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An Empirical Analysis of Property Appraisal and Mortgage Redlining

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Abstract

The recent literature advances a hypothesis that addresses the possibility of mortgage redlining caused by a dynamic information externality in property appraisals and mortgage lending. In particular, Lang and Nakamura (1993) hypothesize that because property appraisals depend on past transactions, appraisals in neighborhoods where transactions were infrequent tend to be less precise. The greater uncertainty about house valuation in such neighborhoods can lead mortgage lenders to impose stringent requirements on borrowers. Lang and Nakamura's article, like most economic analysis of property appraisals, is theoretical. Using a sample of mortgages purchased by Fannie Mae, we present preliminary research results that cast doubt on appraisal behavioral rules such as weighted averages or backward-looking expectations on which Lang and Nakamura and other theoretical studies are based. Instead, our results refocus attention on the moral hazard issues of appraisal. We find that in more than 80 percent of the cases, the appraisal is between 0 and 5 percent above the transaction purchase price, in only 5 percent of the cases is the appraisal lower, and in 30 percent of the cases, the appraisal and transaction prices are identical. It would take a strong statistical model to generate such occurrences. Our resutls also indicate that appraisal outcomes are used as a risk factor with different weights for loans with different characteristics (loan-to-value ratios and house prices). The results suggest that more empirical investigation of appraisal practices be conducted to verify the validity of conventional wisdom embedded in theoretical studies, and we offer an econometric framework toward this end.

Key Words: Appraisal bias, moral hazard, mortgage redlining, panel data estimation

This paper is a commentary on a model of redlining propounded by Lang and Nakamura (1993). We adopt a two-part strategy. First, we present some preliminary empirical evidence that appears to be at odds with the model of appraisals used by Lang and Nakamura and other theoretical studies. Second, we suggest an econometric framework for testing the statistical validity of appraisal bias revealed by our research results.

We compare the appraisal price of a property, which is required for underwriting and validation of a mortgage application, with the actual transaction price. The sample consists of mortgages purchased by Fannie Mae. If an appraisal falls below an accepted purchase price, a deal may be jeopardized. In our data analysis, 80 percent of the cases were appraised at values between 0 and 5 percent above the transaction purchase price, only 5 percent of the appraisals were lower than the transaction price, and in 30 percent of the cases the appraisal and transaction prices were identical.

The results pesented in this paper appear to be inconsistent with appraisal behavioral rules, such as weighted averages or backward-looking expectations, theorized in the literature (e.g., Quan and Quigley, 1991, Geltner, 1993; Lang and Nakamura, 1993). First, our results indicate that in most cases appraisers assign different value estimates only when differences between perceived values and transaction prices are large.[1] More important, our results refocus attention on the moral hazard issues of appraisal. That is, the buyer and seller have a vested interest in completing a transaction. Loan originators have a vested interest in completing sales. No sale means no income for the originators or real estate agent. The appraiser understands the financial implications of having no transactions and, at the same time, wants repeat business via referrals. Accordingly, real estate agents, buyers, originators, and appraisers have aligned interests: to complete and close the transaction. The way to ensure the deal is to appraise slightly high. The appraiser asks for or receives the transaction price and then adds a bit to it. Since mortgage lenders employ the minimum of sales price or the appraisal, whichever is lower, in determining the loan value, no further information is added because of the appraisal. Therefore, it is only the carriers of the default risk who lose in the transaction.

Our results further indicate that appraisal outcomes are used as a risk factor with different weights for different loan types. In fact, our results demonstrate that appraisals lower than the purchase price are more common in loans with low loan-to-value (LTV) ratios (hence high down payments) but high house prices. The results point out that appraisal outcomes are less significant factors for the survival rate (or hazard function) of loans with the above characteristics. In other words, those loans are the ones most likely to be approved despite negative appraisal gaps.

1. Appraisal and Redlining

The housing market has long been characterized by the prevalence of bargaining and search friction. Consequently, asymmetry in the information on market fundamentals available to agents involved in home buying can introduce "noise" into the transaction value of a property. Given the high cost of acquiring necessary information, such suboptimal property pricing is highly likely. For example, accurate estimates of house prices require consideration of national trends in inflation, interest rates, and income; regional variations in income and demographic factors; and neighborhood-level details such as property tax rates, quality of schools, and crime rates. Further, the possibility of speculative housing demand (i.e., pure demand for capital gains) in certain market segments can lead to value estimates that deviate from the equilibrium level.

