Inferring an Investment Return Series for Real Estate from Observations on Sales

Daniel C. Quan* and John M. Quigley**

Accurate measurement of the returns to real estate investment are essential to sound analysis. This paper improves upon the traditionally employed method—collecting comparable sales data. A dynamic model of real estate appraisal is developed in which agents have incomplete information, heterogeneous search costs, and varying expectations. Various types of simulation analysis of the model indicate it performs best in the sense that the return estimate converges to the true value faster than other simpler rules.

INTRODUCTION

The first step in the allocation of an investment portfolio entails an analysis of the return characteristics of alternative investment vehicles. Obviously historical information on average returns is important. Conventional finance theory, however, also stresses the importance of the risk-sheltering attributes of assets. These capabilities are summarized by the variability of returns and the correlation of returns with the market portfolio and with other state variables. Crucial to such an analysis is the construction of an appropriate index of returns. Presumably such an index reflects faithfully changes in the spot prices of assets over time.

Although the underlying data can be obtained easily for most classes of investment opportunities, the absence of spot prices in real estate markets makes direct observation of a comparable index infeasible.

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Real estate transactions occur only infrequently, and thus instantaneous market prices are available for only a small fraction of the stock of real estate. As a result, the current market value of any holdings of real estate cannot be directly observed at any given time; the market value of real estate holdings must be inferred from limited information about recent transactions.

It has therefore become a common practice among investors to condition their investment decisions upon real estate return indices derived from appraisals or imputations. Clearly, the profitability of any investments using such return data depends crucially on the degree with which the estimated return series replicates the true underlying returns. More fundamentally, the accuracy of the appraisal process and an understanding of its relationship to observable prices is a key to sound investment decisionmaking.

The literature on appraisal technique is voluminous, and two well-defined methods are employed: imputations based upon observed sales of "comparable" properties; and imputations based upon suitable capitalization of the income stream attributable to a property. The latter method is inappropriate for residential properties. Presumably, the two methods yield similar estimates of market value for commercial and industrial properties.

The former method of imputation is widely employed, although appraisal tests caution that

exact comparability can never be obtained, if only because of differences in the fixed geographical location of the property. It is possible, nevertheless, through study and analysis of market operations, to adjust for price effects caused by differences in "physical" characteristics in order to obtain "economic" equality essential to an accurate estimate of market value [8, p. 131].

Appraisers also assert that

The greater the number and the more recent the sales of comparable properties, the greater the accuracy and the more convincing are the results obtained . . . [8, p. 131].

In this article, we consider the methodology of real estate appraisal

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1There is an immense literature comparing the performance of real estate holdings with other investment instruments. Most researchers have relied upon professional appraisals to represent market value in the estimation of return series. See [4] for a review of such studies, and [3] for a discussion of the estimation issue.

2A third method, based upon the replacement cost of real property, is recommended by some authorities despite its obvious limitations.

3See also [2], [5] and [14] and other appraisal texts.
based upon imputing valuation by observing sales of comparables. In particular, we consider the implications that the practice of real estate appraisal have for the construction of an investment returns series for real estate. To focus on the essentials, we consider the simplest case where comparable properties are in fact identical. This allows us to abstract from the "study and analysis" that underlies adjustments for "price effects" caused by differences in the physical characteristics of comparable properties.

We consider real estate appraisal in the context of a dynamic model of transactions in which agents have incomplete information, heterogeneous search costs and varying expectations. We take these aspects of the model to be characteristic of the real estate market. Under these circumstances, an observed transactions price can be expressed as a "noisy signal." The noise varies with the condition of the sale and the completeness of market participants' information sets. Given such a signal, an "optimal" appraisal is described, based on some signal extraction procedure. The information so extracted is, in turn, used to revise an appraiser's estimate of market prices and is passed on to market participants. It is this sequence of updated estimates which, over time, yields the return characteristics estimated for a given class of properties.

