The Journal of
Regional Analysis & Policy

JRAP 38(1):19-35.

Urban Location and Housing Prices within a Hedonic Model

John R. Ottensmann[a], Seth Payton[a], and Joyce Man[b]
Indiana University–Purdue University Indianapolis [a] and Indiana University Bloomington [b] - USA

Abstract. A measure of location relative to employment is often included in hedonic housing price models. This is most often distance to the center, based on the monocentric model, which does not consider the decentralization of employment in urban areas. This paper tests the performance of alternative measures of location, considering both distance and time to the center and to multiple employment centers and measures of accessibility to employment and change in accessibility. The measures using multiple employment centers and accessibility perform better than simple distance to the center, with the combination of accessibility to employment and change in accessibility doing best.

1. Introduction

Location within an urban area, particularly with respect to the location of employment, is assumed to be a determinant of land prices within standard urban economic models. And because land prices, *ceteris paribus*, will affect house prices, one or more measures of urban location are frequently included in hedonic housing price models.

The standard urban economic model (Alonso 1964; Mills 1972; Muth 1969) makes the monocentric assumption that employment is located in the Central Business District (CBD). Following this, distance to the CBD has frequently been used as a measure of location. With the continuing movement of employment in metropolitan areas away from the CBD, distances to multiple employment centers or even to all employment in the form of an accessibility measure is increasingly used as an alternative.

This paper examines the performance of alternative measures of urban location within a hedonic housing price model for Indianapolis, Indiana. The goals of the research are to understand better how residence location relative to employment location affects house prices and to provide guidance as to the most effective method for specifying location within hedonic models. The research systematically compares measures of location using both distances and travel times, to the CBD, to multiple employment centers, and used in measures of accessibility to employment. The significance of changes in accessibility to employment is also assessed.

2. Location in Hedonic Models

In their seminal research developing a hedonic model for the prediction of house prices, Kain and Quigley (1970) included structural characteristics of the housing unit, neighborhood characteristics, and distance to the CBD. Reviews of hedonic models (Bowen et al. 2001; Malpezzi 2003) have described such models as including housing structure characteristics, the social and natural environment (neighborhood characteristics), and location within the market.

Heikkila et al. (1989) cited numbers of studies of determinants of residential property or land values using hedonic models, saying that to the extent they have included location, it has generally been distance to the CBD, using the assumption of a monocentric city employed in the standard urban economic model (Alonso 1964; Mills 1972; Muth 1969). The early model developed by Kain and Quigley (1970) included distance to CBD, but it was not statistically significant. Witte et al. (1979), in one of the first attempts to explicitly apply Rosen's (1974) theory of implicit markets to the development of a hedonic housing price model, included distance to the CBD among the neighborhood characteristics, and this loaded heavily on an accessibility measure derived using principal components analysis. The relationship of this accessibility measure to house prices varied in sign and significance in the analyses.

Bender and Hwang (1985) cited numbers of hedonic tests that have not supported the monocentric negative price gradient, with estimates of either significant positive relationships or nonsignificant relationships. Coulson (1991) likewise observed that prior research has had great difficulty in verifying the decline of land prices and land consumption with distance from the CBD, noting in particular that in tests of rent gradients, estimation has often yielded positive or insignificant values. (He does find a negative rent gradient when estimating a hedonic model in the simple, monocentric case of State College, Pennsylvania).

Arguing that the monocentric assumption of employment concentrated in the CBD no longer reflects the patterns of contemporary urban areas, other researchers have examined the use of distances to multiple employment centers to predict population and employment densities and later, land values and house prices. Griffith (1981) developed such a model to predict population densities in Toronto. Gordon et al. (1986) and McMillen and MacDonald (1998) used distances to multiple employment centers in models to predict both population and employment densities in Los Angeles and suburban Chicago respectively. McDonald and McMillen (1990) used distances to multiple centers to predict land values in Chicago (though not in the context of a hedonic model), also including distances to transportation infrastructure (interstate highways and commuter rail). Bender and Hwang (1985) used the distance to the nearest of several employment centers in Chicago in a hedonic model predicting house prices. Orford (1999) combined distances to multiple employment centers with distances to other regional amenities in predicting housing prices. All of these studies found distances to secondary employment centers to be significant, with their inclusion in the models improving predictions beyond those obtained by using only distance to the CBD. Heikkila et al. (1989) used a hedonic model with multiple employment centers to examine land values in Los Angeles, and Waddell et al. (1993) added distances to other regional amenities to predict housing prices. These two studies also found distances to employment subcenters to be significant predictors but come to the provocative conclusion that distance to the CBD may no longer be a significant determinant of land values and housing prices.

An alternative location measure to distances to multiple employment centers is a measure of accessibility to all of the employment opportunities within an urban area. In a hedonic model predicting house prices in South Bend, Indiana, Noland (1979) used a simple accessibility measure that was the sum of employment across subareas weighted by the inverse of distance, and this was significant in the model. Burnell (1985) used the sum of manufacturing employment divided by travel costs in a hedonic model and compared this measure to distance to the CBD, finding the accessibility measure to be a better predictor. Gordon and Richardson (1983) included "weighted average potential employment," a measure of employment accessibility, along with distances to the CBD, to the nearest employment center, and to the Pacific Ocean in a hedonic model to estimate the effects of air pollution. None of the distance or accessibility to employment measures were statistically significant.

Song (1994, 1996) used standard measures of accessibility to employment in predicting residential population densities. These measures were significant and better predictors than distance to the CBD. Adair et al. (2000) estimated a hedonic model using accessibility to employment with travel times for Belfast. They found the accessibility measure to be not significant overall but significant at the submarket level. Franklin and Waddell (2003) estimated a hedonic model using accessibility to four types of employment using congested travel times, all of which were significant. Day et al. (2003) used a standard accessibility measure to calculate accessibilities to shops and primary schools and also included proximities (distances) to the CBD, to transport facilities, and to parks and other amenities but do not present the performance of the individual predictors.

Arguably, travel times to employment may provide better measures of location and accessibility to employment than simple distances. Nelson (1977) examined the use of multiple measures of location in a hedonic model, including in addition to distance to the CBD, peak and off-peak travel times to the CBD, travel times to reach a specified percentage of employment, and employment reachable within a specified travel time, which performed better than distance to the CBD. Commuting time to the San Francisco CBD was significant in a hedonic model developed by Katz and Rosen (1998), but distance to the CBD was not. Mozolin (1994) developed a hedonic model for Moscow using travel times to the CBD and to the nearest subway stations; these were highly significant. Going further, Des Rosiers et al. (2000) used travel times to the CBD and to highways, shopping centers, schools, and universities, employing principal components analysis to extract two accessibility factors which were significant in the model. As mentioned above, Adair et al. (2000) and Franklin and Waddell (2003) also used travel times in computing accessibility measures for hedonic models.

