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The Price of Access to Jobs: Bid-Function Envelopes for Commuting Costs

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Abstract

The relationship between commuting costs and housing prices is a key determinant of urban residential structure. This paper provides the first estimates of both housing/commuting bid functions of heterogeneous households and the associated bid-function envelope. This approach clarifies the distinction between movement along a household's bid function and a change in the slope of the envelope caused by household sorting. It also leads to tests of the hypotheses that households sort according to the slopes of their bid functions and that higher-income households tend to live farther from worksites. Estimates based on house sales in the Cleveland area in 2000 largely support these two hypotheses and indicate that the price of housing is about one-third lower at a location that is 34 minutes from a worksite than it is at a location that requires a minimal commute, all else equal.

JEL Codes: R21, R32, R41

Key Words: Bidding; sorting; commuting; housing prices; hedonics

1. Introduction

The relationship between access to jobs and housing prices is at the core of standard models of urban residential structure. In the most basic model, identical households value access to jobs, and the equilibrium housing price function, also called a bid-rent function (or a bid function for short), indicates how much more a household would pay for housing in a location with better job access. As explained by Alonso (1964) and many subsequent studies, this logic can be extended to a model containing multiple household types, each with its own bid function. In this case, the observed housing price function is the envelope of these bid functions, and the model sheds light on a key feature of American cities, namely, the sorting of households by income and other traits. Although the distinction between bid functions and their envelope is well known, it has been neglected in related empirical research. As Duranton and Puga (2015, p 350) put it, "close to nothing is known regarding the effect of income heterogeneity on the various gradients." This paper draws on the hedonic analysis of amenities in Yinger (2015b) to extend the literature by deriving bid functions that allow for households to differ on observed and unobserved traits, solving for the envelope of this bid-function family, and estimating this envelope using detailed data on house sales in the Cleveland area in 2000.

The approach in this paper has several advantages. First, it can accommodate many different measures of job access, including linear distance, street distance, time along streets, and measures that account for multiple worksites. As explained in Section 2.5, the measures selected for the analysis of the Cleveland data are the ones that appear to best explain homebuyers' commuting cost perceptions or that are closely linked to urban theory. Second, it is compatible with standard models of housing hedonics, which control for multiple housing and neighborhood characteristics. Third, it estimates a derived envelope for the household bid functions and thereby eliminates the confusion in the empirical literature between movement along a household type's

bid function and a change in the slope of the envelope caused by the sorting of different household types into different locations. Fourth, it accounts for the possibility that households' transportation costs and demand for housing—and hence their housing bids—are influenced by many traits, both observable and unobservable, not just by income. Finally, it leads to tests for two key hypotheses about urban residential structure: that households sort according to the slopes of their bid functions and that sorting based on access to jobs is "normal" in the sense that higher-income households tend to live farther from worksites.

2. Model Development and Literature Review

This section begins with a standard derivation of the relationship between the price of housing and the distance to a central worksite. The analysis is then extended to consider household heterogeneity, multiple worksites, a non-radial street network, traffic congestion, transportation mode choice, household perceptions of commuting costs, and neighborhood amenities. The discussion blends a literature review on each topic with an explanation of the model estimated later in the paper, which is designed to take advantage of the Cleveland data.

a. Deriving a Bid Function

In the basic urban model, households are assumed to be homogenous and to commute to work in the central business district, CBD. Households maximize their utility over a numeraire good, *Z*, housing, and location subject to a budget constraint that includes commuting costs. Housing is measured by housing services, *H*, which sell at a price *P*. The daily rental price of a house is *PH*; with a real daily discount rate of *r* and a long expected lifetime for housing, the sales price of a house, *V*, equals *PH/r*. *Y* is household income per day, $T{u}$ is the round-trip cost of commuting *u* miles to the CBD, and $P = P{u}$ varies with location. Thus, a household will

Maximize
$$U\{Z, H\}$$

Subject to $Y = Z + P\{u\}H + T\{u\}$. (1)

The first-order condition of (1) with respect to u is $P'{u}H + T'{u} = 0$. With identical households, this equation is a locational equilibrium condition, usually written as:

$$P'\{u\} = \frac{-T'\{u\}}{H} \,. \tag{2}$$

This result applies for any utility or commuting-cost function. The standard numerator of (2), first presented by Muth (1969) and Mills (1972), assumes that round trip commuting costs per mile, *t*, are constant and equal operating costs, *t*₀, plus time costs, *t*_Y*Y*; that is, $T{u} = tu = (t_0 + t_Y Y)u$ and $T'{u} = t$.¹ As shown by DeSalvo (1985), this approach can be derived from a model that includes a household's time allocation decision. Let λ be the value of commuting time as a fraction of the wage rate. DeSalvo shows that λ will be less than one so long as the disutility of work time is greater than the disutility of commuting time. Then the value of *t*_Y is $(2\lambda)/(8s) = (\lambda)/(4s)$, where *s* is speed in miles per hour (MPH), the 2 indicates a round trip, and the 8 indicates hours in a working day.

Alonso (1964) and Becker (1965) point out that households may focus on commuting time instead of distance. An urban model based on commuting time, v, can be specified by substituting v = u/s into the preceding equations. More generally, if we define $m \in \{u, v\}$ (= <u>miles or minutes!</u>) then

$$P'\{m\} = \frac{-(t_Y^m Y + t_0^m)}{H} \equiv \frac{-t^m}{H}$$
(3)

where

$$t_Y^u \equiv \frac{\lambda}{s4}, \ t_0^u \equiv t_0, t_Y^v \equiv \frac{\lambda}{4}, \text{and} \ t_0^v \equiv t_0 s.$$
(4)

To obtain an explicit form for equation (3), I assume that

$$H = \alpha \left(Y \left(1 - t_Y^m m \right) \right)^{\gamma} \left(P\{m\} \right)^{\eta} , \qquad (5)$$

where α measures determinants of H other than income and price, and γ and η are the income and

price elasticities of demand for *H*, respectively.

A constant-elasticity form has been widely used in empirical research on housing (Zabel 2004), albeit without commuting costs in the definition of net income. So far as I know, the only study that adds these costs is Blackley and Follain (1987). An income term with no adjustment for commuting costs also appears in many urban models, including those in Mills (1967, 1972) and Muth (1969). Kim and McDonald (1987) show that this approach arises when the income elasticity of demand for housing equals zero—a case rejected by the evidence (see Section 2.3).

Equation (5) represents an intermediate case in which time and operating costs affect $T\{m\}$, time costs affect the demand for H, and operating costs either do not appear or else are proportional to income in the demand for H. In other words, either t_0^m drops out of (5) or else it can be incorporated into t_Y^m . Three points support the first possibility: (a) Operating costs are generally thought to be much smaller than time costs and may therefore be ignored by households when they decide how much housing to buy. According to the U.S. Department of Transportation (2016), gas costs were 6.9 cents per mile in 2000. The median family income in the average Cleveland area block group in 2000 was \$46,709, or almost \$25 per hour for a 2,000-hour year. With time valued at half this wage and a commuting speed of 30 MPH, operating costs were only 14 percent of total transportation costs. (b) The operating costs of commuting are blended with the operating costs of shopping, personal, and vacation trips in a household's budget and may therefore not be salient in a household's choice of H^{2} (c) Transit fares in Cleveland in 2000 did not involve distance-based pricing. Alternatively, if t_0^m is proportional to income, t_y^m can be said to incorporate operating costs. When m = v, $t_0^m = t_0 s$, so a link between t_0^m and Y arises if s is linked to Y. Van Ommeren and Dargay (2006) find a link of this type in the United Kingdom: "as incomes rise commuters choose faster modes, despite their higher monetary costs" (p. 294).

Under some circumstances the elasticities in equation (5) can be interpreted as utility function parameters. These circumstances are defined by the "incomplete" demand system developed by LaFrance (1986), in which one set of commodities, Z, is not observed and influences the observed commodity, H, only through a price index. LaFrance shows that this demand system meets the standard integrability requirements, so its coefficients can be given structural welfare interpretations. The indirect utility function, Υ , that yields LaFrance's demand system with the income concept from (5) is

$$\Upsilon\left\{\left(Y\left(1-t_{Y}^{m}m\right)\right),P\{m\}\right\} = \frac{\left(Y\left(1-t_{Y}^{m}m\right)\right)^{1-\gamma}}{1-\gamma} - \frac{\alpha\left(P\{m\}\right)^{1+\eta}}{1+\eta}.$$
(6)

Applying Roy's identity yields equation (5).

Combining equations (3) and (5) yields the differential equation

$$P'\{m\}P\{m\}^{\eta} = \frac{-t^{m}}{\alpha \left(Y\left(1 - t_{Y}^{m}m\right)\right)^{\gamma}}.$$
(7)

The solution is

$$P\{m\}^{(1+\eta)} = C + \left(\frac{1}{\alpha}\right) \left(\frac{t^m}{t_Y^m Y}\right) \frac{\left(Y\left(1 - t_Y^m m\right)\right)^{1-\gamma}}{1-\gamma} = C^* + \psi \left(1 - t_Y^m m\right)^{(1-\gamma)} , \qquad (8)$$

where the C terms are constants,

$$\psi = \frac{t^m}{\alpha \, t_Y^m(Y)^\gamma} \,, \tag{9}$$

and the parentheses in an exponent indicate the Box-Cox form: $X^{(\delta)} = (X^{\delta} - 1)/\delta$ if $\delta \neq 0$; and $X^{(\delta)} = \ln\{X\}$ if $\delta = 0$. Note that t^m may be a function of Y and other variables.

b. Deriving the Bid-Function Envelope

This paper provides the first empirical analysis of housing prices and job access in which

the nature of household heterogeneity is estimated, not assumed. This analysis builds on Alonso (1964, p. 76), who pointed out that the slope of the bid function varies across household types and that the observed market price function is the envelope of the household bid functions. The slope of a bid function varies across locations for a single household type, but household sorting depends only on the slope of a household's bid function relative to that of other households at a given location. As shown in Figure 1, the household type with the steeper bid function at location m^* bids more per unit of H closer to the worksite and therefore wins the competition for housing there. Under a standard regularity condition, called the single-crossing condition, a more general result is that households with relatively steeper functions sort into locations closer to worksites.³

One approach to household heterogeneity is to define discrete household types. Miyao (1975) and Hartwick, Schweizer, Varaiya (1976), for example, derive models with bid functions for any number of discrete income-taste classes. A recent example is Guerrieri, Hartley, and Hurst (2013). This approach is quite limited for empirical purposes, however, because the nature of household heterogeneity must be assumed instead of estimated.

