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COMMUNITY CHOICE AND LOCAL PUBLIC SERVICES: A DISCRETE CHOICE APPROACH

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ABSTRACT

This paper uses a discrete choice approach to estimate the impact of local fiscal and other variables on individual community choices. It employs a combination of a unique micro data set composed of ninety percent of all homeowners in six school districts in Camden County, New Jersey and information on local community characteristics including local crime rates, commercial activity and distance from a metropolitan area. The empirical model implies that all these variables as well as the local per pupil spending on public education and "community entry prices" play a major part in explaining the location of individual households. Estimates of elasticities of the probabilities of a representative individual choosing a particular community with respect to the various variables are calculated and discussed.

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1. Introduction

Much of the modern empirical literature on household location decisions has dealt separately with two related conceptual issues: one group of studies has focused on the effect of personal and *housing* characteristics on individual housing choices, while a second group has concentrated on individual and *community* attributes.[1] Furthermore, two distinct empirical methodologies have been used in each of these research areas: an early hedonic price approach and a more recent use of discrete choice (logit) models.[2] Since we view the latter empirical approach as more instructive, and since most previous discrete choice models have focused mainly on housing characteristics, we propose in this paper to utilize the discrete choice framework to focus explicitly on the *community choice* problem (which had previously been studied mainly using hedonic price models).

Examples of research in both empirical traditions (hedonic pricing and discrete choice) are categorized in figure 1. The early hedonic price literature, for example, paid little attention to community characteristics and public good levels[3] until Oates' (1969) seminal study relating median property values to local public good levels and local tax rates[4] and Kain and Quigley's (1970) study that combines extensive individual housing data with community variables. However, while these studies tested the extent to which tax rates and local public good levels are capitalized into house prices, it remains unclear to what extent empirical evidence on capitalization can inform us about the importance of local fiscal variables in location choice. Edel and Sclar (1974), for example, argue that if the Tiebout (1956) model held perfectly, a regression relating land values to taxes and services (holding other variables constant) would show *no* capitalization of taxes or services.[5]

Like the early hedonic price studies, discrete housing choice models also began by focusing primarily on housing characteristics (as opposed to local public goods). While Quigley (1985) built on an approach suggested in McFadden (1978) by modelling and estimating recently moved renters' choices in three stages in which renters ultimately consider local public goods in the final stage, his focus is decidedly not on this last stage. In fact, although this is not a central result in the paper, he surprisingly finds that school and public expenditures have small *negative* effects on the probability of a renter choosing a community. Other than Quigley (1985), however, the empirical significance of local public goods in discrete household location choice models remains unaddressed. The important contribution of McFadden (1978) and Quigley (1985) therefore lies not so much in the estimates of the effect of public services on location choice as it does in the development of an econometric approach that may yield reliable estimates in the future when better data become available.

While we lack the data to address the empirical importance of community variables in a complete housing choice model that considers explicitly *both* housing and community characteristics, we propose here to focus directly on the discrete choice individuals make over *communities* by analyzing data which combines individual tax data on homeowners with community variables. A unique combination of data from state income and property tax forms provide information on incomes, property holdings and community choices as well as the number of children (imputed from exemptions taken on income tax forms) on a household basis. Furthermore, data on community characteristics such as tax rates, local public good levels (per pupil school spending), crime rates and commercial activity are readily available. Additional federal tax data and Census information on housing characteristics allow for the econometric estimation of private consumption levels for each household in each community.

Two types of models are considered below. In the first, consumers are assumed to choose their optimal community based on local characteristics of that community, local public good levels and private consumption levels available to them under the assumption that their choice of house size would be the same in each community. This enables us to provide the first estimates (that conform with our intuition) of the direct effects of public tax and service variables on discrete location choice. However, the absence of information on individual houses (other than their assessed values) prevents us from extending our analysis to include house characteristics and causes us to make the artificial assumption that individuals would choose identical house sizes in all communities. To see whether our estimates are sensitive to that assumption, we then consider a second model in which we simply regress the discrete community choice on various community variables, individual characteristics as well as *community* house quality and price variables. While this specification has less theoretical justification, it does not impose the artificial assumption that individuals determine house size prior to choosing communities. Estimates of the impact of community variables such as crime and public school quality are shown to be robust across the different specifications. Thus, while data limitations do not permit us at this point to use McFadden's (1978) and Quigley's (1985) insights to include the housing (as opposed to community) choice explicitly, we are able to provide strong suggestive evidence that community fiscal variables are an important part of the housing choice equation.

2. The Model

The theoretical model that forms the foundation for this study is described in Nechyba (1997a). In that model, consumers choose among different house types in different communities and take characteristics of the communities, local public good levels, tax rates and equilibrium house prices into account. Ideally, then, an agent's choice of a community should be considered jointly with his choice of the level of housing services consumed. This would require estimating a model that considers housing, individual and community characteristics jointly in a simultaneous equation[6] or a nested model (as in Quigley (1985) and McFadden (1978)). As mentioned in the introduction, we are limited to abstracting from the dwelling choice and focusing on individual and community characteristics due to our limited and aggregate information on housing from Census data (see Section 3). As a result, we will analyze two separate models, a "random utility model" (Section 2.1) that makes a strong assumption regarding individual housing choices, and a "mixed polytomous choice" or "indirect utility" model (Section 2.2) that relaxes this assumption.

