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Measuring Local Aggregate House Prices

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This study evaluates the ability of a range of popular aggregate house price indexes to predict house prices out-of-sample at the transaction level for a small geographic area. The analysis particularly addresses the utility of spatial econometric methods. The results suggest that spatial econometric methods, which more explicitly consider the spatial aspects of observed house prices, provide better predictive accuracy as compared to more traditional estimation techniques, such as the repeat sales index, a hybrid repeat sales-hedonic price index, and hedonic price models estimated through least squares. The conclusions are drawn from a sample of 38,984 single-family residential real estate transactions for the city of Milwaukee, Wisconsin over the years 2002-2008.

Keywords

House price index; Spatial econometrics; Forecast evaluation

1. Introduction

Residential housing accounts for the third largest share of consumer expenditure, after food and health care. It also accounts for the largest single form of fixed capital investment in the United States (Green and Malpezzi, 2003). Owner occupied housing accounts for almost one third of total household wealth, and houses are often the largest asset for individual homeowners (Case, 2006). Furthermore, the housing sector played a major role in the most recent recession, as well as the recession of the early 1990s (Case, 2006; Bernanke, 2007). As a result, there are a number of decision makers who may benefit from a greater understanding of future real estate values. This need provides the motivation for a vast body of research on the proper identification and construction of aggregate house price measures, or house price indexes (for a recent review, see Case, 2006).

This study addresses the out-of-sample predictive power of a set of commonly accepted house price indexes, including hedonic, repeat sales, and hybrid hedonic-repeat sales techniques. Furthermore, the analysis particularly addresses the utility of spatial econometric methods in the study of aggregate house prices in geographically small areas, called *local* price indexes. Although a number of reported indexes address national, state, and regional aggregate prices, there is a growing need to examine house price trends from a local perspective. A number or indexes are reported for major metropolitan areas, such as the 20 cities tracked by the Case-Shiller Index. This study, however, shows how to successfully construct indexes for smaller cities, with an example from a mid-size Midwestern city.

Each price index is evaluated based on evidence from the single-family residential transaction database of the City of Milwaukee, Wisconsin. The study area is attractive for several reasons. It is not subject to dramatic price or development cycles. It does not exhibit continuous expansion, and the electronic transaction record is freely available through the World Wide Web. As a result, the empirical analysis can be revisited by future research. Milwaukee, on many accounts, is representative of older American industrial cities (McMillen, 2001). The city is one of the hubs of economic activity in the Midwestern section of the United States. The city spans 96 square miles of southeastern Wisconsin with a population density of 6,214 persons per square mile (United States Census Bureau, 2000).

Spatial econometric methods have gained precedence in other areas of real estate research, such as environmental valuation. However, the methods have received little attention in the construction of local aggregate house price indexes.The advantages of other spatial statistical methods have been explored in a limited number of previous studies. For example, Fletcher et al. (2004) demonstrate that hedonic price models have better predictive accuracy when they include neighborhood dummy and interaction variables. Case et al. (2004)

similarly evaluate spatial statistical methods, including Kriging and local regression. Bourassa et al. (2007) also evaluate lattice models, spatial statistics, and simple hedonic models with neighborhood dummy variables. Consistent with these studies, our analysis suggests that spatial econometric methods, which more explicitly consider the spatial aspects of observed house prices, provide better predictive accuracy compared to more traditional methods.

The remainder of the study is organized as follows. Section 2 reviews several measures of aggregate house prices. Section 3 introduces the data used in this study. Section 4 tests the predictive abilities of each index, and Section 5 provides some concluding remarks.

2. Measuring Aggregate House Prices

There are a number of ways to measure aggregate house prices. Methods range from simple summary statistics to highly sophisticated empirical methods. This section introduces a number of the leading measures, including a brief description of the benefits and shortcomings of each method.

Of the various ways to measure aggregate house prices, the most commonly reported estimates are simple median and mean prices (Green and Malpezzi, 2003). These measures are attractive because they are easy to calculate and interpret. Simple summary statistics appeal to a wide audience, and as a result, they are often reported in popular media and policy discussions. However, these measures are highly criticized for their inability to account for the quality of homes sold. For example, if a large number of high quality, and therefore high value, homes are sold in a given period, the mean and median prices will increase. This increase however is not a result of aggregate price appreciation because the sales are not representative of the total stock of homes. Despite their shortcomings, these simple measures of "average" house prices are widely reported and monitored by policy makers, popular media, and the financial industry.