Another approach to household heterogeneity is provided by Montesano (1972) and Duranton and Puga (2015). These scholars assume that household income is characterized by a Pareto distribution and that households have Cobb-Douglas utility functions. With the added assumption that operating costs equal zero, Montesano shows that the bid-function envelope in a monocentric urban model is a power function with an exponent that equals the utility-function exponent on land relative to the utility-function exponent on distance. Duranton and Puga assume that time costs equal zero. This assumption also leads to a bid-function envelope in the



Figure 1. Sorting Based on Access to Jobs

form of a power function, but the exponent is the shape parameter in the Pareto income distribution. Results for power-function envelopes are presented in Section 5.1, but these results cannot determine which of these two models is correct.

This paper provides an alternative approach based on Yinger's (2015b) analysis of neighborhood amenities, in which the hedonic is the mathematical envelope of the household bid functions. This hedonic form, which can be estimated, allows for both operating and time costs, permits variation in income with no assumption about the income distribution, and accounts for other variables in household bid functions, observed and unobserved. Moreover, this approach leads to tests of two well-known theorems: (1) household sorting is determined by the slopes of household bid functions and (2) that household income increases with distance from worksites.

The key to this approach is to identify the factors that determine relative bid-function slopes, because these slopes determine sorting. The relevant slopes are "relative" because they need not account for factors that households share. In the bid function given by equation (8), the relative slope for a household type depends on the constant term in the housing demand function, α , household income, *Y*, and the components of transportation costs, $t_Y^m Y$ and t_0^m . The absolute slope obviously also depends on *m* and *P*, but the relative slope is defined as the slope at given values for these two variables, which are shared by households at any given *m*. Housing demand, and hence the relative slope of the bid function, may also depend, on many household traits, or:

$$\alpha = \alpha^* M^{\rho} \varepsilon^{\zeta} , \qquad (10)$$

where α^* is a constant and household traits are either observed, *M*, or unobserved, ε .

The envelope of a function $P\{m, \psi\}$, where ψ is a parameter, is the function that satisfies $f\{P, m, \psi\} = 0$ and $\partial f / \partial \psi = 0$. The bid function given by equation (8) does not have an envelope because the constant term, *C*, is not a function of ψ , which implies, incorrectly, that the bid

functions never cross. The first step in deriving an envelope, therefore, is to find $C\{\psi\}$.

Consider two households whose bid functions cross at m^* . These households have different values of ψ and hence different bid function slopes, but, by the definition of "cross," they also have the same bid, P^* , at m^* . As shown in Figure 1, therefore, the bid function with the flatter slope must have a smaller intercept. The derivation of an envelope involves solving for the constant term such that $dP/d\psi = 0$ when m is held constant at $m\{\psi\}$, that is, at the value of m associated with the "winning" slope. Applying this approach to (8), we find that

$$\left. \frac{dC}{d\psi} \right|_{m=m\{\psi\}} = -\frac{\left(1 - t_Y^m m\{\psi\}\right)^{1-\gamma}}{1-\gamma} \tag{11}$$

The second step is to assume a form for the hedonic equilibrium, that is, for the equilibrium relationship between m and ψ . The question is: How much does a homebuyer's equilibrium location change as the relative steepness of its bid function changes? Consider first a linear equilibrium:

$$m = \sigma_1 + \sigma_2 \psi, \qquad (12)$$

where the σ s are parameters to be estimated. Because steeper bid-function slopes lead to lower *m*, σ_2 is expected to be negative. This hypothesis is tested in section 5.1.

This form of equilibrium can arise, or be approximately correct, under a wide range of circumstances. In an analysis of neighborhood amenities, such as school quality, Yinger (2015a) focuses on one-to-one matches in which every household type has a unique location. This approach makes it possible to obtain close equilibrium approximations using continuous functions. Yinger proves the following theorem: If the amenity (analogous to *-m*) has the same distribution as a linear transformation of the distribution of ψ , which measures household heterogeneity, then the equilibrium relationship between *m* and ψ is linear. The distributions of *m*

and ψ are unknown, of course, but the online appendix shows that the distribution of *u* from a standard urban model is approximately equal to the distribution of a linear transformation of ψ based on a log-normal distribution of income, ψ 's key component. As shown below, envelopes can also be derived with other assumptions about the form of the hedonic equilibrium.

Substituting (12) into (11) and solving the resulting differential equation yields:

$$C = C_0 + \left(\frac{\left(1 - t_Y^m(\sigma_1 + \sigma_2 \psi)\right)^{2-\gamma}}{\sigma_2 t_Y^m(2 - \gamma)(1 - \gamma)}\right),$$
(13)

where C_0 is a constant of integration. Now the envelope can be derived by substituting (12) and (13) into (8). The result (for γ not equal to 1 or 2) is

$$\left(P^{E}\{m\}\right)^{(1+\eta)} = C_{0}' + \left(\frac{1}{\sigma_{2}}\right) \left(\left(\frac{1}{1-\gamma}\right) \left(m\left(1-t_{Y}^{m}m\right)^{1-\gamma} + \frac{\left(1-t_{Y}^{m}m\right)^{2-\gamma}}{t_{Y}^{m}(2-\gamma)}\right)\right) - \left(\frac{\sigma_{1}}{\sigma_{2}}\right) \left(\frac{\left(1-t_{Y}^{m}m\right)^{1-\gamma}}{1-\gamma}\right),$$
(14)

where $C_0' = C_0 - 1/(1+\eta)$. Equation (14) shows that estimates of the impact of *m* on *P* reflect both determinants of bid functions (t_Y^m and γ) and the nature of the sorting equilibrium (σ_1 and σ_2).

This envelope and bid functions for individual household types are illustrated in the first panel of Figure 2. The second panel plots the slopes of the envelope and of illustrative bid functions. The dotted line shows how the envelope slope increases along an individual bid function as *m* increases and also shifts up as the sorting process leads to a change in household type. This upward shift reflects a change in ψ .

Table 1 presents alternative forms for the right side of the envelope, which arise when the derivation is repeated with the right side of (12) raised to the power (labeled σ_3) ½ or 2. The third row corresponds to equation (14). When the right side of (12) is squared ($\sigma_3 = 2$) the solution to the differential equation corresponding to (14) involves a hypergeometric function, and explicit solutions are available only for specific values of γ . The result in Table 1 reflects the lowest



Figure 2. Bid Functions and Envelopes

Case	Bid-Function Envelope Formula
Square root ψ function; $\gamma \neq 1, 2$, or 3	$\left(\frac{1}{\sigma_2}\right)\left(\left(\frac{\left(1-t_Y^m m\right)^{1-\gamma}}{3-\gamma}\right)\left(\frac{2\left(t_Y^m m(1-\gamma)+1\right)}{t_Y^m (2-\gamma)(1-\gamma)}+m^2\right)\right)-\left(\frac{\sigma_1}{\sigma_2}\right)\left(\frac{\left(1-t_Y^m m\right)^{1-\gamma}}{1-\gamma}\right)$
Square root ψ function; $\gamma = 1$	$\left(\frac{1}{\sigma_2}\right)\left(\frac{m}{t_Y^m} + \frac{m^2}{2} + \frac{\ln\{1 - t_Y^m m\}}{\left(t_Y^m m\right)^2}\right) - \left(\frac{\sigma_1}{\sigma_2}\right)\left(\ln\{1 - t_Y^m m\}\right)$
Linear ψ function; $\gamma \neq 1$ or 2	$\left(\frac{1}{\sigma_2}\right)\left(\left(\frac{1}{(1-\gamma)}\right)\left(m\left(1-t_Y^m m\right)^{1-\gamma}+\frac{\left(1-t_Y^m m\right)^{2-\gamma}}{t_Y^m(2-\gamma)}\right)\right)-\left(\frac{\sigma_1}{\sigma_2}\right)\left(\frac{\left(1-t_Y^m m\right)^{1-\gamma}}{1-\gamma}\right)$
Linear ψ function; $\gamma = 1$	$\left(\frac{1}{\sigma_2}\right)\left(\frac{\ln\left\{1-t_Y^m m\right\}-\left(1-t_Y^m m\right)}{t_Y^m}\right)-\left(\frac{\sigma_1}{\sigma_2}\right)\left(\ln\left\{1-t_Y^m m\right\}\right)$
Quadratic ψ function; $\gamma = 1.5$	$\left(\frac{1}{\sigma_2}\right)\left(\frac{2\left(\arcsin\left\{\sqrt{t_Y^m m}\right\}\right)}{\sqrt{t_Y^m}} - \frac{2\sqrt{m}}{\sqrt{1 - t_Y^m m}}\right) + \left(\frac{\sigma_1}{\sigma_2}\right)\left(\frac{2}{\sqrt{1 - t_Y^m m}}\right)$

Table 1. Bid-Function Envelopes with Alternative Forms for the ψ Function

Notes: This table indicates the right side of the bid-function envelope in various cases. Each right side also has a constant term; *m* is distance from a worksite (in miles or minutes); γ is the income elasticity of demand for housing; and t_{γ}^{m} is the time cost of commuting (as a share of the wage rate). The σ s, which are to be estimated, are the parameters of the ψ function, which describes the sorting equilibrium. The left side is $P\{m\}^{(1+\eta)}$, where the parentheses indicate the Box-Cox form and η is the price elasticity of demand for housing. If η equals -1, the left side is $ln\{P\{m\}\}$. Because they are unrealistic, envelopes with $\gamma > 1.5$ are not presented.

value with a solution: $\gamma = 1.5$. The first and third cases can be written with Box-Cox forms but cannot be reduced to the Box-Cox estimated by Coulson (1991).

