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PRICE DISCOVERY IN TIME AND SPACE: THE COURSE OF CONDOMINIUM PRICES IN SINGAPORE.

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Price Discovery in Time and Space: The Course of Condominium Prices in Singapore*

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A random walk in time and independence in space are maintained hypotheses in traditional empirical models of housing prices. However, there is increasing evidence in the context of hedonic models that housing prices are predictable over time and space. This paper examines the price discovery process in individual dwellings by relaxing both assumptions, using a unique body of data from the Singapore private condominium market in a repeat sales framework. We develop a formal model that tests directly the hypotheses that the prices of individual dwellings follow a random walk over time and that the price of an individual dwelling is independent of the price of a neighboring dwelling. The empirical results clearly support mean reversion in housing prices and also diffusion of innovations over space. This predictability may suggest that excess returns are possible. When aggregate returns are computed from models that assume a random walk and spatial independence, we find that they are strongly autocorrelated. However, when they are calculated from models permitting mean reversion and spatial autocorrelation, predictability in investment returns is completely absent. Despite this, an extensive simulation of investor performance, over different time horizons and with different investment rules, indicates quite clearly that recognition of the spatial and autocorrelated nature of prices substantially improves investor returns. The magnitude of deviations from standard models of price dynamics are small, but their economic implications are quite large in the housing market.

Keywords: House price innovations, excess returns, housing investment
JEL Codes: E31, C23, R32

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I. Introduction

The durability, fixity and heterogeneity of dwellings imply that transactions costs are significant in the housing market. Certainly in comparison to financial markets, and in comparison to the markets for most consumer goods, housing purchases require costly search to uncover the prices and attributes of commodities. Given the many frictions associated with the purchase of housing, it is hardly surprising that observed price behavior deviates from that predicted by simple models of economic markets. Inertia in the price adjustment process, either in aggregate prices (Case and Shiller 1989) or in individual house prices (Englund, *et al.* 1999, Hill, *et al.* 1999) is widely reported. This is often regarded as evidence of housing market inefficiency (e.g., Case and Shiller 1990)

But in this geographical market, price signals exist in space as well as time. Many of the features which can lead to autocorrelation in the time domain could have analogous effects over space. Price information diffuses over space as well as time, and information costs alone can cause prices to deviate from random fluctuations.

This paper examines price discovery in a spatial market using a body of data almost uniquely suited to the problem. We examine the prices of condominium dwellings in Singapore using all sales reported in the country during an eleven-year period. Multiple sales of the same condominium unit are observed, and all dwellings with market transactions are geocoded. We develop a model of housing prices in repeat sales framework that more faithfully represents the temporal and spatial features unique to housing markets, and we incorporate a more general and more appropriate structure of the price discovery process at the level of the individual dwelling.

We develop a model that is more general than other widely used methods of measuring aggregate housing prices. Indeed, the methods used by government agencies (e.g., OFHEO) and commercial firms (e.g., MRAC, Inc.) to estimate the course of house prices are special cases of the model developed below. The model and the data support a direct test of the maintained hypotheses in repeat sales models that the prices of individual dwellings follow a random walk over time and that the price of an individual dwelling is independent of the price of a neighboring dwelling. We link these results to movements in aggregate measures of housing prices and their spatial and temporal properties.

An earlier literature on price discovery in finance examines the temporal links between present and future prices, the effects of trading arrangements on opening and closing prices on securities markets, and the role of market makers (e.g., Amihud and Mendelson 1987, Stoll and White 1990, Leach and Madhavan 1993, Chordia and Subrahmanyam 1995, Blume and Goldstein 1997). The literature on price discovery in housing markets is growing, but again, most applications concentrate on aggregate time series. Following Case and Shiller (1989), others have documented predictable returns in housing markets by demonstrating that aggregate price series exhibit inertia in percentage changes (Guntermann and Norrbin 1991; Gatzlaff 1994; and Malpezzi 1999). Less is known about the dynamics of house prices at the individual level. Englund *et al.* (1999) and Hill *et al.* (1999) using very different techniques, rejected a random walk in individual housing prices by examining repeat sales of single family dwellings.

There are a few recent studies that use spatial econometric methods in analyzing housing prices, but they rely on ad hoc procedures to describe spatial processes.[1] Reliance upon ad hoc procedures to analyze the spatial and temporal pattern of housing prices is understandable, given the infrequency of transactions on dwellings. This means that a panel of houses typically contains a relatively small and irregular number of observations on the sales prices of houses. The temporal correlation in prices depends upon the time interval between sales, and with irregular intervals, inference in a model which also accounts for spatial dependence may be quite difficult. (See, for example, Pace, *et al.,* 1998, 18-22.)

In this paper, we employ an explicit model of the spatial and temporal dependence of housing prices to evaluate the importance of these factors in affecting the course of individual housing prices. We do this using a repeat sales model of price determination, not a hedonic model. Not surprisingly, the introduction of an explicit micro model makes estimation more complicated.

We compare the properties of indices of aggregate housing prices and returns computed from our more general model with indices computed from conventional models. In particular, we find that when aggregate investment returns are estimated from models which assume a random walk in housing prices and spatial independence, they are strongly predictable.

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[1] Can and Megbolugbe (1997) estimated hedonic house price models incorporating lagged values of nearby house prices to reflect neighborhood dependencies in prices. Goetzmann and Spiegel (1997) developed a "distance-weighted repeat-sales" procedure where distance is defined in terms of geographical and socio-economic factors, such as household income, educational attainment and racial composition and where "distance weights" are estimated using an ad hoc procedure. Dubin (1998) postulated a specific form for a correlogram between the prices of housing as a function of distance between houses. Iversen (2001) developed repeat sales index model based on a spatial-temporal Markov random-field model, but spatial and temporal dependence are allowed only at regional levels, not at the level of individual dwellings. Pace, *et al.,* (1998, 2000) developed an empirical model for house prices which evolve through time and space. Their model specified an autoregressive structure of house prices and a spatial dependency among prices. Given an irregular panel of house prices (in which there are few transactions in any period), ad hoc procedures were used to filter house prices sales by time and location. (Indeed, different results are obtained arbitrarily depending upon the ordering of filtering processes.)

