Using Quantile Regression in Hedonic Analysis to Reveal Submarket Competition

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Abstract In this paper, we use quantile regression analysis to explore the role submarket competition plays in setting housing prices in those price ranges where different submarkets occupy homes of similar price. We find evidence of direct competition between submarkets with different preferences for at least some homes in a single neighborhood. By examining hedonic parameter instability at different housing price levels, we uncover not only latent diversity among homeowners but direct competition between them, which calls into question policy and market conclusions drawn from standard hedonic price models, especially large sample hedonic studies.

Urban diversity is increasing, not decreasing. The very premise of New Urbanism relies on the creation of stable, diverse neighborhoods (Florida, 2008, 2005). Indeed capitalizing on such diversity is the intent of new trends in urban design. So, if developers and policymakers are to commit scarce capital to these development initiatives, real estate professionals need to be able to evaluate the structure of local submarkets to anticipate who likely will occupy a particular space. A critical concern is to identify those features that cause a unit to shift ownership from one submarket to another; this requires a deep understanding of the local economic conditions that govern local real estate occupancy patterns. To put this in perspective, at the other end of the spectrum research can seek to explain house price variation in a more regional context (Osland, Thorsen, and Gitlesen, 2007).

Relatively recent work involving quasi-experiments has appeared in the *American Economic Review* (e.g., Banzhaf and Walsh, 2008) to note that small changes in a neighborhood-wide attribute can result in the resorting of different types into that neighborhood and out of that neighborhood, after which the marginal value of the attribute changes significantly even though no other features changed. That, of course, signals that a different type of household now occupies the residence. Interestingly, a single regression with many attributes over a large geographic space that shows very high significance, low multicollinearity, and a high R^2

statistic still failed to capture the true price effect of this attribute change, producing inconsistent attribute estimates. This suggests that it is difficult to analyze submarket effects on price within a single neighborhood from a single-line regression model.

There are numerous benefits to applied real estate economics of modeling the local market details, diversity, and competition among diverse households as we do in this work. The benefits of this line of inquiry penetrate ground level attribute studies as well as real estate macro-market studies, most of which seem to call for greater household differentiation. For example, Seo and Simons (2009) note the effect of school quality on housing prices. Cast in our approach, we expect that submarket identification might sharpen this effect (e.g., telling us what new types might be moving into neighborhoods with higher quality schools). In addition, the greater detail that we propose could provide insight to see if one type ever pays a premium for school quality to resolve its competition with another type. This not only allows developers to improve homes for a given household type in anticipation of a premium paid for an improvement in local school quality, but such market segmentation and detail would be important for shaping local education outreach programs as well.

Shultz and Schmitz (2009) also note considerable variation in the price effect of golf courses and recommend hedonic analyses that are more "course specific." Much of this is surely due to course quality. For their research, our present work suggests that specific residential composition (as course quality or characteristics change) may be able to explain some of the variation detected for an amenity. Even Shultz and Schmitz note that residential composition is not as homogeneous as first impressions suggest.

At a more intermediate level, concerns to examine larger real estate market trends can be improved by sharper submarket contextualization in real estate pricing. For example, meta-analyses of hedonic research studies are used by various federal agencies to set policy. A meta-analysis conducted by Simons and Saginor (2006) seeks an average response across 75 different papers. Our analysis suggests that a lack of finer detail will tend to suppress the magnitudes of the negative effects of 'bads' (such as environmental contamination) or the positive effects of 'goods' (such as environmental amenities), potentially directing national policy away from stronger positions on these issues.

At a macro-market level, we also see the growing need for market stratification in policy and market analyses (Prasad and Richards, 2008), where movements in the real estate macro-market are affected by the relative level of current activity among distinct market segments. In a similar vein, Miles (2008) uses generalized autoregressive conditional heteroscedasticity (GARCH) models to show that across states the signs and magnitudes of explanatory variables vary widely, highlighting the importance of estimating separate GARCH models for each individual market.

Submarket Competition

In diverse urban districts, some households bid for housing units only among members of their own submarket. The house may not appeal to another submarket; one reason might be that income constraints prevent members of a submarket from offering competitive bids. This would make market segmentation an easier process to identify. Yet, within some price ranges in many diverse urban neighborhoods, households may compete with other submarkets for a given unit.

Cross-submarket competition in a local area, if vigorous, is likely to leave a unique empirical mark on home prices in a local area. If a marginal improvement in a single attribute or a collection of related attributes induces cross-type competition for a given unit, theory suggests cross-type competition more often will require a premium to be paid to acquire that unit. If the submarket agent is attracted to the unit because of a marginal improvement in a specific class of attributes and is successful, the overall price for this unit will reflect a higher implicit value for that attribute. If sales from different competitive conditions are incorporated into the same regression that assumes homogeneous agents, the structural differences that could explain the price movements would appear merely as higher overall variance and, potentially, could lead to inconsistent attribute estimates. This work addresses a case where variation in home prices locally includes substantial cross-submarket competition.

We do not attempt to create an estimator to extract a fully efficient market estimate of this competition signal from other noise, in part because in this initial exploratory study the data set is quite small. Instead, we test for the presence of variance (in a small neighborhood) that is consistent with a hypothesis that cross-submarket competition exists and that price premiums are being paid to occupy a unit that does not exist in other price ranges where cross-type competition is unlikely. That is to say, we expect this neighborhood to accommodate multiple household types (with different preferences) that compete with each other for housing. What we find is that, in the price ranges where submarkets might compete against each other for housing, certain hedonic attributes consistently show higher values above the mean than in other price ranges. As a result, some of the overall price variation is, we hypothesize, explained directly by this competition between types; and cross-market competition appears to be resolved (i.e., one household type ends up occupying the house as it outbids another household type) when one type offers a premium for an attribute of particular interest.

The attributes that display a premium in the price ranges where competition occurs between types are those that appear to be especially important to that type given prior analysis of this local real estate market (Lipscomb and Farmer, 2005). For example, the new and expensive houses that are occupied by undergraduate students (renters) have more bedrooms, smaller square footage per room, yet large square footage overall than the homes purchased by established households (mostly owners) in the neighborhood in this *same price range*. Established households in this price range reflect a strong preference for adjacency factors, meaning members of this submarket pay a premium for the composition of immediate and near neighbors. In the price ranges where student housing and established homes realize the same sales price, the value of structural attributes for students and adjacency attributes for established households realizes a premium, suggesting they at times directly compete and submit bids for the same units. Overall, the elements of these broad attribute classes are strong features in the existing analysis of this market. To be answered in this work is whether the significance of these attribute classes could be explained in part by bidding behavior *between* submarkets. Understanding this structure better is important for setting local land use policy, for larger development or redevelopment efforts, and for estimating damages in real estate contamination cases.