2.1. A Random Utility Model of Community Choice

First, we simplify the theoretical model in Nechyba (1997a) by holding the level of housing services (house size) fixed at the time the choice among communities is made; i.e. we assume that individuals choose the number of rooms they require prior to choosing a community. To the extent this assumption is violated, we are therefore excluding house types an agent may have considered when making his residential choice. In Section 2.2 we attempt to correct for this as best we can given the available data. For now we begin by assuming for each agent n an underlying utility function that excludes housing and is of the form[7]

$$u^n(i,x_i,z_{in})=k_i x_i^{\alpha} z_{in}^{\beta} e^{\varepsilon_{in}} \tag{1}$$

where k_i is a community specific constant, x_i is the level of local public services and z_{in} is the level of private good consumption that is possible for individual n in community i. The last of these differs between communities because the "community entry price" as defined by the price (inclusive of tax) of an equally sized house differs across the communities. Furthermore, the parameter k_i depends on characteristics of community i other than public service levels and local taxes, characteristics such as the level of crime and the degree of commercial activity. Taking logs, this utility specification becomes

$$u^n(i,x_i,z_{in}) = \ln k_i + \alpha \ln x_i + \beta \ln z_{in} + \varepsilon_{in} . \tag{2}$$

For estimation purposes one could either use community dummies or more specific descriptive variables to take account of the first term ($\ln k_i$). We test both of these approaches and report results in Section 5. The utility specification used in the rest of the paper, therefore, is

$$u^n(i,x_i,z_i) = \gamma c_i + \alpha \ln x_i + \beta \ln z_{in} + \varepsilon_{in} , \tag{3}$$

where c_i is a vector of community characteristics such as crime rates and degrees of commercial activity (or, in other specifications, a vector of dummy variables (community fixed effects)). If consumer n chooses community i, we assume that $u^n(i,x_i,z_{in}) = \max \{u^n(j,x_j,z_{jn}) \mid j \in J = \text{the set of all available communities}\}$.[8] Following McFadden (1973), we hypothesize disturbances that are independent and identically distributed with Weibull distribution, which implies that the probability of n choosing community i is given by

$$P[\text{n chooses i}] = \frac{e^{\gamma c_i + \alpha \ln x_i + \beta \ln z_{in}}}{\sum_{j \in J} e^{\gamma c_j + \alpha \ln x_j + \beta \ln z_{jn}}} \tag{4}$$

This approach implicitly assumes that the domain of choices in the model includes the communities contained in the actual choice set agents in the sample face and that the independence of irrelevant alternatives (IIA) assumption holds. Although actual choice sets are likely to contain more communities than those in the model, we are careful to chose our six communities in close proximity to one another such that they clearly had to be within the choice sets of each agent residing in any one of these communities.[9] Furthermore, even if agents considered other communities, McFadden (1978) has shown that consistent estimates of parameters can be obtained from a fixed sample of the full choice set. Finally, our statistical tests reported in the body of this paper indicate that the IIA assumption does indeed hold.

It should be noted that there can be endogeneity problems with some aspects of this approach. In particular, as individuals migrate in response to exogenous changes in such community characteristics as crime or distance to work, housing supply responses within communities may lead to changes in housing prices as capitalization occurs. (For an illustration of this in a computable general equilibrium context, see Nechyba (1997b, 1996a,b).) While there is ample evidence in the literature that capitalization of many local variables occurs in different contexts, the extent of capitalization remains an unsettled question in both the theoretical and empirical literatures. With insufficient data to estimate a full general equilibrium, simultaneous equations model, our results below should therefore be interpreted either as partial equilibrium estimates or as long run estimates under the assumption of elastic supply responses. Furthermore, we view endogeneity of school spending as well as the potential endogeneity of crime rates as a less serious concern for the marginal changes we simulate in Section 5.[10]

2.2. A Mixed (Indirect Utility) Polytomous Choice Model [11]

In the previous section we have constructed a random utility model in which the measured variables correspond to variables we expect to enter directly into utility functions. In the process, however, data limitations have forced us to make the somewhat artificial assumption that housing size decisions are exogenous to community choice. We therefore construct a second econometric approach in order to determine the robustness of the estimates when this housing choice assumption is relaxed. In particular, after analyzing estimation results using the first (random utility) model, we run additional logits in which we regress the community choice directly on individual characteristics (like income and family size), community characteristics (like crime rates and school quality) and community housing variables (price and quality). In particular, we model the probability that agent n chooses community i as

$$P[\text{n chooses i}] = \frac{e^{\gamma c_i + \alpha_1 \ln x_i + \alpha_2 p_i + \alpha_3 q_i + \beta y_n}}{\sum\limits_{j \in J} e^{\gamma c_j + \alpha_1 \ln x_j + \alpha_2 p_j + \alpha_3 q_j + \beta y_n}}, \tag{5}$$

where c_i and x_i are interpreted as before, p_i is the marginal price of an additional unit of housing in community i, q_i is the average quality of housing in community i, and y_i is a vector of personal characteristics (like family income and family size) that does not vary with community choice.

While this does not explicitly model the choice of housing and community, it is less restrictive in the sense that it does not fix the housing size choice for the households in the sample. On the other hand, the variables are not directly interpretable as arguments in a utility functions as in the model described in Section 2.1, but they *can* be interpreted as arguments in indirect utility functions. Econometrically the approach complicates the previous model, however, in that some variables are now subscripted *only* by n (thus the term "mixed" polytomous choice).[12] We report results using this alternative approach mainly to illustrate that our estimates from the original model are robust to weakening the housing choice assumption.

3. The Data

The data used in this paper contain information from income tax and homestead rebate forms of 90 percent of all homeowners in six New Jersey school districts for the fiscal year 1987. In particular, income information from New Jersey tax forms is matched with property information from homestead rebate claims for each individual to form a unique data set containing both income and property information on an individual basis. Thus, each individual's income (by category), exemptions, property value, and community (school district) are known.[13]

Federal income taxes for each agent in the New Jersey tax sample were imputed from the IRS Statistics of Income (SOI) Sample for New Jersey. SOI data contains the complete federal income tax forms for approximately 3000 New Jersey residents for the year 1987. This data was divided into two dimensional cells based on the number of claimed exemptions and 24 brackets of the New Jersey definition of gross income. Then, the median federal tax bill within each cell was matched to tax returns in the New Jersey tax sample by both the income brackets and the number of exemptions. We are thus able to add imputed federal tax liability to each individual in the New Jersey tax sample.[14]

In New Jersey, school districts are independent political units that use property taxation as the primary local funding means. Furthermore, school districts are coterminous with local municipalities, with each municipality fully contained in a school district. (Although it is not true for any of the school districts used in this study, some school districts are composed of more than one municipality.) This is particularly convenient for a study such as ours in that we do not have to be concerned about overlapping local jurisdictional boundaries.