One instructive approximation arises with $\gamma = \sigma_3 = 1$. Because $t_Y^m m$ is commuting costs as a share of income, it is a small fraction, and $\ln\{1 - t_Y^m m\} \approx -t_Y^m m$. As a result, the entry in row four of Table 1 reduces to a constant plus $(\sigma_1/\sigma_2)(t_Y^m m) = \beta m$, where β is the estimated coefficient. Assuming $\eta = -1$, $\ln\{P^E\}$ is the dependent variable and this case is the semi-log specification used in most studies. In other words, a semi-log specification for *m* implicitly assumes that $|\eta| = \gamma = 1$ and that the ψ function is linear. Moreover, the coefficient in this specification contains the (unidentified) parameters describing the sorting equilibrium, so the common practice of interpreting this coefficient as a measure of t^m or t_Y^m is not correct.⁴

c. Household Sorting

The usual pattern in American cities is for high-income households to live farther from worksites than do low-income households (Glaeser, Kahn, and Rappaport 2008). I call this "normal" sorting. As shown by Alonso (1964) and Muth (1969), the slope of the bid function, (8), depends on income, and higher-income households have flatter bid functions, and therefore live farther from worksites, whenever the income elasticity of transportation costs per mile, say χ , is less than γ . Becker (1965) derives a comparable result in a time-based model. Wheaton (1977b) finds that $\gamma < \chi$. In this case, basic urban models cannot explain why income tends to rise with distance from the CBD. LeRoy and Sonstelie (1983) and Glaeser, Kahn, and Rappaport (2008) provide a possible explanation, namely, that normal sorting can arise if higher-income households use higher-speed modes, even if, for a given mode, $\gamma < \chi$.

The envelopes derived by Montesano (1972) and by Duranton and Puga (2015) cannot be

used to shed light on normal sorting. Both studies are based on a Cobb-Douglas utility function with $\gamma = 1$. The estimable Montesano envelope also assumes that operating costs equal zero, which implies that $\chi = 1$, too. In this case, sorting based on income does not arise. Duranton and Puga set time costs equal to zero, so that $\chi = 0$, and normal sorting occurs by definition.

With the approach in this paper, normal sorting arises if $\partial \psi / \partial Y < 0$, that is, if bid function slopes get flatter as *Y* increases. The first step in finding the sign of $\partial \psi / \partial Y$ is to calculate ψ using equation (12) and the estimated values of the σ parameters. The resulting ψ then can be regressed on the variables in equation (9), including *Y*. To facilitate an examination of income sorting, I assume that $t^m = t_C^m Y^{\chi}$, where t_C^m is a constant. With this assumption, equation (9) becomes $\ln{\{\psi\}} = C^{**} - \ln{\{a\}} + (\chi - \gamma) \ln{\{Y\}}$, where C^{**} is a constant. The coefficient of $\ln{\{Y\}}$ in this regression provides a direct test of the condition for normal sorting, $(\chi - \gamma) < 0$.

This test focuses on sorting that arises with the current configuration of highways and public transit. It does not provide a full analysis of sorting because this configuration reflects decisions about highways and public transit that were influenced by sorting in the past. Highways may have been built, for example, to please high-income residents in some suburbs. A full analysis of sorting also requires a historical analysis, such LeRoy and Sonstelie (1983). Nevertheless, this test can shed light on the extent to which current transportation networks in an urban area help to maintain sorting based on household income and other factors.

d. Theoretical Analysis of Transportation Networks

Most early urban models approximated commuting distance with straight-line distance from a house to the CBD. Subsequent models account for the street network, mode choice, traffic congestion, and the location of jobs.

Starting with Alonso (1964), several studies address the impact of the street network on a

bid function. Hartwick and Hartwick (1972) and Yinger (1993a) solve urban models with a street grid, and Anas and Moses (1979) introduce mode choice in an urban model with circular streets and a few high speed radial transportation modes. Anas and Moses show that with the standard assumption of identical households, all the people in a particular location select the mode, subway or car, for example that leads to the lowest-cost commute to the CBD. Yinger (1993a) and Baum-Snow (2007) consider commuting arteries. These models are applications of the Anas/Moses approach to the choice of route, instead of the choice of mode. Different transportation networks lead, of course, to different maps, but many do not alter the equations of an urban model or the model's comparative statics results.

Traffic congestion is difficult to introduce into an urban model because commuting costs depend on where people live and where people live depends on commuting costs. ⁵ Nevertheless, several scholars have made progress introducing congestion into an urban model. Mills (1972), introduced congestion into an urban simulation model, and Solow (1972, 1973) solved a simplified urban model with congestion. Yinger (1993b) solves an urban model with congestion in the special case of a horizontal street grid with a single vertical commuting artery through the CBD. Ross and Yinger (2000) review urban models with congestion.

The assumption that all workers commute to the CBD obviously is not realistic. White (1976, 1988) provides an urban model with both a CBD and a suburban employment ring, whereas Wieand (1987) and Yinger (1992, 1993a) explore models with discrete employment locations in the CBD and the suburbs.⁶ With this approach, the households who live in a given location all commute to the same worksite.

e. Empirical Analysis of Transportation Networks

Many empirical studies provide a general test of bid theory by including u or v as an

explanatory variable in a house-value regression. A few scholars address one or more of the above complexities: the street network, mode choice, congestion, and multiple worksites.

First, some scholars (e.g. Coulson 1991) account for the nature of the street network by measuring distance to the CBD along streets instead of straight-line distance. This step may be important for accurate estimates; Yinger (1993a) shows that using straight-line distance can lead to measurement errors if the actual street network is a grid. Coulson (1991) also estimates the relationship between V and u using Box-Cox regression. He rejects both multiplicative and linear forms but does not provide a theoretical explanation for the final form he estimates.

Several studies consider traffic congestion. To account for variation in congestion or the road network (and hence in t), Coulson estimates separate coefficients for u in different directions from the CBD. Ottensmann, Payton, and Man (2008) compare results for bid functions using distance along streets, free-flow commuting time, and congested commuting time.

Bender and Hwang (1985), Ottensmann et al. (2008), and Waddell et al. (1993) estimate housing price models with multiple worksites. These studies calculate distance to employment clusters or average distance to jobs and estimate V as a function of these measures.⁷ The same issues arise in estimating population density functions, which depend on land rents. Heikkila et al. (1989) identify three assumptions: that different worksites are substitutes, complements, or somewhere in between. Allocating each household to a worksite as in Bender and Hwang builds on the first assumption.⁸ The other studies cited above are applications of the third.

The unsettled nature of this literature reflects the fact that we do not know what households perceive about access to worksites when they bid on a house. Many scholars investigate the difference between actual commuting time and distance and commuters' perceptions of time and distance. See, for example, Peer et al. (2014). These studies apply to

commuters, however, not to house buyers. No survey comparing perceived and actual commuting distance or time for house buyers is available. Thus, we have no direct evidence on home buyers' perceptions of job access. They may use estimates of straight-line distance to the CBD, for example, they may take a trial run to their actual worksite, or they may consult an internet mapping program. Moreover, homebuyers might be concerned only with the access of their primary earner to his or her own current job; they might be concerned about access to a range of jobs for other members of their household or for the primary earner in the future; or they might be concerned about the job access of people to whom they might eventually sell their house. These perceptions link back to the three assumptions identified by Heikkila et al. (1989).

An indirect approach to perception is to find the distance or time measures that best explain actual household bids on housing. This strategy is followed by Ottensmann et al. (2008) in their study of Indianapolis and by Diaz and Yinger (2018) in their analysis of commuting in Cleveland. Ottensmann et al. find that accounting for congestion and access to multiple worksites increases the explanatory power of a hedonic regression (the R-squared), but by an insignificant amount. Diaz and Yinger compare the explanatory power of many distance and time measures using several different approaches to the concept of explanatory power, including specification tests and a finite-mixture model.

Diaz and Yinger define nine distance and nine time measures of job access at the Census block group (CBG) level. The first distance measure is actual commuting distance, which is estimated based on the actual time measure and tract-to-tract commuting data from the Census. The second two measures indicate the distance to the Terminal Tower, which is the visual center of the Cleveland downtown. The first of these measures uses straight-line distance, the second uses distance along streets.⁹ Several distance measures are based on five major worksites in the

Cleveland area identified by Yinger (2015b). Four of these sites are clusters of zip codes around a high-employment zip code. The fifth is a beltway. These five sites account for 75.8 percent of the jobs in the Cleveland area. The fourth and fifth distance measures are employment-weighted distances to the five worksites, using straight-line and street distance, respectively. The sixth and seventh distance measures are the first principal component for all the other measures, based on either straight-line or street distance. The eighth and ninth bring in the employment-weighted distance (straight-line or street) to all the zip codes linked to the beltway. Diaz and Yinger also define nine analogous time measures. Their tests indicate that actual commuting distance (time) and straight-line distance (time) to the Terminal Tower are the distance (time) measures with the greatest explanatory power. Moreover, these distance measures have slightly greater explanatory power than the comparable time measures.

f. Neighborhood Amenities

Alonso (1964) includes distance from the CBD, u, in the utility function. His main argument is that households may experience disutility with distance from jobs, but he also mentions that people may care about the "prestige" of a neighborhood. Formal analysis of this possibility was first provided by Polinsky and Shavell (1976), who consider the case of air pollution, and Yinger (1976), who considers the endogenous amenity of neighborhood ethnic composition. These studies assume that some amenity, A, is a function of u and then place $A{u}$ in the household utility function. This approach has advantages for theoretical research on urban models, because it adds amenities without adding another locational dimension.

In empirical research, however, amenities such as school or air quality can be measured independently of u, and a key issue is how to avoid bias in the estimated impact of u (or v) on house values that arises from omitted neighborhood amenities. This issue is addressed in the

literature on "hedonic" regressions, which explores the impact of amenities on house values. This literature builds on Rosen (1974), who applies the logic of bid functions and their envelope to the pricing of multi-attribute commodities, such as housing. His framework shows that observed housing prices are the envelope of the underlying bid functions of heterogeneous households and are not a function of household characteristics, such as income.¹⁰ Recent reviews of this literature include Taylor (2008) and Nguyen-Hoang and Yinger (2011).