The evidence in this work that students and established households may in fact engage in direct competition (bidding for the same unit in this price range) is displayed by an extraordinary price premium for high occupancy structural features by students and a high premium related to adjacency features by established households, limited to the price range where competition is possible. This is identified by a quantile regression analysis on each submarket that estimates a different coefficient vector for attributes at different price ranges (quantiles). Without a premium, the co-existence of two submarkets occupying homes in the same price range may be coincidental; or the different submarkets sort into different units in an orderly fashion without ever directly competing for the same units. When these two groups do bid for the same house, however, one group appears to pay a premium for the particular feature that they most value. This is consistent with offering more for an improvement in those attributes than they have to pay otherwise, consistent with auction theory.

Prior work on this dataset (Lipscomb and Farmer, 2005) also suggests the possibility that the entry and exit of a given type in a neighborhood can be sensitive to specific features, an outcome any investor needs to anticipate in building (or improving) real estate for a given market. A third group of young professionals, for example, does enter the neighborhood in a very narrow price range. Prior evidence suggests they occupy units that are almost universally two-bedroom, one-bath units. One explanation is that if a bedroom or bath is added, this submarket group is quickly outbid by another type. Direct inspection only located these young professionals occupying units officially listed as 3 bedroom or 2 bath homes when those rooms were largely below standard or unsuitable for their listed purpose. Prior work speculated that this might be responsible for negative and significant values for the number of bathrooms variable (Lipscomb and Farmer, 2005). Generally, this hypothesized result is only possible if there is active cross-submarket trading, without which we would have an uncorrupted data array that would observe marginal value gains for another bedroom or bath of moderate to good quality. That this is obviated by the absence of observations of this type occupying residences improved in such a manner suggests that cross-type bidding is present and that this type is usually outbid. Yet this speculation still has to be tested. Corroborating evidence found here has strong implications for investment and redevelopment potential in this neighborhood. Improving units currently occupied by households from this submarket can realize the very high premium paid by an occupant *from another submarket*, an opportunity otherwise undetectable by conventional hedonic analysis.

Who occupies particular dwellings is decided by the highest bid for the particular characteristics of each dwelling. Critically, analyses that model limited heterogeneity will miss this effect. In critical, strategic land use decisions or investments this could have deleterious effects, resulting in investment losses or poor zoning choices. Neighborhood zoning, for example, often prizes homogeneity as a form of continuity. Yet the implications of possible outcomes presented here for real estate developers and remodelers are important, especially in discussions concerning neighborhood redevelopment and New Urbanism principles (Bohl, 2000).

Auction Theory

So why would different household types have to pay a premium for certain characteristics? Auction theory offers a theoretical base for this observed phenomenon. In a Vickrey (1961) auction, a successful bidder only has to outbid the second highest bidder. This is important because final auction prices generally do not extract the entire consumers' surplus of the highest bidder. The final occupant pays something below her highest willingness to pay, outbidding the second highest bidder only by some small incremental amount. If the second highest bidder has similar preferences to the highest bidder, and the second highest bidder is representative of buyers in this market across a regional (or neighborhood) market, hedonic prices for attributes will be quite stable, reflecting the common preferences of this group. The idiosyncratic preferences of each individual will not be reflected in the final market prices, so hedonic analyses are quite stable.

But, what happens when another type of household is attracted to bid for a unit? If two different types compete for a unit in a particular price range, the second highest bidder now may have very different preferences than the second highest bidder's active in other price ranges. If that other household type offers a credible competitive bid that eliminates all other competitors, it becomes the second highest bidder in that auction. Some of the surplus that the successful occupant would have enjoyed by outbidding only a member of the same submarket will have to be sacrificed. Therefore, the successful occupant will offer an additional premium to assure her successful bid over the new contender, a second highest bidder from another submarket.

In such a market competition, sometimes one type will win and sometimes another. Small nuances in the attribute mix may resolve which group representative wins. Each will offer a premium, reducing some of the surplus typically received, to enjoy a particular feature of the house that reflects their preferences. For example, if established households prefer a large yard, then we might observe a premium being paid through the hedonic coefficient on the variable that measures a parcel's lot size for these sales in this price range. These particular house features and the premiums paid for them ought to show up as higher hedonic coefficient estimates within those specific prices ranges (price quantiles) where two different types are observed in the market.

Indeed, using the quantile regression methodology, which allows regression coefficient values to vary across the price range, we find premiums paid for specific attributes only in those ranges where cross-type competition could occur—homes of similar price occupied by different types of households in the same neighborhood. These premiums manifest as higher implicit prices in these specific price ranges across the submarkets. This suggests that some of the price variation observed, even in very local markets, is due to the competition between types for some houses but not for others, leaving a trace in the overall price data as added and unexplained variation in the hedonic price estimates for each individual submarket. If the researcher is not sorting submarkets and not examining trade or competitions between submarkets, much of the richness of the real estate market goes missing from hedonic analysis.

Bidding Theory and Estimating Hedonic Prices

Diversity generates three concerns that need to be addressed empirically which stem from the need to account for market activities among different submarkets. Real estate analysts need to:

1. Sort groups into coherent types that satisfy statistical tests of submarket sorting;
2. Cluster attributes into indexes of variables to manage multi-collinearity; and
3. Estimate the effect of competition on home price data to detail those particular attribute packages that resolve cross-submarket competitions and that predict the final occupant.

To date concern '1' has been attempted by many different authors (Goodman and Thibodeau 1998, 2003, 2007; Bourassa, Hamelink, Hoesli, and MacGregor, 1999; Bourassa, Hoesli, and Peng 2003; Lipscomb and Farmer, 2005). In the majority of these works, submarkets are assumed to correlate to geographic location, governed by a one neighborhood, one type hypothesis. Concern '2' has been attempted by Kain and Quigley (1970), who use factor analysis to reduce the number of location characteristics into a more manageable set of five factors, as well as by Dubin and Sung (1990), who group neighborhood characteristics into three categories: socioeconomic status, quality of municipal services, and racial composition.

As far as we can tell, concern '3' has not been addressed in the real estate or urban economics literatures at the local level, nor have all three concerns been addressed simultaneously. A recent trend in the literature is to conduct quasi-experiments on the 'voting with your feet' thesis. Premised on homogeneity in a single neighborhood, households re-sort among neighborhoods in a Tiebout-style fashion after a significant neighborhood characteristic changes (Smith and Huang, 1995; Sieg, Smith, Banzhaf, and Walsh, 2004; Cameron and McConnaha, 2006; Banzhaf and Walsh, 2008; and Card, Mas, and Rothstein, 2008). Yet the diversity between neighborhoods still relies on the acknowledged modeling convenience of homogeneity *within* the neighborhood (Cameron and McConnaha, 2006). The local homogeneity simplification assures that all bidders in a home sale are drawn from the same submarket which makes for orderly for hedonic estimation (Smith and Huang, 1995; Sieg, Smith, Banzhaf, and Walsh, 2004). It has been noted that such 'vertical' heterogeneity assumptions that attribute all diversity to spatial delineation—one neighborhood, one type—implicitly assume for estimation that two *truly* distinct types never directly compete for the same housing unit. These works need to be augmented by 'horizontal' heterogeneity where some individuals with different, truly distinct marginal valuations offer similar overall values for a home (Banzhaf and Walsh, 2008; Card, Mas, and Rothstein, 2008).