Naturally it would make little sense either computationally or conceptually to use information on all

567 school districts in New Jersey. As noted before, we take the employment decisions by individuals as given which implies that an agent's choice of residence is severely constrained by the location of his job. It would therefore be unreasonable to assume that an agent could have chosen to live in Trenton when his place of work is Atlantic City. Any subset of school districts to be used for the present exercise must therefore comprise a small enough area such that the assumption that any agent in these school districts could feasibly have lived anywhere in the area of study is reasonable. For example, if an agent is observed to reside in Atlantic City, it is reasonable to assume he could have chosen to live anywhere within a 5 mile radius but chose not to. A second advantage of zeroing in on a small area is that local public spending figures as well as private income estimates lose some of their comparative meaning when schools and individuals facing different cost structures in different parts of the state are used. Furthermore, areas (such as communities around New York City) known for their racial and ethnic tensions can be avoided without loss of information. Finally, the communities should exhibit some degree of variation in the variables of interest, most importantly income and local spending on education. Thus, we chose a subset of school districts according to three criteria: (i) the land area of these districts should be relatively small; (ii) the area should be absent any racial or ethnic tension; and (iii) there should be some variation in local fiscal characteristics.

It is on this basis that we chose six school districts in the suburbs of Camden City in Camden County which lies to the southeast of Philadelphia: Cherry Hill, Collingswood, Glouchester, Haddon, Haddonfield, and Pennsauken. Other surrounding school districts could not be included due to data limitations (either too few observations or missing key variables.) The distance between any two of these school districts is less than five miles; fiscal characteristics vary considerably; and they do not include areas with minority populations greater than 5% of total community populations.[15] Furthermore, they are populous enough to comprise 22,739 individual observations in the tax data described above. Since the data set does not include welfare, social security and unemployment compensation information, and since federal tax information for those making over $250,000 was unavailable, only agents with gross incomes between $10,000 and $250,000 are kept in the sample. In addition, since education is taken to be the local public good of interest, anyone with fewer than two exemptions (who could not have children of school age at home) as well as all those above the age of

65 are excluded from the analysis.[16] Finally, a few agents with excessively high home values are discarded.

4. Construction of Variables

The RHS variables x_i and z_{ni} in equation (3) are constructed from the data described above. Note that as agents move between communities, even when we assume the house size to be fixed, both x_i and z_{ni} vary for each agent. Thus, unlike multinomial logits such as Dubins and McFadden (1984) where RHS variables are exogenous characteristics like age and race, all RHS variables in the random utility model are endogenous to the choice of community (while only *some* of the RHS variables in the mixed polytomous choice model are of this nature). An observation for an agent thus consists of not only the values of x_i and z_{ni} that he *actually* chooses, but also the *hypothetical* values of these variables *had he chosen another community*. In other words, each observation consists of six data components: one with the values of the variables x_i and z_{ni} actually observed in the community the agent has chosen to reside in, and five containing the hypothetical levels of x_i and z_{ni} for the five different communities the agent did *not* choose.

4.1. The Local Public Goods

As mentioned above, the school districts we study are coterminous with municipalities that provide municipal services such as public safety, health and welfare services, road maintenance, and recreational services. In terms of public safety, agents are much more likely to be aware of local crime rates than local police expenditures which are highly uncorrelated in our sample. Per resident police expenditures in Pennsauken, for example, were approximately $101 in 1984, while they totalled only $66 in Haddonfield (State of New Jersey (1984)). At the same time, however, the violent crime rate in Pennsauken was over 5 times that of Haddonfield (see Table 2). We therefore include crime rates rather than public expenditures on safety in out logits (see Section 4.3). Health and welfare expenditures tend to be uniform across municipalities as they are largely mandated by the state and federal governments, and we have no access to good data (other than expenditures which are problematic for the same reasons as police expenditures) on road maintenance and recreational expenditures. We therefore merely note that, since the inclusion of municipality fixed effects does little to change coefficients of the variables we are most interested in, we think that these factors play a negligible role. Furthermore, the municipalities are geographically so close to one another that public parks and recreational facilities in any one community are quite accessible from any of the other communities; i.e. many of these facilities are not excludable.

This leaves only one main source of local expenditure which also happens to be the largest category of local spending: primary and secondary education. While there is some evidence in the capitalization literature that per pupil spending may not be a good proxy for student achievement (Rosen and Fullerton (1977)) and thus for school quality, we find evidence that this is less of a problem in our sample. Although we do not have data on all schools in the districts we analyze, we find large correlations between several achievement variables and per pupil spending in those districts (Cherry Hill, Haddon and Haddonfield) for which we have quality data.[17] Furthermore, the proximity of the districts to one another makes it unlikely that there exist any large cost differences that would make the use of a per pupil spending variable problematic. Finally, we think that per pupil spending in the absence of such cost differences can act as a signal to parents of the local commitment to public education even if spending does not automatically translate into greater achievement (Hanushek (1986)).[18] Since education remains the only real (excludable) locally provided good of interest, x_i is thus defined as the level of public education in community i as measured by per pupil spending on education.[19] Furthermore, the hypothetical value for each community that was not chosen is easily obtained by simply determining the level of local per pupil spending on education in the communities the agent did not choose. The school spending regressor is then simply the log of per pupil spending and is labeled *LSCHOOL*.

4.2. Private Good Consumption and Housing Prices

As noted before, in our initial random utility model we assume that agents choose among the six communities holding their house type fixed. The available tax data provide for each agent the assessed value of the house he owns as well as the school district his house is located in. The state of New Jersey publishes the average ratio of assessed to true value of real property (based on actual sales of homes) for each school district on a yearly basis (State of New Jersey (1988)). It is then easy to convert the assessed home values in the New Jersey tax data to estimates of true market values.