In underwriting home purchase mortgage loans, both transaction and appraisal values are required to filter noisy value estimates. The accuracy in property valuation has important implications for assessing credit risk along two major dimensions. First, LTV ratios at the time of loan origination, in which property values are the denominator, are a significant determinant of the likelihood that borrowers will exercise their put option to default. Several studies have indicated that the amount of equity in housing, as reflected by the leverage ratio, is negatively correlated with the probability of default (see Quercia and Stegman, 1992, for a review of studies on mortgage default). Second, accurate estimates of property values can yield sound proxies for resale values in the event of future liquidation. A wide gap between appraisal and transaction values may signal a high uncertainty about the future value of the underlying collateral backing the loan. To be conservative in risk assessment, lenders employ the lower of the transaction value or the appraisal value in their underwriting.

Recent literature has advanced a hypothesis that addresses the possibility of mortgage redlining caused by a dynamic information externality in property appraisals and mortgage lending. In particular, Lang and Nakamura (1993) hypothesize that because property appraisals depend on past transactions, appraisals in neighborhoods where transactions are infrequent tend to be less precise. The greater uncertainty about house valuation in such neighborhoods can lead mortgage lenders to impose stringent requirements on borrowers (e.g., larger down payment for loans). Therefore, reductions in mortgage lending in neighborhoods characterized by few transactions may be self-perpetuating. The analysis further indicates that lending behavior in certain neighborhoods can be suboptimal because of the information externality in property appraisals, even if mortgage lenders behave according to economically rational terms rather than on the basis of racial or ethnic prejudice.

To date, economic analysis of property appraisal has been largely theoretical. For example, Quan and Quigley (1991) and Geltner (1993) argue that the behavior of property appraisers is likely to be governed by an optimal appraisal updating rule, which is influenced by the relative size of marketwide noise (over time) and idosyncratic transaction noise. If the transaction noise is large relative to the marketwide noise, the appraiser will assign more weight to the previous estimate, thus lowering (i.e., smoothing) the second moment of appraisal-based returns. Lang and Nakamura (1993) further applied a similar appraisal updating rule by using the Kalman filter algorithm to demonstrate the role of property appraisal on the level of mortgage lending in a given community.

One shortcoming of these studies is that the authors offered no empirical confirmation of their theoretical arguments. In the following two sections, we aim to fill this gap partially. Specifically, we first describe the extent and pattern of the gaps between transaction values and appraisal values as observed in our sample. Next, we introduce an econometric framework for empirically testing for systematic appraisal bias across communities with different characteristics (mortgage lending activity levels, income, racial composition, and other location variables). We leave the full calibration of the developed model for future research.

2. Patterns of Appraisal Bias

Table 1 presents a percentage distribution of the size of the computed gaps across geographic areas. In particular, we defined 12 location types: four census regions (Midwest, Northeast, South, and West) with three location types in each (metropolitan areas included in central cities, metropolitan areas not included in central cities, and nonmetropolitan areas). For the level of appraisal bias, we define nine categories as shown horizontally in the table. The number in each cell represents the percentage of properties within each location type that show the level of bias associated with that category.

Table 1. Distribution of appraisal bias by location (percent).