Switch points (where one type replaces another in a given housing unit) are likely to be influenced by classes of related attributes, at least under the premises of household production theory. For example, location within the neighborhood is one class of attributes that comprises proximities to several key landmarks (e.g., commercial/retail shopping, highway interchanges, green spaces). Also, a structure bundle comprises structural attributes such as the number of bedrooms and baths, among others. Therefore, tracking competition between submarkets is facilitated by combining several related attributes into a coherent attribute bundle, or index, that is consistent with the very origins and base theory of hedonic pricing (Smith and Huang, 1995).

As so much of the public policy and private investment process is directed at the local level (when diversity is present in a single neighborhood), hedonic price analysis requires vetting multicollinearity among attributes that contribute to similar household services and cross-submarket competition. Our goal in this work is to extend previous literature that establishes local diversity in order to test for the presence of local market forces that allocate homes across competing submarkets. Results suggest that diversity itself and the cross-submarket competition for housing units in this local market explain a significant share of home price variation.

Below we conduct hedonic price analysis in a single neighborhood, which is part of two different census tracts. Lipscomb and Farmer (2005) show that the neighborhood market sorts rather cleanly into three distinct submarkets that value bundles of attributes quite differently. Critically, the largest share of home price variation is explained, first, by sorting households into different submarkets, not the aggregate variation of attributes across the neighborhood. In this work, we identify additional variation in price that can be explained by the effects of cross submarket competition. Variation is due to more than simple co-existence of separate submarkets in one neighborhood. Home pricing patterns reflect predicted variation in attribute bundles' implicit values consistent with very different types offering similar values for the same housing unit.

Adapting Estimation to Submarket Competition

To extract information about the structure of a local market due to cross-type competition, we need more information on households directly, specifically their demographic information. First, a brief survey of households was conducted to elicit very basic demographic data and a few key attitudinal variables that report households' impressions of their houses and their neighborhood. Second, submarkets were identified through a sorting mechanism using household information. The iterative sorting process that utilizes the seemingly unrelated regression (SUR) estimator had been employed already to sort households into types (Lipscomb and Farmer, 2005). The SUR is the classical statistical tool to manage differentiated types of economic actors in a single market, such as submarkets buying and selling homes in a given area (Srivastava and Giles, 1987).

With submarkets identified, property attributes within a submarket were bundled, or indexed, into three attribute classes. We bundled a *structural* attribute among square footage, number of rooms, number of bedrooms and bathrooms, lot size, and presence of a building permit. We created a *location* attribute index composed of different distances of each home to surrounding landmarks. In this way, different submarkets reveal a different best, or optimal, location within their neighborhood. Finally, there is an *adjacency* attribute index composed of the weights assigned to the concentrations of different types of households that occupy residences in the immediate vicinity. Then, to isolate those price ranges (or quantiles) where submarkets might compete for the same unit, we identified those ranges where home prices in any two of the submarkets were similar. To test the hypothesis that premiums are paid for attribute bundles in these price ranges by certain household types, quantile regression analyses estimated different parameter values for each attribute bundle (Structure, Location, and Adjacency) for each submarket at different price quantiles.

Attribute bundling, coupled with a quantile regression analysis, allows the researcher to examine the structure of the market and to answer this question: When two submarkets bid for the same housing unit, is there evidence that some attribute bundle realizes a higher than average implicit hedonic price (i.e., a price premium) by from one submarket that allows it to outbid the other submarket? That evidence would allow the local real estate professional, developer, or urban planner to make more strategically informed decisions and to examine the overall economic stability of a diverse New Urbanism community.

The reason for quantile regression (QR) is that not all price ranges will be subject to cross-submarket competition. Logically, only units similar in price for both submarkets are candidates for competitive bidding between submarkets. So empirically we need to track implicit prices for specific attribute bundles in those price ranges where two submarkets overlap. In this way we can assess if any above average premium is paid for either structural features, adjacency features, or location features to outbid a contender from another submarket.

Data and Methods

Quality data are critical to this study. Household data were acquired from direct stated preference surveys coupled with Multiple Listing Service data. For the renters in the dataset, monthly rental values were adjusted to market sales equivalents using capitalization rates (or rent multipliers) supplied by local real estate agents and validated against existing sales. Prior results suggest that it takes only very modest demographic information about housing occupants to ascertain how submarkets sort across a local space. As such, hedonic price analysis can assist with submarket demarcation at a small geographic scale.

Analyses on the dataset already have partitioned households into three statistically distinct submarkets (Lipscomb and Farmer, 2005; Lipscomb, 2006), each of which has fundamentally different preferences. Type A households are generally low income student renters completing university degrees; Type B households are young adults, mostly graduate students with families or professionals in their early career stages. These residents either rent or own lower-end starter dwellings. Type C households are more established homeowners with incomes below the average for the immediate downtown area who seek affordable urban housing in this community.[1] Exhibit 1 lists the descriptive statistics for variables used in the construction of the attribute bundles.

Attribute Bundling

Using results for each submarket obtained from Lipscomb and Farmer (2005), we create three attribute indexes using the hedonic coefficients from the 14 original independent variables:

Exhibit 1 | Variable List

Dependent Variable

Rental / Selling price of house; continuous in dollars; rental multiplier of 120 used to convert monthly rents to sales prices.

Mean = 148115; Standard Deviation = 69400

Independent Variables

Dwelling Structure Variables (from housing survey, Multiple Listing Service, and City of Atlanta construction database):

Square footage of the house; continuous

Mean = 1323; Standard Deviation = 502

Number of bedrooms; discrete

Mean = 2.38; Standard Deviation = 0.74

Number of baths; discrete

Mean = 1.34; Standard Deviation = 0.53

Number of acres; continuous

Mean = 0.21; Standard Deviation = 0.18

"Have you taken out a building permit in the last three years?"; discrete

Mean = 0.12; Standard Deviation = .32

Condominium; discrete

Mean = 0.06; Standard Deviation = 0.24

Location Variables (from GIS)

Road network distance to nearest brown industry; continuous in meters

Mean = 863; Standard Deviation = 321

Road network distance to the Home Park green space; continuous in meters

Mean = 532; Standard Deviation = 264

Road network distance to 14th Street commercial / retail center; continuous in meters

Mean = 922; Standard Deviation = 391

"Is the dwelling at or above street level?"; dichotomous

Mean = 0.38; Standard Deviation = 0.48

Adjacency Variables (Yes or No dummy variables created from a GIS)

"Do you live adjacent to a renter?"