Furthermore, Census data (U.S. Census Bureau (1993)) provide for each community the distribution of owner-occupied houses based on the number of rooms in the house. Thus, the Census furnishes a frequency distribution of house *sizes* while the tax data provide a frequency distribution of house *values* for each community. We assume that *within* each community, house values are a monotonic function of house size; i.e.

$$\text{value} = f_i(\text{size}) \tag{6}$$

where i denotes a community. Since the tax data include almost all owner occupied houses for each community, this assumption allows us to estimate the house price functions f_i as follows.

For each community, we take the Census specified percentiles of houses of each size (2 rooms, 3 rooms, etc.) and determine the brackets of house values for that community that fall into those percentiles. For example, if the Census data specified that 12 percent of all houses in community i have 3 or fewer rooms and 4 percent of all houses have 2 or fewer rooms, we determine from the tax data the value "x" of a house in the 4th percentile and the value "y" of a house in the 12th percentile. We then say that the bracket [x,y] represents all house values in community i with *approximately* 3 rooms. Furthermore, we take the median in each bracket to be the value of a house in community i that has *exactly* 3 rooms. This procedure yields eight brackets (1 to 9 rooms) and thus eight median points that match a house value to a precise house size in each community. Plots of these points for the different communities reveal an essentially linear relationship between house value and house size. We thus run a linear regression for each community of median house values against number of rooms. The regression utilizes the eight observations derived from the analysis above and yields highly significant estimates of parameters in linear price functions of the form

$$\text{value} = f_i(\text{rooms}) = \lambda_i + \phi_i{*}\text{rooms}. \tag{7}$$

The R^2's for these regressions fall between 0.97 and 0.98, and the coefficients λ_i and ϕ_i for the different communities are reported in Table 1. The marginal price of an additional room varies with the community and is given by ϕ_i which later forms the *PRICE* variable in the mixed polytomous choice model.

The inverse of these price functions,

$$\text{rooms} = f_i^{-1}\,(\text{value}) = \frac{\text{value} - \lambda_i}{\phi_i}\,, \tag{8}$$

then allows us to estimate the actual house size chosen by each individual. This value is assumed to be the same for both the school district the agent actually resides in as well as the communities the agents has chosen not to reside in. It can therefore be used to calculate the estimated house value for each agent in each community not chosen by that agent (using (7)).

The variable z_{in} is intended to measure private good consumption which can be derived by subtracting all tax payments and a payment for housing from each individual's gross income. On 1987 New Jersey tax forms, gross income, adjusted gross income (AGI) and taxable income are defined as follows:

$$\text{Gross Income} = \text{Wages} + \text{Interest} + \text{Dividends} + \text{Other Income} \tag{9}$$

$$\text{AGI} = \text{Gross Income} - \text{Pensions} \tag{10}$$

$$\text{Taxable Income} = \text{AGI} - \text{Medical Expenses} - \text{Alimony} - \text{Residential Deduction} - 1000{*}\text{Exemptions}. \tag{11}$$

Since the elderly are not part of our sample, Gross Income and AGI are equivalent for most agents in out sample. From it we subtract estimated house, alimony, local property tax, state income tax, and imputed federal tax payments to arrive at private good consumption. Actual house payments for agent n in school district i are computed based on the value of the house n resides in and assuming a 30 year fixed interest rate mortgage (with an interest rate of 7%). Hypothetical house payments for the same agent in school district $j \neq i$ are determined in the same way once the true value of a house of the same size in community j is estimated using equation (7). Alimony payments are included in the New Jersey tax data set and are the same regardless of where the agent resides. Actual local property tax payments for agent n residing in community i are also provided in the data set, while hypothetical property tax payments for the same agent in community $j \neq i$ are calculated by multiplying the hypothetical value of the same sized house (determined above) by the local property tax and the assessment ratio in school district j. New Jersey state income taxes are calculated by simply applying New Jersey tax tables to taxable income as defined above. This state income tax liability is virtually the same regardless of where the agent resides (differing only by the residential deduction which does not vary greatly). Finally, federal tax liability is imputed from another data set of New Jersey federal tax payers in a way described previously. Here, the tax liability is assumed to be identical regardless of the place of residence. The private consumption level z_{ni} in each jurisdiction is then just the reported income minus all tax payments, alimony payments and the estimated house payment; (log z_{ni}) enters the logits as *LCONSUMP*.

4.3. Community Characteristics

We consider several other community characteristics: (i) *COMMERCE* is the percentage of land in the local jurisdiction devoted to commercial (but not industrial) activity; (ii) *CRIME* is the annual violent crime rate in each jurisdiction (violent crimes per 1000 residents averaged over the years 1985,86 and 87); and (iii) *DISTANCE* is the average distance (in miles) in each community from a major central business district.[20] Finally, community specific house price and quality variables are used in the mixed polytomous choice model. As noted before, the variable *PRICE* is simply the marginal price (ϕ_i) of an additional unit of housing as reported in Table 1. Further, we use the percentage of houses built since 1980 as a proxy for house quality in each community. This percentage is reported in the *Summary of Detailed Housing Characteristics* published by the US Census and forms our *QUALITY* variable.

5. Results

Estimated logit coefficients for both the random utility model and the mixed polytomous choice (or indirect utility) model are reported in Table 3. Two versions of the random utility model are presented: Model 1 which uses community characteristics (*DISTANCE, CRIME and COMMERCE*) to account for c_i (from equation 3) and Model 2 which uses community dummy variables (*COLLIN, GLOUCH, HADDON, HADDONFI, PENNS*).[21] In both these models, all variables vary across choices and, with the exception of *LCONSUMP*, not across individuals. In the "mixed" Model 3, on the other hand, some variables vary across communities and some across individuals. Those that vary only only across individuals (exemptions, income) have to be introduced analogously to dummy variables in order to prevent singularity problems; i.e. *COLLEXEM*, for example, is equal to zero whenever Collingswood is *not* chosen and is equal to the number of exemptions on an individual's tax return when Collingswood is chosen. Furthermore, to avoid singularity problems, the income and exemption variables (those ending in "*INC*" and "*EXEM*" respectively) for one of the communities (Cherry

Hill) are omitted. Finally, we should note that, by including the community specific variables *PRICE* and *QUALITY* in Model 3, we had to drop one of the other community specific variables (*DISTANCE*) because of lack of sufficient degrees of freedom (given only six communities).