In a parallel to this paper, comparative assessments have been undertaken of the efficacy of alternative measures of location in predicting population density, which the standard model also predicts to decline with distance to employment. Song (1994) compared distance to the center, distances to multiple centers, and a "dispersive density function," which is accessibility to employment using a negative exponential function as described in this paper, and found the latter did best in predicting the distribution of worker residences in Los Angeles. In subsequent work, Song (1996) also considered distances to multiple employment centers both unweighted and weighted by employment and multiple functional forms for accessibility, again finding that one of the accessibility measures performed best.

For the prediction of housing prices in hedonic models, numbers of studies have found that the use of distances or travel times to multiple employment centers or measures of accessibility to employment to be effective measures of location and predictors of housing prices. Some of these have compared the measures to simple distance to the CBD and have found them to be superior. None of these studies, however, have systematically compared the effectiveness of a variety of alternative measures in predicting housing prices. Song (1994; 1996) did such comparisons using a range of measures based on distance for the prediction of population of population density, but those studies do not consider the use of travel times as an alternative to distance.

3. Methods and Data

3.1 Model and Base Hedonic Model Data

Hedonic housing price models of the following form are estimated to assess the effectiveness of alternative measures of location in predicting prices:

$$\boldsymbol{P} = \boldsymbol{\beta_0} + \boldsymbol{\beta_H H} + \boldsymbol{\beta_N N} + \boldsymbol{\beta_L L} + \boldsymbol{\varepsilon} \qquad (1)$$

where $\boldsymbol{P}$ is a vector of house prices, $\boldsymbol{H}$ is a matrix of house characteristics, $\boldsymbol{N}$ is a matrix of neighborhood characteristics, and $\boldsymbol{L}$ is a matrix of one or more location characteristics. The $\boldsymbol{\beta_0}$ is the constant term vector, $\boldsymbol{\beta_H}$, $\boldsymbol{\beta_N}$, and $\boldsymbol{\beta_L}$ are matrices of the corresponding parameters, and $\boldsymbol{\varepsilon}$ is a vector of error terms. Because the house prices are skewed, a semi-log model is used, with $\boldsymbol{P}$ consisting of the natural log of house prices. This is the most commonly-used specification in hedonic housing price models. The log transformation reduces the problem of heteroskedasticity associated with the use of the highly-skewed sales price variable. The models are estimated using Ordinary Least Squares (OLS).

The study area is Marion County (Indianapolis), Indiana. The data on house prices and structural house characteristics are from records of house sales in 1999 obtained from the Multiple Listing Service (MLS) database of the Metropolitan Indianapolis Board of Realtors (MIBOR). MIBOR is a professional organization representing central Indiana Realtors which maintains the MLS database for a 12-county area. These are proprietary data obtained from MIBOR by the Center for Urban Policy and the Environment at Indiana University-Purdue University Indianapolis (IUPUI) through a cooperative agreement with MIBOR. MIBOR estimates that its MLS database contains 80 percent of all house sales in their service area.

The analyses include data on 8,772 house sales recorded in the MLS database for 1999. A small proportion of the sales in the database were excluded because they included missing values on one or more of the variables used in the model, were deemed to represent sales that were not arms-length transactions, or could not be geocoded.

Twelve house characteristic variables derived from the MIBOR records are included in the hedonic model. The means and standard deviations of these variables are presented in Table 1. The first eleven are structural characteristics such as number of rooms, square footage, age, lot size, and the presence of various amenities typical of those included in hedonic models. The effective tax rate was computed as the annual property tax payment divided by the sales price in thousands. The high level of variation in this variable reflects the effect of the unusual method of property tax assessment, not based on market value, that was still employed in Indiana in 1999.

The model also includes four neighborhood characteristics. The first is a measure of school quality, the mean SAT score reported for the school district in which the house was located. Measures of school quality have been included in many hedonic models, beginning with the early work of Kain and Quigley (1970). Hayes and Taylor (1996) provide an example of the significance of school quality as measured by test scores for house prices in hedonic models. These data were obtained from the Indiana Department of Education.[1]

[1] In some contexts, SAT scores can be misleading as measures of school quality because they can be affected by the proportion of students in the schools taking the test. This is not an issue in the current context. SAT scores by school district are highly correlated (r = 0.935) with the scores on the Indiana Statewide Test of Education-

Table 1. Descriptive Statistics

Variable	Mean	Standard Deviation
Sales price	110,888	78,492
Log sales price	11.437	0.621
Number of bathrooms	2.022	0.872
Total number of rooms	7.152	1.863
Floor space (100s sq ft)	16.371	7.592
Has basement	0.416	0.493
Age	37.276	26.882
Lot area <= 0.5 acre	0.843	0.364
Lot area >= 1.0 acre	0.033	0.179
Garage bays	1.622	0.742
Has porch or deck	0.562	0.496
Exterior brick or stone	0.603	0.489
No air conditioning	0.138	0.345
Effective tax rate	1.185	0.783
School district SAT	988.491	36.466
Neighborhood median income	50,837	18,166
Neighborhood percent black	20.736	21.746
Neighborhood percent vacant	7.529	4.161
Distance to CBD (kilometers)	11.710	4.880
Free-flow travel time to CBD	8.670	3.793
Congested travel time to CBD	8.630	3.937
Mean distance to 7 ZIP centers	15.459	3.923
Mean distance to 5 TAZ centers	15.840	4.190
Free-flow travel time to 5 TAZ centers	12.937	3.329
Congested travel time to 5 TAZ centers	12.581	3.223

The remaining neighborhood characteristics, neighborhood median income, percentage of the population African-American, and percentage of housing units vacant, have been derived from data from Census 2000 (U.S. Bureau of the Census 2006). Most often, census neighborhood characteristics have been included in hedonic models using values for the census tract or block group in which the housing unit is located. This approach has two problems. First, a house could be located near the boundary of a tract or block group so the relevant neighborhood characteristic is as much the characteristic of an adjacent area as the characteristic of the area in which the house is located. Second, census tracts and block groups vary greatly in their spatial extent so census tract or block group measures represent characteristics extending at varying distances from the housing unit.

To address these problems in assigning census neighborhood characteristics, the model includes estimates of these values for neighborhoods of a uniform one-mile radius surrounding each of the housing units. These neighborhood variables were estimated from the census block group data, with the values being the means of the census characteristics for the block groups intersecting the one-mile radius neighborhoods weighted by the proportion of the one-mile neighborhood area within each block group. Descriptive statistics for these neighborhood characteristics are included in Table 1.

Several of the models tested include an additional neighborhood variable, location within Center Township. Center Township is the older, inner-city portion of the urban area (see Figure 1 for the location). It is recognized locally as being a generally less-desirable area of the city.