Diamond (1980) and Brueckner, Thisse, and Zenou (1999) show that neighborhood amenities can lead to household sorting. Yinger (2015b) builds on this research by deriving and estimating the envelope of household bid functions for a continuous amenity.¹¹ He finds, for example, "that a one standard deviation increase in *Y* [income] leads, purely because of sorting, to a 0.82 standard deviation increase in" a measure of high school quality. His derivation also shows that a single right-side term for each amenity is not consistent with sorting; two terms are needed. These forms depend on the price elasticity of demand for the amenity, μ . This paper uses Yinger's form for continuous amenities with $\mu = -0.75$, which is the elasticity Yinger estimates for school quality and is close to the values he estimates for some other amenities.

g. Local Taxes and the Final Estimating Equation

A large literature, reviewed in Ross and Yinger (1999), shows that property taxes are capitalized into house values. Define β as the degree of property tax capitalization and τ as the effective property tax rate. Then the standard specification is to add $\beta\tau$ to the capitalization rate so that $V = PH/(r + \beta\tau)$.¹² Some school districts in the Cleveland area also levy an income tax at rate y, which may affect house values. The final estimating equation is a multiplicative function of the envelope for job access, P^E ; tax measures, τ and y; envelopes for neighborhood amenity measures, A_i ; and structural housing characteristics, X.¹³

$$V = \frac{P^{E}\{m\}g\{y\}\prod_{i} f\{A_{i}\}\prod_{j} H_{j}\{X_{j}\}e^{\tilde{z}}}{(r+\beta\tau)}$$
(15)

The error term, $\tilde{\varepsilon}$, reflects unobserved factors and individual bids that differ from market bids because of the relative bargaining skills of the people involved.

3. Data

This study builds on a subset of the data described in Brasington (2007) and Brasington and Haurin (2006), namely, data for all the house sales in the Cleveland MSA in 2000. This data set indicates sales price, housing characteristics, housing location, CBG characteristics, school performance, and air quality, among other things. Additional measures of worksite locations, job access, and neighborhood traits come from Yinger (2015b) and Diaz and Yinger (2018).

The job-access measures examined in this study are listed in Panel A of Table 2. These measures provide a wide range of possibilities for homebuyer perceptions of job access. The first two measures for both distance and time are the "winning" measures in the Diaz and Yinger (2018) analysis: actual average commuting distance (time) and straight-line distance (time) to the Terminal Tower. The second measure corresponds to the formulation in a standard monocentric urban model. The third distance measure is the employment-weighted straight-line distance to the five Cleveland-area worksites described in Section 2.5. This measure corresponds to the "complements" view of worksite access. In other words, it assumes that house buyers care about access to all worksites based on the number of jobs they contain. The "substitutes" version of worksite access is represented by the fourth distance measure: straight-line distance to a residential location's assigned worksite. This measure is the one incorporated into multi-center urban models, which sort households based on their job location. The assignment problem here is simpler, however, because jobs and households have already been allocated in the data and all

Panel A: Definitions									
Measure	Definition		Mean	Minimum	Maximum				
Distance Me	asures (in Miles)								
DIST1 Estimated actual commuting distance									
	(straight line)	7.97	3.01	29.04					
DIST2	Straight-line distance to Term	ninal Tower	13.39	1.11	41.36				
DIST3	IST3 Employment-weighted straight-line								
	distance to worksites		13.20	7.27	39.52				
DIST4	Straight-line distance to assig	gned							
	worksite		6.92	0.01	42.25				
Time Measu	res (in Minutes)								
TIME1	Actual commuting time		25.87	11.11	46.53				
TIME2	Estimated straight-line time t	o Terminal							
	Tower		44.51	9.87	87.48				
TIME3	Employment-weighted straig	ht-line time							
	to worksites		46.31	25.97	86.26				
TIME4	Straight-line time to assigned	l worksite	32.33	4.24	121.39				
Panel B. Correlations									
Distance Me	asures								
	DIST1	DIST2	DIST3		DIST4				
DIST1	1.00								
DIST2	0.64	1.00							
DIST3	0.62	0.97	1.00						
DIST4	0.55	0.71	0.79		1.00				
Time Measures									
	TIME1	TIME2	TIME3	3	TIME4				
TIME1	1.00	1.00							
TIME2	-0.03	1.00	1.00						
TIME3	0.10	0.82	1.00		1 00				
1IME4	0.28	0.30	0.61		1.00				
Cross Correlations									
	DIST1	DIST2	DIST3		DIST4				
TIME1	0.26	-0.01	0.01		0.19				
TIME2	0.63	0.99	0.93		0.67				
TIME3	0.57	0.86	0.90		0.70				
TIME4	0.34	0.35	0.45		0.67				

Table 2. Measures of Job Access

we need to do is ensure consistency between the number of jobs and households associated with a given worksite. See Diaz and Yinger (2018) for details of the allocation procedure.

The four time measures are analogous to these distance measures. The first measure, actual commuting time from a CBG, comes directly from the Census. It obviously accounts for the street network, congestion, and worksite locations. The other three measures are based on a regression of the first measure on dummy variables for every residence-worksite tract combination (see Diaz and Yinger 2018). The coefficients of these variables indicate the time for each possible commuting trip. The second time measure is the estimated commuting time from a given residential tract to the Terminal Tower. The third time measure is the estimated employment-weighted average commuting time from a tract to the five Cleveland-area worksites. The fourth measure is the estimated commuting time to a tract's assigned worksite.

Panel B of Table 2 shows that the four distance measures are highly correlated with each other, whereas the correlations among time measures tend to be much smaller, particularly for correlations that involve TIME1. Moreover, the correlations between the distance and time measures are fairly high unless TIME1 is involved.

4. Estimation Procedures

a. Estimating Stages

The forms in Table 1 are estimated in two stages. The first stage is a regression of $\ln \{V\}$ on housing characteristics, neighborhood (Census block group or CBG) fixed effects, and within-CBG differences in geographic variables.¹⁴ The sample is all sales in CBGs with at least two sales. Each fixed effect captures the net impact on house values of all neighborhood traits, observed and unobserved, shared by the houses in a given CBG. The second stage uses the coefficients of the CBG fixed effects as the dependent variable and estimates the forms in Table

1—with the appropriate additions for amenities and local taxes. The sample is the set of CBGs. The same two-stage procedure with the same data is in Yinger (2015b). The same type of first stage appears in Epple, Peress, and Sieg (2010), although their second stage is different.

This approach has several advantages. First, the CBG fixed effects ensure that the coefficients of the structural housing traits are not biased due to omitted neighborhood variables. Second, this approach isolates the relationship between neighborhood housing prices and neighborhood traits, including job access, and thereby facilitates the consideration of different time and distance measures and of different estimating assumptions. Third, this approach facilitates optimal usage of both the distance and time variables. A distance variable is used to assign houses to worksites and then to control for within-CBG variation in job access, whereas several different time and distance variables are used to estimate bid-function envelopes at the CBG level. The assignment of houses to worksites must use the distance measure because the time variable does not indicate a location on a map. Moreover, because CBGs are relatively compact and homogeneous, variation in bids within a CBG can be explained with variables from a simple distance-based urban model that does not consider sorting around a given worksite. Variation in bid rents across CBGs cannot be explained, however, without considering sorting and the complexities of the urban transportation system. Using the tools developed in Section 2, these factors can be incorporated into the second-stage equation.

4.2. The Hedonic Regression with Geographic Fixed Effects

The first-stage is a regression of $\ln\{V\}$ on housing traits, within-CBG differences, and CBG fixed effects. This regression includes seventeen housing traits and thirteen distance-based variables to measure the difference in those variables between the location of a house and the centroid of a CBG. Within-CBG differences in job access are not large. Nevertheless, CBGs are

sometimes a few miles across, so the first-stage regressions also control for within-CBG differences in job access, based on DIST3. Each within-CBG access variables is the difference between the house and CBG measures for all the CBGs assigned to a given worksite.¹⁵

The first-stage regression is estimated with the STATA "areg" command. The final sample includes 22,880 observations and the R-squared is 0.7893. The variable indicating that a house has one story is not significant, but all other housing characteristics are significant with the expected sign. Nine of the 13 variables measuring within-CBG variation in neighborhood traits are significant, as is the set of 1,665 geographic fixed effects (p=0.000). The five within-CBG commuting variables are all significant at the 1 percent level. See the online appendix or Yinger (2015b), which uses the same first stage.

4.3. The Bid-Function Envelope

The bid-function envelope is estimated in the second-stage regression using the sample of 1,665 CBGs, the dependent variable is the set of coefficients for the CBG fixed effects, and the explanatory variables include one set of job access terms in Table 1, with an extensive set of public services, amenities, local taxes, and other geographic controls—but without the *X*s. See the online appendix. Further discussion of these variables and results with a nonlinear specification for relative elementary test score, high school test score, percent black, and percent Hispanic and a simpler specification for the commuting variables is provided in Yinger (2015b).

I assume that the price elasticity of demand for housing, η , equals -1.0. This assumption implies that the dependent variable takes a log form, which is the approach in most hedonic studies. Some existing estimates suggest that -1.0 may be too high in absolute value for η . Goodman (1988), for example, estimates $\eta = -0.77$. However, Rapaport (1997) estimates a value of η near -1.0 using a model in which housing demand and location are simultaneously determined. Moreover, Yinger (2015b) is unable to reject the hypothesis that $\eta = -1.0$ for several specifications similar to the ones estimated for this paper.

Each right-side expression in Table 1 is based on a particular value of σ_3 and contains four other parameters: σ_1 , σ_2 , γ , and t_{γ}^m . Estimates of γ and t_{γ}^m are available in the literature, and all the forms in Table 1 become linear when these two parameters are known. As a result, my strategy is to estimate the two parameters that describe the sorting equilibrium, σ_1 and σ_2 , using OLS with a range of values for γ and t taken from previous studies. The errors are clustered at the school district level. I consider 3 assumptions about the hedonic equilibrium (= the three values of σ_3 in Table 1), 2 assumptions about λ (0.3 and 1), and 3 assumptions about γ (0.3, 1, and 1.5).

Small, Winston, and Yan (2005) find a median value of commuting time 7 percent below the median wage rate, which suggests $\lambda \approx 1.0$. Other studies indicate that λ may be closer to 0.5 or even 0.3 (Small 2012), Equation (4) links λ and t_Y^m . When m = v, a constant λ implies a constant t_Y^m . In the case of m = u, however, a constant λ does not imply a constant t_Y^m unless commuting speed, s, is constant, too. I assume that commuting speed equals the average speed in Cleveland in 2000: 20.8 MPH.¹⁶ For distance-based models, this treatment of time costs is most accurate when commuting speed exhibits little variation. Another possibility comes from Abrantes and Wardman (2011), who find that at a given wage, λ is higher for longer trips. Because longer trips tend to be taken at higher speed, $\lambda/(4s)$ might be constant despite variation in s.