This article compares the implications of several widely used appraisal techniques for the problem of estimating the returns to real estate investment. In section two below we describe briefly a model of real estate transactions in a world of incomplete and costly information. The model is used to deduce the appropriate appraisal procedures to infer the market prices of the stock of real property from observations on the sales of some properties. Section three indicates the relationship between the "optimal" appraisal and several rules of thumb widely used by appraisers. In the fourth section we compare the static and dynamic implications of appraisal rules by simulating the return series generated by alternative appraisal techniques.

A MODEL OF REAL ESTATE TRANSACTIONS

Several distinguishing features of real estate markets play important roles in the price determination process. Buyers typically undertake a costly search process prior to making a purchase decision. Search is complicated by the fact that potential buyers seldom if ever obtain "complete" information about properties. Thus search and decisionmaking are undertaken in an environment of uncertainty and

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4This section relies heavily on [7].
incomplete information. Imperfect competition also prevails since the condition of the sale, the distress of the parties, or the thinness of the market can each play an important role in the determination of the eventual transaction price.

We take information imperfections, varying expectations, and differing search costs to be characteristic of the real estate market—for both housing and investment properties. This leads to price dispersion in short-run equilibrium, in which the transactions prices for identical properties vary. The law of one price prevails only in some long-run sense, and, as we note below, only under certain conditions.

Consider the long run: let the *ex post* competitive price \( P \) of a particular property be characterized by a \( q \)-factor model

\[
P = P(X_1, X_2, \ldots X_q) = P(I^*),
\]

where the \( X \)'s are the factors. These factors include the physical and financial characteristics of a particular property; \( I^* \) represents the full set of information about the property. \( P \) is a random variable, since some elements of \( I^* \) include realizations of variables following a random process (for example, random physical characteristics whose realizations are observable at any given time).

Buyers estimate the worth of a particular property by computing a threshold price. The expectation of the true price, conditional upon the information \( I^* \) available to the buyer, represents this threshold price. The threshold price, \( P^b \), differs from the true price by an error term, \( e^b \):

\[
P = E[P|I^*] + e^b = P^b + e^b.
\]

Each potential buyer also arrives at a reservation price as a function of the distribution of offer prices and his own search cost.\(^5\) Since a reservation price can be interpreted as the expected gain to the buyer from searching, a market participant is defined as an individual whose reservation price is less than his threshold price. Assuming buyers are heterogeneously informed and have varying search costs, the resulting distribution of reservation prices must be to the left of the distribution of threshold prices for the self-selected market participants.

For sellers the threshold price, \( P^s \), is similarly defined as:

\[
P = E[P|I^*] + e^s = P^s + e^s,
\]

for some given information set \( I^* \), a subset of \( I^* \). For the seller, this price defines his minimum selling price, given available information. If sellers are Nash players, then each determines an offer price that

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\(^5\)For example, under well-known conditions an optimal stopping rule exists for buyers, and the searching procedure has the reservation price property. If a buyer observes an offer price below the reservation price, he will stop searching and conclude a transaction. See [6] or [13].
takes into consideration his potential market share and his probability of a sale, given a distribution of buyers with varying reservation prices. A market participant is one whose expected gain upon a sale (offer price) is greater than his minimum selling price (threshold price). The associated distribution of threshold prices is therefore to the left of the distribution of offer prices for the group of market participants.

Since a transaction cannot occur below a seller’s nor above a buyer’s threshold price, the feasible set of prices from which all transactions must be drawn from is the region between the two prices. A transaction price, $P_T$, is defined as:

$$P_T = \omega P^a + (1 - \omega)P^b$$

(4)

where an arbitrary weight $\omega$, $0 \leq \omega \leq 1$, may be interpreted as the condition of the sale. $\omega$ may represent market conditions or the relative bargaining power of the parties. When $\omega$ is close to 1, this corresponds to a buyer’s market. On the other hand, when $\omega$ is close to 0, the condition of the sale corresponds to one of a seller’s market. By substituting expression (2) and (3) into (4), we can express the observable transactions price as the sum of the true price plus some terms that arise as a consequence of the incompleteness of the buyers’ and sellers’ information:

$$P_T = P - \omega e^a - (1 - \omega)e^b.$$  

(5)

The transaction price $P_T$ represents the “noisy signal” that the appraiser receives. Given such a signal, he must extract an estimate of market value.