However, when aggregate returns are estimated from models permitting mean revision and spatial autocorrelation, predictability in aggregate investment returns is completely absent. Despite the highly localized nature of the estimated spatial and temporal effects, they "matter" enormously in affecting investment returns.

We devote considerable attention to the economic implications of our statistical findings for investment in housing markets. In particular, we demonstrate the importance of these findings for investor returns using a variety of investment rules.

Section II develops a general model of housing prices that supports explicit tests for the spatial and temporal pattern of price movements. This section links our model to the widely employed method for measuring housing prices proposed almost forty years ago by Bailey, Muth, and Nourse (1963), as well as its subsequent extensions (e.g., Case and Shiller, 1987). The data are described tersely in Section III. Our empirical results are presented in Sections IV, V and VI. We test for random walks in space and time against the alternative of mean reversion, and we examine the link between pricing deviations at the individual level and aggregate price movements. We also investigate investor behavior in some detail. Section VII is a brief conclusion.

II. A Micro Model of House Prices

The objects of exchange in the housing market are imperfect substitutes for one another. Indeed, the fixity of housing implies that dwellings with identical physical attributes may differ in market price simply because the price incorporates a complex set of site-specific amenities and access costs. But few dwellings have identical physical characteristics; thus comparison-shopping is more difficult and more expensive than in most other markets.

Moreover, housing transactions are made only infrequently, so households must consciously invest in information to participate in this market. As a result, the market is characterized by a costly matching process. Market agents, buyers and sellers are heterogeneous and differ in information and motivation; commodities are themselves heterogeneous. Consequently an observed transaction price for a specific unit may deviate from the price ordained in the fully informed perfect market of the intermediate micro textbook.

Buyers, sellers, appraisers, and real estate agents estimate the "market price" of a dwelling by utilizing the information embodied in the set of previously sold dwellings. The usefulness of these sales as a reference depends upon their similarity across several dimensions: physical, spatial, and temporal. Inferences about the "market price" of the dwelling can be drawn only imperfectly from the set of past sales, because dwellings differ structurally, enjoy different locational attributes, and are valued under different market conditions by different actors over time. Because dwellings trade infrequently, the arrival of new information about market values is slow. From an informational standpoint, the closest comparable sale across these various dimensions may be the last sale of the same dwelling. Alternatively, the most comparable sale may be the contemporaneous selling price of another dwelling in close physical proximity.

An attempt to uncover the market value of a dwelling is further complicated by the fact that an observed sales price is not only a function of observable physical characteristics, but also of unobserved buyer and seller characteristics such as their urgency to conclude a transaction (Quan and Quigley, 1991). For any given sale, all that is known is that an offer was made by a specific buyer that was higher than a specific seller's reservation price.

We develop a model with spatially and temporally correlated errors in a repeat sales framework. Innovation processes over time are assumed to be continuous, but sales are observed sporadically. At any point in time, the prices of houses are dependent over space. In the determination of the price of a house, the weights attributable to neighboring houses depend upon their proximity to the house. But the prices of neighboring houses are also observed only infrequently.

Let the log sale price of dwelling i at time t be

(1) $$V_{it} = P_t + Q_{it} + e_{it} = P_t + X_{it}\beta + e_{it},$$

where V_{it} is the log of the observed sales price of dwelling i at t, and P_t is the log of aggregate housing prices. Q_{it} is the log of housing quality, and can be parameterized by X_{it}, the set of housing attributes and by a set of coefficients, β, which price those attributes. If a sale is observed at two points in time, t and τ, and if the quality of the dwelling remains constant during the interval, then

(2) $$V_{it} - V_{i\tau} = P_t - P_\tau + (X_{it} - X_{i\tau})\beta + e_{it} - e_{i\tau}$$

$$= P_{it} - P_{i\tau} + e_{it} - e_{i\tau}.$$

With constant quality, (2) identifies price change in the market.

Let the error term, e_{it}, consist of two components that are realized for each individual dwelling at the time of sale: η_{it}, an idiosyncratic innovation without persistence; and ε_{it}, an idiosyncratic innovation with persistence, $\varepsilon_{it} = \lambda\varepsilon_{i,t-1} + \mu_{it}$. In addition, assume that the value of any particular dwelling depends also on innovations that occur to other dwellings contemporaneously. We assume this spatial correlation depends on the distance between units.

(3) $$e_{it} = \rho\sum_{j=1}^{N} w_{ij}e_{jt} + \xi_{it} = \rho\sum_{j=1}^{N} w_{ij}e_{jt} + \varepsilon_{it} + \eta_{it} = \rho\sum_{j=1}^{N} w_{ij}e_{jt} + \lambda\varepsilon_{i,t-1} + \eta_{it} + \mu_{it},$$

where w_{ij} is some function of the distance between unit i and j and N is the number of dwellings in the economy. Let $E(\eta_{it}\eta_{jt}) = 0$ and $E(\varepsilon_{it}\varepsilon_{jt}) = 0$, $E(\eta_{it}^2) = \sigma_\eta^2$, $E(\mu_{it}^2) = \sigma_\mu^2$.

The value of a particular dwelling depends, not only on its own past and contemporaneous innovations, but also on innovations of other dwellings, past and contemporaneous. Note that the model of housing prices in (2) and (3) specializes to that of Bailey, Muth and Nourse (1963) when $\lambda = \rho = 0$, to that of Case and Schiller (1987) when $\lambda = 1$, $\rho = 0$, and to that of Quigley and Redfearn (2000) when $\rho = 0$.

