SPACE-TEMPORAL MEASUREMENT OF HOUSE PRICE APPRECIATION: IMPLICATIONS FOR LENDING IN UNDERSERVED AREAS

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INTRODUCTION

In recent years, there has been an aggressive promotion of mortgage lending to populations and neighborhoods traditionally considered underserved. Although the definition of underserved varies, typically it includes low-moderate income, minority households and the neighborhoods where these households are likely to reside. For instance, underserved households might have incomes at or below 80 percent of area median income. Alternately, they might live in census tracts with minority populations in excess of 30 percent.

The promotion of lending to underserved populations and areas has been accomplished, primarily, through the introduction of loan products that use flexible underwriting guidelines. These flexible underwriting guidelines have been designed to capture creditworthiness by nontraditional means as well as to minimize any potential increase in lending risks that might ensue.

Mortgage underwriting involves the evaluation of several factors related to the borrower and the property proposed as collateral. These factors are often referred to as the "three C's of underwriting"–capacity, credit reputation and collateral. Typically, in evaluating the risks of lending in affordable efforts, researchers have examined how each of the three factors, and their interactions, are related to loan performance over time. Unfortunately, consideration of loan performance over time has only been partial. Researchers have examined the role of equity at origination (captured with the loan to value at origination) but have not examined the appreciation potential of the properties themselves in their examination of risks in affordable lending.

This does not mean that there has not been research interest on house price appreciation in general. To the contrary, this has been one of the research areas that has received the most attention in the literature. Studies include seminal pieces such as those by Goodman (1977, 1988), Case and Schiller (1989), Case and Quigley (1991), and others. It is the topic of appreciation in low-income or underserved neighborhoods that has received little attention.

To our knowledge, only one study has examined the dynamics of house appreciation in low income neighborhoods specifically. Pollakowski, Stegman, and Rohe (1991) examine whether low and moderately priced homes had different rates of price appreciation than higher valued dwellings. Specifically, the authors define affordable housing units as those having an initial value in the lowest 20 percent and then the second-lowest 2 percent of an area's value distribution. They compare their rates of appreciation with those of housing units in the highest 60 percent of the value distribution. Using AHS data for five metropolitan areas for the 1974-83 period, the authors find that lowest value dwellings appreciated at least as much as the higher valued ones. In one area, Baltimore, the lower valued units appreciated over 12 percent more than their higher valued counterparts. The authors conclude that modest owner occupied housing is as good an investment as higher valued homes.

As suggestive as these findings are, their generalizability might be limited. During the period under study house values were generally rising. Recession, and the concomitant collapse of housing markets in the late 1980s and early 1990s might well have had different effects on different housing submarkets.

This paper attempts to address temporal and spatial variation of house price appreciation with specific attention paid to the relationship between house price appreciation and neighborhoods. In particular, using census tract to define neighborhoods, we assess whether housing in "underserved" tracts appreciates at different rates than other housing in the same metropolitan area.

We begin the paper with a discussion of the problems associated with estimating and modeling housing appreciation rates. We then develop a methodology to begin to unravel variations in appreciation rates. Using data from Dade County, Florida, we estimate annual appreciation rates and evaluate the extent to which appreciation rates are related to locational characteristics. We end the paper with a discussion of the results and their implications for policy and further research.

LITERATURE REVIEW

A central, though implicit, assumption in most studies of house price appreciation is that there exists a single price index for each portion of the housing stock, for example single family detached housing, in a local area. If such market wide price indices exist, two general approaches can be used to estimate them (Case, Pollakowski, and Wachter 1991).

The hedonic approach uses housing attributes and sale prices to arrive at yearly constant-quality price indices. However, difficulties with correctly specifying the functional form and regressors may introduce bias in the estimates. Typically, the approach is also inefficient because it does not include information that remains constant over time. In this case, the difference in transaction prices between two dates is assumed to be affected only by the intervening time period and changes in hedonic characteristics of the property. Thus, as Case, Pollakowski and Wachter (1991, 289) state "the hedonic price model fails to take advantage of the 'controls' inherent in repeat transactions."