Mean = 0.82; Standard Deviation = 0.38

"Do you live adjacent to a college student?"

Mean = 019; Standard Deviation = 0.39

"Do you live adjacent to a college graduate?"

Mean = 0.76; Standard Deviation = 0.42

"Do you live adjacent to a household that has made home improvements in the last two years?"

Mean = 0.33; Standard Deviation = 0.47

$$\begin{aligned} STRUCTUREq &= \hat{\beta}_1^q \ln(SQFT) + \hat{\beta}_2^q \ln(BEDS) + \hat{\beta}_3^q \ln(BATHS) \\ &\quad + \hat{\beta}_4^q \ln(ACRES) + \hat{\beta}_5^q BLDGPERM + \hat{\beta}_6^q CONDO \\ LOCATIONq &= \hat{\beta}_7^q \ln(D\_COMM14) + \hat{\beta}_8^q \ln(D\_GREEN) \\ &\quad + \hat{\beta}_9^q \ln(D\_MEINEKE) + \hat{\beta}_{10}^q \ln(STREET\_LEVEL) \\ ADJACENCYq &= \hat{\beta}_{11}^q \ln(ADJ\_RENTER) + \hat{\beta}_{12}^q \ln(ADJ\_UGRAD) \\ &\quad + \hat{\beta}_{13}^q \ln(ADJ\_COLLEDUC) \\ &\quad + \hat{\beta}_{14}^q \ln(ADJ\_HOMEIMPROVE). \end{aligned} \quad (1)$$

The STRUCTURE index for example is created using the coefficient estimates β_1 through β_6 for each submarket q as index weights. The weighted indexes are group specific, drawing values of β_1 through β_6 (or different weights) from each submarket regression.[2] See Exhibit 1 for a summary.

For this work, we regress the natural log of sales price [ln(*Price*)] for each submarket q against the three newly created index variables. Notice that the dependent variable and the indexes are log transformed to extract *scale neutral* coefficient estimates; or the estimated coefficients of each attribute bundle λ_{iq} measure the *percentage* change in housing price due to a 1% change in the overall value of the index for that attribute for that submarket.[3] Three submarket regressions are then estimated:

$$\begin{aligned} LN(PRICE)_q &= \lambda_{oq} + \hat{\lambda}_{1q} STRUCTURE_q + \hat{\lambda}_{2q} LOCATION_q \\ &\quad + \hat{\lambda}_{3q} ADJACENCY_q + \mu_q. \end{aligned} \quad (2)$$

Results for the submarket regressions using bundled attributes are reported in Exhibit 2a. They are compared, for completeness, to a one-line regression that makes no distinctions between submarkets and aggregates all households into a single model. Critical to our argument, the pooled regression (Exhibit 2b) displays almost no explanatory value for this model. As predicted, a low R^2 (0.08) suggests a large share of the variance in home prices in this neighborhood would be explained by household diversity. We argue that a "one neighborhood, one type" regression assumption could easily mispecify an hedonic equation. Indeed, when the analyst accounts for household diversity, R^2 improves considerably (0.32) for this study and even more (R^2 = 0.43) in a prior study using a somewhat larger set of regressors (Lipscomb and Farmer, 2005).

The role of Exhibit 2a in forming hypotheses is discussed below; but results estimate λ_{iq} as the price elasticity to a unit change in an attribute index, i, for

Exhibit 2a | SUR with Composite Goods (N = 357)
System R^2 = 0.32

	Index	Coeff.	Z-Stat.	Prob.
Type A	Structure	0.073	1.46	.148
	Location	0.032	0.46	.645
	Adjacency	0.066	0.95	.344
	Constant	11.46	12.20	.000
Type B	Structure	−0.046	−2.26	.025
	Location	0.085	1.61	.109
	Adjacency	−0.038	−2.40	.017
	Constant	12.71	15.50	.000
Type C	Structure	−0.013	−0.84	.400
	Location	−0.001	−0.05	.963
	Adjacency	0.098	3.66	.000
	Constant	11.78	46.31	.000

Exhibit 2b | One Line Regression with Composite Goods (N = 357)
R^2 = 0.08

Index	Coeff.	Z-Stat.	Prob.	F statistic	RMSE
Structure	0.013	3.23	.001		
Location	−0.005	−1.92	.056	11.01	.427
Adjacency	0.007	0.55	.581	(p = .000)	
Constant	11.79	424.98	.000		

submarket q. So in submarket q, a 1% change in the size of an attribute index, i, leads to a λ_{iq} percent change in expected sales price. This approach is consistent with household production theory where sets of housing amenities supply different services to the household that complement other purchases outside the housing market. For example, bundles of kitchen amenities complement food purchases or bundles of indoor/outdoor spaces complement other recreation purchases (Lancaster, 1966). So we do not impose $\Sigma_{iq}\lambda_i = 1$, which would impose the assumption that attributes serve only narrow housing needs rather than broader household services. Yet this functional form for indexing does impose *weak separability* (Deaton and Muellbauer, 1980), whereby elements within a single index are partially substitutable (e.g., fewer bedrooms for greater square footage), but trade-offs across indexes are traded-off only as a group (e.g., less structure for better location), regardless of the element in each group responsible for the increase or decrease.

The critical test for submarket competition is whether some λ_{iq} realize unusual values in the price ranges of competition between types. Specific hypotheses regarding which λ_{iq} are expected to display high or low values in the competitive price ranges are generated and tested by quantile analyses described below.

Generating Hypotheses for Attribute Index Estimates

We expect to observe a submarket premium, defined as a higher than average λ_{iq} coefficient, to be paid for at least one of the bundled attributes when a member of a submarket successfully occupies the property. If there is no competition between submarkets in these price ranges, then no change (or premium) in the values of any amenity bundles would be observed. If an amenity is not active in resolving competition between submarkets, no premium is expected to be observed for that particular amenity.

We also allow for negative attribute amenity predictions, where a type frequently loses bidding contests with another type. Some types may succeed by offering a premium for a highly valued amenity; they may also succeed by accepting some diminution in a lower valued amenity. As a specific example, established households and students order preferences for adjacency very similarly—or, their rankings from best to least preferred conditions of the immediate neighborhood on Exhibit 2a are similar, but the magnitude for established households is higher. Students may succeed in a bidding contest with established households by offering a premium for favorable structural features but also by accepting a slightly inferior set of adjacency features. Given the premium price paid for the structural amenities to outbid established households, any multicollinearity among attributes that exists (which we expect with so relatively few observations) would appear as if the agents were paying more for a less attractive array of adjacency features. We posit six such 'spurious' negative attribute values in our results.