THE DYNAMICS OF APPRAISAL

Consider the appraiser’s updating rule. Let $I_{t-1} = \{P_{T,1}, P_{T,2}, \ldots, P_{T,t-1}\}$ be the set of all previously observed transaction prices available to the appraiser and $E[P|I_{t-1}]$ be his estimate of the price based on this information. The appraiser observes a transaction price at time $t$, $P_{T,t}$; he must determine $E[P|I_{t-1}, P_{T,t}]$, the revised estimate of the true price taking into account the new information, $P_{T,t}$. In this section, we develop an updating rule that is consistent with the model of real estate transactions introduced above. The rule is then compared with other commonly used appraisal rules. We restrict the discussion to linear updating rules of the following form:

\[ E[P|I_{t-1}, P_{T,t}] = \beta_1 P_{T,t} + \beta_2 E[P|I_{t-1}] \]  

(6)

Although this may initially seem restrictive, it will be shown that the most commonly used appraisal rules can be expressed in this form.

From equation (5) the transaction price can be expressed as the following noisy signal:

\[ P_{T,t} = P + \epsilon_t \]  

(7)

For convenience, we assume that \( \epsilon_t \) is an iid normal random variable with variance \( \sigma^2 \). From (5), it follows that

\[ \sigma^2 = \omega^2 \sigma^2_b + (1 - \omega)^2 \sigma^2_s + 2\omega(1 - \omega)\sigma_{bs} \]  

(8)

where \( \sigma^2_b, \sigma^2_s \), and \( \sigma_{bs} \) represent the variance of the buyer’s and seller’s errors and their covariance respectively. It is important to note that the unconditional expectation of \( \epsilon_t \) is not zero even though its conditional mean must be zero. The unconditional mean of \( \epsilon_t \) represents the systematic bias in the agents’ estimate of the true price, given their restricted information. As such, the linear updating process is:

\[ P_{T,t} = 1B + \tilde{\epsilon}_t \]  

(9)

where \( \tilde{\epsilon}_t \) has mean zero and, \( 1 = [1, 1] \) and \( B = [\alpha, P]' \) are two-dimensional vectors.

The optimal updating procedure for an appraiser, given an initial information set \( I_{t-1} \) and an additional piece of information, \( P_{T,t} \), is the so-called least squares or recursive projection (see [12] chapter 10, [10] or [11]):

\[ E[B|P_{T,t}, I_{t-1}] = E[B|I_{t-1}] + K_t[P_{T,t} - E(P_{T,t}|I_{t-1})], \]  

(10)

where \( K_t \) is a column vector whose elements are \( K_{1t} \) and \( K_{2t} \).

A new appraisal is made by augmenting the current appraised value of an identical ("comparable") property by some weighting, \( K_t \), of last period’s error. The last term of (10) is the updating component. By defining \( B_{it} = E[B|P_{T,t}, I_{t-1}] \) and \( B_{it-1} = E[B|I_{t-1}] \) and noting that \( E(P_{T,t}|I_{t-1}) = P_{T,t,-1} \), equation (10) can be rewritten as:

\[ B_{it} = B_{it-1} + K_t(P_{T,t} - 1B_{it-1}) \]  

(11)

where \( K_t \) can be interpreted as a regression coefficient,

\[ K_t = (E(B_t - B_{it-1})(P_{T,t} - P_{T,t,-1}))(\text{Cov}(P_{T,t}, I_{t-1}))^{-1}. \]  

(12)

Define \( S_{a,it-1} = E[(B_t - B_{it-1})(B_t - B_{it-1})'|I_{t-1}] \) to be the variance covariance matrix of the estimation error at time \( t \), given information up to \( t - 1 \) for the parameters \( \alpha \) and \( P \). \( S \) is a 2 by 2 diagonal matrix.