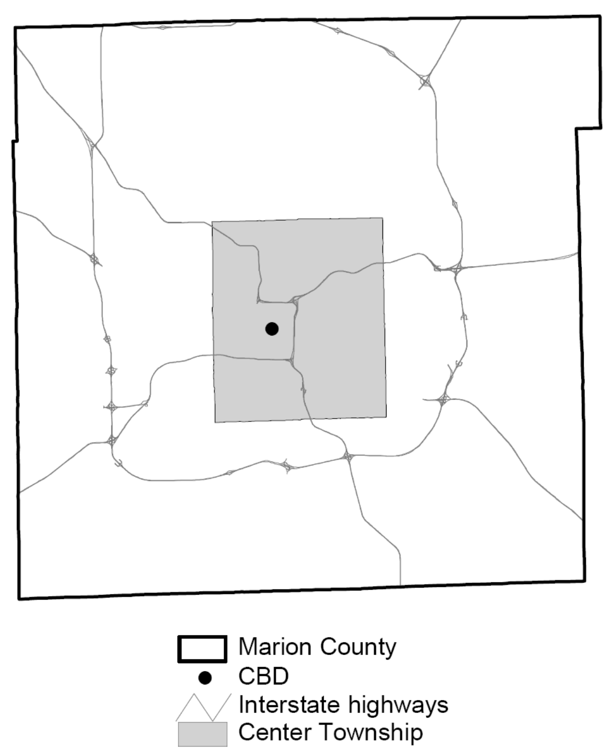

Figure 1. Location of Center Township

al Progress (ISTEP), which is taken by all students. The SAT score variable was selected because it had a slightly higher level of significance in the model.

3.2 Employment Data

The analyses test location measures related to the location of employment. Two sources of employment data are used, one with employment for the traffic analysis zones (TAZs) used for transportation planning and a second with employment for ZIP code areas. Marion County is the inner part of the larger Indianapolis metropolitan area. Because accessibility to employment outside of Marion County is relevant to residents of the county, both sets of employment data include employment for Marion County and for the surrounding 8 counties. This area includes all of the counties in the Metropolitan Statistical Area (MSA) as defined in 2000 along with one additional county, Madison County, a separate MSA deemed potentially significant for employment accessibility.

The first dataset has employment in 2000 for the 1285 TAZs in the 9-county area. These data were developed from the ES-202 workforce data collected by the Indiana Department of Workforce Development. The data were assembled and provided by the Indiana Department of Transportation. The boundaries of the TAZs are shown in Figure 2. In addition to distance, the analyses also use the free-flow and congested road travel times between each pair of TAZs.[2] These travel times were developed and provided by Cambridge Systematics, Inc. using a travel demand model originally created by the Indianapolis Metropolitan Planning Organization. These are travel times from the nodes within each TAZ at which trips to and from the TAZ are loaded onto the road network. The analyses involving travel times from houses to TAZ employment use the travel times from the TAZ node closest to the house to the employment TAZ nodes. For the analyses involving distance, the distances are the airline distances from the actual house locations to the employment TAZ nodes.

The second employment dataset includes employment for both 1995 and 2000 for 100 ZIP code areas in the same 9-county area. These are also from the ES-202 workforce data collected by the Indiana Department of Workforce Development. The Indiana Business Research Center at IUPUI created the tabulations of these data by ZIP code for the Center for Urban Policy and the Environment.[3] The boundaries of the ZIP code areas are shown in Figure 3. Distances of house sales to ZIP code employment are the direct airline distances from the house locations to point locations within each ZIP code.[4]

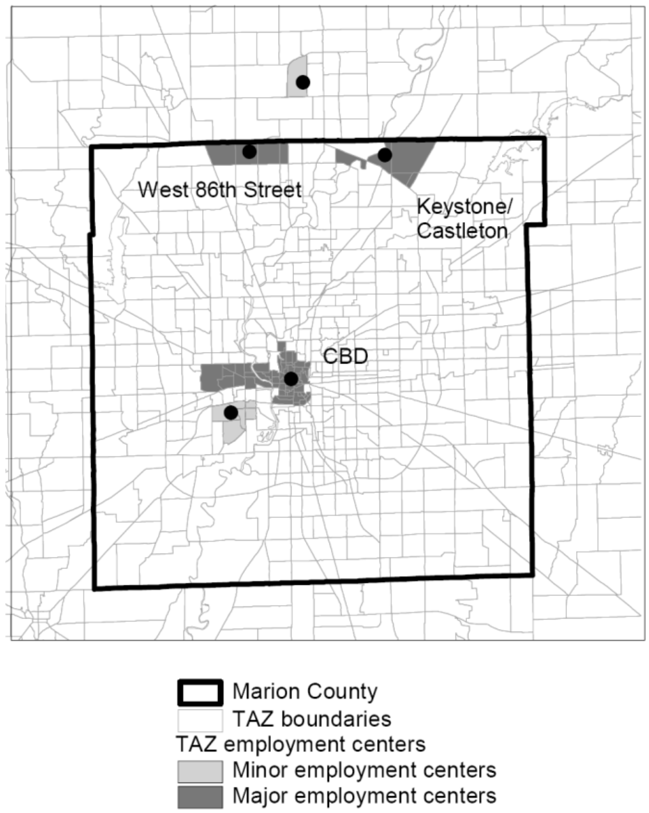

Figure 2. TAZ Boundaries and Employment Centers

The two employment datasets are used for several reasons. Only the ZIP code dataset includes employment at two points in time, allowing examination of the effect of recent changes in accessibility to employment. The travel time data correspond to the TAZ data, requiring the use of those data for the analyses involving travel time. Comparison of the distance analyses using the two datasets also provides for consideration of the effect of the spatial resolution of employment data on the performance of measures of location.

[2] The free-flow travel times are the times for the shortest paths over the road network based upon the travel speeds on the network links under non-congested conditions. The congested travel times are the shortest paths taking into account the assignment of all peak period trips to the network, with the consequent reduction in travel speeds on some links as a result of the assigned trip volumes.

[3] Employment for non-spatially-extensive ZIP codes such as post offices and individual firms and buildings (point locations) were added to the employment for the ZIP code areas in which those points were located.

[4] The point locations used for the ZIP codes are from the file of 5-digit ZIP points provided by ESRI with the ArcView software rather than the ZIP code centroids. Prior research has found that these points correspond more closely to the centers of the population and employment distribution within the ZIP code areas than the centroids. No documentation is provided, however, as to exactly how those point locations were established.