We subdivide the price distribution for each submarket into five quantiles (quantiles 0.1, 0.3, 0.5, 0.7, and 0.9). Direct observation reveals three price ranges where submarkets realize similar marginal prices. These constitute the candidate ranges for possible cross-type competition:

1. Price Quantile 0.3 for Type A overlaps with Price Quantile 0.1 for Type B;
2. Price Quantile 0.9 for Type A overlaps with Price Quantiles 0.5 and 0.7 for Type C; and
3. Price Quantile 0.9 for Type B overlaps with Price Quantile 0.1 for Type C.

If premiums paid in competition are responsible for much of the price variation within a submarket, prior results including the attribute value estimates on Exhibit

2a in each submarket help to generate specific hypotheses regarding which premiums for attributes in which submarkets are expected to be observed.

The total number of hypotheses is 18. There are three attributes for each submarket in a given range of competition along with two submarkets engaged in competition in each particular range. With three overlapping price ranges, this makes for 18 specific hypotheses in specific competitive price ranges overall. The column of hypotheses listed in Exhibit 3 includes eight outcomes where we expect statistically significant positive premiums for specific attributes, organized into six groups (two competitive ranges for each of the three types). The other ten are not listed; but we hypothesize that there will be the realization of six *negative* attribute values and four attributes not expected to play any role in resolving competition.

The hypotheses, listed as Hypothesis 1 to Hypothesis 6, in Exhibit 3 are discussed in order.

Hypothesis 1 and Hypothesis 2. Student renters in this neighborhood occupy some very expensive homes (and some of the cheapest). Therefore, it is no surprise that attributes may not show evidence of overall significance if students compete with other submarkets at the low end and at the high end of their housing price range in this market, realizing premiums at both ends of the distribution. At low prices,

Exhibit 3 | Summary of Hypotheses Predicting Positive Premiums

Submarket Type	Hypothesis	One-Tail Test Outcome (*p*-value)
Type A	1. Structure, Location and Adjacency Premium Paid at Quantile 0.3	Type A: $\beta_{\text{STRUCTURE}}$ = 0.14 (0.034)** Type A: β_{LOCATION} = 0.09 (0.173) Type A: $\beta_{\text{ADJACENCY}}$ = 0.17 (0.093)*
Type A	2. Structure Premium Paid at Quantile 0.9	Type A: $\beta_{\text{STRUCTURE}}$ = 0.16 (0.088)*
Type B	3. Location Premium Paid at Quantile 0.1	Type B: β_{LOCATION} = 0.12 (0.038)***
Type B	4. Location Premium Paid at Quantile 0.9	Type B: β_{LOCATION} = 0.15 (0.078)*
Type C	5. Adjacency Premium Paid at Quantiles 0.5 and 0.7	0.5 Quantile Type C: $\beta_{\text{ADJACENCY}}$ = 0.14 (0.000)*** 0.7 Quantile Type C: $\beta_{\text{ADJACENCY}}$ = 0.16 (0.000)***
Type C	6. Adjacency Premium Paid at Quantile 0.1	Type C: $\beta_{\text{ADJACENCY}}$ = 0.09 (0.003)***

Note:
*Significant at the .10 level for hypothesized one-tail tests.
**Significant at the .05 level for hypothesized one-tail tests.
***Significant at the .01 level for hypothesized one-tail tests.

the lowest in the neighborhood, we expect students will be concerned with avoiding bads, which generates Hypothesis 1.

Hypothesis 1: At quantile 0.3, students compete with and largely succeed in outbidding young professionals, Type B. Therefore, we expect all three attributes (location, immediate neighborhood conditions, and structural features) to demonstrate a positive premium.

At high quantiles, we expect students to value the structural amenities and to pay a premium for *this* attribute at those high quantiles. Though the structure variable is only close to significant overall (t-statistic = 1.46) on Exhibit 2a, our hypothesis that this attribute may exert a uniquely high influence at the highest price levels. This would be consistent with the initial result. Since established households are likely to care more about adjacency, or the mix of their immediate and nearby neighbors (which are similar in ranking to students but stronger in magnitude), we expect the following results from students who occupy property in this price range:

Hypothesis 2: At quantile 0.9, students compete with and occasionally outbid established households, Type C. Therefore, we expect the structural attribute to demonstrate a positive premium.

As student renters and established households rank adjacency attributes similarly, but established households demonstrate a stronger marginal preference, we also expect at quantile 0.9 a negative and lower than average attribute value for adjacency for student renters.

Hypothesis 3 and Hypothesis 4. Results on Exhibit 2a suggest Type B young professionals, often with young families, value location conveniences as the particular feature they value strongly enough to make them competitive in this real estate market. Lack of within-submarket diversity by young professionals suggests they lose most bidding contests; and as such, they find it difficult to penetrate the market beyond the two bedroom/one bath homes they occupy. On both sides of the competition, small increases in structural features such as a bedroom, bathroom, or overall square footage makes the unit more attractive to students who value occupancy or to established households who value space (for a bedroom converted office), convenience (bathroom), or recreation (square footage and lot size). Similarly, immediate neighborhood conditions matter to students for safety reasons and to established households for aesthetics. Yet location is important to young professionals. Young professionals are observed to occupy units with access to close-by convenience shopping and to road network connections to multiple downtown locations.

Hypothesis 3: At quantile 0.1, young professionals compete with and occasionally succeed in outbidding student renters, Type A. Therefore, we expect the location attribute to demonstrate a positive premium.

From the narrow position of Type B in this market and results on Exhibit 2a, at quantile 0.1 we expect a negative and lower than average attribute value for structure and adjacency attributes.

Hypothesis 4: At quantile 0.9, young professionals compete with and occasionally succeed in outbidding established households, Type C. Therefore, we expect the location attribute to demonstrate a positive premium at that quantile.

From the narrow position of Type B in this market and results on Exhibit 2a, at quantile 0.9 we expect a negative and lower than average attribute value for structure and adjacency attributes.

Hypothesis 5 and Hypothesis 6. Exhibit 2a also provides information about established households (Type C). These households occupy units almost wholly at or above the median home price in the neighborhood. We expect adjacency attributes to be positive and significant as these households search for pockets of improved homes occupied largely by other established households. That expectation is borne out by the adjacency index variable.

Hypothesis 5: At quantiles 0.5 and 0.7, established households compete with and often succeed in outbidding student renters, Type A. Therefore, we expect the adjacency attribute to demonstrate a positive premium.

In competition with young professionals at quantile 0.1, we also expect:

Hypothesis 6: At quantile 0.1, established households compete with and largely succeed in outbidding young professionals, Type B. Therefore, we expect the adjacency attribute to demonstrate a positive premium.

As established households and young professionals rank location attributes similarly, but young professionals demonstrate a stronger marginal preference, we also expect at quantile 0.1 a negative and lower than average attribute value for location for established households.

Finally, we generate four specific hypotheses of *no effect* on attribute values due to competition in the ranges of potential competition. For Type A student renters, we do not expect Location at quantile 0.9 to differ from average values. Similarly, for Type C established households, we do not expect Structure at quantile 0.1 to differ from average values; and we do not expect Type C Structure and Location at quantiles 0.5 and 0.7 to differ from average values.