5.1. Strength of the Models

Coefficient estimates for both *LSCHOOL* and *LCONSUMP* (as well as that for *PRICE* in Model 3) are highly significant even when we correct the standard errors due to the presence of estimated values (from the regressions in Table 1) in the logit equations.[22] This implies that both local school spending and community entry prices (i.e. housing prices and local tax rates) play a significant role in predicting individual community choices. The degree of commercial activity (*COMMERCE*) and the average distance from a metropolitan area (*DISTANCE*) seem to also play a role. In particular, increases in commercial activity and distance from the metropolitan center (i.e. shopping opportunities, restaurants, etc.) raise the probability a community is chosen. The variable *CRIME* is significant and negative in all models which indicates a decrease in the probability that a community is chosen as the violent crime rate increases. Finally, higher marginal housing prices decrease the probability of choosing a community while higher housing quality increases that probability (all else equal). The only counterintuitive result is the sign on *DISTANCE* which, urban economists would suggest, ought to be negative. We conjecture the following: while *DISTANCE* measures the distance from the nearest metropolitan center (Philadelphia), it also captures the distance from Camden City (a suburb between Philadelphia and the communities we study). Camden City had a high fraction of minority residents (68% compared with less than 5% in surrounding communities) and had 27 violent crimes per 1000 residents in 1987 (compared to an average of 2 in the sample of communities in this study). Negative spillover effects captured in the *DISTANCE* variable may therefore outweigh other factors.

The Hausman-McFadden (1984) test for the assumption of independence of irrelevant alternatives (IIA) was performed on all versions of the model and the resulting test statistics are reported in Table 3, all of which pass the Hausman-McFadden test at the 0.01 level.[23] Since R-squareds and pseudo R-squareds are difficult to obtain and interpret in regressions of this kind, we instead compare predicted numbers of residents to actual numbers of residents for the different communities in Table 4 and observe that, with the exception of Collingswood, the two numbers are fairly close to one another.

5.2. Interpretation of Results from the Random Utility Model

While the signs and t-statistics in Table 3 are informative, the coefficients cannot be directly tied to marginal effects. We therefore calculate the elasticities of the probabilities with respect to changes in the variables in the logits.[24] Throughout this section, we use mainly Model 1 to analyze the impact of community variables. While similar analysis has been conducted for Models 2 and 3, much of this analysis goes unreported here because predictions (concerning the impact of changes in community variables on probabilities) are comparable in both magnitude and direction to those predicted by Model 1. At the end, we comment on additional results from Model 3.

Ceteris paribus, a 1 percent increase in the level of per pupil spending on education raises the probability of the average resident choosing a particular community by anywhere from 1.65% to 3.06%. Per pupil spending can easily vary by 30 percent or more between neighboring jurisdictions,[25] which implies that the predicted impact of public education spending on community choice is quite large. For example, were Glouchester to raise its per pupil spending on education through an exogenous grant (i.e. without decreasing private good consumption levels) to levels observed in Cherry Hill, the model would predict an 73% increase (from 0.063 to 0.109) in the probability an average agent would choose Glouchester. Thus, the data strongly support the notion that local public good levels have a significant impact on location choices. Furthermore, we have run logits similar to Model 1 in which we have interacted *LSCHOOL* with the number of exemptions a household claimed. Results are virtually identical to those reported here with the number of exemptions making little difference in the analysis. This is re-enforced by the results in Model 3 in which most of the coefficients on the number of exemptions are statistically insignificant.

Just as school spending therefore seems to be quite important, community "entry" prices have significant impacts as well. A 1% increase in an average household's private good consumption within a particular community (because of either higher taxes or higher house prices) can change the predicted probability of that agent choosing this community by anywhere from 0.7% to 1.3%. Thus, a $1000 difference in annual consumption levels for a family with household income of $30,000 makes a difference of approximately 2.5% in the probability that this family chooses the community. Furthermore, this change in probabilities differs substantially with family income. For example, for a family with annual income of $15,000 the change in probability is over 5%, while for a family with income of $50,000 this predicted change is below 1.5%.[26] (This is also consistent with the negative signs on income variables in Model 3.)

It should be noted that coefficient estimates for *LSCHOOL* and *LCONSUMP* are of similar magnitude across all model specifications we ran (some of which are reported in Table 3) regardless of what other control variables we include in the logits. At the same time, it is clear from the results in Table 3 that local public good levels and community entry prices, while important, are not the only community factors significant in location choices. In particular, both crime and local commercial activity seem to matter as well. A 1% increase in the violent crime rate, for example, can decrease the predicted probability of an agent choosing a particular community by between 0.1% and 0.4%. Given that crime rates range from 0.9 to 4.63 in the sample, these predicted effects are quite large. For instance, were the crime rate in Pennsauken, a relatively high crime area, to decline from 4.63 violent crimes per 1000 to 3.63 violent crimes per 1000, the predicted probability of an average agent choosing Pennsauken would rise by 9.1% (from 0.2621 to 0.2860), and a decline in the violent crime rate to the level of Haddonfield's (0.9) would cause this predicted probability to rise by nearly 34% (from 0.2621 to 0.3512). We furthermore interpret the coefficients on the *DISTANCE* variable as additional evidence that crime matters a great deal in household location choices. In particular, while we might expect a negative sign on this coefficient, we hypothesized above that the actual positive sign is due to negative spillovers from Camden City which, among other undesirable characteristics, features an exceedingly high violent crime rate (approximately 27 violent crimes per 1000 residents).[27] According to the estimates provided by Model 1, a 1% increase in distance from Philadelphia leads to anywhere from a 0.25% to a 0.7% increase in the probability an agent chooses a particular community. Equivalently, an increase of 1 mile from Philadelphia (and Camden City) causes an increase of 7.0% (from 0.0776 to 0.0830) in the probabilities of an agent choosing Haddonfield. Finally, commercial activity within a community, too, plays a role. A 1 percent increase in commercial activity raises the probability of an agent choosing a community anywhere from 1.2% to 2.5%.