The repeat sales methodology addresses some of the above concerns. In this approach, properties are included only if they are transacted at least twice during the study period. Differences in prices between two transactions are considered to be a function of time. Pooling data on transactions that take place within a given study period, it is possible to determine annual appreciation rates for the entire period.

Crone and Voith (1992) compare several methods for estimating house price appreciation. Parametric methods, specifically hedonic and repeat sales methods, performed much better than standard non-parametric methods in predicting actual house price appreciation. Using the absolute value of the prediction error and controlling for sample size, the repeat sales methodology was found to be the most accurate prediction method[1].

Two issues make the measurement of house appreciation difficult: the temporal effects and the spatial effects. Heterogeneous temporal or spatial effects may violate a basic assumption typically used in estimation. Temporal effects that create estimation problems involve differential rates of obsolescence related to age of a house. Depreciation, or the obsolescence of housing amenities might occur at different rates related to housing characteristics at the beginning of the study period, the original value of the house, the specific amenities included in the housing package or other factors that are not accounted for in models that do not specifically account for intertemporal heterogeneity.

Spatial effects which influence house price appreciation typically violate the assumption of statistical independence of observations. If we assume that house prices are interrelated, e.g. the price of a house is influenced by characteristics and sale price of nearby houses, we have admitted non-independence of our observations. Biased and inefficient parameter estimates will be obtained if spatial segments do indeed exist and are not accounted for. To different degrees, studies have addressed these issues in a number of ways.

Temporal Effects

There are three standard methods used in hedonic models for estimating models that account for temporal variation in parameters. These are fixed effects models, random effects models and Seemingly Unrelated Regression (SUR) models. The main difference between the methods involves how the estimated parameters are allowed to vary over time. In fixed effects models, it is assumed that intertemporal variation in parameters is captured in the intercept term. In random effects models, either the estimated parameters are allowed to vary randomly over time, or the random component of the model (e.g. the residual) is decomposed into time-specific and individual components. In SUR models, a multiple equation specification is used which allows separate parameters to be estimated for each time period. The error components of the equations are linked in the estimation process to account for the non-independence of the observations.

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[1] Crone and Voith found that the hedonic price method performed best when using the mean square of the prediction error as the accuracy criterion. However, both the repeat sales and hedonic methods performed well using both criteria.

Space Effects

It has long been recognized that urban housing markets consist of geographically connected submarkets with their own price schedules (Rothemberg et al. 1994). In terms of the hedonic price function, the presence of segmentation in the housing market implies spatial variability in the parameters of the hedonic price function (Can 1996), e.g, varying marginal attribute prices depending on neighborhood context (Can 1990). That is, there are different price structures on the basis of geographic location. It directly corresponds to the effect of neighborhood characteristics on housing market outcomes. If neighborhood effects enter as direct determinants of housing prices, like a premium, this implies the presence of a uniform housing market under investigation since there will be one price schedule. If, on the other hand, neighborhood differentials lead to varying attribute prices, this will indicate the presence of independent price schedules, and thus the existence of a spatially segmented market (Can 1996, 2).

There are two alternative ways to incorporate spatial variability into house price models within a hedonic framework. The first is called spatial switching regressions which has been the most commonly used method for the examination of housing market segmentation. Under this approach, spatial variability is expressed as a discrete function of geographic space. The second approach uses the expansion methodology, which offers a continuous modeling of spatial variability in house price outcomes.

We have not, as yet, encountered space-temporal models using the repeat sales method. In this paper we explore some approaches to account for spatial and temporal variation in price appreciation using the repeat sales method to account for temporal variation. We use the repeat sales method to estimate annual housing appreciation rates for the Miami metropolitan area. We then stratify the sample according to tract types using three different designations for “underserved.” A repeat sales model analogous to a fixed effects specification is estimated to account for different appreciation rates across tract types. Separate regressions are run for each tract type to determine whether there is a spatial component in annual appreciation rates. The annual rates are compared for each tract type to the full sample estimates to illustrate this “spatial” variability of coefficients.