One method to overcome this shortcoming is to rely on empirical methods which directly control for quality differences across houses, called *constant quality indexes*. One alternative, the hedonic price method, decomposes the price of a home into the value of each of its characteristics as a way to control for quality differences (Rosen, 1974). The hedonic price model takes the form:

$$y = X\beta + \varepsilon \tag{1}$$

where y is an N×N vector of observed prices. The matrix X contains the K quantifiable characteristics of each house, with dimensions N×K. To estimate the price appreciation for the "average" home, X contains a set of temporal indicator variables, such as monthly or annual dummy variables, to mark the period in which each transaction occurs.

Hedonic price models are an attractive alternative to estimate aggregate house prices because they are computationally simple and are almost always consistent with intuition (Kawamura and Mahajan, 2005). The method is often criticized, however, because it is data-intensive (Green and Malpezzi, 2003). The estimation requires a large set of quantifiable characteristics for each observation and often requires a large dataset to ensure sufficient degrees of freedom.

The repeat sales method is another popular constant quality price index. By tracking price changes of individual homes that sold in multiple periods, the repeat sales index is able to remove the effects of changes in quality of the stock of homes. The repeat sales index was first suggested by Bailey, Muth, and Nourse (1963) (the BMN model) and takes the form:

$$\ln\left(\frac{P_{it1}}{P_{it2}}\right) = \sum_{t=1}^{T} \alpha_t D_{it} + \varepsilon_{it1\ it2} \tag{2}$$

where P_{it1} denotes the *initial* sales price of property i in period t with $i = 1,...,n$ and $t = 0,...,T,$ and P_{it2} denotes the *second* observed sales price of property i in period t with $i = 1,...,n$ and $t = 0,...,T.$ Thus, the subscript 1 represents the initial sale of each observation, and the subscript 2 marks the second transaction for each house. The time dummy variables D_{it} take the value of –1 if $t = t_1$, the value of +1 if $t = t_2$, and zero otherwise, and α_t denotes the estimated coefficient for each time dummy. Note that an intercept term is set to zero so that the price index is normalized to 1 at the initial time period.

Similar to the hedonic price index, the repeat sales index is a data-intensive procedure. The estimation procedure discards observations of homes which sold in only a single period. This can be an inefficient use of data and can limit the inference of small data sets. Also, the index can not account for new construction (Case et al., 1991).

Given the shortcomings of both the repeat sales method and hedonic price indexes, several authors suggest the use of hybrid models which blend the two techniques. Case et al. (1991) suggest that hybrid models avoid most of the sources of bias and inefficiency of both repeat sales and hedonic methods. However, it can also be argued that hybrid models multiply the deficiencies of repeat sales and hedonics, such as the need for quantifiable property characteristic data and a large number of observations. The hybrid model defined by Clapp and Giaccotto (1998) follows the BMN model with the addition of control variables which track the changes in observed characteristics between sales.

$$\ln\left(\frac{P_{it1}}{P_{it2}}\right) = \sum_{t=1}^{T} \alpha_t D_{it} + \sum_{k=1}^{K} \beta_k (x_{kt2} - x_{kt1}) + \varepsilon_{it1\ it2} \tag{3}$$

The additional variables track the changes in the observed characteristics of each property between observed transactions. It can clearly be seen that the index represents a blend of Equations (1) and (2).

The purpose of this study is to examine the predictive ability of spatial econometric specifications of hedonic price indexes. Spatial econometric methods provide an attractive alternative for examining aggregate house prices because they explicitly address spatial dependence inherent in the data. Spatial dependence is a special case of cross-sectional dependence in which the structure of the covariation between observations at different locations is subject to spatial ordering (Anselin, 1988). Spatial dependence may lead to biased and or inefficient least squares estimates, and it can arise from three distinct sources: (i) prices are affected by prices of neighboring observations (spatial spillover), (ii) spatially correlated variables have been omitted which lead to nonspherical errors, and (iii) the functional form is misspecified or suffers from measurement error (Willhelmsson, 2002).

A number of previous studies explore sources of spatial dependence in house prices. Bowen et al. (2001) argue that prices are often influenced by real estate professionals, so the local housing market conditions may play a role in each observed transaction. Also, neighborhoods tend to develop at the same time, which lead to similar structural characteristics of homes within neighborhoods. Neighboring houses by definition share a number of locational amenities, and neighborhoods may serve as a proxy for other variables, such as income and occupational status of homeowners (Basu and Thibodeau, 1998; Gelfand et al., 1998).