So far, then, Model 1 has provided empirical evidence for the importance of a variety of community specific factors in household location choices. These results remain unchanged when some additional community fixed effects are added to the model, although it becomes increasingly difficult to obtain convergence. Model 2 takes the different approach of focusing on only local public good (school spending) and entry price (consumption) variables and "catching" all remaining unobserved community differences in dummy variables. We report these results mainly to illustrate the relative robustness of the coefficients we are mainly interested in, in particular local public expenditures on education.

5.3. Additional Results from the Mixed Polytomous Choice Model

As discussed in Section 2, the main restriction imposed in Models 1 and 2 is the artificial assumption that the choice of house size (number of rooms) is independent of the community choice. Model 3 relaxes this by combining the community characteristics from Model 1 with individual characteristics as well as community house price and quality variables on the RHS. Instead of calculating private consumption levels (that implicitly incorporate community entry prices) under the assumption that house size is fixed, we include household income (which does *not* vary with community choice (*COLLINC, GLOUCHINC, HADDINC, HADFINC,* and *PENSINC*)) as well as *PRICE* and *QUALITY* directly in the logits. (We also include exemptions as RHS regressors.)

While the limited degrees of freedom arising from the presence of only six communities in the sample do not allow us to include all community characteristics, we find little change in the coefficients for *CRIME, COMMERCE* and *LSCHOOL*. Furthermore, the interpretations of these coefficients are essentially identical to those in Model 1 and therefore are not discussed here. As noted before, adding the number of exemptions, this time as additional regressors, does not improve the model significantly; in fact, with the exception of *PENSEXEM*, all variables ending in "*EXEM*" are statistically insignificant. Thus, just as interacting *LSCHOOL* with exemptions in Model 1 makes little difference, including exemptions explicitly in the logits is largely inconsequential. Additional children (beyond one) in the household therefore seem to have little impact on community choice. Again, our main observation concerning Model 3 is the robustness of the community level coefficient this paper concentrates on even when the most restrictive assumptions in Models 1 and 2 are relaxed.

The additional coefficients of interest, then, are those on *PRICE* and *QUALITY*. As expected, higher housing prices, all else being equal, result in reductions in the probability that a particular community is chosen, while higher house quality levels result in increases in these probabilities. Furthermore, the magnitudes of the impact of these variables on probabilities is sizable. A 1% increase in the price of an additional room, for example, reduces the probability that an agent chooses this community by between 0.6% and 0.8% for the different communities. While this may initially seem small, marginal prices vary by as much as 71% between the communities in the sample. Similarly, despite a fairly crude measure of house quality (percentage of homes built since 1980), Model 3 suggests that quality matters as much as price.[28]

6. Conclusion

This paper represents a first step in analyzing directly the impact of local public service levels and community entry prices on individual location choices. It utilizes a unique data set containing both income and housing data on an individual level to conclude that individual community choices can be explained in part through local fiscal variables such as local commitment to public education and local house and tax prices as well as other community characteristics including local crime rates, distances from metropolitan (and high crime) areas and degrees of commercial activity. These results, in particular those regarding education and crime, confirm anecdotal evidence and explain such trends as the increasing emphasis on public safety and educational quality in planned communities.

In the process of the analysis, additional questions arise which provide fertile ground for future research. One of the models used here, for example, abstracts away from the important simultaneous choice individuals make over communities and levels of housing services by holding fixed house sizes in each agent's choice set, while the other relaxes this assumption without explicitly modelling the simultaneous choice of dwelling and community. Furthermore, the model is still quite partial equilibrium in nature. An adaptation of current econometric methods to allow for the estimation of a framework that models housing and community choices jointly and that endogenized some of the variables might strengthen the tentative conclusion of this paper that public service levels and local entry prices play a substantial role in explaining where individuals choose to live and may furthermore shed light on the largely unexplored relationship between community and housing choices. Finally, a replication of this type of approach with a different data set may establish the robustness of the results presented here.

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Footnotes

* The authors would like to thank William T. Bogart for providing the New Jersey tax data set used in this paper as well as Marcus Berliant, participants of the 1995 Western Regional Science Meetings and two anonymous referees for their comments. All remaining errors are the authors'.

1 Clearly the two literatures are related, and in fact few studies fall completely into either of the above categories. Examples of theses different approaches are discussed below. Interest in the first of these issues is concentrated primarily among urban economists, while the latter issues fall mainly in the domain of local public finance that has arisen from Tiebout's (1956) classic paper.

2 Discrete choice models have been employed elsewhere to study tenure and transportation choices in, among others, Boehm, Herzog, and Schlottmann (1991), Lee and Trost (1978), King (1980), Ellickson (1981), Anas and Chu (1984) and Anas (1982). Pollakowski (1982) used a multinomial logit model to estimate the role of commuting costs in residential location choices.

3 Ridker and Henning (1967) had previously found a positive correlation between property values and public school expenditure in a study aimed at demonstrating the effects of air pollution on single family house prices in St. Louis. Witte, Sumka and Erekson (1979) developed a more sophisticates hedonic price model (but did not include community variables).

4 See, for example, Pollakowski (1973) and King (1977) as well as Oates (1973). Oates finds median property values to be positively correlated with local school spending and negatively correlated with local tax rates.

5 Hamilton (1976) and Epple, Zelenitz and Visscher (1978) come to a similar conclusion. Pollakowski (1982) however, points out that a weaker version of the Tiebout hypothesis does lead to capitalization.

6 See, for example, King (1980), Lee and Trost (1978) and Dubin and McFadden (1984). King (1980) and Lee and Trost (1978) relate most closely to this paper in that they investigate the discrete tenure choice and housing expenditures simultaneously. Thus, the discrete choice in these papers concerns renting versus owning and picking communities.

