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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

$$\begin{array}{ll} \text{Maximize} & U\{Z,H\} \\ \text{Subject to} & Y = Z + P\{u\}H + T\{u\} \ . \end{array} \tag{1}$$

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>m</u>iles or <u>m</u>inutes!) then

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

where

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

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

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

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

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

Applying Roy's identity yields equation (5).

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

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

The solution is

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

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.

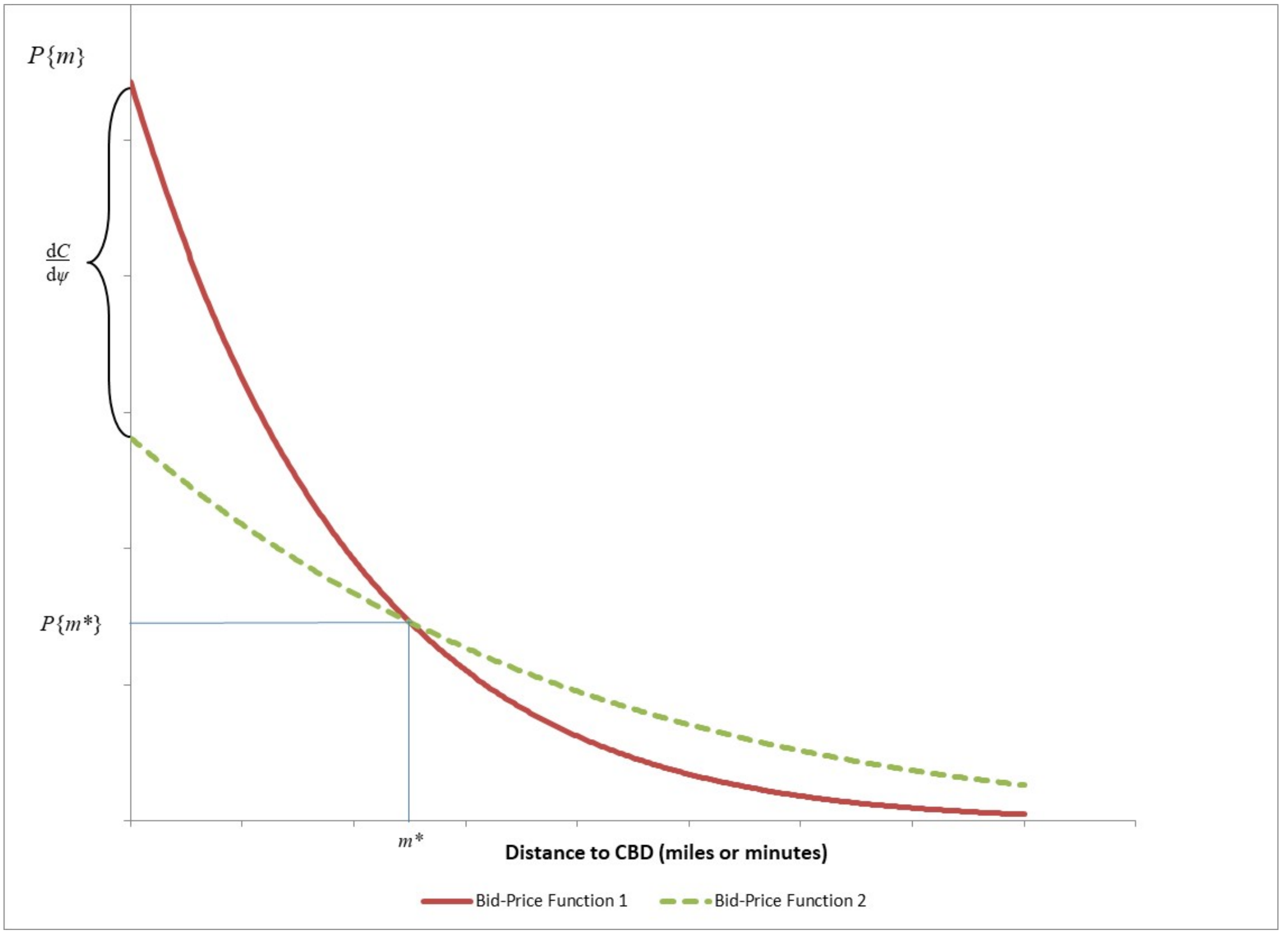
b. Deriving the Bid-Function Envelope

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:

$$\alpha = \alpha^* M^\rho \varepsilon^\zeta \ , \tag{10}$$

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:

$$m = \sigma_1 + \sigma_2 \psi , \tag{12}$$

where the σs 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:

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

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

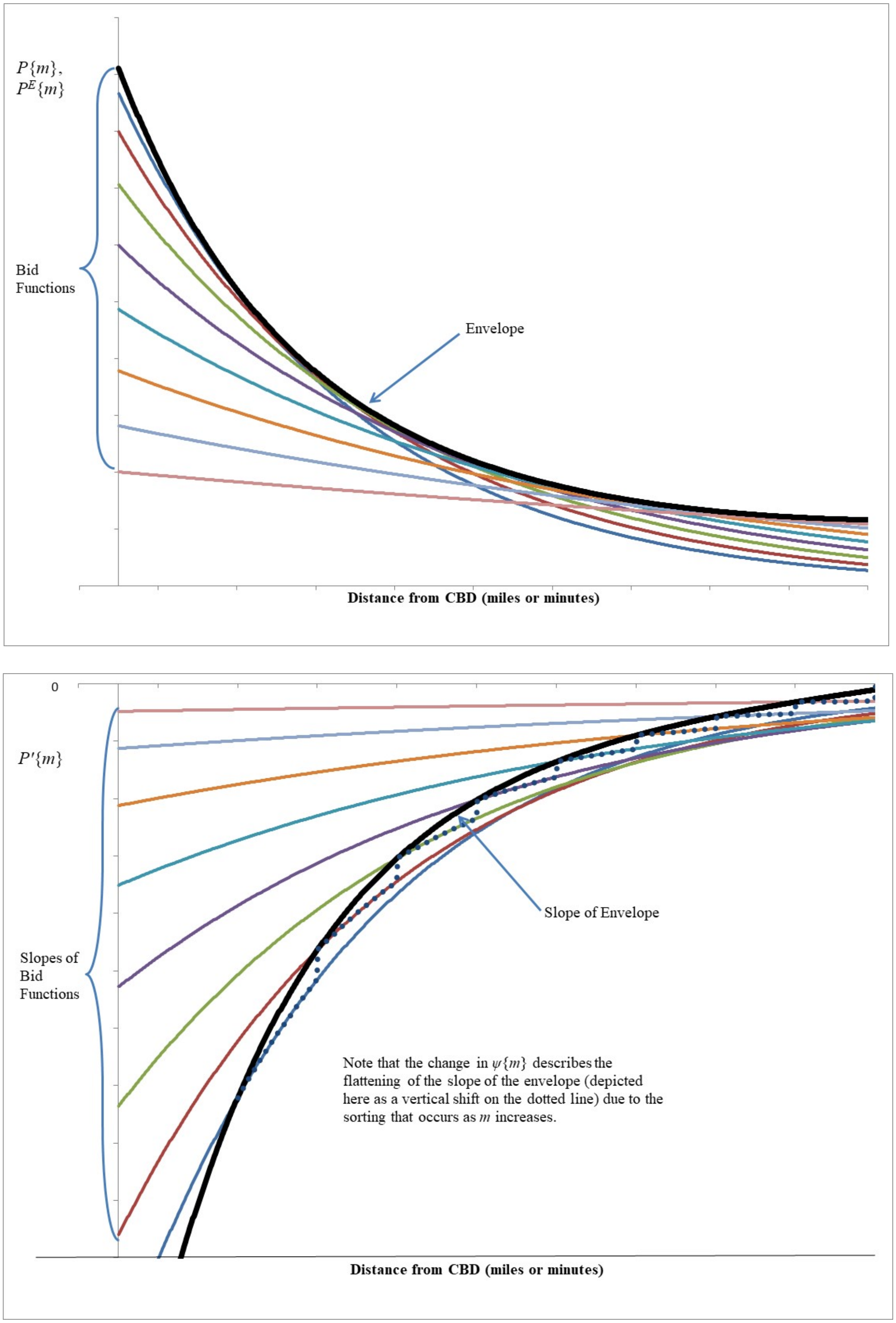
$$\left(P^E\{m\}\right)^{(1+\eta)} = C_0' + \left(\frac{1}{\sigma_2}\right)\left(\left(\frac{1}{1-\gamma}\right)\left(m\left(1-t_Y^m m\right)^{1-\gamma} + \frac{\left(1-t_Y^m m\right)^{2-\gamma}}{t_Y^m(2-\gamma)}\right)\right) - \left(\frac{\sigma_1}{\sigma_2}\right)\left(\frac{\left(1-t_Y^m m\right)^{1-\gamma}}{1-\gamma}\right), \tag{14}$$

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



Note that the change in $\psi\{m\}$ describes the flattening of the slope of the envelope (depicted here as a vertical shift on the dotted line) due to the sorting that occurs as m increases.