\(^7\)As indicated below, the normality assumption is not binding if we restrict ourselves to linear filtering rules. See [1], chapter 3.
whose diagonal elements are $\sigma^2_{\alpha_{\tilde{t},t-1}} = E[(\alpha_t - \alpha_{t-1})^2|I_{t-1}]$ and $\sigma^2_{P_{\tilde{t},t-1}} = E[(P_t - P_{t-1})^2|I_{t-1}]$. By observing that $P_{T,t} - P_{T_{\tilde{t}},t-1} = 1(B - B_{t-1}) + \varepsilon_t$, the updating rules (11) can be written as:

\begin{align}
\alpha_{\tilde{t},t} &= K^1_t[P_{T,t} - P_{\tilde{t},t-1}] + (1 - K^1_t)\alpha_{\tilde{t},t-1} \tag{13a} \\
P_{\tilde{t},t} &= K^2_t[P_{T,t} - \alpha_{\tilde{t},t-1}] + (1 - K^2_t)P_{\tilde{t},t-1}, \tag{13b}
\end{align}

where

\begin{align}
K^1_t &= \sigma^2_{\alpha_{\tilde{t},t-1}}[\sigma^2_{\alpha_{\tilde{t},t-1}} + \sigma^2_{P_{\tilde{t},t-1}} + \sigma^2_\varepsilon]^{-1} \tag{14a} \\
K^2_t &= \sigma^2_{P_{\tilde{t},t-1}}[\sigma^2_{\alpha_{\tilde{t},t-1}} + \sigma^2_{P_{\tilde{t},t-1}} + \sigma^2_\varepsilon]^{-1}, \tag{14b}
\end{align}

Appraisal proceeds by computing a weighted average of the price recorded for the last transaction and the appraiser's previous estimate, with the weights depending on the second moments of the error distributions. Since the variance of the errors collapses to zero as the system becomes more and more informative, the informational content of the system is summarized in its variance.

Consider the simple case in which the appraiser has perfect information. For this case, $K_t = 0$, since $S_a = 0$, and the current appraisal is identical to that of the last period. Since no additional information can be conveyed by the transaction price $P_t$, no weight is assigned to it. Conversely, if both the buyer and the seller have perfect information but the appraiser does not, then $\sigma^2_t = 0$ in (14a) and (14b); the weights assigned to the two prices will depend on the estimate of systematic bias, $\alpha$. If $\alpha$ is known, then $\sigma^2_{\alpha_{\tilde{t},t-1}} = 0$, $K^1_t = 0$ and $K^2_t = 1$, and the revised estimate will be the observed transaction price adjusted by the value of $\alpha$. Only in the special case where the appraiser has perfect information regarding the true price is the best prediction of a property value the last sale price of a comparable property.

In general, however, the best prediction of the current value of a property is not the last sale price of an identical "comparable" property. Moreover, it is not the average sale price of identical properties.

**SIMULATING INVESTMENT RETURNS**

In this section we compare the implications of the optimal appraisal rule, as defined in the previous section, with three common rules of thumb used by appraisers and noted in the appraisal literature. In this comparison, we pay particular attention to the investment return series implied by these alternative techniques.
Alternative Appraisal Rules

The alternative appraisal techniques can be expressed as rules for revising the current estimate of market value. Rule 1 is named the "naive rule" in which the best estimate of the market value of a property is the last observed transaction price of a comparable property. Rule 2 is more sophisticated. Under this rule, estimates of the population mean are continuously revised as more transactions become available. Under rule 3, prices are modelled as some factor or rate of growth of the previous estimate of market prices. The factors themselves are estimated from the pool of transaction prices. These are linear rules, consistent with equation (6) above.

Under rule 1, the estimate of real estate values is the last observed transaction price of an identical property, that is,

**Rule 1:**

\[ E[P|_{t-1}, P_{t-1}] = P_{t-1} \]  

(14)

This is simply the linear rule with \( \beta_1 = 1 \) and \( \beta_2 = 0 \). Thus, no history is used in determining a new estimate of market value. Clearly this method is not efficient since the information contained in the previous transactions is discarded.