7 This is the simplest possible utility function consistent with the theoretical model in Nechyba (1997a).

8 Throughout it is therefore necessary to assume that each individual's observed community choice is in fact his optimal equilibrium choice. Although moving costs clearly inhibit frequent consumer adjustments, we think that the relatively large degree of intra-metropolitan mobility provides some reason to believe consumers adjust their local community choice frequently enough to justify the assumption that most consumers reside in their optimal community at any point in time. (This large degree of mobility is in the literature on housing and tenure choice (Hanushek and Quigley (1978), Ioannides

(1987)) where it is pointed out that approximately 20 percent of metropolitan residents move each year, two thirds of which move within their metropolitan area. While this figure includes renters and is thus higher than that for homeowners, we suspect that homeowners, given their lower propensity to move, are more likely to take both current and expected future community characteristics into account when purchasing their home.) If Tiebout's hypothesis holds, an agent's location should then be attributable in part to local fiscal characteristics; i.e. he is residing in his current location and not elsewhere at least in part because of his consideration of the implicit tradeoff he faces between local public and private consumption.

9 It is our view that consumers in general choose their location in two stages. In the first stage, they choose a general region (such as a metropolitan area) based largely on job opportunities. Second, they take house prices, community characteristics and local fiscal variables as given and choose a particular community and school district within that general area. We focus here on the latter stage. This serves, at least in part, to justify the procedure of picking several geographically close communities for our analysis, which takes the first stage as given.

10 Finally, we note that by using personal income we have accounted for potential sorting by education level (as these are obviously correlated). Age and race compositions of the communities we study are roughly the same and thus not considered in the analysis.

11 We thank an anonymous referee for pointing this alternative approach out to us.

12 This means that running regressions with these variables will result in singularity problems. Therefore, these variables have to be constructed as community dummy variables multiplied by the actual variables. This implies that the variable family income (which is the same regardless of community choice), for example, is constructed as six variables. Each of these variables is set to zero for five of the community choices and set to the actual income value for one. See Greene (1990), page 696 for details.

13 This data set contains information on over 90 percent of New Jersey home owners and was generously provided by Prof. William T. Bogart, Case Western Reserve University. For a more detailed description of the data, see Bogart (1990).

14 For a more complete description of the federal tax data set, see Internal Revenue Service (1987).

15 We excluded the City of Camden due to its large minority population.

16 With nontaxable income absent from our data, the income figures for those reporting less than $10,000 are likely to be significantly too low. This implies that when imputed house payments are subtracted to derive consumption levels, these often become negative (since not all income has been accounted for). Within the income range discussed, only 1.3% of the sample was composed of people above the age of 65.

17 For verbal SAT scores, for example, we find a 96% correlation. Similar correlations are observed for the percentage of

students going to four year colleges. School quality data was found in College Entrance Examination Board (1990).

18 Increased spending by schools may in fact allow parents to devote their time to activities other than monitoring their children's educational advancement. Evidence indicating that parents decrease their educational efforts at home when schools become better is provided in Houtenville (1996). For a further discussion of issues relating to parental concerns over per pupil spending, see Nechyba (1996b).

19 These figures are published in New Jersey Associates (1989). The school variable is the three year average of per pupil spending on secondary public education for the years 1985,86,87.

20 For data sources, see Table 2 which summarizes the characteristics of the five school districts.

21 Note that no dummy variable for Cherry Hill is excluded in order to prevent singularity problems.

22 For the general problem of using estimated values in regressions, see Pagan (1984) and Murphey and Topel (1985).

23 For the Hausman/McFadden test statistics reported in Table 3, we dropped Pennsauken as an alternative. We also performed the same test by dropping each of the other alternatives. In all cases, the models passed the Hausman/McFadden test at the 0.01 level.

24 (See Greene (1990) for a derivation.) More generally,

$$\frac{\partial P_j}{\partial x_j} = P_j(1-P_j)\beta \text{ and } \frac{\partial P_j}{\partial x_k} = -P_jP_k\beta \text{ when } j \neq k.$$

This gives rise to a matrix of scale factors:

$$\begin{bmatrix} P_1(1-P_1) & -P_1P_2 & \cdots & -P_1P_5 \\ -P_2P_1 & P_2(1-P_2) & \vdots & -P_2P_5 \\ \vdots & \vdots & \ddots & \vdots \\ -P_5P_1 & -P_5P_2 & \cdots & P_5(1-P_5) \end{bmatrix}.$$

This matrix is evaluated at the sample means using Model 1 and presented in Table 5. Individual marginal effects can then be determined by multiplying the appropriate scale factor with the relevant coefficient. For example, to determine the effect on the probability of a representative resident choosing Cherry Hill if local per pupil spending rises by $100, one would multiply the relevant β (7.2590) by the appropriate scale factor from the above matrix (0.24931 in Table 5) and then by (log (4.871)–log (4.771)) (i.e. the difference between the value of *LSCHOOL* with and without the additional $100 in spending) to get 0.03441. In other words, a $100 increase in per pupil spending on education in Cherry Hill raises the probability of a representative agent choosing Cherry Hill by approximately 3.4 percentage points. Note that this calculation assumes that private consumption levels remain constant; i.e. the calculation treats the $100 increase in local per pupil spending on education as if it were funded by an exogenous block grant.

25 See, for example, figures for Collingswood and Cherry Hill in Table 2.

26 It may be tempting, at this point, to conduct a "balanced budget" analysis in which we attempt to calculate the change in the probability an average agent chooses a particular community when that community increases per pupil spending *and* raises sufficient tax revenues to accomplish this. Given the relatively higher impact of per pupil spending on the probabilities, such an analysis would clearly indicate that the probability of an average agent choosing a community that pursued such a policy would rise. However, given that this is a partial equilibrium model, given that we have been unable (due to data limitations) to endogenize prices which would capitalize changes in policy (see Section 2), and given that this analysis is true only for an "average" agent, we do not consider this "balanced budget" approach to be particularly instructive.

27 As mentioned before, two thirds of the residents of Camden City are members of minority groups, particularly blacks and hispanics. To what extent the desirability (on the part of mainly non-minority households in our sample) of living away from Camden City is due to high crime or racial attitudes is difficult to judge.