We empirically evaluate two of the leading spatial econometric models: the spatial lag model (SLM) and the spatial error model (SEM). The SLM captures spatial dependence in the regressant by including spatially weighted values of the dependent variable on the right hand side of the equation (Anselin, 1988). The model takes the form:

$$y = \rho Wy + X\beta + \varepsilon \tag{4}$$

where W is an $N \times N$ spatial weights matrix and ρ is an unknown scalar spatial parameter. The elements of the spatial weights matrix are nonzero when the two observations are related in some meaningful way, and by definition, no observation can be a neighbor to itself. Therefore, the diagonal elements of W are zero. As the spatial lag term is endogenous, the model cannot be estimated through ordinary least squares (OLS). Alternative estimation procedures include instrumental variables or maximum likelihood (Anselin, 1988).

SEM addresses problems associated with spatial dependence in the regression disturbances (Anselin, 1988). The model takes the form:

$$y = X\beta + u \tag{5a}$$

$$u = \lambda W u + \varepsilon \tag{5b}$$

where u is a collection of disturbances which are assumed to follow a spatial autoregressive process. The process is a function of the unknown spatial parameter λ and an exogenous spatial weights matrix W. It can be seen that the error terms u are nonspherical. Thus, SEM is estimated through maximum likelihood or generalized moments (Anselin, 1988).

3. Data

To evaluate the predictive power of each index, we examine the electronic real estate transaction record of the City of Milwaukee, Wisconsin (City of Milwaukee Assessor's Office, 2009). The dataset contains the complete transaction record for all residential properties within the City of Milwaukee over the period January 2002 to December 2008. After data cleaning, the set yields a total of 38,984 single family residential transactions. To control for inflation effects, prices were deflated using the Consumer Price Index (CPI) for the Milwaukee-Racine, Wisconsin metropolitan area (Bureau of Labor Statistics, 2010). Each transaction contains the sales price of each home along with its structural characteristics. The electronic transaction record is free and publicly available on the World Wide Web at:
http://assessments.milwaukee.gov/mainsales.html.

Table 1 Data Summary

	Training Set		Testing Set	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Price (US Dollars)	120,105.70	63,325.54	120,710.90	67,595.33
Age (Years)	69.79	25.26	73.85	25.98
Bedrooms	3.47	1.16	3.46	1.14
Full bathrooms	1.42	0.57	1.41	0.57
Half bathrooms	0.26	0.49	0.26	0.48
Proportion				
2002	14%			
2003	15%			
2004	17%			
2005	29%			
2006	26%			
2007			69%	
2008			31%	

The primary goal of this study is to examine the ability of each index method to predict transaction-level house prices out of sample. In order to evaluate the merit of each method, we divide the transaction record into two subsets. First, the *training* set is used to estimate each index: hedonic, repeat sales, and hybrid. The training set is defined as all transactions over the period 2002-2006. The estimated coefficients of each index are then used to create the predicted transaction prices in the second subset, the *testing* set, which spans the remaining years 2007 and 2008. Both sets are summarized in Table 1. The mean transaction price is roughly $120,000 in the training set and $121,000 in the test set. The other variables include the structural characteristics of each home used for the hedonic index, as well as the hybrid hedonic-repeat sales index,and the structural characteristics appear consistent across the two periods.

Table 2 Repeat Sales and Hybrid Index Coefficient Estimates

	Repeat Sales			**Hybrid**		
	Coefficient	**Std. Error**		**Coefficient**	**Std. Error**	
2003	0.097	0.014	***	0.100	0.014	***
2004	0.214	0.014	***	0.212	0.014	***
2005	0.251	0.012	***	0.251	0.013	***
2006	0.541	0.012	***	0.531	0.015	***
Age				– 0.026	0.005	***
Age squared				0.000	0.000	***
Bedrooms				0.168	0.021	***
Full bathrooms				0.009	0.032	
Half bathrooms				0.055	0.040	

The coefficient estimates of the repeat sales and hybrid indexes are reported in Table 2. Both measures suggest that aggregate house prices exhibit a general upward trend throughout the sample period 2002-2006. It is important to note that the indexes retain only a small number of observations from the complete transaction record, approximately 25% of the observations. Our analysis includes three specifications of the hedonic price index: OLS, SEM, and SLM. The estimated coefficients of each specification are reported in Table 3.

The estimate average annual appreciation rate for each index is reported in Table 4. Consistent with Figure 1, the repeat sales index yields the largest suggested annual average appreciation rate, followed closely by the hybrid price index. The hedonic price indexes offer very similar estimates of average annual price appreciation. Finally, the annual median price series exhibits the smallest price change estimates.