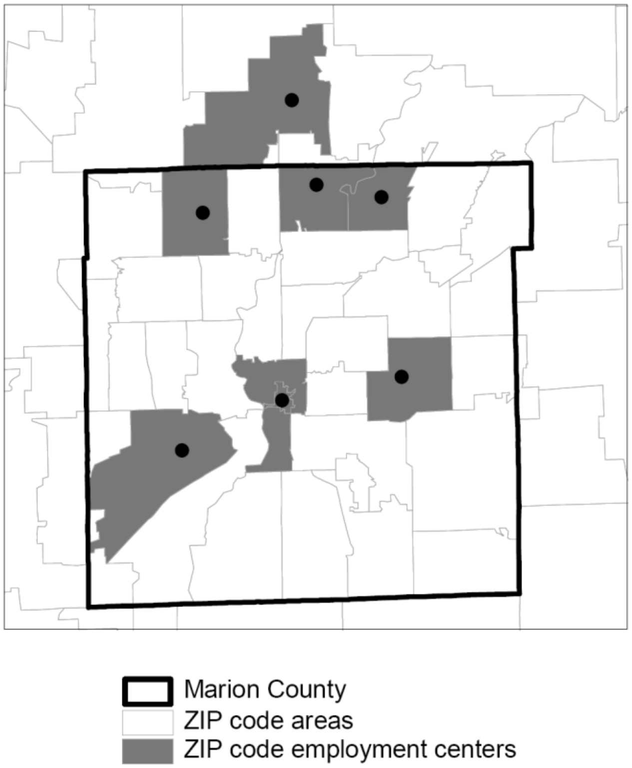

Figure 3. ZIP Code Boundaries and Employment Centers

3.3 Location Measures

The first set of location measures tested are distances and travel times to the CBD. The point location for the CBD for Indianapolis is defined as Monument Circle, which is the recognized center of the downtown area. The means and standard deviations for these measures are given in Table 1.

The analysis then examines distances and travel times to multiple employment centers, which necessarily requires the delineation of those centers. Given that the distribution of employment in metropolitan areas is not limited to a small number of discrete locations, the issue arises as to how such centers are to be identified. Any such delineation will necessarily be somewhat arbitrary. Different employment centers at different locations can be specified for any urban area.

Guiliano and Small (1991) developed an objective procedure for the identification of employment centers in Los Angeles. They defined an employment center as consisting of contiguous (or nearby) zones having an employment density of at least 10 employees per acre and a minimum total employment of 10,000 in the contiguous zones. This method for delineating employment centers has been subsequently employed (sometimes with variations) by other researchers, including Song (1994), Small and Song (1994), and McMillen and MacDonald (1998).

The Guiliano and Small method is employed here in delineating employment centers using the TAZ employment data. Using the criterion of a minimum employment density of 10 employees per acre produced five sets of contiguous clusters of TAZs having over 10,000 total employees. (One isolated TAZ also met the density threshold but had fewer than 10,000 employees.) These TAZ-based employment centers are shown in Figure 2. Three of the centers are north of the CBD, two at the edge of Marion County and one farther north, outside the county. One is an industrial area to the southwest, close to but separate from the CBD. The points within each area are the points to which distances and times from the house locations to the centers are determined. The three centers that are highlighted and labeled have the largest numbers of employees and will be used separately in some of the analyses.

For the ZIP code areas, an alternative approach to employment center delineation was required. Because of the large areas of many of the ZIP codes, areas with substantial employment do not necessarily have high employment densities. Only three ZIP codes, two in the CBD, met the criterion of 10 employees per acre. Using lower employment density thresholds still did not provide reasonable results, as some ZIP codes with significant employment but with especially large areas did not meet the lower density cutoffs. At the same time, some very small ZIP codes (in terms of area) met the density requirement in spite of relatively smaller levels of employment. The employment density standard was abandoned, and ZIP code areas with total employment of 20,000 or more workers were classified as employment centers. The seven ZIP code-based employment centers are shown in Figure 3. Descriptive statistics for the mean distances to the TAZ and ZIP code employment centers are presented in Table 1.

The final set of analyses involve the use of measures of accessibility to employment and change in accessibility to employment. While a wide variety of accessibility measures can be developed and have been employed in various studies, by far the most commonly used is based upon a generalization of the measure originally proposed by Hansen (1959). This measure was employed in many of the papers included in a recent volume on transportation accessibility (Levinson and Krizek 2005), for example. The basic form of the model for accessibility to employment used here is:

$$A_i = \Sigma_j E_j f(C_{ij}) \tag{2}$$

where A_i is accessibility to employment for house i, E_j is the employment in zone j (TAZ or ZIP code), and $f(C_{ij})$ is a declining function of travel cost from i to j. Following the most common choice, a negative exponential function of distance d_{ij} (or time t_{ij}) is used, as in the monocentric model:

$$f(C_{ij}) = \exp(-\beta\, d_{ij}) \quad (3)$$

where β is an empirically-determined accessibility coefficient.

The change in accessibility to employment from 1995 to 2000 using the ZIP code employment data is also tested as a measure of location. The assumption is made that the accessibility coefficient is the same in both years, with the calculation actually being of accessibility to change in employment, which is mathematically equivalent to the change in accessibility to employment using this assumption.

For the calculation of the accessibility measures, the issue arises as to the estimation of the value of the accessibility coefficient β, which cannot be estimated within the OLS estimation of the hedonic model. The estimation of the accessibility coefficients for the various measures of accessibility is described below in the sections dealing with the model estimation and results for accessibility.

4. Data Analysis

4.1 Distance/Travel Time to Center

The first set of analyses considers the monocentric measures of location using distances and travel times to the CBD. The basis for comparison is the base hedonic model which includes the house and neighborhood characteristics with no measure of location. The regression coefficients and t values for this base model are shown in the first column of results in Table 2. All of the regression coefficients have the expected signs and are statistically significant at the 0.001 level. R^2 for the model is 0.8579, so over 85 percent of the variation in the log of house sales prices is accounted for by the base model.[5]

Since the dependent variable is the natural log of house sales price, including distance to the CBD in the model implies a negative exponential relationship between distance and price. This is consistent with the functional form most often predicted and used in testing the standard monocentric model (Mills 1972; Muth 1969). The second model in Table 2 shows the results of including distance to the center (in kilometers) in the hedonic model. While the regression coefficient for distance has the expected negative sign, the estimated coefficient were not statistically significant. This parallels the experience with many prior hedonic housing price models that have included distance to the CBD as the measure of location, which have found the coefficient on distance to be not significant or, in some cases, even positive.

Prior applications of this hedonic model have included a dummy variable for location within Center Township. The Center Township variable was included based upon both local knowledge and examination of residuals as representing an area with negative neighborhood externalities that adversely affect house prices. The third model in Table 2 provides the results for the base model plus the Center Township dummy. The regression coefficient for Center Township was negative and statistically significant. This implies that the other neighborhood measures included in the model are not fully capturing the effects of all neighborhoods on house prices.

In addition to serving as a proxy for negative neighborhood effects, the Center Township dummy is obviously also a measure of location. If the monocentric model is correct in predicting the decline of house prices with distance from the center, however, then the Center Township variable is more important in capturing the neighborhood effects than as a measure of location, since its sign is negative. The final column in Table 2 shows the results of including both Center Township and distance to the CBD in the model. The regression coefficient for Center Township changed little. But now the coefficient for distance was both negative and statistically significant. House prices are now shown to decline with distance when controlling for the negative effects of location within Center Township.