In the case of γ , the value of 0.3 comes from Goodman (1988) and Zabel (2004). The value of 1.5 for γ is higher than any estimate in the recent literature, but it is required to consider the case of $\sigma_3 = 2$. Because this case cannot be estimated with other values for γ , the final number of cases is $(2 \times 3 \times 3 - 2 \times 2) = 14$.

5. Empirical Results

a. Job-Access Envelopes

Linear, power, and quadratic job-access envelopes appear in Table 3. The access coefficient for a linear envelope is negative and significant at the 5 percent level in every case except DIST1. As shown in Section 2.2, a linear form can approximate a theoretically derived envelope if $\sigma_3 = \gamma = 1$. These results are consistent with this case. Recall, however, that the coefficient in this case is $(\sigma_1/\sigma_2)(t_Y^m)$, so σ_1, σ_2 , and λ cannot be identified.

Results for the power function envelopes derived by Montesano (1972) and Duranton/Puga (2015) are in the second column. In five of the eight cases, the estimated coefficient is significant and positive as predicted by the Montesano model. We have no way of knowing, however, whether the implied utility weights on land are realistic. These results are also consistent with the Duranton/Puga model, because they imply a positive shape parameter for the Pareto income distribution. However, the implied shape parameters, which range from 0.10 to 0.18, are far smaller than the shape parameters estimated for the two income measures (described in Section 5.2) in the Cleveland data, namely, 0.66 and 1.02.¹⁷

The coefficients for the quadratic form are both statistically significant for DIST1, DIST3, and TIME1. Neither coefficient is significant for the other access measures.¹⁸

Table 4 provides selected estimates of σ_1 and σ_2 using the forms in Table 1. For the access measures DIST1, DIST3, and TIME1, all fourteen cases yield significant coefficients (5 percent level or higher) with the expected signs for σ_1 and σ_2 (positive and negative, respectively). For DIST2 most cases produced a significant coefficient for σ_1 , but not for σ_2 . However, one case resulted in significant coefficients for both parameters and two others resulted in a significant coefficient for σ_1 and a coefficient for σ_2 that is significant at the 10 percent level. Despite its

		T .	T	Quadratic,	Quadratic,			
		Linear	Log	First Term	Second Term			
Distance Measures (in Miles)								
DIST1	Estimated actual commuting distance (straight line)							
	Coefficient	-0.00259	-0.05066	-0.02390	0.00075			
	t-Statistic	(-0.97)	(-1.72)	(-2.39*)	(2.47*)			
DIST2	Straight-line distance	to Terminal To	wer					
	Coefficient	-0.00830	-0.10296	-0.01492	0.00014			
	t-Statistic	(-3.64**)	(-2.17*)	(-1.49)	(0.75)			
DIST3	Employment-weighted	l straight-line d	istance to worl	ksites				
	Coefficient	-0.00946	-0.20813	-0.02919	0.00043			
	t-Statistic	(-4.42**)	(-5.24**)	(-3.34**)	(2.29*)			
DIST4	Straight-line distance	to assigned wor	ksite					
	Coefficient	-0.00449	-0.01195	-0.00624	-0.00002			
	t-Statistic	(-5.53**)	(-1.36)	(-1.41)	(-0.20)			
Time M	easures (in Minutes)							
TIME1	Actual commuting tim	e						
	Coefficient	-0.00307	-0.08781	-0.01462	0.00021			
	t-Statistic	(-2.77**)	(-2.77**)	(-2.28*)	(2.03*)			
TIME2	Estimated straight-line time to Terminal Tower							
	Coefficient	-0.00498	-0.17443	-0.00315	-0.00002			
	t-Statistic	(-2.93**)	(-2.06*)	(-0.62)	(-0.44)			
TIME3	3 Employment-weighted straight-line time to worksites							
	Coefficient	-0.00437	-0.18173	-0.00188	-0.00003			
	t-Statistic	(-5.06**)	(-4.72**)	(-0.44)	(-0.61)			
TIME4	Straight-line time to assigned worksite							
	Coefficient	-0.00094	-0.02033	-0.00069	0.00000			
	t-Statistic	(-2.05*)	(-1.68)	(-0.59)	(-0.25)			

Table 3: Access Envelopes Estimated with Simple Forms

Notes: The dependent variable is the constant plus the CBG fixed-effect from the first-stage regression; 1,665 observations (CBGs); other explanatory variables are the 58 locational traits listed in the online appendix or in Yinger (2015b) ; standard errors are clustered at the school-district level; significance: * = 5%; ** = 1%

	А	ssume	ed				
	V	alue o	of	Estin	Estimated Value of		
Access						R-	
Measure	λ	γ	σ3	σ_1	σ_2	Squared	
DIST3	0.3	0.3	0.5	1083.64	-200.77	0.7016	
				(4.22**)	(-2.27*)		
DIST3	0.3	1.0	1.0	33.66	-4.38	0.7018	
				(6.60**)	(-2.39*)		
DIST3	0.3	1.5	2.0	5.88	-0.48	0.7019	
				(11.20**)	(-2.47*)		
DIST1	1.0	1.0	0.5	298.73	-274.03	0.6967	
				(8.22**)	(-2.76**)		
DIST1	1.0	1.5	1.0	16.55	-10.17	0.6967	
				(13.75**)	(-2.60**)		
DIST1	1.0	1.5	2.0	4.00	-1.40	0.6966	
				(24.03**)	(-2.51*)		
DIST1 (IV)	1.0	1.0	1.0	25.08	-6.04	0.6723	
				(1.98*)	(-1.00)		
TIME1	1.0	0.3	0.5	1207.76	-577.41	0.6963	
				(7.12**)	(-2.15*)		
TIME1	1.0	1.0	1.0	34.93	-10.93	0.6962	
				(12.13**)	(-2.10*)		
TIME1	0.3	1.5	2.0	5.92	-1.09	0.6952	
				(22.17**)	(-2.09*)		
DIST2	0.3	1.0	0.5	-72723.48	-1847.04	0.7004	
				(-34.70**)	(-2.33*)		
DIST4	1.0	1.5	0.5	1932.34	-3591.63	0.6989	
				(2.05*)	(-1.26)		

 Table 4. Illustrative Access Envelopes Estimated with Theoretically Derived Forms

Notes: The dependent variable is the CBG fixed-effect from the first-stage regression; 1,665 observations (CBGs); based on functional forms in Table 1; other explanatory variables are the 58 locational traits listed in the online appendix or in Yinger (2015b) (which measure school quality, ethnic composition, environmental quality, crime rates, and tax rates, among other things, plus county and worksite fixed effects); standard errors are clustered at the school-district level; significance: * = 5%; ** = 1%.

importance in urban models, DIST4 yielded a single significant coefficient: the one for σ_1 with $\sigma_3 = 0.5$, $\lambda = 1$, and $\gamma = 1.5$. The results for TIME2, TIME3, and TIME4 are almost all insignificant and often have an unexpected sign. In fact, the only significant coefficient for these three measures is one estimate of σ_1 using TIME4.

These results support four central conclusions. First, insight into the structural parameters of the urban equilibrium, at least using the forms in this paper, is limited to estimations based on DIST1, DIST3, and TIME1. Second, the significant results for these three measures reveal that access to jobs can have a substantial impact on housing prices. To be specific, the price of housing at the location with the least-valued access compared to the location with the best access is about 12 percent lower for DIST1, 26 percent lower for DIST3, and 34 percent lower for TIME1. Homebuyers clearly care about job access. Third, the access measures with explanatory power all account for the existence of multiple worksites and support the "complements" view of job access, not the "substitutes" view. Fourth, the highly significant, negative estimates for σ_2 for these three measures provide strong support for the hypothesis that household sorting, that is, the allocation of households to locations with different job access, depends on the relative slopes of households' bid functions, which are measured by ψ .

Panel A of Figure 3 compares envelopes for the four distance measures when $\sigma_3 = \lambda = 1$ and $\gamma = 0.3$.¹⁹ Results for other cases are similar. The envelopes for DIST1 and DIST3, which are the only ones based on significant estimates of σ_1 and σ_2 , contain a surprise, namely, that their slope becomes positive at large distances.²⁰ The effect is particularly pronounced for DIST1. In fact, the envelope is higher at the maximum than at the minimum distance. A milder version of this effect also appears for DIST3. In both cases, the turn-up in the envelope affects a small minority of the observations (between 16 and 59 out of 1,665), but this phenomenon, which also



Figure 3. Access Envelopes for Various Access Measures Panel A: Distance Measures with $\lambda = \gamma = \sigma_3 = 1$

Panel B: Distance and Time Measures with $\lambda = \gamma = \sigma_3 = 1$



appears in the quadratic envelopes, obviously needs explaining, and we will consider it below.

The highest explanatory power (= R-squared) is provided by DIST3, but differences across envelope specifications are small and insignificant, Panel A of Figure 4 shows how the results for this measure vary with various assumptions about λ and γ in the case of a linear hedonic equilibrium ($\sigma_3 = 1$). The envelopes in this panel are all similar, but the curvature is somewhat higher with a high income elasticity ($\gamma = 1.5$). In addition, the quadratic envelope is virtually indistinguishable from the theoretically derived envelope with low values for λ and γ . Panel B illustrates the impact of σ_3 on the hedonic in the case of a low value for λ and a high value for γ . The envelope has the highest curvature with $\sigma_3 = 0.5$ and the lowest curvature with σ_3 = 2. The quadratic envelope is similar to the theoretically derived envelope with $\sigma_3 = 1$.

Now consider the puzzle that the envelope turns upward at large distances, particularly for DIST1. The key to understanding this puzzle is a point in Section 2.5, namely, that we are estimating the impact of buyer perceptions on house values. Even if a distance measure accurately captures miles traveled from a house that is for sale to a prospective buyer's actual or anticipated job site, we do not know how the buyer gains information about distance or if the buyer adjusts distance measures to account for commuting speed or, in the case of straight-line measures, for route choices. As shown in equation (4), the difference between $(t_Y^m m)$ in a distance-based model and a time-based model is that a constant commuting speed appears in t_Y^m in the distance-based version whereas varying commuting speed implicitly appears in *m* in the time-based version. This difference arises regardless of which formula in Table 1 is used. When one switches from a distance-based model to a time-based model, therefore, one is adding variation in speed. Now suppose homebuyers "correct" observed distance measures for their perceptions about actual speed. Because speed increases with distance from worksites, this



Panel B. Envelopes with $\lambda = 0.3$ and $\gamma = 1.5$



Figure 4. Access Envelopes for DIST3

correction implies that moving another mile from worksites may increase bids because it is accompanied by an increase in commuting speed. In the case of DIST1, speed equals DIST1/TIME1. A regression of this speed measure on DIST1 indicates that a 10-mile increase in distance leads to a 3.2-MPH increase in speed. The comparable figure for DIST3 is 0.3 MPH. Both estimates are highly significant. In short, the impact of a speed increase may outweigh the impact of a distance increase—causing an upturn in the envelope.