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

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

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_Y^m is the time cost of commuting (as a share of the wage rate). The σs, 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

Table 3: Access Envelopes Estimated with Simple Forms

		Linear	Log	Quadratic, First Term	Quadratic, 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 Tower				
	Coefficient	-0.00830	-0.10296	-0.01492	0.00014
	t-Statistic	(-3.64**)	(-2.17*)	(-1.49)	(0.75)
DIST3	Employment-weighted straight-line distance to worksites				
	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 worksite				
	Coefficient	-0.00449	-0.01195	-0.00624	-0.00002
	t-Statistic	(-5.53**)	(-1.36)	(-1.41)	(-0.20)
Time Measures (in Minutes)					
TIME1	Actual commuting time				
	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	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)

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%

Table 4. Illustrative Access Envelopes Estimated with Theoretically Derived Forms

	Assumed Value of			Estimated Value of		
Access Measure	λ	γ	σ_3	σ_1	σ_2	R-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)	

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%.

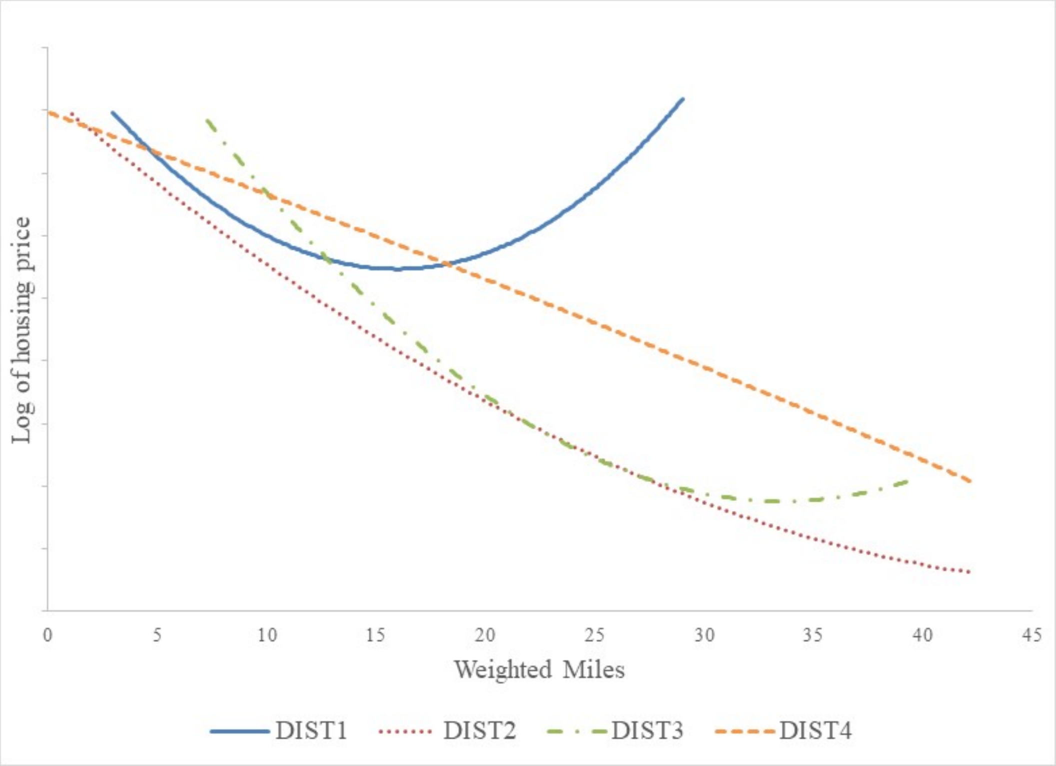
importance in urban models, DIST4 yielded a single significant coefficient: the one for σ_1 with $\sigma_3 = 0.5$, $\lambda = 1$, and $\gamma = 1.5$. The results for TIME2, TIME3, and TIME4 are almost all insignificant and often have an unexpected sign. In fact, the only significant coefficient for these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