Finally, applying the parameter estimates from the repeat sales models to individual dwellings, we generate “residual” appreciation, the difference between actual appreciation rates and appreciation rates predicted with a repeat sales model. We then analyze the residuals to account for spatial variation. In the following section, we present the methodology and a discussion of the data used to apply the method.

METHODOLOGY AND DATA

If we assume that yearly appreciation rates predictions using the repeat sales method are unbiased and relatively efficient, then it is possible to analyze the prediction error for individual dwellings in the same way that residuals are decomposed in the random or fixed effects models mentioned above. For this study we want to determine whether there we can model spatial variation in appreciation rates once the time component is accounted for. Following Crone and Voith (1992), we estimated the real yearly housing appreciation rates for the entire sample. This uses the standard approach derived from the growth identity:

$$P_t = P_{t-k} \Pi_{i=1}^{k-1} (1 + r_{t-i})$$

where: P_t = real market sale price of the house in year t
P_{t-k} = real market previous sale price of the house in year t-k
r_i = the rate of price appreciation between years i and i-1

Taking the natural log of both sides and rearranging yields the estimation equation:

$$lpr = \Sigma_{i=72}^{93} \beta_i D_i + \varepsilon$$

where: lpr = the natural log of the ratio of the last sale price and the previous sale price, e.g. $\ln(P_t/P_{t-k})$

D_i = a dummy variable taking the value 1 when i is between the sale years

As shown in Crone and Voith (1992), the estimated coefficients (β_i) will equal $\ln(1+r_i)$. The annual appreciation rate is easily solved for: $r_i = e^{\beta_i} - 1$.

A "fixed effect" variant can be estimated by incorporating variables to stratify the sample. For the purposes of this paper, we will stratify the sample according to tract type to see if appreciation rates "shift" across strata. The estimation equation is modified as follows:

$$lpr = \Sigma_{i=72}^{93} \beta_i D_i + \Sigma_{i=1}^{K} \gamma_k T_k + \varepsilon$$

where: T_k = "tract" designation
γ_k = the average shift in appreciation rates associated with tracts of type k

A "Seemingly Unrelated Regression" variant of the repeated sales method can also be estimated. This involves estimating separate equations for each stratification and linking them by estimating all the equations simultaneously. Although we do not estimate this variant, we will estimate the equations separately and test to see whether there is intertemporal variation in the parameters across strata.

Once we estimate the annual appreciation rates, we can apply them to each observation to predict its appreciation. This can be compared to the actual appreciation rates to generate prediction errors in the same way that residuals are generated in ordinary least squares regressions. The estimation of appreciation in this case is a little more complicated since transactions for specific houses take place at different times within the study period and, therefore, have specific expected appreciation rates based on the exact subperiod within which the house was owned between sales.

While the preliminary estimation equations provide interesting results, we are mainly interested in studying spatial aspects of the prediction error. In this very preliminary work, we assess whether the appreciation rates vary non-randomly across census tracts (underserved versus other census tracts).

The bulk of the data for this project comes from the 1993 tax assessment file for Dade County, Florida. The data includes housing characteristics, housing locations and sale prices for the last two sales for all residences in the county. Only single-family, detached dwellings that were sold twice between 1972 and 1993 were selected for the investigation. The final sample consists of 20,272 houses, or about 10 percent of all dwellings in the county.

The housing data was merged with census-tract level data on average housing and population characteristics of the tract provided by the 1990 Census of the United States. The data include socio-economic characteristics of the tract, racial/minority distribution of the population in the tract, and housing size and prices in the tract. All nominal dollar values were deflated using the CPI-U. Data on prices were obtained directly from the US Bureau of Labor Statistics.

Each observation in the sample includes the most recent and previous sale price, the dates of the sales, hedonic characteristics of the house, and the location of the house. Hedonic characteristics include living area, land area, number of bedrooms, number of baths, and age of the house. The location of the house is determined on several levels--census tract, nine-digit zip code, and exact longitude and latitude coordinates of the structure.

