Maximum Score Model Predicted		Total
		No	Yes		No	Yes	
Actual	No	125	86	No	139	72	211
	Yes	48	231	Yes	52	227	279
Total		173	317		191	299	490
Correct		356	(72.7%)		366	(74.7%)	

Pittsburgh (664 households)

		Probit Model Predicted			Maximum Score Model Predicted		Total
		No	Yes		No	Yes	
Actual	No	369	57	No	394	32	426
	Yes	111	127	Yes	124	114	238
Total		480	184		518	146	664
Correct		496	(74.7%)		508	(76.5%)	

Phoenix and Pittsburgh pooled (1154 households)

		Probit Model Predicted			Maximum Score Model Predicted		Total
		No	Yes		No	Yes	
Actual	No	500	137	No	508	129	637
	Yes	159	358	Yes	161	356	517
Total		659	495		669	485	1154
Correct		858	(74.4%)		864	(74.9%)	

Note: A naive approach of always predicting moving in the Phoenix model, and staying in the Pittsburgh model and pooled model, would predict correctly in 56.9% of the cases in Phoenix (279/490), 64.2% of the cases in Pittsburgh, and 55.2% of the cases in the pooled model.

Table 6

Estimates of Moving Costs for "Typical" Household, as Percentage of Income

Household Characteristics	Pittsburgh: Flow Measure as % of Monthly Income	Pittsburgh: Stock Measure as % of Annual Income	Phoenix: Flow Measure as % of Monthly Income	Phoenix: Stock Measure as % of Annual Income
Baseline: Non-minority household, age = 44, Tenure of 4 years, no spouse, 2 kids	10.2%	8.2%	16.8%	10.7%
Baseline + 10 years age (i.e., age = 54, tenure = 4 years, etc.)	13.9%	11.1%	33.9%	21.6%
Baseline + 5 years tenure (i.e., 9 years tenure)	20.0%	16.0%	44.5%	28.3%
Baseline, except minority household	14.2%	11.4%	25.4%	16.2%

Note: All figures in this table are stated as percentage of average household income: $432/month, or $5,184 a year. Calculations also assume non-housing expenditure of $285 a month, and are based on separate maximum score estimates for Pittsburgh and Phoenix respectively. The resulting formula for the percentage of monthly income flow measures, for a household with characteristics $\underline{X}_0$ is [285-exp(-$\underline{A}'\underline{X}_0/B_n$ + ln(285))]/432, where B_n is the non-housing expenditure coefficient.

For the stock measures, the Pittsburgh calculations assume 2.7% per month mobility rate and 1.5% per month discount rate; Phoenix calculations assume 7.35% per month mobility rate and 1.5% per month discount rate. These monthly mobility rates are consistent with observed one-year mobility rates for sample households of 60% in Phoenix and 28% in Pittsburgh at enrollment in the experiment. The 1.5% per month discount rate is consistent with a one year discount rate of 20%. As explained int eh text, the stock calculations assume that household will only pay any extra rent for a year. The stock variable S is then equal to the flow variable F times a constant, as follows:

$$S = 1/12\, F\left(\left(1 + \frac{1-m}{1+r} + \ldots + \left(\frac{1-m}{1+r}\right)^{11}\right) = F\left(\frac{1}{1-d} - \frac{d}{1-d}\right)^{12} / 12$$

where m is the monthly mobility rate, r the monthly discount rate, and d = (1-m)/(1 + r), and the division by 12 converts the figures to percentages of annual income.

Table 7

Estimates of WTP for Amenities in Pittsburgh

Amenity	WTP from Mobility Model	Hedonic Rent Change	WTP from Hedonic Model
Neighborhood Physical Condition	2.1%	.7%	.5%
Crime Reduction	1.0%	.05%	NA
School Quality	1.6%	wrong sign	NA

Note: All figures for WTP are stated as percentage of income for average income household, for an improvement in the amenity of "one standard deviation," that is, the standard deviation in this sample of changes in these amenities (see Table 1). The resulting mobility-based WTP formula is (1/432) $[\exp[B_h S_h/B_n) + \ln(285)]-285]$, where B_h is the neighborhood coefficient, S_h the standard deviation of the neighborhood variable, B_n the coefficient on non-housing expenditure, \$432 is average monthly income, and \$285 is average monthly non-housing expenditure. For neighborhood physical condition, the hedonic measures are equal to .26 (this variable's standard deviation) times the rent and WTP measures in the first row of Table 3 in Bartik (1986). For crime reduction and school quality, the hedonic rent changes are calculated from Table 7-5 in Bartik (1982), and are calculated at the sample means for the crime level and school quality level.