In vector notation, expression (3) is

$$\text{(4)} \qquad \mathbf{e}_t = \rho \mathbf{W} \mathbf{e}_t + \xi_t ,$$

where $\mathbf{e}_t$ is a vector of e_{it} for all the dwellings at time t, $\mathbf{W}$ is a weight matrix, some measure of the distance between dwellings, and ξ_t a vector of $\xi_{it} = \lambda \varepsilon_{i,t-1} + \eta_{it} + \mu_{it}$, for all dwellings. By solving for $\mathbf{e}_t$ and taking the difference between two sales at times *t* and *s*, we have

$$\text{(5)} \qquad \mathbf{e}_t - \mathbf{e}_s = (\mathbf{I} - \rho \mathbf{W})^{-1} (\xi_t - \xi_s).$$

The variance-covariance matrix of (5) is

$$\text{(6)} \qquad E\left[(\mathbf{e}_t - \mathbf{e}_s)(\mathbf{e}_t - \mathbf{e}_s)'\right] = (\mathbf{I} - \rho \mathbf{W})^{-1} E\left[(\xi_t - \xi_s)(\xi_t - \xi_s)'\right](\mathbf{I} - \rho \mathbf{W})^{-1} .$$

Transactions on dwellings occur only infrequently. Consider the covariance in errors between a dwelling *i* sold at *t* and *s* and another dwelling *k* sold at τ and ς, $E[(e_{it} - e_{is})(e_{k\tau} - e_{k\varsigma})]$.

Let $\mathbf{\Psi} = E\left[(\xi_t - \xi_s)(\xi_\tau - \xi_\varsigma)'\right]$ and $\mathbf{\Pi} = (\mathbf{I} - \rho \mathbf{W})^{-1}$. Thus,

$$\text{(7)} \qquad E\left[(\mathbf{e}_t - \mathbf{e}_s)(\mathbf{e}_\tau - \mathbf{e}_\varsigma)'\right] = \mathbf{\Pi \Psi \Pi} = \begin{bmatrix} \boldsymbol{\pi}_1' \\ \boldsymbol{\pi}_2' \\ \vdots \\ \boldsymbol{\pi}_N' \end{bmatrix} [\boldsymbol{\psi}_1 \ \boldsymbol{\psi}_2 \cdots \ \boldsymbol{\psi}_N][\boldsymbol{\pi}_1 \ \boldsymbol{\pi}_2 \cdots \ \boldsymbol{\pi}_N].$$

The elements of this expression are,

$$\text{(8)} \qquad E[(e_{it} - e_{is})(e_{k\tau} - e_{k\varsigma})] = \boldsymbol{\pi}_i' \mathbf{\Psi} \boldsymbol{\pi}_k .$$

Now consider an element of the covariance matrix, $\mathbf{\Psi}$. Note that

$$(9)\qquad E\left(\xi_{it}\xi_{j\tau}\right)=\lambda^{|t-\tau|}\left(\frac{\sigma_{\mu}^{2}}{1-\lambda^{2}}\right)+I(t=\tau)\sigma_{\eta}^{2},\ \text{if } i=j,$$

$$= 0 \qquad\qquad\qquad\qquad , \text{otherwise.}$$

where $I(\bullet)$ is an indicator function. For sales of a given dwelling at time t, s, τ and ς,

$$(10)\qquad E\left[\left(\xi_{it}-\xi_{is}\right)\left(\xi_{i\tau}-\xi_{i\varsigma}\right)\right]=\left(\lambda^{|t-\tau|}-\lambda^{|t-\varsigma|}-\lambda^{|s-\tau|}+\lambda^{|s-\varsigma|}\right)\left(\frac{\sigma_{\mu}^{2}}{1-\lambda^{2}}\right)$$

$$+\left(I(t=\tau)-I(t=\varsigma)-I(s=\tau)+I(s=\varsigma)\right)\sigma_{\eta}^{2}.$$

Therefore, the variance-covariance matrix is

$$(11)\qquad \mathbf{\Psi}=E\left[\left(\xi_{t}-\xi_{s}\right)\left(\xi_{\tau}-\xi_{\varsigma}\right)'\right]=E\left[\left(\xi_{it}-\xi_{is}\right)\left(\xi_{i\tau}-\xi_{i\varsigma}\right)\right]\times\mathbf{I}.$$

Finally, the variance-covariance matrix of innovations between a dwelling *i* sold at *t* and *s* and another dwelling *k* sold at τ and ς is

$$(12)\qquad E\left[\left(e_{it}-e_{is}\right)\left(e_{k\tau}-e_{k\varsigma}\right)\right]=\boldsymbol{\pi}_{i}'\,\mathbf{\Psi}\,\boldsymbol{\pi}_{k}=\boldsymbol{\pi}_{i}'\left\{E\left[\left(\xi_{it}-\xi_{is}\right)\left(\xi_{i\tau}-\xi_{i\varsigma}\right)\right]\times\mathbf{I}\right\}\boldsymbol{\pi}_{k}$$

$$=\left\{\left(\lambda^{|t-\tau|}-\lambda^{|t-\varsigma|}-\lambda^{|s-\tau|}+\lambda^{|s-\varsigma|}\right)\left(\frac{\sigma_{\mu}^{2}}{1-\lambda^{2}}\right)+\right.$$

$$\left.\left[I(t=\tau)-I(t=\varsigma)-I(s=\tau)+I(s=\varsigma)\right]\sigma_{\eta}^{2}\right\}\boldsymbol{\pi}_{i}'\boldsymbol{\pi}_{k}.$$

Equation (12) indicates how the variance-covariance matrix of residuals from the regression specified in (2) can be used to identify the temporal and spatial components of house price persistence, λ and ρ, respectively. Identification requires observing at least two transactions for each dwelling and observing the distance of each dwelling from all others in the market.