Descriptive statistics for the sample are presented in Table 1.

Table 1. Means and St. Dev. of Model Variables

Variable	Mean	Std Dev
Housing Characteristics		
Price ($ 1982-84)	98789.95	80984.06
Bedrooms	3.0900000	0.7679076
Baths	1.8900000	0.7292712
Living area (sq. ft.)	1892.29	836.5801341
Land area (sq.ft)	12867.35	11194.10
Age	28.3650888	15.1616182
Years between sales	7.8698698	5.4922934
Census Tract Characteristics — 1990		
Proportion minority	0.2302846	0.2416819
Ownership rate	0.6522726	0.1760914
Vacancy rate	0.0683023	0.0453277
HH median income	38244.54	16151.59
Number of obs: 20272		

ECONOMETRIC RESULTS

Estimates of annual real appreciation rates are presented in Table 2. The rates vary dramatically from year to year, with highs of 9.02% in 1972 and 1978 and a low of -8.49% in 1975. The intertemporal variation generally corresponds with macroeconomic fluctuations. Negative rates coincide with the recessions of 1975 and 1982 and the credit crunch of the late 1980s. Positive rates coincide with the more robust markets of the late 1970s and early 1990s.

Table 2: Annual Price Appreciation Rates

Variable	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	% Price Appreciation
INTERCEPT	0.1358	0.0184	7.39	0.0001	
D72	0.0863	0.0384	2.25	0.0245	9.02
D73	0.0837	0.0360	2.33	0.0199	8.73
D74	-0.0373	0.0376	-0.99	0.3217	-3.66
D75	-0.0887	0.0361	-2.45	0.0141	-8.49
D76	-0.0825	0.0307	-2.69	0.0072	-7.92
D77	0.0032	0.0269	0.12	0.9066	0.32
D78	0.0864	0.0249	3.47	0.0005	9.02
D79	0.0349	0.0254	1.37	0.1703	3.55
D80	0.0125	0.0278	0.45	0.6544	1.25
D81	-0.0750	0.0305	-2.46	0.0139	-7.22
D82	0.0008	0.0295	0.03	0.9774	0.08
D83	-0.0434	0.0255	-1.71	0.0880	-4.25
D84	-0.0346	0.0241	-1.44	0.1511	-3.40
D85	-0.0360	0.0229	-1.58	0.1147	-3.54
D86	0.0215	0.0208	1.03	0.3025	2.17
D87	0.0049	0.0198	0.25	0.8056	0.49
D88	0.0487	0.0195	2.50	0.0125	4.99
D89	-0.0271	0.0206	-1.32	0.1873	-2.68
D90	-0.0383	0.0160	-2.40	0.0166	-3.75
D91	-0.0315	0.0103	-3.04	0.0023	-3.10
D92	0.0303	0.0126	2.41	0.0160	3.08
D93	0.0631	0.0149	4.23	0.0001	6.52

The parameter estimates are generally statistically robust as well. Half of the 22 coefficients are statistically significantly non-zero at the .05 level. Of course, it is not clear whether statistical significance is directly relevant, given that real appreciation rates around zero are not unexpected.

In this preliminary work, we added dummy variables to designate housing located in underserved tracts. “Underserved” was defined in three ways: 1) tracts with median income below 90% of the MSA median income (UND1); 2) tracts with more than 30% minority households and less than 120% of MSA median income (UND2);and, tracts with median incomes below 80% of the MSA median.[2] The first two definitions are standard HUD classifications, while the latter designates tracts as special underserved areas for affordable lending efforts.

Analogous to the estimation of fixed effects models, the dummy variables designating tract types were added to the regression reported in Table 2. The estimated coefficients are presented in Table 3 below. For the sample, houses in underserved tracts, using the first definition of underserved, had, on average, 0.99% higher than average price appreciation for the study period. Housing in underserved areas defined including minority density had 5.9% lower than average appreciation rates. This suggests that housing in these underserved tracts were a worse investment during the study period than housing in other tracts. Finally, housing in tracts designated using the third definition of underserved show an 10.2% higher than average appreciation rate during the study period.