28 We do not include effective property tax rates as a RHS variable because there is essentially no variation is these rates across communities (see Table 2).

FIGURE 1

Classification of Some Previous Studies in the Literature

Important Variables \ Econometric Approach	Hedonic Price Models	Discrete Choice Models
Housing Characteristics (Urban Economics)	Ridker and Henning (1967)* Witte, Sumka & Erekson (1979)	Quigley (1985)*
Community Characteristics (Local Public Finance)	Oates (1969) Rosen and Fullerton (1974)	
Community *and* Housing Charactersitics	Kain and Quigley (1970)	McFadden (1978) (theoretical framework)

*While these papers do include some treatment of local public goods (in particular, public schools), they do not focus on these and sometimes get counter-intuitive parameter estimates.

TABLE 1

Community Specific Parameter Estimates for Equation (5)
(and t-statistics)

	Cherry H.	Colling.	Glouch.	Haddon	Haddonf.	Pennsau.
λ_i	-0.7502 (-1.28)	0.9861 (2.94)	-0.9046 (-2.49)	1.2897 (3.09)	3.0513 (5.78)	0.1003 (0.34)
ϕ_i	1.3945 (14.15)	0.8478 (15.07)	0.8170 (13.42)	0.9365 (13.37)	1.1408 (12.88)	0.7879 (16.07)
R^2	0.97	0.97	0.97	0.97	0.97	0.98

TABLE 2

Community Characteristics

	Cherry H.	Colling.	Glouch.	Haddon	Haddonf.	Pennsau.
Per Pupil School Spending[i]	$4,771	$3,654	$3,588	$3,835	$4,453	$4,070
Effective Prop. Tax Rates[ii]	3.02	3.26	3.18	3.05	2.93	3.00
Violent Crimes per 1000[iii]	2.23	1.87	1.25	1.30	0.90	4.63
Distance from CC (in miles)[iv]	9.5	7.5	6.5	9.2	10.1	4.4
Percent Commercial[v]	25.5	14.2	22.9	14.3	13.1	35.2
Median House Room Number[vi]	7.2	5.5	5.8	5.9	6.9	6.2
Percent of Houses built since 1980[vi]	15.0	0.2	4.2	2.6	1.4	7.6

i School spending figures are averaged for the years 1985, 1986 and 1987 and can be found in New Jersey Associates (1989).

ii These are effective tax rates for 1987 as reported in State of New Jersey (1988).

iii Crime rates are for the year 1986 and can be found in New Jersey Department of Law and Public Safety (1987).

iv The distance figures were calculated by the authors as the distance to the nearest central city from the center of the school district.

v See New Jersey Associates (1989).

vi See U.S.Census Bureau (1993).

TABLE 3

Logit Coefficient Estimates (and t-statistics)

Variable	Model 1		Model 2		Model 3	
DISTANCE	0.0755	(3.25)				
CRIME	-0.1234	(-5.20)			-0.1993	(-5.28)
COMMERCE	9.4910	(24.80)			11.3421	(3.01)
LSCHOOL	7.2590	(13.21)	6.6500	(12.01)	8.1321	(6.69)
LCONSUMP	3.1799	(30.22)	4.2332	(37.23)		
PRICE					-16.5911	(-6.64)
QUALITY					25.6051	(6.92)
COLLIN			-0.3330	(-10.51)		
GLOUCH			-0.7657	(-23.87)		
HADDON			-4.5598	(-29.43)		
HADDFI			-1.4309	(-44.06)		
PENNS			-0.1136	(-6.63)		
COLLEXEM					0.0314	(1.57)
GLOUCHEXEM					0.0270	(1.19)
HADDEXEM					-0.0179	(-1.02)
HADFEXEM					0.0275	(1.16)
PENSEXEM					-0.0479	(-3.54)
COLLINC					-0.9521	(-18.89)
GLOUCHINC					-1.5330	(-26.57)
HADDINC					-0.8856	(-25.31)
HADFINC					-0.9378	(-14.97)
PENSINC					-1.1481	(-31.93)
Chi-Sq.	27,826		26,321		18,014	
Test for IIA (Hausman/McFadden)	173.43		162.85		98.42	
Number of Observations	22,739		22,739		22,739	

Table 4

Predicted vs. Actual Populations

	Cherry H.	Collingsw.	Glouches.	Haddon	Haddonf.	Pennsauken
Probability	0.473821	0.025078	0.063278	0.098068	0.077618	0.262137
Predicted N	10,774	570	1,439	2,230	1,765	5,961
Actual N	11,002	1,662	1,376	2,310	1,155	5,234

Table 5

Matrix of Scale Factors (Model 1)

	Cherry H.	Collingsw.	Glouches.	Haddon	Haddonf.	Pennsauken
Cherry Hill	0.249314638	-0.011882582	-0.029982285	-0.046466605	-0.036777231	-0.124205931
Collingswood	-0.011882582	0.024449315	-0.001586893	-0.002459370	-0.001946534	-0.006573934
Glouchester	-0.029982285	-0.001586893	0.059273651	-0.006205515	-0.004911520	-0.016587435
Haddon	-0.046466605	-0.002459370	-0.006205515	0.088450615	-0.007611883	-0.025707240
Haddonfield	-0.036777231	-0.001946534	-0.004911520	-0.007611883	0.071593850	-0.020346679
Pennsauken	-0.124205931	-0.006573934	-0.016587435	-0.025707240	-0.020346679	0.193421221

Table 6

Elasticities of Probabilities (Model 1)

	Per Pupil Spending	Private Consumption	Violent Crime	Commercial Activity	Distance from CC
Cherry Hill	1.651	0.723	-0.145	1.273	0.377
Collingswood	3.058	1.340	-0.225	1.314	0.552
Glouchester	2.938	1.287	-0.144	2.036	0.460
Haddon	2.829	1.239	-0.145	1.224	0.626
Haddonfield	2.893	1.268	-0.102	1.147	0.703
Pennsauken	2.315	1.014	-0.422	2.465	0.245