III. Data

The analysis below is based upon all condominium sales in Singapore during an eleven-year period. Non-landed properties (apartments and condominiums) account for roughly two-thirds of the Singapore housing stock, and units in condominiums account for almost forty percent of private residential housing in land scarce Singapore[2].

The data have been complied by the Singapore Institute of Surveyors and Valuers (SISV) and consist of all transactions involving condominium dwellings during the period from January 1, 1990 to December 31, 2000. SISV gathers transactions data from a variety of sources including legal registration records and developers' sales records. The dataset is complete – each condominium sale in the entire country is recorded. In addition, an extensive set of physical characteristics of dwellings is recorded. The date of the sale is recorded as well as the date of occupancy. In addition, the address, including the postal code, is reported. The postal code identifies the physical location – the block of flats or, often, the specific building. A matrix of distances among Singapore's fifteen hundred postal codes permits each dwelling to be located spatially. The data set includes transactions among dwellings in the standing stock, sales of newly constructed dwellings, and presales of dwellings under construction (where the sales contract date may be several months before the date construction is actually completed).

The panel nature of the data permits us to distinguish dwellings sold more than once, and the multiple sales feature of the data identifies the models specified in Section II. By confining the sample to dwellings in multifamily properties, we eliminate types of dwellings for which additions and major renovations are feasible. The sample of multifamily dwellings is thus less likely to include those for which the assumption of constant quality between sales (see equation 2) is seriously violated.

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[2] See Sing (2001) for an extensive discussion of the condominium market in Singapore.

Singapore data offer another advantage in estimating the model of housing prices, namely a spatial homogeneity of local public services (e.g., police protection, neighborhood schools), especially when compared to cities of comparable size in North America. During the decade of the 1990s, there was no discernible trend in the quality of neighborhood attributes of the bundle of housing services.[3]

Table 1 presents a summary of the repeat sales data used in the empirical analysis reported below. There are several points worth noting. First, confirming the infrequency of housing transactions, the number of dwellings sold more than once is less than twenty percent of the population of dwellings sold during the eleven-year period. Only three percent of the 52,337 dwellings were sold more than twice in the eleven-year period.

Second, the average selling prices tend to be higher for dwellings sold more frequently. The rate of appreciation is also higher. On average, dwellings sold five times appreciate almost twice as fast as dwellings sold only twice. For the dwellings sold more frequently, price appreciation tends to be more volatile. Transactions involving high-turnover dwellings are apparently riskier, but this risk is compensated by higher returns.

Third, the intervals between sales are longer for dwellings sold infrequently. In part, this is an artifact of the fixed sampling framework. For presold dwellings, the average length of time between sale and completion of construction is highest for those sold least frequently, which is not consistent with the popular belief in Singapore that presales are associated with speculation in the housing market.

Fourth, there are some differences in the characteristics of dwellings sold more frequently. They tend to be larger in area, containing more rooms, and they are more centrally

[3] One possible exception to this may be accessibility, where improvement in the transport system and its pricing may have altered the workplace access of certain neighborhoods.

located relative to the central business district (CBD), but their transit access is similar to the dwellings sold less frequently.

The data on condominium sales supports a regression model of the form

$$(13)\quad V_{it} - V_{is} = P_t D_{it} - P_s D_{is} + \gamma\kappa_{it} - \gamma\kappa_{is} + e_{it} - e_{is},$$

where D_{it} is a variable with a value of 1 for the month t in which condominium i is sold and zero in other months a,nd P_t is the estimated coefficient for this variable. There are 132 of these time variables, one for each month between 1990 and 2000. If dwelling i has been presold, κ_{it} is the time interval between the transaction date and the completion of construction. For dwellings sold after completion of construction, κ_{it} is set to zero. Thus, the estimated coefficient γ measures the monthly discount rate for presold dwellings, i.e., the discount for unrealized service flows from dwellings which have been purchased but which are not yet available for occupancy. The purchase of a dwelling before completion, or even before construction, is not uncommon in Singapore. One aspect of this institution is, however, uncommon – namely that the entire purchase price is paid at the time the contract is signed, not at the time the dwelling is first occupied. Pre-sale contracts provide insurance against unanticipated price increases in the market.

Of the 11,883 pairs of transactions noted in Table 1, 305 consist of presale pairs. For another 5,204 pairs, the first sale was made sometime before the property was completed.

IV. The Diffusion of House Price Innovations

The model can be estimated by maximum likelihood methods. In particular, if we assume the error terms in equation (3), η_{it} and μ_{it}, are normally distributed, the log likelihood function for the observed sample of condominium sales is

(14) $$\log L\left(P,\gamma,\lambda,\rho,\sigma_\eta^2,\sigma_\mu^2\right)=-\log\left(|\mathbf{\Sigma}|\right)-\left(\boldsymbol{\delta}'\mathbf{\Sigma}^{-1}\boldsymbol{\delta}\right),$$

where $\mathbf{\Sigma}=\left[\boldsymbol{\pi}_i'\,\mathbf{\Psi}\,\boldsymbol{\pi}_k\right]$ and $\boldsymbol{\delta}=\left[V_{it}-V_{is}-P_tD_{it}-P_sD_{is}+\gamma\kappa_{it}-\gamma\kappa_{is}\right]$.