Table 3: Relative Appreciation for Underserved Tracts[3]

Variable	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	% Price Appreciation
UND1	0.0096	0.0138	0.69	0.4881	0.99
UND2	-0.0608	0.0107	-5.70	0.0001	-5.92
UND3	0.0967	0.0178	5.42	0.0001	10.15

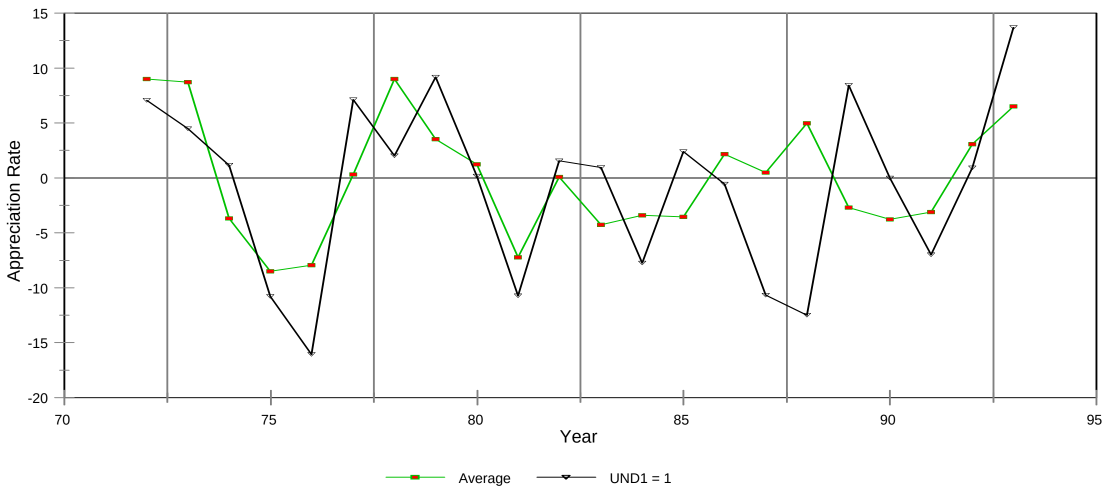
This suggests evidence of spatial variation in appreciation rates, so long as tract characteristics capture spatial variation.

To further illustrate the spatial variation in appreciation rates, separate regressions were run to estimate appreciation rates for underserved areas. We have plotted the annual coefficients for each model against the overall county appreciation rates. These appear in Charts 1 through 3. The yearly appreciation rates varied considerably between areas. A Chow test was performed to determine whether the explanatory power of the model was increased by running separate regressions. The test was statistically significant at the .001 level, indicating different appreciation structures across stratifications. While the coefficients for the first and third definition of underserved were fairly similar, in both cases the variation in annual appreciation rates fluctuated

[2] From the 1990 Census of the United States (www.census.gov)

[3] The estimated coefficients on the yearly variables were very similar for the estimations and are not reported here. The authors will furnish a full set of regression results on request.