Since only certain price ranges are relevant for each submarket, we now employ quantile regression analysis to test our hypotheses.

Quantile Regression Methodology

A quantile regression generates a different coefficient value estimate for each independent variable at different levels (quantiles) of the dependent variable. A premium is consistent with a higher coefficient value at a predicted price than at others. The seminal work on quantile regression is Koenker and Bassett (1978). Since then, this method also has been used to estimate the demand for electricity (Hendricks and Koenker, 1991), to estimate stock market returns via a Capital

Asset Pricing Model (Barnes and Hughes, 2002), and to estimate relationships in the field of ecology (Cade and Noon, 2003). The method of quantile regression is based on the minimization of a weighted sum of the absolute deviations,

$$\min_{\{b_j\}_{j=0}^{k}} \sum_i \left| y_i - \sum_{j=0}^{k} b_j x_{j,i} \right| h_i, \tag{3}$$

to estimate conditional quantile functions.[4] Here, the weight h_i is defined as $h_i = 2q$ if the residual for the i^{th} observation is strictly positive or as $h_i = 2 - 2q$ if the residual for the i^{th} observation is negative or zero, where q varies between zero and one and is the quantile to be predicted.

We employ five quantiles in this analysis (0.1, 0.3, 0.5, 0.7, and 0.9). It is important to remember that a quantile regression is an efficiency correction, similar to generalized least squares (GLS) or spatial weights matrices (SWM). Quantile regressions are estimated simultaneously; so the degrees of freedom are not calculated by quantile but as a system. If there are five quantiles, n observations in the entire sample and m variables, the degrees of freedom for the quantile estimator is $n - (m + 5)$. Therefore, an *individual* quantile may have only n_m observations that can fall below $m + 5$ with no loss of efficiency; it is a system estimator.

Results

Exhibit 4 reports the estimated coefficients for each of the five quantiles by each submarket. It also reports the mean value of each attribute across quantiles for each submarket for use in comparison. Exhibit 4 highlights for each submarket the quantiles that are active in cross-type competition (e.g., 0.3 and 0.9 for Type A). It also highlights which specific attribute estimates in those quantiles are expected to show a positive attribute value premium.

In addition to stating hypotheses, Exhibit 3 reports the level of statistical significance of the posed one-tail test for hypotheses. Hypothesis 1, as an example, finds that the estimated structure coefficient rejects the null hypothesis of no premium for the attribute at quantile 0.1 with 96.9% confidence.

Overall, seven of the eight specific attribute positive premiums expected that are listed in Exhibit 3 reject the null with at least 90% confidence (the hypotheses for quantiles 0.5 and 0.7 for Type C collapse to one hypothesis, Hypothesis 5, with two test points). For Hypothesis 1, only the location attribute for Type A student renters was expected to show a significantly positive premium but did not. The location coefficient on Exhibit 4 (and Exhibit 5) displays high variability across quantiles for Type A, which may obscure any difference; yet location on

Exhibit 4 | Quantile Regression Estimates

Panel A: Type A Households (N = 68)					
QUANTILE	0.1	0.3	0.5	0.7	0.9
CONSTANT	13.96	10.32	10.98	11.74	13.36
STRUCTURE INDEX	0.01	0.13	0.03	0.00	0.16
LOCATION INDEX	−0.21	0.11	0.06	0.00	0.00
ADJACENCY INDEX	−0.04	0.20	0.03	0.00	−0.20
Panel B: Type B Households (N = 160)					
QUANTILE	0.1	0.3	0.5	0.7	0.9
CONSTANT	12.41	10.87	11.74	11.73	14.41
STRUCTURE INDEX	−0.10	−0.05	0.00	0.00	−0.02
LOCATION INDEX	0.11	−0.02	0.00	0.00	0.15
ADJACENCY INDEX	−0.05	−0.01	0.00	−0.06	−0.05
Panel C: Type C Households (N = 129)					
QUANTILE	0.1	0.3	0.5	0.7	0.9
CONSTANT	10.93	11.09	11.35	12.39	12.26
STRUCTURE INDEX	0.01	0.03	−0.01	−0.03	0.02
LOCATION INDEX	−0.04	0.02	0.00	0.00	−0.01
ADJACENCY INDEX	0.12	0.05	0.18	0.08	0.03

Exhibit 4 (and illustrated in Exhibit 5) is still far higher than the average value for location by Type A.

Next, Exhibits 5–7 provide a visual display of the estimates for each submarket type across five quantiles that are recorded in Exhibit 4.

In an initial focus group (of students only), students living in lower priced units expressed concern for location and for the condition of immediate neighbors (adjacency) while students living in higher priced homes expressed concerns for high occupancy and clean, newer units. This would seem to be borne out, represented by results on Exhibit 6.

Hypothesis 1: Students avoid 'bads' at low quantile prices, which conforms to student focus group statements.

We expect they will display a premium for all three attribute bundles at quantile 0.3. Only location failed to realize a significant premium, perhaps due to the low Location value at quantile 0.1 (affecting the variance around the mean value for location).