These results raise an issue for the subsequent examination of alternative measures of location in the hedonic model: Should the Center Township dummy variable be included? Viewed as a proxy for neighborhood effects, it should be included to provide a more complete specification of the model. However, the Center Township variable is most definitely also a measure of location, with the potential to confound estimation of the effects of other measures of location. For all of the measures of location considered and reported in this paper, models were estimated both with

[5] Since models with different numbers of independent variables are being compared in this paper, comparisons of the fit of the models might more appropriately be made using the *Adjusted* R^2 rather than R^2. Given the large number of cases used in the estimation of these models, however, the differences in the comparisons resulting from using the *Adjusted* R^2 are smaller than the level of significance to which the R^2 values are reported, so only the unadjusted R^2 values are reported.

Table 2. Models with and without Distance to CBD and Center Township (t-values)

Independent Variables	Model 1 Base Model	Model 2 CBD Distance	Model 3 Center Township	Model 4 Center + CBD
Number of bathrooms	0.1104*	0.1103*	0.1132*	0.1121*
	(21.19)	(21.14)	(22.08)	(21.88)
Total number of rooms	0.0130*	0.0131*	0.0110*	0.0114*
	(6.15)	(6.16)	(5.28)	(5.48)
Floor space (100s sq ft)	0.0211*	0.0210*	0.0214*	0.0214*
	(34.06)	(34.04)	(35.23)	(35.21)
Has basement	0.0974*	0.0970*	0.1087*	0.1036*
	(15.44)	(15.13)	(17.43)	(16.43)
Age	-0.0024*	-0.0024*	-0.0021*	-0.0024*
	(15.71)	(14.65)	(14.17)	(15.07)
Lot area <= 0.5 acre	-0.0492*	-0.0493*	-0.0416*	-0.0426*
	(6.23)	(6.24)	(5.35)	(5.49)
Lot area >= 1.0 acre	0.0956*	0.0959*	0.0951*	0.0996*
	(6.10)	(6.11)	(6.18)	(6.47)
Has garage	0.0855*	0.0855*	0.0842*	0.0843*
	(19.81)	(19.81)	(19.83)	(19.88)
Has porch or deck	0.0477*	0.0478*	0.0456*	0.0470*
	(8.66)	(8.67)	(8.42)	(8.68)
Exterior brick or stone	0.0840*	0.0841*	0.0777*	0.0784*
	(13.95)	(13.96)	(13.12)	(13.25)
No air conditioning	-0.2511*	-0.2512*	-0.2444*	-0.2451*
	(29.12)	(29.11)	(28.80)	(28.91)
Effective tax rate	-0.2393*	-0.2393*	-0.2385*	-0.2376*
	(70.28)	(70.20)	(71.24)	(71.01)
School district SAT	0.0004*	0.0004*	0.0003*	0.0003*
	(5.56)	(5.45)	(4.60)	(3.66)
Neighborhood median income	0.0051*	0.0051*	0.0049*	0.0058*
	(22.36)	(17.88)	(22.15)	(20.54)
Neighborhood percent black	-0.0005*	-0.0005*	-0.0009*	-0.0010*
	(3.31)	(3.31)	(6.73)	(6.99)
Neighborhood percent vacant	-0.0216*	-0.0216*	-0.0135*	-0.0129*
	(22.34)	(22.34)	(12.74)	(12.08)
Center Township			-0.1748*	-0.1886*
			(17.50)	(18.25)
Distance to CBD		-0.0004		-0.0055*
		(0.35)		(5.10)
R^2	0.8579*	0.8579*	0.8627*	0.8631*

*Significant at p<0.001

and without the Center Township dummy. The substantive conclusions one would make regarding the performance of the alternative location measures are the same in nearly all instances. Since the focus of this paper is on the performance of the measures of location, the results without the additional measure of location provided by the Center Township variable are reported.

Travel times to the CBD provide alternative monocentric measures of location that may more accurately represent accessibility to employment. Since 95 percent of workers in Marion County who commuted to work in 2000 used cars or trucks, and only 2.3 percent took public transit, travel time on the road network is the relevant measure for nearly all workers (U.S. Bureau of the Census 2006). Free-flow travel times are those estimated for conditions under which traffic volumes do not adversely affect speeds. Congested travel times are estimated for the peak period, taking into account traffic volumes that reduce speeds. Congested travel times thus may be more appropriate for accessibility to employment, with a high proportion of commuting taking place during the peak periods.

Results for distance, free-flow travel time, and congested travel time to the CBD are presented in the top portion of Table 3. (From this point forward, results are presented only for the location variables and the overall R^2 value for the model, as the regression coefficients for the other variables in the model are not significantly affected by the location measures.) As observed above, distance to the CBD was not significant. However, both free-flow and congested travel times to the CBD were significant and have the expected negative signs for the regression coefficients. In addition, the regression coefficient and *t* value for congested travel time are twice as large as for free-flow travel times. So travel times to the CBD (especially congested times) are significantly better predictors of house prices and better measures of accessibility to employment.

Table 3. Models for Distance/Travel Time to CBD and Multiple Employment Centers

Location Variable(s)	Regression Coefficient	Standard Error	t	Sig	R^2
Base Model					0.8579
Distance/Travel Time to CBD					
Distance to CBD	-0.0004	0.0011	-0.3471	0.7285	0.8579
Free-flow travel time to CBD	-0.0033	0.0013	-2.6385	0.0083	0.8580
Congested travel time to CBD	-0.0066	0.0012	-5.2895	0.0000	0.8583
Distance/Travel Time to 3 TAZ Employment Centers					
Distance to CBD	0.0005	0.0012	0.4542	0.6497	0.8605
Distance to Keystone/Castleton	-0.0008	0.0006	-1.2444	0.2134	
Distance to West 86th Street	-0.0048	0.0006	-7.9205	0.0000	
Free-flow travel time to CBD	-0.0032	0.0014	-2.3359	0.0195	0.8608
Free-flow time to Keyston/Castleton	-0.0015	0.0006	-2.3661	0.0180	
Free-flow time to West 86th Street	-0.0060	0.0006	-9.2329	0.0000	
Congested travel time to CBD	-0.0050	0.0013	-3.8608	0.0001	0.8610
Congested time to Keystone/Castleton	-0.0010	0.0006	-1.7612	0.0782	
Congested time to West 86th Street	-0.0063	0.0007	-9.4799	0.0000	
Mean Distance/Travel Time to Employment Centers					
Mean distance to 7 ZIP centers	-0.0096	0.0008	-11.6072	0.0000	0.8601
Mean distance to 5 TAZ centers	-0.0089	0.0008	-11.8679	0.0000	0.8601
Mean free-flow time to 5 TAZ centers	-0.0129	0.0010	-13.4577	0.0000	0.8608
Mean congested time to 5 TAZ centers	-0.0138	0.0010	-14.0707	0.0000	0.8610

4.2. Distance/Travel Time to Employment Centers

The increasing decentralization of employment within metropolitan areas has led to the questioning of the continued appropriateness of the monocentric assumption of the standard model. Observation of the emergence of multiple employment centers within metropolitan areas has led to suggestions that accessibility to employment in those multiple centers would provide a better measure of location within hedonic models.