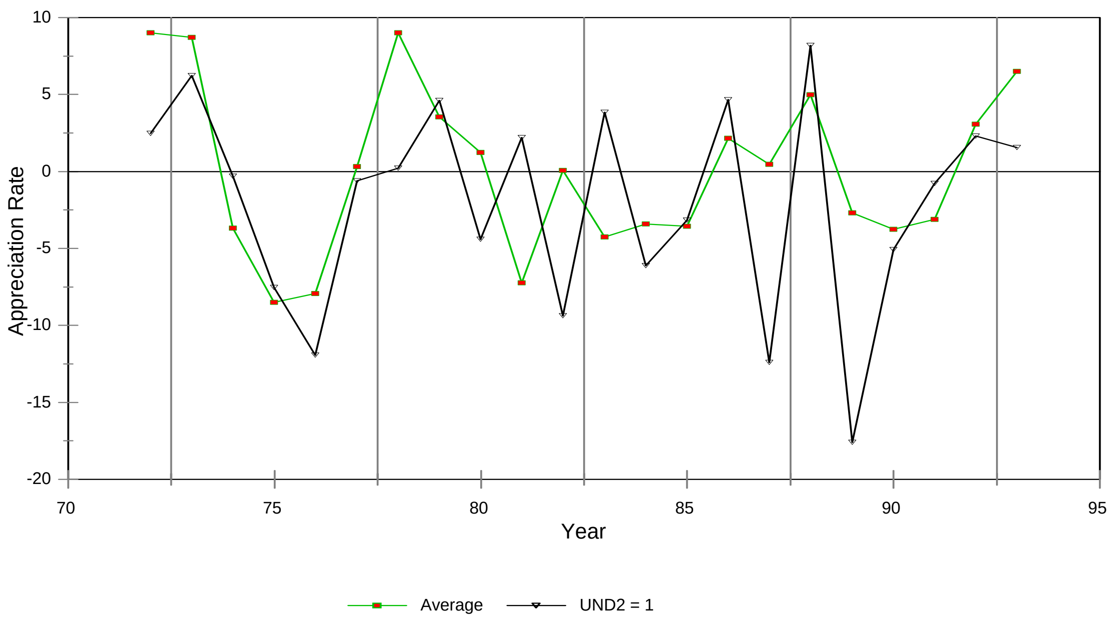
Chart 1: Annual Price Appreciation



more widely than the overall rates for the county. The appreciation rates for houses falling in tracts designated as underserved using the second definition fluctuated more dramatically than any of the other three.

In Charts 1. and 3. one can see the wider fluctuations in the appreciation rates for houses in underserved areas. In particular, during the recessions of 1975 and 1982

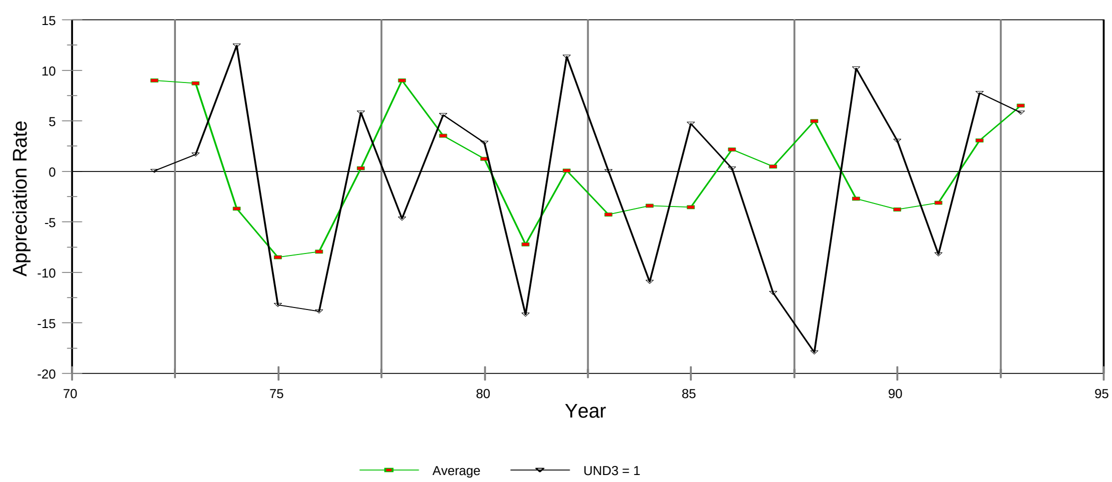
Chart 2: Annual Price Appreciation



appreciation rates fell further in underserved areas than average. There was also a large fall in appreciation rates during the credit crunch of the late 1980s and early 1990s with price depreciation between 10% and 16% in 1988. Recovery of housing prices has been better than average in these underserved areas since 1992.