Exhibit 5 | Coefficients on Hedonic Indices for Submarket C Households

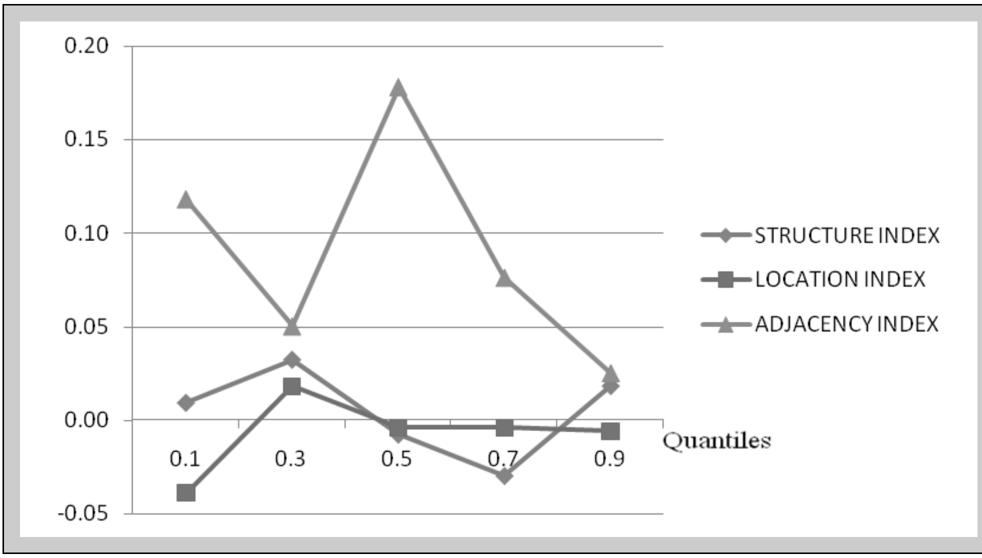


Exhibit 6 | Coefficients on Hedonic Indices for Submarket A Households

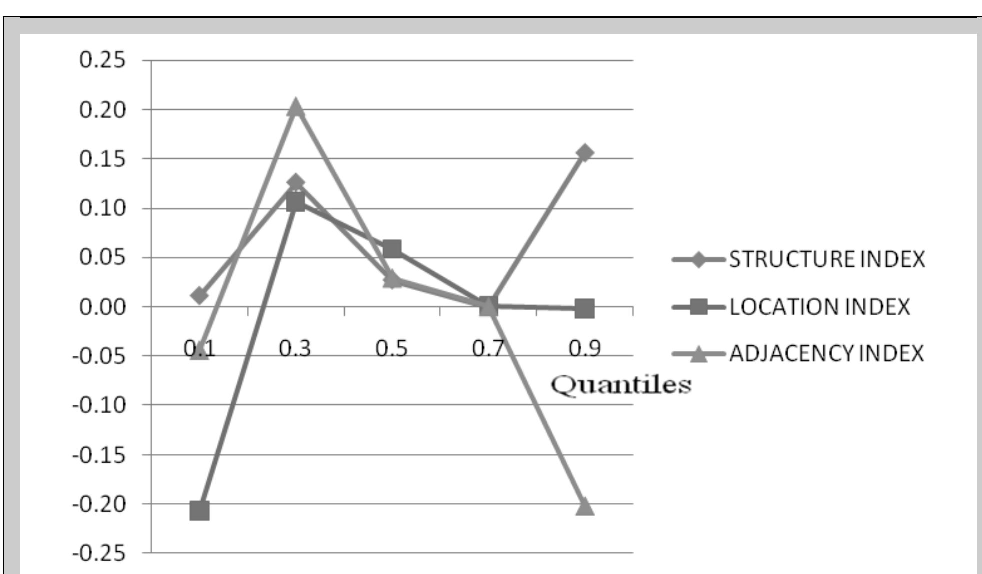
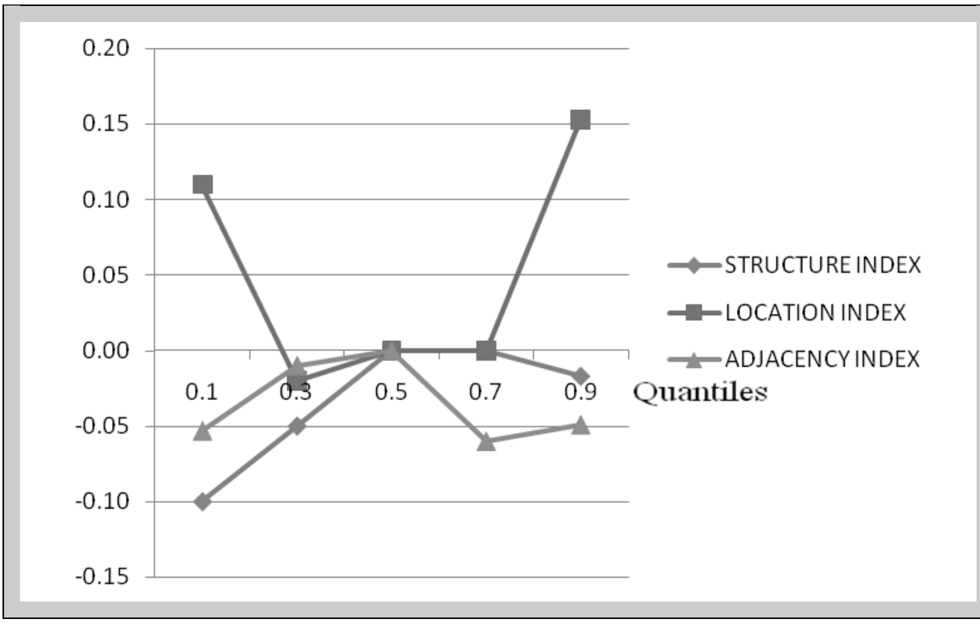


Exhibit 7 | Coefficients on Hedonic Indices for Submarket B Households



Hypothesis 2: Students pay a premium for features that favor high occupancy.

At quantile 0.9, the structure coefficient value realizes a premium as hypothesized with 91.2% confidence. These more expensive, higher occupancy homes (mostly four-bedroom with a few five-bedroom homes) tend to appear in clusters, which would indicate less concern for Adjacency and Location at the higher price end.

In competition with Type C, students trade-off newer, high occupancy units against adjacency and location valued at lower quantiles.[5] The negative attribute value predicted for adjacency at 0.9 is also observed on Exhibit 6. With similar but weaker preferences for adjacency than Type C, student renters combine offers of higher bids with reductions in adjacency to successfully compete with established households.

Type B young professionals occupy a narrow range of local housing stock—two bedroom, one bath homes almost exclusively. They value location as a weighted index that shows preferences for being close to convenience stores, the university, and major thoroughfares. Exhibit 7 illustrates a clear positive value for location at the tails where competition occurs.

Hypothesis 3: The predicted Type B premium for location is displayed at quantile 0.3.

Hypothesis 4: The predicted Type B premium for location is displayed at quantile 0.9.

There are also four weak hypotheses regarding Type B (not listed in Exhibit 3). The structure and adjacency attributes could be significantly negative at quantiles 0.1 and 0.9. Three of these four are significantly negative above the 90% confidence level—the negative value for structure at quantile 0.9 is still negative but not statistically significant.

Type C households prefer to be adjacent to their own type and discount at different levels of intensity adjacency to other types. Illustrated in Exhibit 5, regression results show a strong positive value for adjacency at prices where competition occurs.

Hypothesis 5: The predicted Type C premium for adjacency is displayed at quantile 0.1.

Hypothesis 6: The predicted Type C premium for adjacency is displayed at quantiles 0.5 and 0.7.

The negative value predicted for location is demonstrated in Exhibit 5. As established households and young professionals rank location attributes similarly, but young professionals show a stronger preference magnitude, established households at their lowest quantile outbid young professionals by offering a combination of higher bids for adjacency with modest reduction in location to compete successfully.

The quantile results for this market tend to conform to the prior SUR submarket estimates of Lipscomb and Farmer (2005) and attest to the benefit of attribute bundling and quantile regression analysis. Where competition is expected, our hypotheses that certain types are willing to pay higher than average implicit values for specific bundles to resolve cross-submarket competition are supported empirically.

Implications for Investors

Since the first collection of the data for this study in 2002, two profitable trends in real estate improvements and development have accelerated. Many of the highest valued two bedroom, one bath homes (Type B) have been improved by home additions—an added bathroom or bedroom. That these investments arise near other high value Type B or Type C (established household) houses suggests that when these units enjoy favorable adjacency features, strategic home additions yield a high return. Similarly, conversion or often demolition of the lowest priced Type B homes to build new and larger homes for student renters have been profitable. New, large homes built in areas where the immediate neighborhood creates less attractive adjacency features seems risky; but consistent with results here, if structural features favor high occupancy, students will pay a substantial premium to occupy those units anyway.