Evidence that this type of correction is at work appears in a comparison of the envelopes for DIST1 and TIME1, which both refer to actual commuting patterns (Panel B of Figure 3). As predicted by the role of speed, the envelope is steeper and the upturn is less pronounced for TIME1 than for DIST1. Further evidence about the cause of this upturn can be obtained by assuming that the distance variables are measured with error because they do not account for variation in speed. One obvious way to address this problem is with instrumental variables connected with a homebuyer's perceptions of commuting speed but without a direct link to house values. One such list contains the population density in a CBG's zip code in 1990, the distance of the CBG from the point with average latitude and longitude in the metropolitan area, the difference between the employment-weighted straight-line and google distances to worksites, and the square of this difference. With these instruments and $\sigma_3 = \gamma = \lambda = 1$, the upward turn in the envelope almost disappears. See Panel B of Figure 3.²¹ This evidence supports the "measurement error" hypothesis, but the estimate of σ_2 has a t-statistic of only -1.0. See Table 4.

Despite these results, the exclusion of speed from distance measures cannot be the full explanation for the turn up, because the TIME1 envelope turns up as well—but only for 55 observations. Another possibility is that homebuyers are willing to pay for reliability, that is, for a lower variance in travel time, and that reliability is higher at greater distances, which involve more freeway travel far from downtown. Evidence that people care about reliability is provided

by Brownstone and Small (2005), Carrion and Levinson (2012), and Li et al. (2010). Yet another possibility comes from the finding that commuters place a higher value on their expected commuting time in congested situations (Small 2012). If homebuyers follow this pattern for their expected commuting time, then a constant value of travel time, which the estimates behind Figure 3 assume, overstates expected commuting costs at more distant, less congested locations. Actual bids are based on perceptions of congestion and how it is valued, so they may exceed bids based on a constant λ in distant locations. These possibilities cannot be investigated with the Cleveland data, but they are excellent topics for future research.

Several additional sets of regressions were conducted to determine the robustness of these results. Separate envelopes were estimated for each worksite. The σ parameters for these envelopes were almost always insignificant. Moreover, neither dropping the worksite dummies nor using a parsimonious set of control variables (as defined in Yinger and Nguyen-Hoang, 2016) led to a substantial change in the estimated job-access envelopes.

5.2. Household Sorting

The significant estimates of σ_2 in Table 4 show that sorting depends on bid-function slopes. The next question is whether and how these slopes depend on household income. Estimates of σ_1 and σ_2 make it possible to calculate the relative slope of a household's bid function, ψ , using equation (12), and hence to estimate equation (9), which provides and answer to this question. This section explores sorting for DIST1, DIST3, and TIME1.

The upturn in the estimated access envelopes poses a theoretical and an empirical challenge for a sorting analysis. The theoretical challenge is that with the formulations in this paper a positive slope for the envelope requires a negative value for ψ . This requirement can be satisfied by assuming that the *t* term in (13) is negative, which implies that something, such as

increased travel-time reliability, leads people to place a higher value on longer commutes under some circumstances. When *t* switches from positive to negative at the minimum of the access envelope, the logic of sorting changes, too. Outside this minimum point, normal sorting arises if households' now upward-sloping bid functions become steeper as income increases. It follows that normal sorting will arise in these locations if a higher income leads to a steeper bid function, that is, if the coefficient on the income term, $(\chi - \gamma)$, is positive.

The empirical challenge is that sorting may differ for job access above and below the level at the access-envelope minimum (AEM). I address this challenge in two ways. First, I drop the (few) observations with access below this level when estimating my main models. Second, I divide job access into two regions (above and below access at the AEM) and estimate an endogenous switching model in which people select one of these regions. This model estimates the traits that sort a household into the region with access below access at the AEM and the traits that determine ψ in each region.

Estimating (9) requires data on homebuyers' traits, especially their income. This paper makes use of two data sets for these traits. The first is the Home Mortgage Disclosure Act (HMDA) loan file for the Cleveland area in 2000. The HMDA data have the great advantage for our purposes that they describe the traits of actual homebuyers, that is, of the households who made the purchases in the Cleveland data set. Moreover, this data set identifies the tract in which the sale took place, so it is possible to observe the average income of actual buyers in each tract. This data set also includes the sex, race, and ethnicity of the borrower and co-borrower, and whether the borrower took out a Veterans' Administration or Federal Housing Authority loan. It is therefore possible to measure, for example, the probability that a home buyer in a given tract is African American. The disadvantages of this data set are that it does not include all home

purchases, cannot be linked to Census blocks, and only describes a few household traits.²²

The second data set comes from the U.S. Census, which provides household traits at the block-group level.²³ These data can be used to estimate (9) under the assumption that households buying homes in a CBG in 2000 have traits that are similar to those of the households who already live in that CBG. This data set has information on many household traits, including the average age and education of household heads, the share of households who are recent movers, and whether the household speaks English as a second language. These are the traits of all households, however, not of recent homebuyers. The correlation between the HMDA and Census income measures is 0.56 (or 0.59 for their logs).

I estimate two versions of equation (9) for each parameter set, one with HMDA income plus the available homebuyer characteristics in the HMDA data and one with Census income and selected household characteristics at the block-group level. The sample for each regression is the set of observations inside the AEM. Each regression yields an estimate of the income coefficient, $(\chi - \gamma)$, which provides a test for normal sorting. Overall, fourteen cases are estimated for three access measures (DIST1, DIST3, and TIME1) and two income variables (HMDA and Census). Examples of these results appear in Table 5.²⁴

The results support normal sorting for every access/income combination except one. All 14 cases indicate normal sorting (i.e., a negative, significant coefficient for the income variable) using Census income and any of the three access measures or using HMDA income and DIST1. These results for DIST1 also hold for the IV regression in Figure 3. The results using HMDA income and TIME1 provide somewhat weaker support for normal sorting; all 14 coefficients are negative, 4 are significant at the 5 percent level, and 10 are significant at the 10 percent level. The one exception arises with HMDA income and DIST3, where all the coefficients are positive

				Incom	e Coefficient	for:		
Data Source	λ	γ	σ3	DIST1	DIST3	TIME1		
Regressions for Downward-Sloping Portions of Envelope								
HMDA	1.0	0.3	0.5	-0.0893	0.0351	-0.0484		
				(-3.45**)	(1.48)	(-1.71)		
HMDA	0.3	0.3	1.0	-0.1035	0.0075	-0.0614		
				(-5.76**)	(0.28)	(-2.05*)		
HMDA	1.0	1.0	1.0	-0.1006	0.0159	-0.0544		
				(-4.62**)	(0.55)	(-1.85)		
HMDA (IV)	1.0	1.0	1.0	-0.0760				
				(-4.11**)				
Census	1.0	0.3	0.5	-0.1962	-0.1961	-0.1709		
				(-5.57**)	(-3.88**)	(-2.37*)		
Census	0.3	0.3	1.0	-0.2620	-0.2609	-0.1882		
				(-6.41**)	(-4.35**)	(-2.58**)		
Census	1.0	1.0	1.0	-0.2786	-0.2953	-0.1858		
				(-5.93**)	(-4.67**)	(-2.49*)		
Census (IV)	1.0	1.0	1.0	-0.1267				
				(-5.98**)				
Endogenous Switching Regressions for Entire Envelope								
HMDA	0.3	0.3	1.0	_				
Downward Slope				-0.0986				
				(-5.54**)				
Upward Slope				-6.3477				
				(-4.67**)				
HMDA	0.3	0.3	1.0					
Downward Slope						-0.0757		
-						(-2.56*)		
Upward Slope						1.0317		
						(2.37*)		

Table 5: Illustrative Normal Sorting Tests

Notes: The dependent variable is an estimate of ψ using equation (12); there are between 1,606 and 1,649 observations for the first panel and 1,665 for the second. HMDA regressions include the probability that a loan applicant is black, Hispanic, a single male, a single female, part of a male couple, part of a female couple, a recipient of an FHA loan, or a recipient of a VA loan; HMDA regressions also identify observations filled in with loan amount or Census income. Census regressions also include CBG household shares that are over 65, have kids, are married, speak English as a second language, are Asian, moved in the last year, graduated from high school, have some college, have a BA degree, and have an advanced degree. Switching regressions are identified by various CBG traits. Illustrative full regression results are in the online appendix. Significance: * = 5%; ** = 1%.

but small and insignificant, indicating no sorting based on income.

Table 5 also includes results for selected endogenous switching models. The model for DIST1 with $\lambda = \gamma = 0.3$ and $\sigma_3 = 1$ and with HMDA income supports the conclusion from the simpler models that sorting is "normal" when the job-access envelope has a negative slope. In contrast, the switching model indicates that sorting is reversed when the envelope's slope turns positive at locations with poor job access. These results suggest that high-income households are drawn to the locations where the AEM for DIST1 occurs. These results also arise for a variety of endogenous switching model for TIME1 and HMDA income. Table 5 also presents results from an endogenous switching model for TIME1 and HMDA income. In this case, normal sorting arises both inside and outside of the access-envelope minimum. This result holds for a variety of specifications for the endogenous switching model with HMDA income. Presumably because of the limited number of observations above the AEM, models with TIME1 and Census income or with DIST3 and either income measure do not converge.

6. Conclusions

The core of urban economics is the impact of commuting costs on housing prices—and the associated household sorting. This paper estimates the first bid-function envelopes (i.e. hedonics) explicitly derived from job-access bid functions for heterogeneous households. The results shed light on many features of urban residential structure.

A linear specification for a job-access envelope yields a significant coefficient for the access variable with seven of the eight access measures considered in this paper. Despite its widespread use in the literature, however, this specification cannot identify transportation costs because the coefficient of the access variable includes parameters of the hedonic equilibrium. A log specification yields a significant coefficient for the access variable in five of the eight cases.