With distances or times to multiple employment centers, the issue arises as to how those centers would collectively influence house prices. Small and Song (1994) and Anas et al. (1998) lay out three alternatives (focusing on population densities rather than house prices). Assume that the effect of any employment center on house prices is an estimated house price value at that center times a negative exponential function of distance or time from that center, as generally assumed with the monocentric model. In the first alternative, if the centers are perfect substitutes, the effect on house prices is the maximum of the values predicted for the various centers. In other words, each center independently affects house prices for those houses within its "sphere of influence." At the other extreme, if the centers are complements, with the residents of each house valuing access to every employment center, the effect of the centers is the product of their individual effects. This has the very convenient property that when taking the log of the dependent variable, the effects of the distances or times are additive, making the model easy to estimate. Finally, the third alternative represents an intermediate case, with the negative exponential effects of distance or time on house prices being additive. This method requires nonlinear estimation. It has been employed by Griffith (1981), Gordon et al. (1986), Song (1994), and Small and Song (1994) in predicting population densities but not within the more complex context of a hedonic housing price model. Most commonly used is the second formulation assuming that the centers are complements, undoubtedly due to the ease of estimation. This paper employs that approach, followed by a brief discussion of (unsuccessful) attempts to estimate the model for the other extreme, assuming the centers are substitutes.

The obvious first attempts involved estimation of models for multiple employment centers by including the distances or times from the house sales locations to the all of the centers. The results for such models for both the TAZ and ZIP code centers were seriously compromised by multicollinearity. Regression coefficient values and signs for the distance and time variables were virtually random. Variance Inflation Factors were extremely high. The relatively close proximity of the employment centers in Indianapolis apparently produced these levels of multicollinearity, as opposed to, for example, the more widely separated employment centers for which similar models were successfully estimated for Los Angeles (Heikkila et al. 1989).

For the TAZ-based employment centers, three of the five centers identified had substantially greater employment than the other centers. These are the centers shown darker and labeled in Figure 2. Models were estimated using the distances and times to just these three major employment centers. The results are shown in the middle of Table 3. Looking first at the overall performance of the models, the R^2 values show increases over the base model, rising from 0.858 to about 0.860 to 0.861, as opposed to negligible increases for the models using only distances or times to the CBD. (It should be noted that the objective sought in considering the alternative measures of location was not, however, to substantially improve the predictive power of the model, which is already very high. Rather, it was to provide for a more complete specification of the model.) As with distance to the CBD, the travel times performed better than distance, with congested travel times slightly better than free-flow times.

For the two models using travel times, the regression coefficients for the times to each of the three centers were statistically significant. For the model using distance, only one of the coefficients, distance to Keystone/Castleton, was significant. Distance to the CBD and the other employment center were not. This is the one additional case in which differences are observed when the Center Township dummy variable was included in the model. With Center Township included to account for the negative neighborhood effects, the regression coefficients for both distance to the CBD and to the West 86th Street center were significant, paralleling the results obtained for the models using only distance to the CBD.

The ZIP code-based centers outside of the CBD did not have the significant differences in total employment levels observed for the TAZ centers. It was therefore not possible to identify a subset of major employment centers that could be used for estimating comparable models.

Distances and times to all of the employment centers can be included in models if one makes the assumption that the coefficients for the negative exponential decline of house prices are the same for each of the centers. With this assumption, models can be estimated using the means of the distances or times from the house locations to all of the employment centers. These results are shown in the final section of Table 3 for both ZIP code and TAZ employment centers. R^2 values are almost exactly the same as for the models using the 3 TAZ employment centers. The regression coefficients for mean distances and times were all statistically significant. Virtually no difference is observed for distances to the ZIP code and TAZ employment centers. Once again, travel times to the TAZ centers performed slightly better.

The multiplicative model assuming complementarity of the effects of the employment centers does not reflect the effect of the levels of employment in the various centers. Ihlanfeldt and Sjoquist (1990), Ihlanfeldt (1993), and Song (1996) have used the means of distances to multiple employment centers weighted by the employment in those centers. Models were estimated here using such weighted means. The results were similar to those reported using the unweighted means, but the fit of the models was slightly poorer. Weighting by the log of the center employment raised the performance to the level of the unweighted means, but it seems simpler to just use the unweighted means.

Efforts were made to estimate models using the assumption that the centers are substitutes rather than complementary, with the predictor of house prices being the maximum of the predictions from the various centers. The idea was to start by assigning each of the houses to the nearest center and estimating a model using distances to those centers. Then predictions could be made of the effects of each center on each house, enabling a reassignment to the centers making the maximum prediction, with the process being repeated to a stable solution. Using the 5 TAZ centers and estimating the effects for each center, two of the regression coefficient for distance were positive, which would not be consistent with making predictions for reassignment of the centers. Limiting the analysis to the 3 major centers, the regression coefficient for distance to the CBD was still positive. So this attempt was unsuccessful.

4.3. Accessibility to Employment

An alternative to using distances or times to multiple employment centers (with the issue of the delineation of those centers) uses as the measure of location the accessibility to all of the employment within the area. As described above in the section on data and methods, the measure of accessibility being used is the sum over all zones of employment times a negative exponential function of distance or travel time. This raises the issue of the estimation of the value of the accessibility coefficient β, which cannot be estimated within the OLS estimation of the hedonic model. A trial-and-error approach was employed to find the value for the accessibility coefficient that produced the best prediction—lowest mean-squared error—in the hedonic model. Multiple measures of accessibility were calculated for a wide range of coefficients. Models were estimated using each accessibility measure to determine the accessibility coefficient giving the best prediction (as measured by the lowest standard error of estimate). Additional accessibility measures were created for a narrower range of accessibility coefficients around the coefficient that produced the lowest error to find the measure with the accessibility coefficient that produced the best prediction in the hedonic model. The process was repeated, using more closely spaced accessibility coefficients, continuing until the value for the accessibility coefficient producing the best prediction was determined to two significant digits. Comparisons of the accessibility measures using final sets of accessibility coefficients varying by values of one for the second significant digit showed changes only in the fifth through seventh significant digits in the standard error of estimate.[6]

The results for four models using accessibility to employment as the measure of location relative to employment are presented in the top portion of Table 4. The goodness-of-fit measures for the models are virtually the same as for the models using multiple employment centers, with R^2 values from 0.860 to 0.861. The regression coefficients for all of the accessibility coefficients were highly significant, with t values ranging from 10 to over 14. Differences across the four models were modest. Accessibility using distances to the TAZ employment had a higher t value than accessibility using distances to the ZIP code areas, suggesting a small advantage associated with the more spatially disaggregated TAZ employment data. Among the three TAZ-based accessibility measures, the better performance with travel times, especially congested travel times, observed in the earlier analyses did not hold.