Note that the parameters in the $\mathbf{\Sigma}$ matrix are $\lambda,\rho,\sigma_\mu^2,\text{and}\,\sigma_\eta^2$. Conditional on values for λ and ρ, the consistent estimates of the error variances, σ_μ^2 and σ_η^2, can be obtained from the regression

(15) $$\left(\hat{e}_{it}-\hat{e}_{is}\right)^2=2\left(1-\lambda^{t-s}\right)\left(\frac{\sigma_\mu^2}{1-\lambda^2}\right)+2\sigma_\eta^2,$$

where the vector $\left(\hat{e}_{it}-\hat{e}_{is}\right)$ is the set of residuals from a first-stage regression using equation (13). Then, the remaining parameters of the repeat sales model can be estimated by generalized least squares using equation (12). The vector of residuals, δ, and the matrix **Σ**, computed from λ and ρ, are sufficient to compute the values of the log likelihood function. The function can be maximized by a grid search over λ and ρ.

Consider the matrix **Σ**. It is the product of three submatrices, $\boldsymbol{\pi}_i'$, $\mathbf{\Psi}$ and $\boldsymbol{\pi}_k$. The matrix $\mathbf{\Psi}$ is large, with rows and columns equal to the number of dwellings in the sample, but it is diagonal. The elements of the matrix are computed from the time intervals between sales, given λ, according to equation (10). Absent spatial correlation, i.e., when $\rho=0$, the matrix $\boldsymbol{\pi}_i$ is the *i*-th vector of the identity matrix. And $\boldsymbol{\pi}_k$ is the *k*-th vector of the identity matrix. Thus the matrix **Σ** is block diagonal. The size of each block is determined by the number of paired sales for a given house. Using techniques appropriate for large sparse matrices, the inverse matrix, $\mathbf{\Sigma}^{-1}$, can be computed.

As noted in Section I, there is ample reason to expect mean reversion in house prices. We begin by assuming no spatial dependence, and we analyze autocorrelation. Assuming $\rho=0$

(and hence the matrix $\mathbf{\Sigma}$ is block diagonal and sparse), the likelihood function is well-behaved with a maximum at $\lambda = 0.72$. The estimation is based on 11,883 observations on repeat sales on 10,288 dwellings sold two or more times. Likelihood ratio tests reject a random walk in house prices ($\lambda = 1$) and serially uncorrelated house prices ($\lambda = 0$) by wide margins, χ^2 =2,489.68, and χ^2 =32,129 respectively. The estimated value of λ suggests that the half-life of a one-unit shock to housing prices is about 33 days.

We now estimate the parameters of spatial and temporal autocorrelation simultaneously. As noted above, when $\rho \neq 0$, the $\mathbf{\Sigma}$ matrix is no longer block diagonal. Thus, it may be quite difficult to compute its inverse. Note, however, that $\boldsymbol{\pi}_i$ is the *i*-th row of $(\mathbf{I} - \rho\mathbf{W})^{-1}$, and when $\mathbf{W}$ is sparse, most of the elements of $\boldsymbol{\pi}_i$ will be zero. This, in turn, will make the $\mathbf{\Sigma}$ matrix sparse, since $\mathbf{\Sigma} = [\boldsymbol{\pi}_i' \boldsymbol{\Psi} \boldsymbol{\pi}_k]$. One inconsequential way of making $\mathbf{W}$ sparse is to set small values of weights to zero, implying that when two dwellings are sufficiently far apart, then there is no spatial correlation between them. In following, we assume that the elements of the weight matrix are the reciprocals of the distance between the dwellings, and that dwellings further apart than a given distance (250 meters) are not spatially correlated.

When spatial and temporal autocorrelations are considered simultaneously, the values of λ and ρ that maximize the log likelihood function are 0.78 and 0.55, respectively. The ML estimate of the serial correlation coefficient, λ, is rather similar to that reported for the simpler model, but the half-life of a unit shock is now estimated to be 53 days, more than 60 percent longer. The value of 0.55 for the spatial correlation coefficient, ρ, is quite modest. An exogenous impulse quickly dissipates over the space and most of the impulse is dissipated within a couple of hundred meters.

Figure 1 presents estimates of the monthly price index, equation (13), under different assumptions about the error structure. Price index estimates for months in the first two years tend to be insignificantly different from each other. The monthly price series is quite precisely estimated after mid-1982. (In part, this reflects the sampling design: there are more observations for later years, which allow more precise estimation of coefficients for later years.) Among three indices, the two that assume stationary processes for error terms tend to move more closely. The estimated coefficients of the price index are reported in detail in Appendix Table A1. The other coefficients are reported in Figure 1.

The estimated coefficients for γ, the period between sale and dwelling completion (for presold units), are about 10-12 basis points. This represents a 1.2 to 1.5 percent annual discount for a dwelling unit sold today for occupancy a year hence. The magnitude of the discount is not trivial: aggregate housing prices rise, on average, by 0.3 percent monthly, and this discount for presold units reduces the net price appreciation for consumers by one third to one half.

V. The Course of Condominium Prices and Investment Returns

Although Figure 1 reports similar patterns for the course of housing prices for Singapore dwellings, the returns implied by these housing indices are quite different.

The economic returns from investment in housing depend upon the course of real prices and rents. In particular, ignoring transactions costs and leverage, the real return in any period, R_t, is the change in the value plus the dividend (i.e., the rental stream, r_t, enjoyed during the period)

$$(16) \qquad R_t = \left(\frac{P_t + r_t}{P_{t-1}}\right)\left(\frac{I_{t-1}}{I_t}\right),$$

where I_t is an index of the cost of living, less housing.

Figure 2 uses the estimates, the monthly non-housing CPI in Singapore to chart the course of investment returns during the eleven-year period.[4] Although the mean returns differ by less than ten percent, the patterns of estimated returns and the volatility of returns estimted from the three models are strikingly different.