This specification also cannot provide any information about transportation costs, and there is no way to determine whether it identifies the utility coefficient in Montesano (1972; which assumes no operating costs) or the income distribution parameter in Duranton and Puga (2015; which assumes no time costs). Moreover, neither of these specifications accurately approximates the shape of the envelope estimated with a more general specification.

Both terms in a quadratic specification of the access variable are significant for three access measures (DIST1, DIST3, and TIME1). This form cannot identify structural parameters, but it provides a close approximation to the shape of the theoretically derived access envelope, especially in the case of a linear hedonic equilibrium ($\sigma_3 = 1$).

Three job-access measures yield significant estimates of the structural parameters σ_1 and σ_2 using the forms in this paper: DIST1, DIST3, and TIME1. These results imply that minimal job access can lower the price of housing in a neighborhood by as much as 12 to 34 percent, depending on the access measure. These three measures all account for multiple job sites and are consistent with the "complements" view of job access. The two forms most closely related to urban models, DIST2 and DIST4, do not yield significant estimates on a consistent basis.

The theorem that household sorting across locations with different job access depends on bid-function slopes is fundamental to urban economics. The significant estimates of σ_2 for DIST1, DIST3, and TIME1 provide the first direct confirmation of this theorem.

The shape of the job-access envelope is similar for different assumptions about the value of time (λ) and income elasticity (γ) parameters within the range in the literature. It is also similar for different forms for the hedonic equilibrium, that is, for different values of σ_3 .

The shape of the envelope is different, however, for different measures of access. To some degree, the large difference between the envelopes for DIST1 and TIME1 appears to

reflect the (probably inaccurate) assumption of a constant commuting speed in the DIST1 formulation. Introducing instruments that account for factors that might influence expected commuting speed dramatically lowers the difference between the DIST1 and TIME1 envelopes.

Even after accounting for the potential measurement error in DIST1, however, the envelopes for DIST1, DIST3 and TIME1 all exhibit an unexpected upward slope when access is near its minimum. This turn-up affects only a few observations, but it is not consistent with the standard assumptions about job access. This result is consistent, however, with the possibility that some feature of commuting that households value, such as low variance in trip time, increases so much as access declines in these low-access locations that it more than offsets the loss of access itself. Further investigation of this phenomenon clearly is warranted.

All three measures with significant envelope parameters (DIST1, DIST3 and TIME1) have approximately equal explanatory power. One challenge for future research is to determine why these relatively uncorrelated measures of access can each lead to a statistically significant access envelope.²⁵ Another promising topic is whether the widespread availability of mapping software boosts the explanatory power of access measures that account for the street network.

Finally, the estimated bid functions almost always indicate normal sorting, defined as an equilibrium in which higher-income households live in locations with poorer job access. One important exception arises with the DIST3 access measure using the HMDA income measure. Yet another challenge for future research is to determine why normal sorting arises with some access measures but not with others.

References

- Abrantes, Pedro A.L., and Mark R. Wardman. 2011. "Meta-analysis of UK Values of Travel Time: An Update." *Transportation Research Part A* 45 (1) (January): 1–17
- Alonso, William. 1964. Location and Land Use. Cambridge, MA: Harvard University Press.
- Anas, Alex, Richard Arnott, and Kenneth A. Small. 1998. "Urban Spatial Structure." *Journal of Economic Literature* 36 (3) (September): 1426-1464.
- Anas, Alex, and Leon N. Moses. 1979. "Mode Choice, Transport Structure and Urban Land Use." *Journal of Urban Economics* 6 (2): 228–246.
- Arnott, Richard, Tilmann Rave and Ronnie Schöb. 2005. *Alleviating Urban Traffic Congestion*. Cambridge, MA: MIT Press.
- Bayer, Patrick, Fernando Ferreira, Robert McMillan. 2007. "A Unified Framework for Measuring
 Preferences for Schools and Neighborhoods." *Journal of Political Economy* 115 (4) (August): 558-638.
- Baum-Snow, Nathaniel. 2007. "Suburbanization and Transportation in the Monocentric Model." *Journal of Urban Economics* 62 (November): 405-423.
- Becker, Gary S. 1965. "A Theory of the Allocation of Time." *The Economic Journal* 75 (299) (September): 493-517.
- Beckman, M. J. 1969. "On the Distribution of Urban Rent and Residential Density." *Journal of Economic Theory* 1 (1) (June): 60-67.
- Bender, B. and H. Hwang. 1985. "Hedonic House Price Indices and Secondary Employment Centers." *Journal of Urban Economics* 17 (1): 90-107.
- Blackley, Dixie M., and James R. Follain. 1987. "Tests of Locational Equilibrium in the Standard Urban Model." *Land Economics* 63 (1) (February): 46-61.

Brasington, David M. 2007. "Private Schools and the Willingness to Pay for Public Schooling."

Education Finance and Policy 2 (2) (Spring): 152-174.

- Brasington, David M. and Donald R. Haurin. 2006. "Educational Outcomes and House Values: A Test of the Value-Added Approach." *Journal of Regional Science* 46 (2) (May): 245-268.
- Brownstone, David and Kenneth A. Small. 2005. "Valuing Time and Reliability: Assessing the
 Evidence from Road Pricing Demonstrations." *Transportation Research Part A: Policy and Practice*39 (4) (May): 279–293.
- Brueckner, Jan K., Jacques-Francois Thisse, and Yves Zenou. 1999. "Why Is Central Paris Rich and Downtown Detroit Poor? An Amenity-based Theory." *European Economic Review* 43 (1) (January): 91-107.
- Carrion, Carlos, and David Levinson. 2012. "Value of Travel Time Reliability: A Review of Current Evidence." *Transportation Research Part A: Policy and Practice* 46 (4) (May): 720-741

Center for Neighborhood Technology. Undated. "Cleveland OH CMSA." Chp-pub-hl06-cleveland.pdf.

- Coulson, N. Edward 1991. "Really Useful Tests of the Monocentric Model." *Land Economics* 63 (3) (August): 299-307.
- DeSalvo, Joseph S. 1985. "A Model of Urban Household Behavior with Leisure Choice." *Journal of Regional Science* 25 (2) (May): 159 174.
- Diamond, Douglas B., Jr. 1980. "Income and Residential Location: Muth Revisited." *Urban Studies* 17: 1-12.
- Diaz, Carlos, and John Yinger. 2018. "Perceptions of Commuting Costs." Working Paper, Syracuse University, August.
- Duranton, Gilles, and Diego Puga. 2015. "Urban Land Use," In *Handbook of Regional and Urban Economics*, Volume 5A, edited by G. Duranton, J.V. Henderson, and W. Strange (North-Holland): 467-560.

- Epple Dennis, Michael Peress, and Holger Sieg. 2010. "Identification and Semiparametric Estimation of Equilibrium Models of Local Jurisdictions." *American Economic Journal: Microeconomics* 2 (4): 195-220.
- Goodman, Allen C. 1988. "An Econometric Model of housing Price, Permanent Income, Tenure Choice, and Housing Demand." *Journal of Urban Economics* 23 (3) (May): 327-353.
- Goodspeed, Timothy J. 1989. "A Re-examination of the Use of Ability to Pay Taxes by Local Governments," *Journal of Public Economics* 38 (3): 319-342.
- Glaeser, Edward L., Matthew E. Kahn, and Jordan Rappaport. 2008. "Why Do the Poor Live in Cities? The Role of Public Transportation." *Journal of Urban Economics* 63 (1) (January): 1–24.
- Grant, A. 2014. Traffic Congestion Easing across Northeast Ohio." Cleveland.com. Advance Digital, 12 Aug. 2014. Web. 11 Oct. 2016.
- Guerrieri, Veronica, Daniel Hartley, and Erik Hurst. 2013. "Endogenous Gentrification and Housing Price Dynamics." *Journal of Public Economics* 100 (April): 45-60.
- Hartwick, P.G. and J.M. Hartwick. 1972. "An Analysis of an Urban Thoroughfare." *Environment and Planning A* 4: 193–204.
- Hartwick, John, U. Schweizer, and P. Varaiya. 1976. "Comparative Statics of a Residential Economy with Several Classes." *Journal of Economic Theory* 13 (3): 396-413.
- Heikkila, E., P. Gordon, J. I. Kim, R. B. Peiser, H. W. Richardson, and D. Dale-Johnson. 1989. "What Happened to the CBD-Distance Gradient?: Land Values in a Policentric City." *Environment and Planning A* 21 (2): 221-232.
- Kim, Kyung-Hwan and John F. McDonald. 1987. "Sufficient Conditions for Negative Exponential Densities: A Further Analysis." *Journal of Regional Science* 27 (2) (May): 295-298.
- LaFrance, Jeffrey T. 1986. "The Structure of Constant Elasticity Demand Models." *American Journal of Agricultural Economics* (August): 543-552.

- LeRoy, S, and Jon Sonstelie. 1983. "Paradise Lost and Regained: Transportation Innovation, Income and Residential Location." *Journal of Urban Economics* 13 (1) (January): 67–89.
- Li, Zheng, David A. Hensher, and John M. Rose. 2010. "Willingness to Pay for Travel Time Reliability in Passenger Transport: A Review and Some New Empirical Evidence." *Transportation Research Part E: Logistics and Transportation Review* 46 (3) (May): 384–403
- McMillen, Daniel P. and Stefani C. Smith. 2003. "The Number of Subcenters in Large Urban Areas." Journal of Urban Economics 53: 321–338
- Mills, Edwin S. 1967. "An Aggregative Model of Resource Allocation in a Metropolitan Area." *The American Economic Review* 57 (2) (May): 197-210.
- Mills, Edwin S. 1972. *Studies in the Structure of the Urban Economy*. Baltimore: The Johns Hopkins University Press.
- Miyao, Takahiro. 1975. "Dynamics and Comparative Statics in the Theory of Residential Location," *Journal of Economic Theory* 11: 133-146.
- Montesano, Aldo. 1972. "A Restatement of Beckman's Model on the Distribution of Urban Rent and Residential Density." *Journal of Economic Theory* 4 (2) (April): 329-354.
- Muth, Richard F. 1969. *Cities and Housing: The Spatial Pattern of Urban Residential Land Use*. Chicago: University of Chicago Press.
- Nguyen-Hoang, Phuong, and John Yinger. 2011. "The Capitalization of School Quality into House Values: A Review." *Journal of Housing Economics* 20 (1) (March): 30-48.
- Ottensmann, John R., Seth Payton, and Joyce Man. 2008. "Urban Location and Housing Prices within a Hedonic Model." *Journal of Regional Analysis and Policy* 38 (1):19-35.
- Peer, Stefanie, Jasper Knockaert, Paul Koster, and Erik T. Verhoef. 2014. "Over-reporting vs. Overreacting: Commuters' Perceptions of Travel Times." *Transportation Research Part A* 69: 476-494.