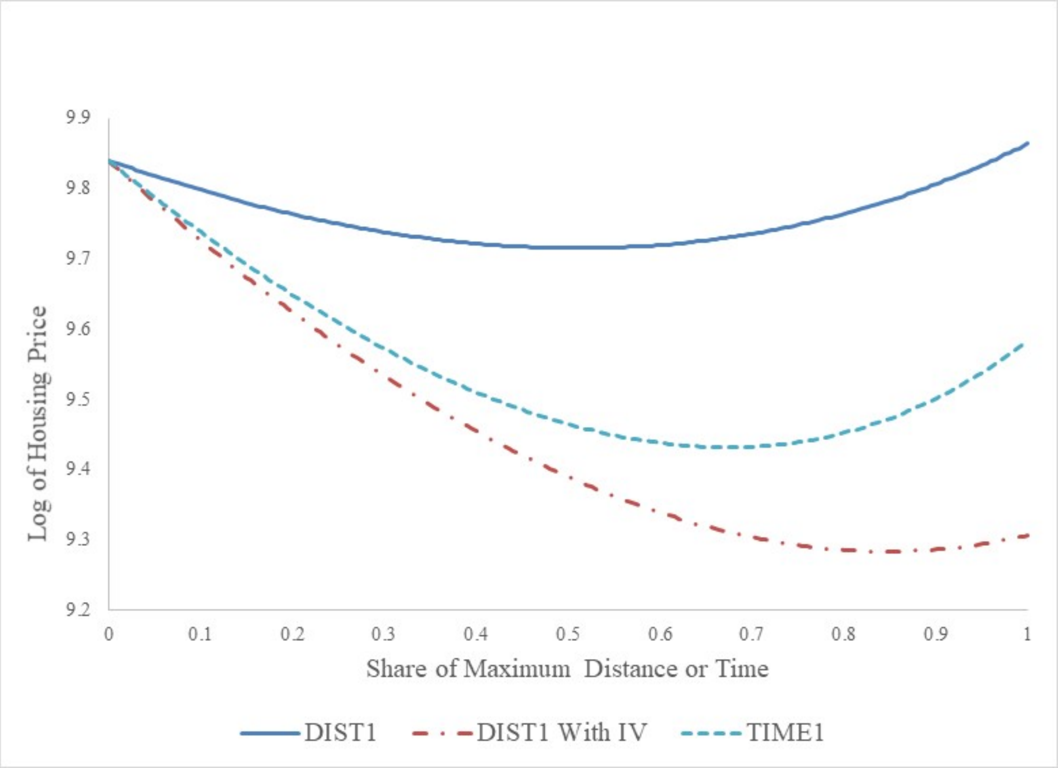
Panel A of Figure 3 compares envelopes for the four distance measures when $\sigma_3 = \lambda = 1$ and $\gamma = 0.3$.[19] Results for other cases are similar. The envelopes for DIST1 and DIST3, which are the only ones based on significant estimates of σ_1 and σ_2, contain a surprise, namely, that their 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 $\lambda = \gamma = \sigma_3 = 1$



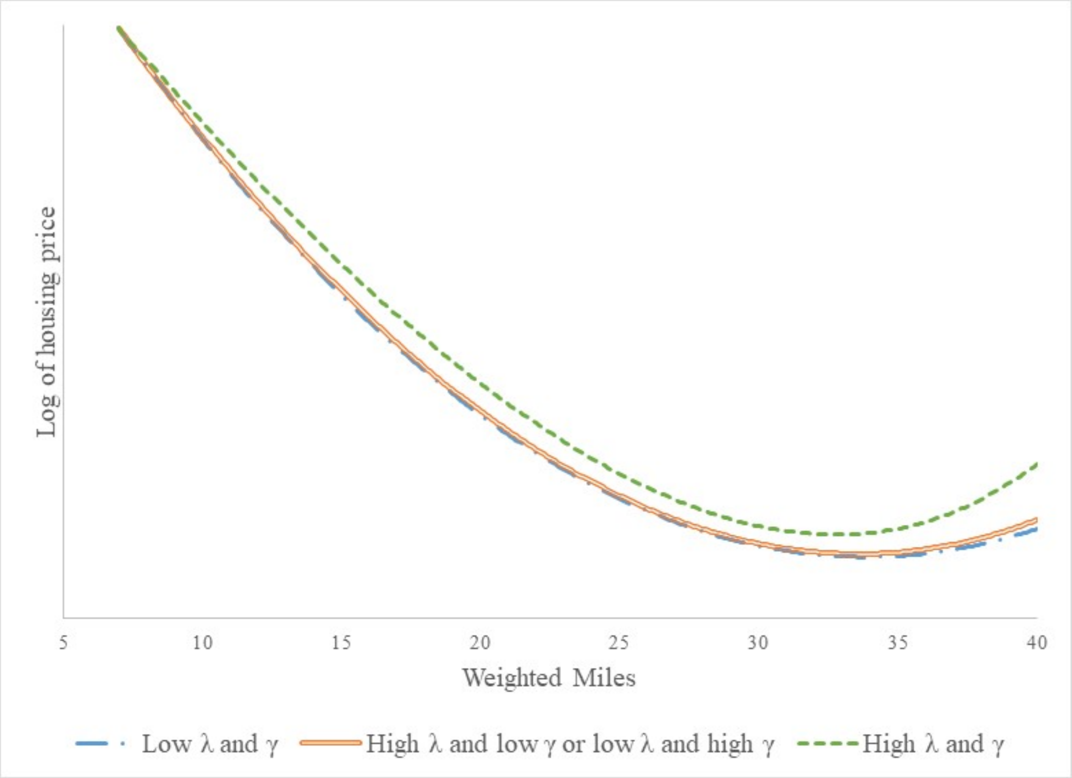
appears in the quadratic envelopes, obviously needs explaining, and we will consider it below.