Table 2 reports the forecastability of monthly investment returns based upon lags of returns of one, two, three and four months. As reported in the table, there is considerable disparity in the forecastability of returns implied by the three sets of estimated prices and returns. With a random walk and no spatial correlation, there is clear evidence of overshooting in monthly returns (See Regression I). Thus, a contrarian investment strategy would appear to maximize investment returns: sell on price increases, buy on price decreases. There is no evidence that a more complicated lag structure (See Regressions II, III, and IV) improves the forecastability of investment returns. With mean reversion but no spatial autocorrelation, there is still strong evidence of overshooting, but there is also evidence that the more complicated lag structure improves forecastability. However, based upon the maximum likelihood estimates incorporating mean reversion and spatial dependence ($\lambda = 0.78$, $\rho = 0.55$) reported in Regressions IX through XII, there is no evidence of forecastability in aggregate house prices at all. When the modest level of spatial autocorrelation in prices is recognized, there is absolutely no predictability in aggregate returns.

VI. Investment Performance

These results may have significant implications for investment in the housing market. Consider an investment decision in housing based on housing price determination models such as (1). In this context, a better specification of the error structure can lead to superior investment

[4] We assume the implicit rent on owner-occupied condominiums, $r_t = 0.01P_t$ (See Englund, *et al.,* 2002).

decisions in two ways. First, improvement may arise through better estimates of aggregate housing price trends. In the regression models graphed in Figure 1, different assumptions about error structure have rather small effects on the large sample properties of slope coefficients, but (as indicated in Appendix Table A1) they have larger effects on efficiency with which those parameters are estimated. Thus, investment decisions based on the appropriate error structure are more important when investment horizons are relatively short. Second, improved performance would arise from basing the investment decision on more complete information. For example, when errors are spatially correlated, knowledge of past and present innovations in some specific dwellings may provide valuable information, useful for predicting the future course of prices for other dwellings. The empirical issue is whether these improvements are economically importamt.

This section investigates the consequences of different assumptions about error structures on measured investment performance in the housing market. We summarize an extensive simulation of investor activity which utilizes the results of the previous section. We use investment rules which depend upon forecasts of future housing returns. These forecasts are based on investors' assumptions about the underlying housing price generating processes.

The investment rule applied in this section is quite simple. Given assumptions on error structures and the consequent parameter values governing the house price processes, an investor makes forecasts for housing returns using all the available historical information. The investor is instructed to "buy" if the expected return is greater than some preset threshold. When the investor decides not to buy, she is assumed to invest in some alternative asset that generates a risk free return. The threshold may be interpreted to as the known transactions costs in the housing market plus the opportunity cost of the investment. We set the risk free rate equal to zero for these simulations.

Transactions costs vary with housing market characteristics, financial market characteristics and tax systems, so it is difficult to specify a precise level. The *ex post* opportunity cost of housing investment in Singapore during the period 1990-2000 was in any case quite low. (Annual stock market returns averaged 0.1 percent; treasury bill yields were about the same.) We use 0 percent, 5 percent and 10 percent as investment thresholds, comparable with a range of plausible transactions and opportunity costs.[5] The investment holding period is set at 24 months, 48 months, 60 months and 72 months.

When spatial correlations exist among dwellings, error distributions of individual dwelling prices are heteroskedastic (since dwellings have different neighborhoods). Further, the variance-covariance matrix of error terms depends on distances to neighbors, so this varies across dwellings. In this exercise, we specify a uniform spatial density of housing on a 1.5-kilometer square, with each dwelling on a grid located 30 meters away from its neighbors. It is possible to consider the investment performance for any or all of the dwellings, but for convenience, we concentrate on the dwelling at the center of the grid.

In each of 1000 simulations, two sets of time series prices for each of the 2500 dwellings in the grid are generated. A time series of prices for 24 months is generated for each dwelling and then a monthly time series for each of the four different holding periods is generated using the parameter values obtained in the maximum likelihood estimation along with an appropriate weight matrix. The first set of prices for 2500 dwellings for 24 months is assumed to be observed by the investor, who uses this prior information together with her estimates of the parameters (λ and ρ) to make a price forecast for the next 24, 48, 60 or 72 months. If the

[5] For more systematic examination of likely transactions costs in real estate, see Söderberg (1995) or Quigley (2002).

forecasted return exceeds the threshold, then she will invest. The second set of prices is then used to evaluate the performance of her investment.

We consider three investors with differing amounts of information. The fully informed investor is armed with the ML estimates that $\rho = 0.55$ and $\lambda = 0.78$, reported in as Model 1 in Figure 1. She uses this information together with 24 months of history on housing prices to generate a price forecast for the particular house at the end of each of the different holding periods. The partially informed investor is armed with less complete information; she assumes (as in Model 2) that $\rho = 0$ and $\lambda = 0.72$. The uninformed investor assumes no spatial correlation and a random walk in house prices, i.e., $\rho = 0$ and $\lambda = 1$.

We simulate this process 1000 times and compute the empirical distribution of investor returns. We can compare the investor performance for the "fully informed" investor (who knows that $\lambda = 0.78, \rho = 0.55$), the "partially informed" investor (who thinks that $\lambda = 0.72, \rho = 0$) and the "uniformed" investor (who assumes spatially independent, random walk prices $\lambda = 1, \rho = 0$). Figure 3 reports one such comparison, for a 5 percent investment rule. As the figure shows, the distribution of returns for the better informed investor lies to the right of the distribution for the less well informed investor. The mean return is much higher for the better informed investor.