There is quite a different story in underserved areas using the second minority definition. While the appreciation rates tracked average appreciation rates during the 1970s, dramatic fluctuations occurred in the 1980s and 1990s. These tracts were

Chart 3: Annual Price Appreciation



particularly hard hit during the credit crunch with annual appreciation bottoming out around -18% in 1989. Housing in these tracts rarely appreciate at rates faster than average. Recovery since 1990 has been a little slower than average in these areas.

These findings suggest three things: there is good reason to believe that there is a spatial component in house price appreciation rates; housing in underserved tracts are riskier investments than housing in the rest of the county; and, it is probably worth the effort to estimate the model using a SUR variant of the repeat sales method.

Housing appreciation rates vary more dramatically due to exogenous, macroeconomic factors. If we add the fact that individual-level effects, like job loss, are also more likely occurrences during economic downturns for underserved populations, it seems likely that default rates will be higher for loans made in these areas. This has direct bearing on affordable mortgage lending.

Consider an “affordable” loan made in an underserved tract in 1985. Let’s say the loan was made with a 95% loan to value ratio at the time of origination. If the borrower experienced any difficulty making loan payments during the first five years of the mortgage, default would be likely given that the property experienced several years of price depreciation. If the loan had been made in an underserved area based on definition two, the real value of the property would have declined, on average, 3% in 1985, more than 13% in 1987, more than 18% in 1989, and more than 5% in 1990. The 4% and 8% appreciations in 1986 and 1988 would hardly be offset by these large drops. By the end of 1990, the home owner would be sitting on a loan with 22% negative equity. In tracts designated using definition 1 the homeowner would be faced with 14% negative equity, while those living in tracts designated using definition 3 would face 11% negative equity. Average households in the county would have 1.4% positive equity left in their homes and a much less difficult and stressful situation with which to deal.

It is noteworthy that underserved tracts defined by minority density and those defined strictly based on median income do not coincide. This is illustrated in the Table 4:

Table 4. Distribution of Houses by Tract Type

>30 % Minority HHs in tract and <120% of MSA median income		<90 % of MSA median HH income		<80% of MSA median HH income		
		UND1=1	UND1=0	UND3=1	UND3=0	Total
	UND2=1	2220 10.95%	2347 11.58%	1159 5.72%	3387 16.71%	4546 22.43%
	UND2=0	2199 10.85%	13506 66.62%	1023 5.05%	14703 72.53%	15726 77.57%
	Total	4419 21.80%	15853 78.20%	2182 10.76%	18090 89.24%	20272 100%

About half of the homes falling in underserved tracts using definition 1 also fall in underserved tracts using definition 2. Similarly, about half of the homes in underserved tracts using definition 3 also fall into underserved tracts by definition 2.

To distinguish HH income effects from minority density effects on appreciation two other dummy variables were created: UND4=UND1 * UND2; UND5=UND3*UND2. These variables designate the high minority density and low income cells in Table 4. Adding these variables to the regression reported in Table 2. yields the results presented in Table 5.

Table 5: Relative Appreciation for Underserved Tracts

Variable	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	% Price Appreciation
UND4	-0.0509	0.0189	-2.70	0.0070	-4.97
UND5	0.1316	0.0254	5.20	0.0001	14.07

The negative parameter estimate for UND4 and the positive parameter estimate for UND5 suggest that the lower than average appreciation measured for housing in high minority density tracts is attributable to housing in “moderate” income (between 80% and 120% of MSA median HH income) tracts.

Finally, using the estimation presented in Table 2., annual house price appreciation was predicted for each dwelling in the sample. The price at which the dwelling was last sold was used to calculate the actual appreciation rate. “Relative appreciation” (RELAPP) is defined as the difference between the actual and predicted price appreciation. A positive (negative) value of RELAPP indicates that the dwelling appreciated at a faster (slower) than average rate between its two sale points.

Table 6 below presents some descriptive statistics for RELAPP. The mean relative appreciation rate for the full sample was very close to zero. If RELAPP were a regression residual, it would sum to zero because the least squares method imposes that condition on residuals. RELAPP does not sum to zero because houses enter and leave the sample at different points in time. It is reassuring, however, that RELAPP sums to something close to zero--indicating that we have done a fairly good job of predicting appreciation for the sample over the sample period.