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 $\sigma_3 = 2$. The quadratic envelope is similar to the theoretically derived envelope with $\sigma_3 = 1$.

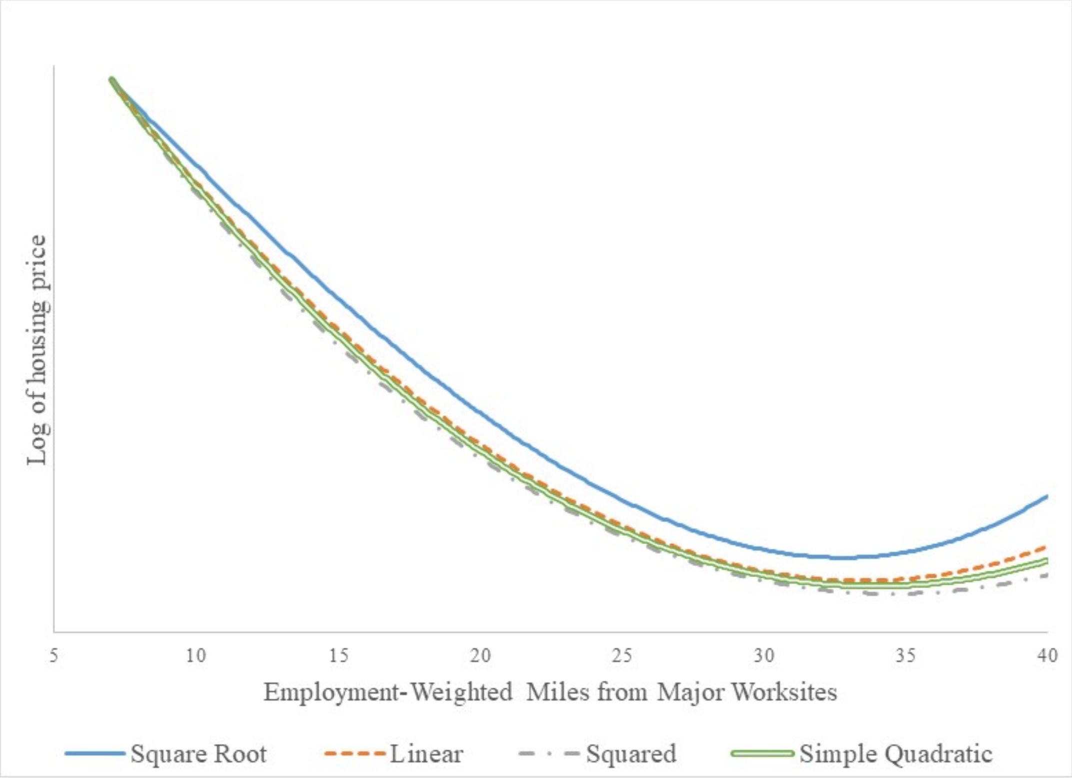
Now consider the puzzle that the envelope turns upward at large distances, particularly for DIST1. The key to understanding this puzzle is a point in Section 2.5, namely, that we are estimating the impact of buyer perceptions on house values. Even if a distance measure accurately captures miles traveled 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

Figure 4. Access Envelopes for DIST3

Panel A. Envelopes with $\sigma_3 = 1$



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



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

Table 5: Illustrative Normal Sorting Tests

				Income Coefficient for:		
Data Source	λ	γ	σ_3	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*)

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 models and with Census 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.

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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).