	Negative Appraisal Bias					Positive Appraisal Bias				
Location	Below −10 Percent	Between −10 and −5 Percent	Between −5 and −1 Percent	Between −1 and 0 Percent	0 Percent	Between 0 and 1 Percent	Between 1 and 5 Percent	Between 5 and 10 Percent	Above 10 Percent	Total
Midwest										
MSA-CC	0.22	0.56	1.93	1.24	33.77	26.04	27.20	5.62	3.42	100.00
MSA-NCC	0.30	0.69	2.73	1.97	33.85	28.39	24.53	4.70	2.85	100.00
Non-MSA	0.70	1.37	3.72	1.30	33.70	17.61	28.71	7.77	5.12	100.00
Average	0.33	0.74	2.64	1.69	33.81	26.39	25.79	5.34	3.29	100.00
Northeast										
MSA-CC	0.67	1.24	2.74	1.17	32.59	15.33	27.72	9.79	8.75	100.00
MSA-NCC	0.47	0.92	2.91	1.53	29.25	22.46	29.86	7.38	5.23	100.00
Non-MSA	0.85	1.00	2.50	1.10	23.35	16.04	32.62	12.35	10.18	100.00
Average	0.52	0.97	2.86	1.45	29.40	21.00	29.70	8.04	6.06	100.00
South										
MSA-CC	0.28	0.51	1.97	1.19	25.97	23.74	32.52	8.42	5.38	100.00
MSA-NCC	0.29	0.60	2.03	1.53	24.07	28.56	31.08	7.39	4.44	100.00
Non-MSA	0.66	1.09	2.73	1.37	27.01	17.74	30.95	10.63	7.83	100.00
Average	0.33	0.63	2.10	1.41	25.01	25.78	31.52	8.09	5.13	100.00
West										
MSA-CC	0.21	0.53	2.23	1.75	36.95	25.21	23.37	5.37	4.01	100.00
MSA-NCC	0.24	0.54	2.05	1.76	35.56	27.03	22.75	5.92	4.15	100.00
Non-MSA	0.59	1.09	3.52	1.83	36.37	20.13	25.00	6.57	4.90	100.00
Average	0.28	0.61	2.33	1.77	36.20	25.36	23.30	5.94	4.20	100.00
Total	0.35	0.71	2.42	1.57	30.68	25.02	27.79	6.86	5.49	100.00

Note: Appraisal bias = 100 * $(P^A - P^T)/P^T$, where P^A is appraisal value and P^T is transaction value. Hence, negative appraisal bias means that appraisal value is less than transaction value, while positive appraisal bias means that appraisal value is greater than transaction value.
MSA-CC = metropolitan areas included in central cities, MSA-NCC = metropolitan areas not included in central cities, non-MSA = nonmetropolitan areas.

The two main data sources used in our analysis are the Fannie Mae loan acquisition file for 1993 and the 1990 decennial census. The first data set contains borrower, loan, and property characteristics (including both transaction and appraisal values of each property) as well as location codes for metropolitan statistical areas, counties, and census tracts. After sampling and data editing, we retain in our sample more than 600,000 observations of home purchase loans. Additional location variables are compiled from the census data set.

We find that for more than 30 percent of our sample, the appraisal and transaction values are identical (shown under the 0 percent gap in the table). In addition, the percentage distribution is skewed toward the positive side: More than 80 percent of all observations show either a zero gap or less than a 5 percent surplus in appraised value. The result implies that in many cases property appraisals are discrete rather than continuous: appraisers assign different value estimates only when differences between perceived values and transaction prices are large. More important, institutional settings surrounding property appraisals may require appraisers to impose a heavier burden of proof for negative than for positive appraisal bias (i.e., when appraisal values fall below transaction prices). As another possibility, appraisers and lenders may communicate in developing final estimates. For example, lenders may not want negative appraisal bias for loan applications that they would like to approve. If the appraiser produces a lower price, the deal will probably collapse because the seller will likely reject it. If the appraiser produces a slight surplus, the buyer will think that he or she got a good deal and probably will not back out during closing. The distribution of appraisal gaps is a conditional distribution—conditional on the loan being made. This induces a positive skewness, in part because it is likely that negative appraisal bias is more common in rejected loan applications.[2] The total number of properties that receive appraisals lower than the purchase price amounts to approximately 5 percent of our sample.

Across the four census regions, the West and Midwest demonstrate higher proportions of properties with zero gaps (36.2 and 33.8 percent, respectively) than the Northeast and South (29.4 and 25.0 percent, respectively). The Northeast has the highest proportion of negative appraisal bias (5.80 percent), followed by the Midwest (5.40 percent), the West (4.99 percent), and the South (4.47 percent). In addition, properties in nonmetropolitan areas are most likely to exhibit negative appraisal bias, except in the Northeast, where the three location types display virtually the same percentage of negative appraisal bias. Metropolitan properties outside the central cities are more likely than central-city properties to have negative appraisal bias.

We now examine the correlation between the proportions of properties that show negative, zero, and positive appraisal bias and selected borrower and loan characteristics. As shown in Table 2, the proportion of properties that exhibit negative appraisal bias is negatively correlated with LTV ratio; that is, on average, borrowers with negatively biased appraisals have lower LTV ratios (hence, higher down payments). However, these borrowers have higher means for family income and house price and exhibit higher standard errors for all variables except percent in central city. More detailed correlation patterns are revealed when we further disaggregate the sample into three groups based on first-quartile, median, and third-quartile values of LTV ratio (Table 3) and house price (Table 4) and compute percentages of properties with the three different types of appraisal bias (negative, zero, and positive) for each group. The results more clearly demonstrate that, on average, properties with negative appraisal bias have lower LTV ratios and higher house prices.