A more systematic evaluation of investor performance can be obtained by applying consistently the criterion of mean-variance dominance or stochastic dominance. It is well known that with a normal distribution of returns or with quadratic investor utility, mean-variance dominance is strictly meaningful. The interpretation of dominance is thus rather restrictive, but the measure remains popular due to analytical tractability and its rich empirical implications (Huang and Litzenberger, 1988). In contrast, the criterion of stochastic dominance is more general in the sense that it considers entire distributions of returns, rather than just their first two moments. Three measures of stochastic dominance can be defined, depending on the restrictions on preferences. (See Rothchild and Stiglitz, 1970.) The first measure assumes that an investor's utility is increasing in wealth. The second measure assumes, in addition, that an investor is risk averse. The third measure of stochastic dominance assumes, in addition, that the absolute risk aversion of an investor is decreasing.

Table 3 compares investor performance based on these two criteria. The table reports the results of a "horse race" between a fully informed investor and one who does not recognize the spatial and/or temporal nature of housing returns. The table reports the mean return in percent and the variance in returns for different assumed holding periods and thresholds. These results are reported for the fully informed investor (I), the partial informed investor (II), and the uninformed investor (III). As the table indicates some knowledge of the spatial and temporal pattern of prices has a very substantial impact on investor performance. For differing thresholds and holding periods, the mean return for the better informed investor is higher. The variance in returns is usually smaller for the better informed investor. The table also provides explicit tests of investor performance using three stochastic dominance criteria. These comparisons take into consideration the entire distributions of returns and the sampling errors of the distributions, using the nonparametric test developed by Anderson (1996). Of the 30 comparisons between investor I and III, the performance of the better informed investor exhibits first order stochastic dominance 29 times. Of the 30 comparisons between investor I and II, the performance of the better informed investor exhibits first order stochastic dominance 5 times, and second order stochastic dominance 23 times.

It is quite clear that the better econometrician is the more successful investor – by a substantial margin. It seems clear: even though the spatial autocorrelation in prices is quite small, taking it into account really "matters" in improving investment behavior.

VII. Conclusion

Because of the special features of the housing market, we may anticipate that price discovery and the diffusion of price information is more complicated than in many other markets. In this paper, we test the departures from instantaneous diffusion of price information over time and over space. Using information on all condominium sales in Singapore during an eleven-year period, we test for random walks, mean reversion and serial correlation in house prices. We rely upon multiple sales of more than ten thousand dwellings over the period to analyze the structure of pricing errors.

Our empirical results quite clearly support mean reversion in house prices. Our statistical tests reject the hypothesis of a random walk and they also reject the hypothesis of no serial correlation against the alternative hypothesis of mean reversion. We also find significant spatial dependence in prices.

The maximum likelihood estimate of serial correlation, 0.78 per month, suggests rapid dissipation of any innovation in housing prices. After two months, about 48 percent of any mispricing error is dissipated (i.e., $1-.78^2$). After six months, 77 percent is dissipated, and after a year 98 percent is dissipated. The maximum likelihood estimate of spatial correlation, 0.55 per 100 meters, suggests rapid dissipation of any innovation in housing prices over space (eg., 71 percent after 200 meters).

Our estimates of the level of housing prices, derived from the repeat sales model, suggest that there are only small differences in the house price levels estimated when serial and spatial correlation is recognized as compared to estimates which ignore these features. However, there are substantial differences in the estimated returns to housing investment.

The finding of mean reversion and spatial autocorrelation at the micro level may suggest that aggregate housing prices are forecastable and that excess returns are possible for investors in this market. We use the monthly price series derived from condominium sales to investigate this issue. We compute gross monthly real returns. In missspecified models, we do find evidence of a one-period lag in real returns, i.e., real returns today are inversely related to real returns last month. However. when aggregate house prices are calculated from micro models that permit mean reversion and spatial autocorrelation, the predictability in investment returns is completely absent.

Finally, we investigate the economic value of information about the spatial and temporal autocorrelation in house prices in affecting investment returns in the housing market, using two criteria, mean-variance dominance and stochastic dominance. Our analysis suggests that the recognition of these spatial and temporal factors, can substantially increase the returns to investment in the housing market. This is true even though the magnitudes of the autocorrelation and mean reversion parameters are rather small. The magnitude of the deviations from standard models of price dynamics are small, but their economic implications are quite large.

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Table 1. Summary of Sales Data on Singapore Condominiums

1990 – 2000

			Price			Average Interval				Distance to ℵ	
Number of Times Sold	Number of Dwellings	Total Number of Sales	Average*	Average Appreciation+	Std of Appreciation++	Between Sales**	Presale Interval♦	Average Size◇	Number of Rooms	Nearest Subway Station	CBD
1	42,169	42,169	861				31.98	129.93	2.77	1.421	9.239
2	8,791	17,582	913	0.52%	0.71%	47.77	8.48	137.44	2.74	1.437	8.577
3	1,195	3,585	1,030	0.68%	1.13%	28.33	2.51	154.42	2.76	1.500	7.464
4	190	760	1,087	0.73%	1.29%	20.88	1.53	159.51	2.63	1.383	6.838
5	28	140	1,418	0.92%	1.53%	15.23	2.06	208.90	2.90	1.427	4.633
6	4	24	1,129	0.86%	1.60%	15.85	0.00	187.40	2.80	1.362	6.296

* Thousands of current Singapore Dollars
** Number of months
\+ Average price appreciation between sales divided by average interval between sales in months.
++ Standard deviation of price appreciation between sales divided by average interval between sales in months.
♦ Average number of months from sales to completion of construction of dwellings.
◇ Average size of dwellings in square meters.
ℵ Average distance in kilometers.