Under rule 2 the sample mean of sale prices is used as an estimate of the population mean of property values. The sample mean is updated as additional transaction prices become available. The intuitive justification for such a procedure is the belief that each transaction price is an unbiased estimate of the true stationary price. Thus sample means are unbiased and are efficient estimates of the true price. This rule can also be interpreted as the application of mass appraisal procedures using hedonic regressions. In this context, including new transactions in the hedonic regression, reestimating the parameters and using these parameters to make revised estimates has the same result. To express this rule in linear form, let \( P_{t-1} = [P_{t-1}, \ldots, P_{t-1}]' \) be a column vector of \( t - 1 \) transaction prices and \( 1_{t-1} \) be a row vector of \( t - 1 \) 1's. The appraiser's estimate at time \( t - 1 \) is then:

**Rule 2:**

\[ E[P|_{t-1}] = (1/(t - 1))1_{t-1}P'_{t-1}. \]  

(15)

Upon obtaining a transaction price \( P_{t,1} \), the appraised value of property is:

\[ E[P|_{t-1}, P_{t,1}] = (1/t)1_{t}P'_{t} = (1/t)P_{t} + ((t - 1)/t)E[P|_{t-1}]. \]  

(16)

Rule 2 is merely equation (6) with \( \beta_1 = 1/t \) and \( \beta_2 = 1 - \beta_1 = (t - 1)/t \).

Rule 3 is a commonly used method for adjusting estimates of market values to reflect secular changes. Some general rate of appreciation of real estate values is estimated from transaction prices; this rate or
factor is used to adjust the previous estimate of market values. This procedure can be expressed as:

\[ E[P|I_{t-1}] = \theta_{t-1} E[P|I_{t-2}] \]  \hspace{1cm} (18)

If \( \theta \) is chosen arbitrarily, then this is clearly the linear case with \( \beta_1 = 0 \) and \( \beta_2 = \theta \). However, it is reasonable that, with each new observation on \( P_{T,t} \), \( \theta \) is revised. Assume that \( \theta \) is the coefficient arising from regressing the sequence of transaction prices on a lagged sequence of the same transaction prices. Let \( P_{t-1} = [P_{T,1}, \ldots, P_{T,t-1}]' \) be a column vector of \( t-1 \) elements of transaction prices, \( P^*_{t-1} \) be a \((t-1) \times 1\) vector of lagged values of \( P_{t-1} \). (That is, the first element of \( P^*_{t-1} \) is \( P_{T,0} \) and the last element is \( P_{T,t-2} \).) In this case,

\[ \theta_{t-1} = (P^*_{t-1}'P^*_{t-1})^{-1}P^*_{t-1}'P_{t-1}. \] \hspace{1cm} (19)

When a new transaction price becomes available, the revised regression coefficient is:

\[ \theta_t = (P^*_t'P^*_t)^{-1}P^*_t'P_t, \] \hspace{1cm} (20)

and the estimate of market value is therefore:

**Rule 3:** \[ E[P|I_{t-1}, P_{T,t}] = \theta_t E[P|I_{t-1}]. \] \hspace{1cm} (21)

It is easily seen that \( \theta_t \) can be decomposed in terms of the new and the old transaction prices:

\[ \theta_t = (P^*_t'P^*_t)^{-1}(P_{T,t}P_{T,t-1} + P^*_{t-1}'P_{t-1}). \] \hspace{1cm} (22)

By substituting this expression into (21) and rearranging terms, it is clear that rule 3 does have the linear form with

\[ \beta_1 = (P^*_t'P^*_t)^{-1}P_{T,t-1}E[P|I_{t-1}], \]
\[ \beta_2 = (P^*_t'P^*_t)^{-1}P^*_{t-1}'P_{t-1}. \] \hspace{1cm} (23)

**Numerical Results**

As noted in the introduction, for well-known reasons investment decisions depend upon the mean return, its variance and the covariances of returns generated by alternative instruments. In considering real estate investment, these returns arise from imputations. In this section we simulate the return series generated by reliance upon alternative appraisal rules, and compare them with the signal extraction procedure proposed in the third section.