- Polinsky, A.Mitchell and Steven Shavell. 1976. "Amenities and Property Values in a Model of an Urban Area." *Journal of Public Economics* 50 (1-2) (January/February): 119-129.
- Pogodzinski, J.M. and D.L. Sjoquist. 1993. "Alternative Tax Regimes in a Local Public Good Model." Journal of Public Economics 50 (1): 115-141.
- Rapaport, Carol. 1997. "Housing Demand and Community Choice: An Empirical Analysis," *Journal of Urban Economics* 42 (2) (September): 243–260.
- Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *The Journal of Political Economy* 82 (1) (January/February): 34-55.
- Ross, Stephen L., and John Yinger. 2000. "Timing Equilibria in an Urban Model with Congestion." 2000. *Journal of Urban Economics* 47 (3) (May): 390-413.
- Ross, Stephen L., and John Yinger. 1999. "Sorting and Voting: A Review of the Literature on Urban Public Finance." In *Handbook of Urban and Regional Economics, Volume 3, Applied Urban Economics*, edited by P. Cheshire and E. S. Mills (North-Holland): 2001-2060.
- Sieg, Holger, V. Kerry Smith, H. Spencer Banzhaf, and Randy Walsh. 2002. "Interjurisdictional Housing Prices in Locational Equilibrium." *Journal of Urban Economics* 52 (1) (July): 131-153.
- Small, Kenneth A. 2012. "Valuation of Travel Time." *Economics of Transportation* 1 (1–2) (December): 2-14.
- Small, Kenneth A. Clifford Winston, and Jia Yan. 2005. "Uncovering the Distribution of Motorists"Preferences for Travel Time and Reliability." *Econometrica* 73 (4): 1367-1382.
- Solow, Robert M. 1973. "Congestion and the Use of Land for Streets." *Bell Journal of Economics and Management Science* 4 (2) (Autumn): 602-618.
- Solow, Robert M. 1972. "Congestion, Density, and the Use of Land in Transportation." *Swedish Journal of Economics* 74 (1) (March): 161-173.

- Taylor, Laura O. 2008. "Theoretical Foundations and Empirical Developments in Hedonic Modeling." In *Hedonic Methods in Housing Markets: Pricing Environmental Amenities and Segregation*, edited by A. Baranzini, J. Ramirez, C. Schaerer, and P. Thalmann (Springer): 15-54.
- Thaler, R. H. 1999. "Mental Accounting Matters." *Journal of Behavioral Decision Making* 12 (3): 183–206.
- U.S. Department of Transportation, Bureau of Transportation Statistics. 2016. "Table 3-14: Average Cost of Owning and Operating an Automobile." Available at: <u>https://www.bts.gov/content/average-cost-owning-and-operating-automobile</u>.
- Van Ommeren, Jos, and Joyce Dargay. 2006. "The Optimal Choice of Commuting Speed:
 Consequences for Commuting Time, Distance and Costs." *Journal of Transport Economics and Policy* 40, Part 2 (May): 279-296.
- Waddell, Paul, Brian J. L. Berry, and Irving Hoch. 1993. "Residential Property Values in a Multinodal Urban Area: New Evidence on the Implicit Price of Location." *The Journal of Real Estate Finance* and Economics 7 (2) (September): 117-141.
- Wheaton, William C. 1977a. "A Bid-Rent Approach to Housing Demand." *Journal of Urban Economics* 4 (2) (April): 200-217.
- Wheaton, William C. 1977b. "Income and Urban Residence: An Analysis of Consumer Demand for Location." *American Economic Review* 67 (4) (September): 620-631.
- White, Michelle J. 1988. "Location Choice and Commuting Behavior in Cities with Decentralized Employment." *Journal of Urban Economics* 24 (2) (September): 129-152.
- White, Michelle J. 1976. "Firm Suburbanization and Urban Subcenters." *Journal of Urban Economics* 3 (4) (October): 383-396.
- Wieand, Kenneth F. 1987. "An Extension of the Monocentric Urban Spatial Equilibrium Model to a

Multicenter Setting: The Case of the Two-center City." *Journal of Urban Economics* 21 (3) (May): 323-343.

- Yinger, John. 2015a. "Hedonic Equilibria in Housing Markets: The Case of One-to-One Matching." Journal of Housing Economics 29 (September): 1-11.
- Yinger, John. 2015b. "Hedonic Markets and Sorting Equilibria: Bid-Function Envelopes for Public Services and Neighborhood Amenities." *Journal of Urban Economics* 86 (March): 9-25.
- Yinger, John. 1993a. "Around the Block: Urban Models with a Street Grid." *Journal of Urban Economics*, 33 (3) (May): 305-330.
- Yinger, John. 1993b. "Bumper to Bumper: A New Approach to Congestion in an Urban Model." Journal of Urban Economics 34 (2) (September): 249-274.
- Yinger, John. 1992. "City and Suburb: Urban Models with More than One Employment Center." *Journal of Urban Economics*, 31(2) (March): 181-205.
- Yinger, John. 1979. "Estimating the Relationship between Location and the Price of Housing." *Journal of Regional Science*, 19 (3) (August): 271-286.
- Yinger, John. 1976. "Racial Prejudice and Racial Residential Segregation in an Urban Model." *Journal of Urban Economics* 3(4) (October): 383-396.
- Yinger, John, and Phuong Nguyen-Hoang. 2016. "Hedonic Vices: Fixing Inferences about Willingness to Pay in Recent House-Value Studies." *Journal of Benefit-Cost Analysis* 7 (2) (Summer): 248-291.
- Zabel, Jeffrey A. 2004. "The Demand for Housing Services." *Journal of Housing Economics* 13 (1) (March): 16-35.

Endnotes

¹ Alonso (1964, p. 134) suggests something similar, namely to "measure time and cost to each location, and to have bid price be a function of both these variables."

² This point can be interpreted as an application of the notion of "framing" from behavioral economics (Thaler 1999). If households classify items into different "mental accounts," then commuting costs may appear in the "transportation" mental account and have no impact on decisions about H.

³ These points were introduced by Alonso (1964, ch. 5).

⁴ With homogeneous households, equation (12) is the market price function. If $\eta = 0$, this function

approximates a semi-log, but the coefficient of m is $[(1-\gamma) t^m]$, so t^m is still not identified.

⁵ Arnott, Rave, and Schöb (2005) and others explore traffic congestion outside an urban model.

⁶ Graphs (but not formal models) of these and similar cases can be found in Alonso (1964),

⁷ McMillen and Smith (2003) and Yinger (2015b) discuss methods to identify worksites.

⁸ Anas et al. (1998) acknowledge the first assumption but say "We are not aware of any empirical support for this form, however, and it is rarely used in applied work" (p. 1441).

⁹ Distance along streets is measured using a mapping program. This distance applies to 2013 but no significant new highways were built in Cleveland between 2000 and 2013 (Grant 2014).

¹⁰ This paper does not include neighborhood income because, thanks to sorting, it is highly correlated with individual income, which does not belong in an envelope. See Yinger (2015b).

¹¹ Alternative approaches to amenity bids and envelopes can be found in Epple, Peress, and Sieg (2010) and Bayer, Ferreira, and McMillan (2007).

¹² Several school districts in the Cleveland area have an income tax, usually with a 1 percent rate.

Goodspeed (1989) and Pogodzinski and Sjoquist (1993) model the capitalization of such taxes.

¹³ Sieg et al. (2002) discuss the conditions under which this specification, which is a price index

multiplied by a quantity index, is "consistent with locational equilibrium models" (p. 139).

¹⁴ A few CBGs are split because they are divided by a school district boundary.

¹⁵ Diaz and Yinger (2018) find that the CBG fixed effects based on regressions with different distance measures are almost perfectly correlated. The focus on DIST3 is not consequential.

¹⁶ Based on Center for Neighborhood Technology (Undated), I use a speed of 20.8 in all distance regressions. Although this document is undated it presents statistics from the 2000 Census.

¹⁷ These parameters were estimated by creating a histogram for each income measure in STATA, collecting the shares and midpoints, and regressing the log of the shares on the log of the midpoints. The shape parameter is the negative of the midpoint coefficient minus one.

¹⁸ Adding 1/m to a quadratic yields an approximation to the second form in Table 1 ($\sigma_3 = 0.5$ and

 $\gamma = 1$). This approach (not shown) does not yield a significant σ_1 or σ_2 for any access measure.

¹⁹ These envelopes are anchored at their minimum and adjusted to have the same starting price.

²⁰ Equation (13) implies a positive slope whenever $\sigma_2 < 0$ and $m > \sigma_1$.

²¹ The first-stage Cragg-Donald Wald F-statistic is 12.7. The associated Stock-Yugo weak ID test critical value for a 15 percent maximal IV size is 9.93 and for a 5 percent IV relative bias is 11.04. The Hanson J statistic is 0.518, which has a Chi-squared P-value of 0.7718.

²² HMDA data are not available for 335 of the 1,665 observations. The HMDA income variable and race/ethnicity variables were filled in with the Census data for these observations, and the HMDA regressions include a dummy for this fill-in. A few observations included all HMDA variables except income; for these 19 observations income was filled in using the loan amount.

²³ Median owner income is in my data set only at the tract level. I estimate median owner income as a function of other tract-level traits that are also observed at the block-group level and then use the estimated coefficients to predict median owner income at the block-group level.

²⁴ CBG race and ethnicity are neighborhood amenities in the first-stage regression (Appendix Table B1), so it is not appropriate to include them in a bid-function regression based on Census income.

²⁵ Diaz and Yinger (2018) find that the principal component for variation in all distance (time) measures does not have as much explanatory power as DIST1 or DIST3 (TIME1).