[6] Surprisingly, in estimating each of the models to determine the best-fit accessibility coefficients, minima were found for two coefficient values differing by nearly two orders of magnitude, e.g., 1.1 and 0.020 for the model using distances to ZIP code employment. In three of the four models, the standard error of estimate was lower using the larger accessibility coefficient, while in the fourth, the standard error of estimate was identical (to four significant digits). We report only the results using the larger accessibility coefficients.

Table 4 Models for Accessibility to Employment and Change in Employment.

Location Variable	Regression Coefficient	Standard Error	*t*	Sig	R^2
Accessibility to Employment					
Distance accessibility to ZIP employment (coefficient = 1.1)	0.0059	0.0006	10.1156	0.0000	0.8595
Distance accessibility to TAZ employment (coefficient = 1.6)	0.0205	0.0014	14.5388	0.0000	0.8612
Free-flow travel time accessibility to TAZ employment (coefficient = 2.2)	0.0273	0.0019	14.5371	0.0000	0.8612
Congested travel time accessibility to TAZ employment (coefficient = 2.1)	0.0232	0.0017	13.8811	0.0000	0.8610
Accessibility to Change in Employment					
Distance accessibility to change in ZIP employment (coefficient = 0.081)	0.0081	0.0006	13.5473	0.0000	0.8608
Accessibility to Employment and Change in Employment					
Distance accessibility to ZIP employment (coefficient = 1.3)	0.0048	0.0007	6.9897	0.0000	0.8616
Distance accessibility to change in ZIP employment (coefficient = 0.067)	0.0069	0.0006	11.4801	0.0000	
Accessibility to Employment, Change in Employment, Mean Distance to ZIP Centers					
Distance accessibility to ZIP employment (coefficient = 1.3)	0.0048	0.0007	6.9896	0.0000	0.8616
Distance accessibility to change in ZIP employment (coefficient = 0.067)	0.0075	0.0012	6.0354	0.0000	
Mean distance to 7 ZIP employment centers	0.0008	0.0017	0.4736	0.6358	

In his comparison of the performance of alternative accessibility measures in predicting population densities, Song (1996) chose to use the natural log of accessibility to predict density rather than using the natural form as was done here. Tests were made using the log of the accessibilities, and the fits of the models (after finding best-fit accessibility coefficients associated with using the logs) were no better.

4.4. Change in Accessibility to Employment

All of the applications involving the use of measures of accessibility to employment to predict densities or house prices have used accessibility to levels of employment at a single point in time. Attention has not been given to the possible effect of changes in accessibility to employment over time. However, if accessibility to employment has a significant effect on house prices, then changes in accessibility to employment in the recent past, which may be seen as being predictive of future changes in accessibility, might also affect house prices. A study examining changes in accessibility to employment in Milwaukee over more than three decades found these changes were associated with a range of neighborhood characteristics (Ottensmann 1980). In the estimation of predictive models for an urban simulation model, change in accessibility to employment was included along with current accessibility in the prediction of the change from nonurban to residential land use (Ottensmann 2005).

A model was estimated examining the effect on house prices in the hedonic model of changes in accessibility to employment from 1995 to 2000 using the distances to ZIP code employment. The assumption is made that the accessibility coefficient is the same in both years, with the calculation actually being of accessibility to change in employment, which is mathematically equivalent using this assumption. The best-fit accessibility coefficient was determined as for accessibility to employment. The results are shown in the next portion of Table 4. The fit of the model was about as good as for the various accessibility measures (and even better than for accessibility to ZIP code employment). Accessibility to employment change was statistically significant.

If both accessibility to employment and change in accessibility to employment are effective measures of location for use in the prediction of house prices, it is not unreasonable to consider that the combination of the two might result in even better predictions. A model including both accessibility measures was estimated, with the results presented in the next section of Table 4. Estimation began by using the best-fit accessibility coefficients estimated for accessibility and change in accessibility when used separately. Both coefficients were then adjusted iteratively until the combination of accessibility coefficients producing the lowest standard error of estimate was found.[7] This model has an R^2 value of 0.862, which is higher than for any of the other models examined. The regression coefficients for both accessibility to employment and change in accessibility to employment are statistically significant, with the latter having the higher t value. So change in accessibility to employment is a significant predictor of house prices after controlling for the effects of the level of accessibility to employment. Together, the two provide the best measure of location for predicting house prices.

With both accessibility to employment and change in accessibility significant predictors of house prices, the question arises as to whether distances to the multiple employment centers would also contribute in measuring location. The mean distance to the ZIP employment centers was added to the previous model, and the results are shown in the final section of Table 4. Mean distance to the employment centers was not statistically significant, and the regression coefficients for the accessibility measures changed little. The combination of the two accessibility measures appears to capture the effect of employment location, with the location of multiple employment centers adding nothing.

5. Conclusions

The measures of location were statistically significant predictors of sales price in the hedonic model. However, their addition to the model produced only small increases in R^2. This raises the question as to the relative importance of location as opposed to house and neighborhood characteristics in determining house prices. Table 5 presents the predicted changes in sales price for changes in the independent variables for a house with the mean sales price of $110,888. Changes for the house and neighborhood variables have been calculated using the regression coefficients estimated for the base model without location. For the changes in distances and times, changes are shown for 10 kilometer and 10 minute changes in those measures. Changes for the house and neighborhood measures are for unit changes in those measures, with the exception of the effective tax rate and the school district SAT, for which more intuitive levels of change were used.

As expected, the house characteristics are major determinants of sales price. Unit changes in four of the variables—number of bathrooms, lot size greater than one acre, and presence of a basement and air conditioning—resulted in changes in sales price greater than 10 percent. The effects of the neighborhood variables were smaller, though the percentage of units in the neighborhood vacant and, especially, school district SAT scores, had substantial effects.

Considering distance and travel time to the CBD, the effect of distance was small, but this variable was not significant in the model. Travel times to the CBD had a much larger effect, with 10 minute increases in travel times being associated with 3.3 and 6.4 percent declines in sales price for the free-flow and congested travel time models respectively. Mean distance and travel times to the multiple employment centers had greater effects on sales price, with 10 kilometer or 10 minutes increases in the means predicting 9.1 to 12.9 percent decreases in sales prices, decreases in prices for a house with the mean price ranging from $9,500 to $12,900. These are substantial effects of location with respect to employment on house prices.