Table 2. Summary statistics by direction of bias.

Characteristics	Negative Bias*		Zero Bias		Positive Bias	
	Mean	SE	Mean	SE	Mean	SE
Loan-to-Value Ratio (%)	75.36	15.57	80.78	13.70	81.31	13.53
Monthly Income ($)	5,663	6,194	4,995	4,203	5,050	4,492
Purchase Price ($)	150,015	72,695	129,960	62,641	127,746	58,954
Percent in Central City	0.21	0.39	0.26	0.42	0.24	0.41
Average Bias	-3.63	5.75	0.00	0.00	3.64	1.19

*Appraised bias is defined as in Table 1. SE = standard error.

Table 3. Distribution of appraisal bias by loan-to-value (percent).

Loan-to-Value Ratio (Percent)	Negative Bias	Zero Bias	Positive Bias
Below 75	8.32	30.26	64.75
75–80	6.52	28.73	64.75
80–90	4.65	31.66	63.69
Over 90	3.19	30.69	66.12

Table 4. Distribution of appraisal bias by house prices (percent).

House Price ($)	Negative Bias	Zero Bias	Positive Bias
Below 96,000	3.62	31.41	64.97
96,000–137,450	4.63	29.84	65.53
137,450–180,000	5.70	29.14	65.16
Over 180,000	7.80	31.97	60.24

Note: House prices $96,000, $137,450, and $180,000 represent the first quartile, median, and third quartile in our sample, respectively.

The above results make intuitive sense because loans with low LTV ratios and high house prices are most likely to be approved despite negative appraisal gaps. For example, the negative appraisal gap as a proxy for uncertainty in liquidation may be used as a less significant risk factor for loans with low LTV ratios than for those with high LTV ratios. As a result, the survival rate or hazard function for mortgages will be more influenced by appraisal outcome for loans with high LTV ratios. For example, the default risk of loans with LTV ratios below 80 percent is usually absorbed by private mortgage insurers rather than by primary market lenders or secondary market purchasers. However, further explanations for these observed patterns and any firm conclusion can be derived only after a full-blown econometric analysis.

3. Econometric Testing of Appraisal Bias

3.1. Model Specification

Quan and Quigley (1989, 1991) delineate the process of house price formation and the role of property appraisers therein. In particular, they demonstrate that the information content of transaction prices consists of two main components: the correlation coefficient with the "full-information price" (which is influenced by the urgency of buyers and sellers to conclude a transaction) and the error term (which is a function of the estimation errors of buyers and sellers and the strategic parameters of each agent). The main task of appraisers is to extract a useful signal by observing the tansaction price to infer the full-information (or market) value.

Specifically, the property appraiser's problem is defined as identifying the best estimate of the property or the optimal appraisal $P^*_{i,t}$ transacted at neighborhood $i(i = 1, \ldots, N)$ at time $t(t = 1, \ldots, T)$, with the observation of the transaction price of that property $P^T_{i,t}$ and an information set $(I^A_{i,t-1})$ formed from sales of comparable properties in the same neighborhood in earlier periods. In formal terms, the appraiser's task can be specified as $P^*_{i,t} = E[P_{i,t} \mid P^T_{i,t} I^A_{i,t-1}]$, where $P_{i,t}$ is the unobservable full-information price. Therefore, both the cross-sectional variability of house prices in a community (for housing of a given quality) and the areawide price variability over time influence the optimal appraisal.[3]

In empirically testing the variation in appraisal precision, we use the framework employed by Gyourko and Voith (1992) in which they analyze house price appreciation at the metropolitan level. We develop a similar model with a smaller geographic unit of analysis. In particular, the intertemporal change in transaction prices of properties of a given quality in community i, $P^T_{i,t} - P^T_{i,t-1}$, can be specified as a linear function of two factors: a community-specific trend ϵ_i and a random fluctuation $\rho_{i,t}$. The second term is further decomposed into three elements: general areawide movement of house price over time β_t, the extent of neighborhood-specific persistence in error $\eta_i \rho_{i,t-1}$, and white noise $v_{i,t}$(i.e., $\rho_{i,t} = \beta_t + \eta_i \rho_{i,t-1} + v_{i,t}$),[4] such that

$$P^T_{i,t} - P^T_{i,t-1} = \epsilon_i + \beta_t + \eta_i \rho_{i,t-1} + v_{i,t}. \tag{1}$$