The quantile results here are very important for developers. Very expensive student houses tend to become their own immediate neighborhood. A cluster of low value student housing mixed with lower valued young professional homes is a very different neighborhood than a cluster of newly improved and larger student homes with well-lighted front areas.

Real estate investors could profitably expand several adjacent student units in very low valued student areas or remodel lower valued young professionals' homes surrounded by other established households. Significantly, these nuanced and local real estate market structures are often considered out of reach of hedonic analysis; yet with modest effort they arise in our results.

Results explain real world investors' choices regarding whether or not to upgrade and to remodel Type B homes by adding a bath or bedroom. Results explain why investors occasionally upgrade or remodel these homes as they can realize a premium, not from the young professionals currently living in these units but from students to whom they can now rent these units. For cases where homes are rebuilt as larger 4–5 bedroom homes, these developments violated zoning until recently; but now they seem to generate positive externalities to the rest of the neighborhood. At times even established households bid for these units.

For such a small data set and the local diversity examined, it would be hard to imagine a more consistent statistical performance. As diversity becomes a policy objective for urban areas, such as New Urbanism, the identification and the stability of local diversity rises as a real estate market concern, and a critical policy objective. As the scales of most of these initiatives are considerably larger than the local market examined here, presumably results in a similarly diverse market setting would be even sharper.

Conclusion

Smaller scale hedonic price analyses face numerous obstacles: lack of local amenity variation, small numbers of observations, generally less demographic variation, and time to complete such a detailed study. Yet, with some effort we can evaluate areas that retain local diversity by improving the quality of information regarding each observation, namely better demographic information. Part of the concern regards what is to be evaluated. At the local level, we show that a great deal of local real estate market structure can be identified that allows the analyst to assess what clusters of characteristics place a unit in competition between two different household types and how that competition is resolved. This provides direct information on strategic house remodeling or property investment.

Here, among 357 observations, exist three separate submarkets with clearly definable demographic distinctions that rationalize the submarkets identified.

Competition between submarkets appears only in specific price ranges, or house price quantiles, for each submarket as we might expect. The premiums required to be the highest bidder in cross-submarket competition skew the variance in housing prices within a given submarket in response to changes in attribute clusters. It is this insight that rewards our effort in modeling a local real estate market.

The strong improvement in overall explanatory power for the entire market due to the introduction of the SUR estimator, from 0.10 to 0.32 [or to 0.42 using a few more unbundled individual variables included in Lipscomb and Farmer (2005)], shows the value of the submarket articulation. Consistent with cross-type competition, more of the movement in prices is explained by the need at times for groups to pay a premium to prevail in that competition. Consistent with cross-type competition, a Vickery auction model predicts that prevailing over the second highest bidder from another submarket can require a more profound premium, one that arises usually due to a single class of attributes rather than all attributes, such as the preference for multiple bedrooms in large homes by students. The quantile analyses above show surprising conformity with a price premium paid for attributes as being strongly marked at those very specific prices ranges where submarkets might compete.

Given the data size and market diversity, some parsimony is required to conduct these analyses. Bundling of attributes into service clusters—Structure, Location, and Adjacency—allows us to use quantile regression analysis to capture cross-market competition effects on housing price. The high conformity in the performance of specific quantile predictions at specific home price quantiles shows promise for future real estate research.

Lastly, our results mimic in a larger sense observed patterns in larger hedonic studies. Large price variation across a space occurs in part due to demographic or preference diversity among groups of residents. The variance within a group is quite small due the homogeneity of preferences within group. This allows the analyst to measure the average price response to an amenity change. Yet there may be lessons here for much larger hedonic studies. To the extent that large studies show considerable parameter instability, even changing sign from study to study in the same market, they do so with especially attractive diagnostic features: very high individual parameter statistical significance, very high R^2 statistics, and in the largest studies almost undetectable multicollinearity. The patterns observed may signal more about what is measured: overall price variation across a large market with many diverse submarkets.

A key goal of this work is to establish the *prima facie* case that a high level of submarket diversity can exist in an urban neighborhood and that these markets interact with sufficient vigor to impact price variation. Hedonic analyses for many uses will have to attend more closely to this issue, using revised tools and estimation strategies that are theoretically consistent with the market phenomenon. While this work does not value each sub-attribute for each submarket, nor does it intend such an outcome, the larger concern for market structure and pricing patterns does reveal an important level of diversity that affect markets of concern to research.

It is unclear at this time how much this influences large hedonic price studies; but the results suggest that the largest sources of variation come from sorting submarkets into different types of households and then from understanding more about how those types interact in that market. More work to individualize parameter estimates for different respondents such as random coefficients models will extend the work here to sort groups into distinct submarkets. The benefits of such individualization of hedonic price estimates should be revealing, as the implications of tying household demographics to more favorable housing characteristics are important to real estate developers seeking to alter the local housing supply and investors seeking to diversify their real estate portfolios.

Endnotes

[1] Condominium owners seem to be an emerging fourth type (as they have above average Z-scores compared to all other Type C households) with the "mindset" or "lifestyle" of owners but the physical dwelling characteristics of Type B residents. Given the small number of condominium owners in this dataset (23), we do not have enough observations to classify them as a fourth household type.

[2] Many individual elements in the index from the SUR were not significant. F-tests comparing results with and without groups of insignificant variables revealed significant loss of information at the 95% level when only significant elements were used to create each attribute index. This significance in the group clustered effect is a key motivation for variable clustering.

[3] We observe a key control for scaling effects that can induce spurious heterogeneity across the range of dwelling prices is the choice of a double-log functional form for all continuous variables in the hedonic equations. An effect that alters the price of a $500,000 dwelling by $10,000 is clearly proportionally less influenced by that attribute change than a $100,000 dwelling that realizes the same $10,000 improvement. Instead of regressing raw housing price against dwelling attributes, we regress percentage shifts in the dependent variable against percentage changes in the continuous independent variables; so our coefficient estimates are expressed as elasticities.

[4] This quasi-artificial segmentation of the dependent variable (sales price) by quantiles should not be misinterpreted as support for the segmentation of households along a single dimension, a mistake made and realized by Rosen (1974). Even Heckman (1979) argues that any dependent variable truncation may create biased parameter estimates and should be avoided.

[5] The only other unexpected attribute elasticity is location for Type A at quantile 0.1. We had no prior theory, but the result is not inconsistent with a trade-off among these lowest quality and lowest valued units. It seems that adjacency (which students attach to safety) and structure (which students in these areas associate with functionality) would also show a trade-off against location (which students associate with convenience).

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