In the following simulations, we incorporate learning on the part of the agents. In [7], it was shown that if market participants observe an appraisal prior to making a transaction, then participants in any given period will be no worse informed than participants in the previous period. Thus even though aggregate errors in estimation may occur
in the short run, such errors are reduced over time as information is revealed.

The structure of the simulations considers five distinct circumstances. In all cases, the true price, \( P_t \), is generated by \( P_t = \theta P_{t-1} + u_t \) where \( u_t \sim N(\mu_u, \sigma^2_u) \) represents the systematic uncertainty. With \( \theta = 1 \), the true price series is constant, and the returns from investment are zero; \( (\theta - 1) \) is a measure of the true rate of return to the investment. Transaction prices at time \( t \), \( P_{T,t} \), are related to the true prices by \( P_{T,t} = P_t + \epsilon_t \) where \( \epsilon_t \sim N(\mu_{\epsilon,t}, \sigma^2_{\epsilon,t}) \) is due to the incompleteness of each agent’s information. Learning is introduced by allowing \( \mu_{\epsilon,t} = .97 \mu_{\epsilon,t-1} \) and \( \sigma^2_{\epsilon,t} = .96 \sigma^2_{\epsilon,t-1} \) for some initial values of \( \mu_{\epsilon,0} \) and \( \sigma^2_{\epsilon,0} \). The simplest scenario is one in which the true price is constant. We also consider the case of rising and falling real estate prices in both a stable and unstable economic environment. Table 1 summarizes the five scenarios in which the simulations are conducted. For each environment, it lists the specific parameters used to simulate a series of 200 transactions observed in the market.

For each series we estimate the market returns to real estate investment using the three linear rules presented in equations (14), (15) and (21). We compare these estimates to the optimal filter defined in equations (11) and (12).

Figure 1 presents the return series estimated for the benchmark case of constant prices. Plotted are every fourth of the last 150 observations computed for the four methods. It can be seen that the sample average approach provides the smoothest estimate whereas the AR1 and the last transaction approach give essentially the same results. In general, the filtering method performs best. Its return estimate converges to the

**TABLE 1**

Initial Conditions for Simulating Investment Appraisal Methods

<table>
<thead>
<tr>
<th>Simulation Model</th>
<th>( P_{T,t} = P_t + \epsilon_t )</th>
<th>( P_t = \theta P_{t-1} + u_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning Process</td>
<td>( \mu_{\epsilon,0} = 30,000 )</td>
<td>( \sigma^2_{\epsilon,0} = 50,000 )</td>
</tr>
<tr>
<td></td>
<td>( \mu_{\epsilon,t} = .97 \mu_{\epsilon,t-1} )</td>
<td>( \sigma^2_{\epsilon,t} = .96 \sigma^2_{\epsilon,t-1} )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>MODEL NUMBER</th>
<th>MODEL 1</th>
<th>MODEL 2a</th>
<th>MODEL 2b</th>
<th>MODEL 3a</th>
<th>MODEL 3b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Description</td>
<td>Constant Price</td>
<td>Increasing Price</td>
<td>Declining Price</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \theta )</td>
<td>1.000</td>
<td>1.002</td>
<td>1.002</td>
<td>0.998</td>
<td>0.998</td>
</tr>
<tr>
<td>( \mu_u )</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( \sigma^2_u )</td>
<td>60,000</td>
<td>40,000</td>
<td>60,000</td>
<td>40,000</td>
<td>60,000</td>
</tr>
</tbody>
</table>
Figure 1
(Model 1, Theta = 1)

Figure 2
(Model 2b, Theta = 1.002)
true value faster. In Figure 2, the simulated results are plotted for the case of a market characterized by rising prices. Once again, the last transactions and the AR1 procedures provide similar estimates. They track the true path of returns rather poorly. In contrast the filtering method is very sensitive to the turning points of the true return series. The filtering method also converges to the true series faster. Figure 3, which simulates a market with decreasing prices, provides quite similar results regarding the reliability of the methods used. The filtering procedure performs best. Return estimates converge more rapidly to the true values and the turning points are well estimated.