Next, following Lang and Nakamura (1993), the optimal updating rule of property appraisal can be written as

$$P^*_{i,t} = P^*_{i,t-1} + \delta_{i,t-1}(P^T_{i,t-1} - P^*_{i,t-1}), \tag{2}$$

where $\delta_{i,t-1}$ is the adjustment parameter, which is a decreasing function of the variance of estimation errors in appraisal at time $t - 1$ and, in turn, an increasing function of the number of property sales. As such, it varies both serially and cross-sectionally. By subtracting $P^T_{i,t}$ from both sides, equation 2 can be rewritten as

$$P^*_{i,t} - P^T_{i,t} = P^*_{i,t-1} - P^T_{i,t} = \delta_{i,t}(P^T_{i,t-1} - P^*_{i,t-1}). \tag{3}$$

By substituting P_{it}^T in the right-hand side from equation 1 and rearranging terms, we transform equation 3 into

$$P_{i,t}^T - P_{i,t}^* = (1 - \delta_{i,t})(P_{i,t-1}^T - P_{i,t-1}^*) + \eta_i \rho_{i,t-1} + \epsilon_i + \beta_t + \nu_{i,t} \qquad (4)$$

The main implication of equation 4 is that, after controlling for general time- and location-specific price movements (i.e., β_t and ϵ_i), the deviation of the transacted house price from its optimal appraisal value is influenced by two factors. The first factor is a one-period lagged value of the dependent variable (the first right-side term in the equation) and the level of error persistence ($\eta_i \rho_{i,t-1}$). The second factor can be measured in terms of the level of serial correlation in house price appreciation.

The proper data set for estimating the above model is panel data in which each community serves as a cross-sectional observation point and each period as a serial observation unit. To calibrate the model fully, we must make one simplifying assumption. As mentioned earlier, the adjustment parameter of property appraisals ($\delta_{i,t}$) varies both over time and across communities. In the actual estimation, however, we focus only on the cross-sectional variation (i.e., δ_i rather than $\delta_{i,t}$) to conserve degrees of freedom in parameter estimation. By incorporating this change, we specify the testing model as

$$\mathrm{GAP}_{i,t} = \alpha_i \mathrm{GAP}_{i,t-1} L_i + \eta_i \mathrm{APP}_{i,t-1} L_i + \beta_t D_t + \gamma_i (1 - \alpha_i - \eta_i) L_i + \epsilon_i, t. \qquad (5)$$

where $\mathrm{GAP}_{i,t} = P_{i,t}^T - P_{i,t}^A$ (where $P_{i,t}^A$ is the appraised value for housing of the same quality); L_i is a dummy variable for location (or neighborhood) i; $\mathrm{APP}_{i,t} = P_{i,t}^T - P_{i,t-1}^T$, D_t is a time dummy; $\alpha_i (= 1 - \delta_i)$, β_t, γ_i, and η_i are parameters to be estimated; and $\epsilon_{i,t}$ is random disturbance. The two interaction explanatory variables ($\mathrm{GAP}_{i,t-1} L_i$ and $\mathrm{APP}_{i,t-1} L_i$) capture the community-specific effect of the persistence of appraisal bias and that of the level of house price appreciation, respectively. In estimating equation 5, the degrees of freedom are $NT - 3N - T - 1$. This may be a problem when the sample includes a small number of serial observation points (i.e., T) but a large number of cross-sectional observation units (i.e., N).

Once we estimate the location effect with the above testing model, we can further measure the effects of more specific location variables on the obtained cross-sectional variation of appraisal bias. The estimated parameters in equation 5 (i.e., α_i, γ_i, and η_i) are used as inputs in formulating the variable representing the extent of appraisal bias for a given community and serve as the dependent variable in this stage. The right-side variables include such factors as the total number of home sales in each neighborhood, the percentage of minority population (to test racial bias in appraisal), and other economic and demographic factors (e.g., median family income, age distribution, vacancy rate). We then test the simultaneity between the dependent variable and the included explanatory variables (e.g., transaction volume). For illustration, the testing model in the second step can be specified as

$$\mathrm{BIAS}_i = \Sigma_k \psi_k X_{ik} + \mu_i, \qquad (6)$$

where BIAS_i is the estimated location effect for community i from the first stage; $X_{i,k}$ and ψ_k are the kth explanatory variable observed in community i and its regression coefficient, respectively, and μ_i is random disturbance. Based on the estimation results of equations 5 and 6, we can compute elasticities of appraisal bias with respect to specific location variables (i.e., X_k).[5]