Table 3 Hedonic Index Coefficient Estimates

	OLS			Spatial Error			Spatial Lag		
	Coefficient	Std. Error		Coefficient	Std. Error		Coefficient	Std. Error	
Constant	11.310	0.021	***	11.358	0.021	***	0.476	0.102	***
Age	0.000	0.001		– 0.005	0.001	***	– 0.001	0.000	*
Age squared	0.000	0.000	***	0.000	0.000	**	0.000	0.000	***
Bedrooms	0.025	0.003	***	0.058	0.002	***	0.044	0.002	***
Full bathrooms	0.190	0.006	***	0.120	0.004	***	0.101	0.004	***
Half bathrooms	0.212	0.006	***	0.097	0.004	***	0.068	0.004	***
2003	0.061	0.009	***	0.077	0.006	***	0.072	0.006	***
2004	0.155	0.009	***	0.182	0.006	***	0.178	0.006	***
2005	0.089	0.008	***	0.223	0.006	***	0.208	0.006	***
2006	0.132	0.009	***	0.284	0.006	***	0.266	0.006	***
Lambda (We)				0.742					
Rho (Wy)							0.926	0.009	***

Figure 1 Aggregate House Price Indexes 2002 – 2006 (2002 = 100)

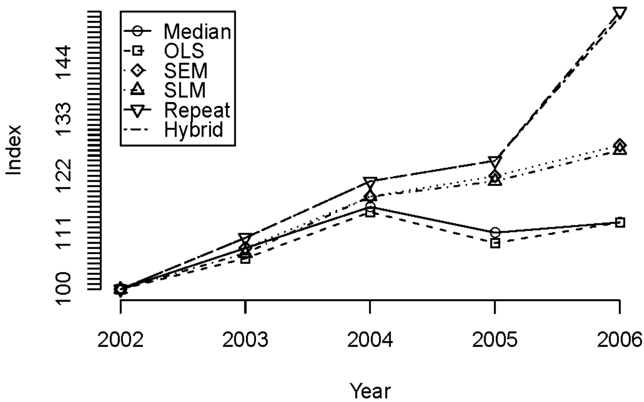

Table 4 Average Annual Price Appreciation, 2002 – 2006

Index	Rate
Repeat	11.66
Hybrid	11.44
OLS	3.29
Error	6.48
Lag	6.10

4. Testing and Evaluation

Two performance measures are used to evaluate each index at the transaction level. The measures examine the difference between the *observed* and *predicted* transaction prices, based on the coefficient estimates of the training set. A more thorough presentation of each measure is presented in Fildes and Ord (2002). The two measures take the form:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{N}|e_i| \tag{6}$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}e_i^2} \tag{7}$$

where e_i is the prediction error of each observation.

The measures for each index are reported in Table 5. Both the MAE and RMSE results suggest that the SEM-hedonic index has the greatest predictive power at the transaction level, a result of the spatial correction. The SEM specification includes additional information to correct for the potential problems related to spatially related omitted variables. The SLM specification also outperforms the traditional indexes. The repeat sales index appears to have the least predictive accuracy, followed closely by the hybrid repeat sales-hedonic index. As seen in Figure 1, these estimates exhibit the greatest amount of implied price appreciation. The upward bias of the repeat sales index has been well documented in previous studies (see Case, 2006; Wallace and Meese, 1997).

Table 5 Forecast Evaluation

Index	MAE	RMSE
Repeat	0.523	0.679
Hybrid	0.514	0.671
OLS	0.374	0.509
Error	0.303	0.412
Lag	0.332	0.431

5. Conclusions

There is a strong need to develop accurate measures of aggregate house prices in small geographic areas. Information with regards to current and future real estate values directly benefits a number of individuals and firms, such as homeowners, policy makers, and major financial institutions. This study has examined the ability of the leading methods to predict house prices out-of-sample at the transaction level. In particular, the analysis has focused on the utility of spatial econometric methods, and the results suggest that spatial econometric methods provide a greater predictive accuracy compared to the other leading methods, including repeat sales, hybrid, and OLS hedonic indexes.

The major difference between this study and many widely reported house price indexes is the choice of spatial scale. This study examines the predictive accuracy of several methods for a single mid-sized US city, while other studies address much larger geographic areas, such as national, regional, or state wide aggregates.

It has been shown that spatial dependence is, to a large degree, scale dependent. Thus, the advantage of spatial econometrics in constructing aggregate house price indexes is also likely to vary with spatial scale. Finally, although the results suggest the spatial econometric specifications of the hedonic price index provide the greatest predictive accuracy, it could be the case that the optimal index may actually involve a combination of several aggregate price measures. For example, Bates and Granger (1969) argue that when several alternative forecasts are available, a weighted average of the individual models may provide an optimal combined forecast. This issue is left for future research.

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