Table 2 indicates the mean square error of the four methods. The filtering approach clearly dominates the alternatives. The table compares errors in a stable (Model 2a and 3a) and a volatile (Model 2b and 3b) market. It can be seen that the filtering approach is less affected by an increase in volatility than the others. This reflects the fact that the filtering procedure tracks turning points in the true underlying series rather well. Alternatively, this result suggests that in a very stable environment, the nonfiltering approaches may provide returns estimates that are sufficiently accurate.

**Figure 3**

(Model 3b, Theta = .998)
### TABLE 2
Mean Square Error of Estimated Returns*

<table>
<thead>
<tr>
<th>Rules</th>
<th>Optimal Appraisal</th>
<th>1 Last</th>
<th>2 Average</th>
<th>3 AR1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant Price</td>
<td>.0054</td>
<td>.0061</td>
<td>.0067</td>
<td>.0058</td>
</tr>
<tr>
<td>Increasing Price</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stable Market</td>
<td>.0078</td>
<td>.0418</td>
<td>.0187</td>
<td>.0427</td>
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<tr>
<td>Volatile Market</td>
<td>.0084</td>
<td>.0600</td>
<td>.0269</td>
<td>.0605</td>
</tr>
<tr>
<td>Decreasing Price</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stable Market</td>
<td>.0186</td>
<td>.1074</td>
<td>.0748</td>
<td>.1080</td>
</tr>
<tr>
<td>Volatile Market</td>
<td>.0229</td>
<td>.1562</td>
<td>.0975</td>
<td>.1572</td>
</tr>
</tbody>
</table>

*last 150 of 200 returns generated by each model

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### REFERENCES


COMMENTS ON

Inferring an Investment Return Series for Real Estate from Observations on Sales

by James R. Follain*

One advantage that stems from being a co-editor of this volume is the ability to choose the paper I want to discuss. This paper is of particular interest because I am also interested in the "appraiser's problem;" however, it appears we have different ideas as to the nature of the appraiser's problem.

FRAMEWORK

The framework for the analysis—discussed more fully in an earlier paper, Quan and Quigley [4]—differs considerably from most others within the literature aimed at explaining variations in housing prices. The bulk of this literature focuses upon the hedonic approach in which the price of a house is explained as a function of a variety of housing and neighborhood characteristics. Such single equation models are usually estimated using cross-section data at one point in time. Whereas the previous literature emphasizes the heterogeneity of housing, this one emphasizes the fact that housing trades infrequently. Consequently, information about the movements in the true price of housing over time is costly to obtain.

Because we know comparatively little about the movements in real estate prices over time, this is a welcome change in focus. A better understanding of the ways in which housing prices vary over time is needed to understand the full impact of a number of key policy issues. For example, much of the work on the impact of tax reform on real estate says little about the short-run effects of tax reform on asset prices, instead it focuses upon the effect of tax reform on the new long-run equilibrium rent levels, e.g., Hendershott, Follain and Ling [2]. It does so because little is known about the time path of housing

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prices and the speed at which rents adjust to their new equilibrium levels.

A key feature of the framework is the explicit modeling of the asymmetric information that exists among buyers, sellers, and appraisers. This feature could be used to determine the willingness by either buyers or sellers to pay for up-to-date and accurate information. The model could also be used to compute the value of the services of an appraiser. If this is done, they should try to explain what I take to be a stylized fact—the price of a single-family appraisal is cheap, e.g., $200. Is this because the methods of the appraiser are so poor or the adjustment of housing prices is so predictable? In either case, the Quan and Quigley model should ultimately shed light on the questions.