[7] In searching for the best combination of accessibility coefficients, both the high and low estimates of the accessibility to employment coefficients as described in the previous footnote were used as starting points. Once again, different combinations of accessibility coefficients yielded two different minima with nearly identical standard errors. One had a negative regression coefficient for accessibility. Results for the model in which both coefficients were positive, as expected, are reported.

Table 5. Change in Sales Price at Mean Sales Price

Dependent Variable Change	Sales Price Change	Percent Change
Number of bathrooms	$12,945	11.67
Total number of rooms	$1,453	1.31
Floor space (100 sq ft)	$2,359	2.13
Has basement	$11,347	10.23
Age	-$263	-0.24
Lot area <= 0.5 acre	-$5,321	-4.80
Lot area >= 1.0 acre	$11,119	10.03
Garage bays	$9,902	8.93
Has porch or deck	$5,420	4.89
Exterior brick or stone	$9,714	8.76
No air conditioning	-$24,626	-22.21
Effective tax rate (tax per $100)	-$2,622	-2.36
School district SAT (100 points)	$4,592	4.14
Neighborhood median income	$564	0.51
Neighborhood percent black	-$51	-0.05
Neighborhood percent vacant	-$2,373	-2.14
Distance to CBD (10 kilometers)	-$408	-0.37
Free-flow travel time to CBD (10 minutes)	-$3,642	-3.28
Congested travel time to CBD (10 minutes)	-$7,039	-6.35
Mean distance to 7 ZIP centers (10 kilometers)	-$10,144	-9.15
Mean distance to 5 TAZ centers (10 kilometers)	-$9,483	-8.55
Mean free-flow travel time to 5 TAZ centers (10 minutes)	-$13,426	-12.11
Mean congested travel time to 5 TAZ centers (10 minutes)	-$14,307	-12.90

Distance and travel times to the CBD were the least effective measures of location in predicting house prices in the hedonic model. Distance to the CBD was not even statistically significant in the base model. It was, however, significant when location in Center Township (the inner city) was included in the model to control for externalities negatively affecting house prices. These results may provide some insight into the frequent results of insignificant or even positive coefficients for distance to the CBD in hedonic models (Bender and Hwang 1985; Coulson 1991). If there are negative neighborhood effects in inner-city areas that are not completely reflected in the neighborhood characteristics included in a hedonic model, effects that are related to distance to the center, the finding of no significant negative decline of house price with distance may reflect incomplete specification of the neighborhood effects in the model. This suggests caution is in order in the interpretation of findings of a lack of significant decline in house prices with distance from the CBD. For example, Heikkila et al. (1991) emphasized the result that, in their hedonic model including distances to multiple employment centers in Los Angeles, distance to the CBD is the one measure that was not statistically significant. While it certainly may be true that the Los Angeles CBD does not affect house prices in the area, it is also possible that the failure to observe an effect resulted from an inadequate specification of neighborhood effects that are associated with distance to the CBD. This finding emphasizes the importance of correctly specifying neighborhood effects in hedonic models.

Measures of location including employment outside of the CBD yielded better predictions and more significant measures of location. Measures of distance or time to multiple employment centers performed about as well as the measures of accessibility to employment. These results do not show clearly better performance for the accessibility measures as found by Song (1994; 1996) in models predicting population density.

Across the models using distances or times to the CBD and to multiple employment centers, travel times consistently performed better than distances. Among the alternative travel time measures, congested travel times did better than free-flow travel times. This pattern did not hold, however, for the accessibility to employment measures. For accessibility to employment, the measures of accessibility to the more spatially-disaggregated TAZ employment performed better than accessibility to employment in the ZIP code areas.

Recent change in accessibility to employment proved to be a significant measure of location affecting house prices. This variable, calculated using ZIP code employment change, actually performed better than accessibility to ZIP code area employment. The combination of accessibility to employment with change in accessibility was the best overall measure of location in predicting house prices, with both measures significant.

Location with respect to employment is a significant predictor of house prices within a hedonic model, supporting the general assumption embedded in the standard urban economic model. With the decentralization of employment that has occurred, the findings do not, however, support the specific assumption of the standard monocentric model of employment located only in the CBD. Measures of location that include employment outside of the CBD do better than the simple measures of distance or time to the CBD.

These results are not only important for understanding the nature of the effects of accessibility to employment on house prices. They also have important implications for public policy. Most obvious is the use of hedonic house price models and other types of models for property assessment for tax purposes. Increasing use is being made of such models for the appraisal of real property and for real estate assessment (see, e.g., Detweiler and Radigan 1996; Pagourtzi et al. 2003; Renne 2003). Obtaining accurate assessment depends upon the proper specification of the models used. Because location with respect to employment has a significant effect on house values, failure to include appropriate measures of such accessibility can result in significant errors in assessment.

Hedonic house price models are frequently employed to estimate the benefits or costs associated with location-based amenities or disamenities, often with the goal of informing public policymaking to address the amenities or disamenities. It is a truism that the misspecification of a model can result in errors in the estimation of the model coefficients, though often the direction and magnitude of such errors is unknown. However, in at least some applications of hedonic models to estimate the negative effects of disamenities, the effect of failure to properly specify location with respect to employment can be quite clear. Consider the case of the effect of airport noise on property values. (See Nelson 2004 for references to a large number of such studies.) Areas near airports are frequently major employment centers. If accessibility to that employment is not included in the hedonic model, predicted house prices near the airport will be underestimated. This may then result in an underestimate of the negative effect of airport noise on those properties affected. Two studies (Espey and Lopez 2000; Tomkins et al. 1998) have used hedonic models to simultaneously estimate the effects on property values of both airport noise and proximity to the airport. Both studies considered the airport as a potential amenity, not as an employment center, and no measures of location with respect to employment were included in either model. Both found negative effects of airport noise on property values, but they differed as to whether proximity had a positive or negative effect. Tomkins et al. (1998) found proximity to the Manchester airport led to higher values. Espey and Lopez (2000) found a negative effect for the Reno-Tahoe airport, but they noted that the area surrounding that airport is primarily residential, so it may not be a significant employment center. Another example where disamenities might be associated with employment concentrations would be air pollution and certain types of manufacturing employment.

Hedonic models using measures of accessibility based on travel times provide an opportunity to estimate the value people place on travel time savings. Such estimates can be used in valuing the benefits associated with travel time reductions associated with planned transportation system improvements. At least one author (Nelson 1977) has directly employed a hedonic house price model for this purpose.

Because it is a significant predictor of house prices, location with respect to employment should be included for the proper specification of hedonic housing price models. The combination of accessibility to employment and change in accessibility to employment provides the best specification of location, but the necessary data may not always be available. But certainly location with respect to employment should include either distances or times to multiple employment centers or a measure of accessibility to all employment, as the assumption that access to employment in the CBD would be sufficient is not supported.

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