3.2. *Econometric and Data Issues*

Several econometric issues must be considered in estimating the previous model. The first issue relates to sample selectivity bias caused by various sources. One general source of selection bias is that observations in the sample usually include only transacted units even though inferences may be drawn for both transacted and nontransacted units (Quan, 1993). The second source of bias relates to the segmented nature of the mortgage market. For example, mortgage loans can be differentiated by type of default insurance (Federal Housing Administration insurance versus private insurance), conformance to secondary market acquisition standards (conforming versus nonconforming conventional loans), and the mortgage instrument itself (adjustable-rate versus fixed-rate loans).

The next econometric issue pertains to both cross-sectional and serial aggregation bias. With regard to cross-sectional bias, no generalizable economic definition of neighborhood exists. At the same time, data availability largely defines the level of geographic aggregation that can be used in empirical analysis. In estimating the model, one can explore alternative definitions of neighborhood based on census-tract-level data. In particular, several key location variables (such as median family income and proportion of minority population) can be used to define neighborhood types based on similar values of these variables. Any bias possibly caused by such a procedure must be tested for.[6] As to serial aggregation bias, Calhoun, Chinloy, and Megbolugbe (1994) tested the bias caused by employing alternative time intervals (including months, quarters, and years) in the context of measuring the extent of appraisal smoothing. Similar testing should be performed to identify the proper unit of intertemporal aggregation.

4. Concluding Remarks

Our results indicate that property appraisals are governed largely by institutional factors. It is essential to consider three layers of information in accurately estimating house prices: national-level macro factors, regional-level shifts in relevant variables, and neighborhood and structural conditions. The primary role of property appraisal is to provide detailed information for the third layer. Compared with the first two categories, the collection and analysis of information for the third layer is generally more costly and labor intensive—precisely the reason that property appraisals are needed as a mechanism for checking the validity of transaction values. However, given the improved availability of useful microdata sets and today's fast-advancing computing technologies, the efficiency of property appraisals will be enhanced in the near future through careful time-series and cross-sectional studies. The model introduced in this paper offers one such framework.

The full calibration of the model with proper consideration of the econometric issues identified earlier will document systematic patterns of property appraisals across different neighborhoods. Our further analysis will offer empirical evidence of the existence (or absence) of systematic appraisal bias in communities with certain characteristics. However, interpreting the results as evidence of redlining (of a particular type) requires a careful analysis of other related issues. For example, if we assume that redlining is a consequence of differential treatment of certain areas (due to either unobservable risk factors or prejudice) by a particular group of economic agents involved in the mortgage lending process, the presence of the differential treatment at the micro level may be a necessary but not sufficient condition for researchers seeking evidence of redlining in market outcomes. That is, given the existence of a segregated market in which nondiscriminatory market if such a market exists. Therefore, proving the existence (or absence) of redlining requires additional analytic steps for which the results of our model calibration can be used as inputs.

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Notes

1. We credit this point to the anonymous reviewer.
2. This argument is a hypothesis to be tested in future research. Authors are currently processing the same data used by Munnell, Brown, McEneaney, and Tootell (1993) to test this and other hypotheses.
3. The specification of the optimal appraisal updating rule is offered by several recent studies (e.g., Quan and Quigley, 1989). Lang and Nakamura (1993) derive a formal specification of the optimal updating rule by using the Kalman filter algorithm.
4. Another possible source of error is the spatial dependence of neighborhoods in some metropolitan areas. This issue can be addressed by employing some recent estimation techniques for controlling spatial autocorrelation (see Can, 1991, for details).
5. One alternative econometric framework calls for modeling the appraisal precision and endogenous location variables (e.g., transaction volume) simultaneously rather than using the two-step estimation procedure suggested above. Although this approach can be regarded as more conceptually sound, it involves a complex estimation framework that incorporates a panel simultaneous-equation model with lagged endogenous variables.
6. One type of error that can be caused by aggregating the sample on the basis of location characteristics is called data-snooping bias. Lo and MacKinlay (1990) discuss this issue in detail.

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