Another interesting application concerns the endogeneity of the number of transactions. I would think the model might be used to determine circumstances under which more or less trading might occur. For example, if new or inside information is obtained by sellers relative to buyers, then one might observe more trading if buyers feel prices are too low. More generally, perhaps the model can be used to learn more about the determinants of variations in the number of housing sales over time, a very volatile series.

APPRAISER'S PROBLEM

Quan and Quigley apply their methodology to analyze time-series rules that can be used by an appraiser of single-family housing. I am less optimistic about the benefits of this application than the authors. Several operational problems seem likely with this application.

The first involves the number of observations needed to utilize Kalman filtering models of the type they employ. The original filtering estimators were developed for problems with huge and ever-increasing numbers of observations. For example, missile path trackers sought to estimate the path of the missile at various points in time given information about its previous path. New information was obtained every second or millisecond. Rather than continuously recompute the inverse of the $X'X$ matrix, it was noted that the new path coefficients could be computed using a weighted average of the previous path estimate and the path predicted by the new information. As such, it was a computational tool, not a behavioral model. My concern is that the number of observations needed to take full advantage of the Kalman filter approach is unlikely to be found in any but the largest housing markets. This is certainly true if one tracks identical houses, e.g., repeat sales.

Second, incorporating information about the cross-sectional variation in housing characteristics and prices is likely to be quite difficult. Although Quan and Quigley suggest that the incorporation of such
information would not change the nature of their results, the model is
already so complex, incorporation of the entire vector of housing and
neighborhood characteristics would likely cause some serious computa-
tional problems. This is especially true given the recent results by
Ondrich [3] that indicate the basic hedonic equation can be estimated
more efficiently by estimating the hedonic jointly with the demand
equations for the characteristics.

Third, I suspect that some of the really interesting problems regard-
ing changes in the time path of housing prices involve changes in the
underlying structural model. For example, housing prices are influ-
enced by interest rates, tax rules, both local and national, expected
inflation, and a wide variety of exogenous variables that drive the
demand for housing. Exactly how unexpected changes in such informa-
tion would affect the Quan and Quigley model is not clear to me. My
guess is that incorporating it would be difficult, especially given that
much of this information is observed over different time intervals, i.e.,
some is monthly, some is quarterly, and some is annual.

Although I have concerns about the applicability of the model to the
"appraisal problem" as defined by Quan and Quigley, the model may
be applicable to another appraisal problem. Recent work by Firsten-
berg, et al. [1] focuses on the discrepancy that exists between two series
on the returns to nonresidential real estate: one constructed using data
on frequently traded REITs (real estate investment trusts) and one
based upon infrequently traded properties, the Frank Russell Index.
The latter index relies upon appraised valuations to construct its
quarterly index whereas the REIT index uses actual trades. One ques-
tion is whether the frequency of the traded information affects the
accuracy of the indexes. Another is whether the valuations of the
appraisers are biased; in particular, they may be slow to adjust to rapid
changes in the market, i.e., autocorrelation may exist.

These issues might be explored with the Quan and Quigley model by
examining the impact of the frequency of trading on price estimates.
For example, Quan and Quigley might compute the response of a
return series as more or fewer transactions are observed per period. It
would be particularly interesting to do this using different assump-
tions about the role of past information, e.g., different autocorrelation
parameters. They currently focus upon positive autocorrelation, but
some might argue that appraisers tend to be too cautious, i.e., apprais-
ers downplay the importance of rapid rises or declines. In such a case,
negative autocorrelation might be preferred.

Lastly, this work might be linked to the more general literature on
the existence of bubbles in stock markets. What kinds of information
patterns are needed to get housing price patterns that rise or decline
rapidly or even explode. There are several examples of this in recent
years; Toronto, Vancouver, portions of California, Boston, New York, and others. What is going on to generate such extreme increases and what causes them to stop, sometimes quite suddenly?

In sum, I like the model. It is rich, different, and likely to be applicable to a wide variety of issues. My principal concern is that it will not be particularly useful in the application selected in this paper.

REFERENCES