Table 6. Descriptive Statistics for Relative Appreciation Rates (RELAPP)

Stratification	N	Mean	St.Dev
Full Sample	20272	-0.0005	0.6064
UND1=1	4419	0.0183	0.5815
UND2=1	4546	-0.0466	0.6377
UND3=1	2182	0.0644	0.6143
UND4=1	2199	0.0023	0.6135
UND5=1	1159	0.0681	0.7004

The mean values for housing falling in the variously defined underserved areas generally correspond with the regression results presented above. With the exception of the positive mean for UND4=1, the signs are all correct. The general observations made above still hold: housing in underserved tracts designated by income only yield higher average appreciation rates than other housing in the county; housing in tracts with high minority density have lower appreciation rates; and, the negative effects associated with high minority density seems to occur in tracts with moderate income levels.

NEXT STEPS

This work in progress is the first step in our effort to examine house price appreciation in underserved areas, controlling for spatial and temporal effects. Controlling for temporal effects only (similar to the work of Pollakowski, Stegman and Rohe 1991), preliminary findings indicate that appreciation rates in underserved areas are at least as high as those in other areas, when underserved areas are defined in term of median income. Conversely, when underserved areas are defined in terms of minority concentration, appreciation rates appeared to be significantly less than those in the market overall. The negative minority density effect appears to be concentrated in moderate income tracts.

Appreciation rates in underserved areas are more volatile than other areas, regardless of how we designate the underserved tracts. If this finding stands the test of closer scrutiny, it will have implications for the riskiness of affordable loans made in underserved tracts.

These findings should be taken with caution. First and foremost, they are preliminary in nature. Second, we have not fully controlled for spatial effects yet. Using tract types to capture spatial effects is ad hoc, at best. As mentioned above, this leads to inefficient estimation. There are a variety of methods one might employ to disentangle the myriad of variables which might affect house price appreciation. Clearly, there is a lot of value in incorporating finer spatial distinctions to account for locational characteristics. We intend to do this next.

The repeat sales method for estimating price appreciation uses very little information on dwelling types or changes in dwellings to explain appreciation. However, the method presented here (adding controls for spatial effects) is a simple and possibly powerful way to measure the investment value of housing, particularly as it relates to affordable loans and lending efforts in underserved areas.

As discussed above, hedonic price methods can be used to capture the effects of housing features and amenities on appreciation. It will be interesting to compare the results of the hedonic method versus the repeat sales method in a similar way to the work of Crone and Voith. This, too, we intend to pursue in the future.

REFERENCES

Anselin, Luc. 1998. Spatial Econometrics Methods and Models. Dordrecht: Kluwer Academic.

Can, Ayse. 1990. The Measurement of Neighborhood Dynamics in Urban House Prices. Economic Geography 66:254-72.

Can, Ayse. 1996. Spatial Segmentation in Urban House Prices: Alternative Approaches. Washington, DC: Fannie Mae Foundation. Mimeo.

Carter Hill, R., J.R. Knight, and C.F. Sirmans. 1993. Estimating Capital Asset Price Indexes. Center for Real Estate and urban Economics Studies. Working Paper #9331-108.

Case, Bradford, Henry O. Pollakowski and Susan M. Wachter. 1991. On Choosing Among House Price Index Methodologies. AREUEA Journal 19(3): 286-307.

Case, Bradford and John M. Quigley. 1991. The Dynamics of Real Estate Prices. The Review of Economics and Statistics. 73:50-58.

Case, Karl E. , and Robert J. Shiller. 1989. The Efficiency of the market for Single-Family Homes. American Economic Review 79(1): 125-137.

Crone, Theodore M. and Richard P. Voith. 1992. Estimating House Price Appreciation: A Comparison of Methods. Journal of Housing Economics 2:324-338.

Pace, R. Kelly, and Ronald Barry. 1997. Sparse Spatial Autoregression. Statistics & Probability Letters 33:291-297.