Table 2. Forecastability of Investment Returns,
Singapore Condominiums, 1990-2000
(t ratios in parentheses)

$$R_t = \alpha_o + \sum_i^n \alpha_i R_{t-i} + \xi_t$$

	Model 3 : λ=1, ρ=0				Model 2: λ=0.72, ρ=0				Model 1 : λ=0.78, ρ=0.55			
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	0.003 (0.5350)	0.003 (0.6204)	0.004 (0.7289)	0.002 (0.5022)	0.002 (0.5616)	0.002 (0.6090)	0.002 (0.6590)	0.002 (0.5026)	0.002 (0.5892)	0.002 (0.5151)	0.002 (0.5426)	0.001 (0.3579)
R_{t-1}	-0.332 (4.1575)	-0.399 (4.5480)	-0.397 (4.4443)	-0.389 (4.4217)	-0.196 (2.4396)	-0.201 (2.2651)	-0.198 (2.2785)	-0.210 (2.3438)	-0.125 (1.5106)	-0.099 (1.0991)	-0.115 (1.2959)	-0.123 (1.3603)
R_{t-2}		-0.160 (1.8958)	-0.133 (1.3938)	-0.102 (1.0854)		-0.047 (0.5654)	0.059 (0.6666)	0.064 (0.7249)		0.083 (0.9866)	0.167 (1.8771)	0.156 (1.7469)
R_{t-3}			-0.011 (0.1241)	0.044 (0.4633)			0.122 (1.5063)	0.142 (1.5981)			0.104 (1.2529)	0.113 (1.2511)
R_{t-4}				0.249 (2.6255)				0.128 (1.5651)				0.139 (1.6644)
σ_R^2	0.0030	0.0029	0.0030	0.0028	0.0017	0.0017	0.0017	0.0017	0.0012	0.0013	0.0012	0.0012
$\bar{R}^2$	0.1121	0.1281	0.1191	0.1517	0.0370	0.0239	0.0413	0.0412	0.0098	0.0043	0.0272	0.0366
DW	2.1330	1.9795	1.9741	1.9832	2.0108	1.9533	2.0220	1.9845	1.9259	1.9788	1.9944	1.9724
F test*	17.420	10.568	6.888	6.850	5.998	2.611	2.891	2.430	2.300	1.295	2.236	2.267

Note: Each regression is based upon 131 observations on monthly returns computed from regression estimates reported in Appendix Table A1 using Equation (16).

* Test of the joint hypothesis that the coefficients of lagged dependent variables are each equal to zero.

Table 3. Comparison of Investor Performance
Means and Variances of Investment Returns for Fully Informed (I), Partially Informed (II) and Uninformed Investors (III) for Different Thresholds and Holding Periods (in Percent)
(1000 Replications)

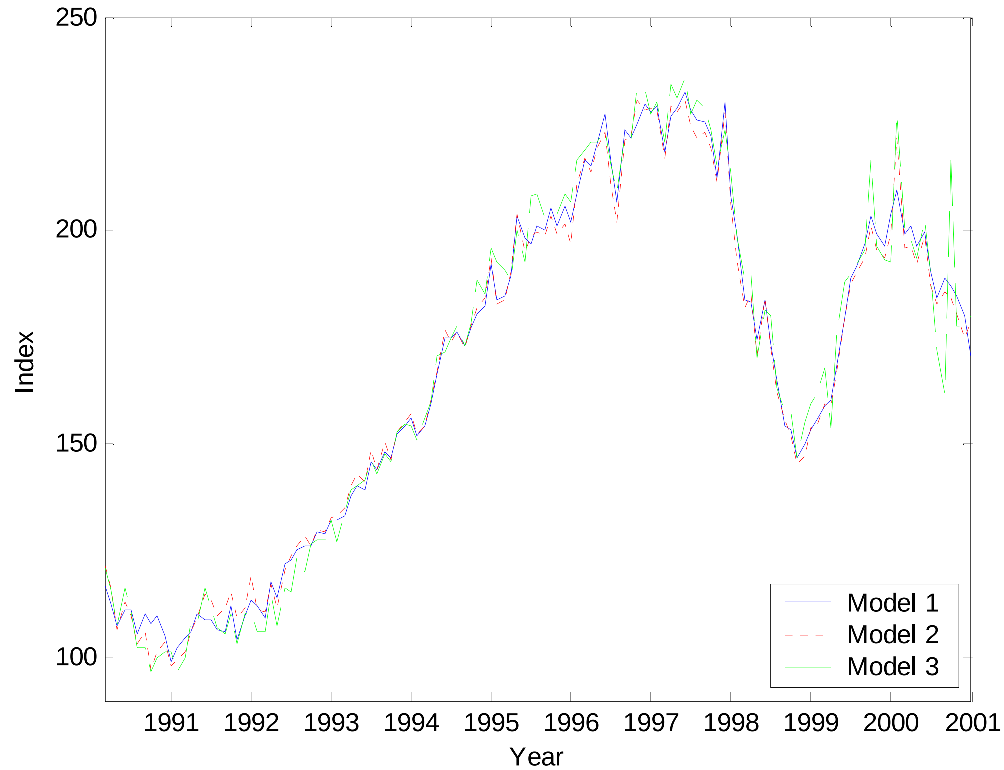
Threshhold (Percent)		0			2			4			6			8	
	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III
24 month															
Mean	9.98	7.98	4.89	10.27	8.52	3.73	9.75	7.96	2.32	10.65	7.83	0.68	9.25	8.95	0.04
Variance	24.56	24.44	32.29	22.47	24.92	33.62	22.47	22.45	29.41	22.87	22.96	7.28	21.48	22.82	1.26
Stochastic		F			F			F			F			x	
Dominance*		S			S			F			x			x	
36 month															
Mean	11.89	9.14	3.71	13.33	10.53	4.21	11.50	9.65	5.48	10.28	8.48	3.68	10.07	9.15	0.92
Variance	26.79	29.17	34.35	26.20	27.93	33.79	24.47	26.30	36.84	23.49	25.07	32.14	24.22	23.70	12.53
Stochastic		F			F			F			F			F	
Dominance*		F			S			S			S			F	
48 month															
Mean	12.13	11.98	7.58	12.17	11.70	7.84	12.32	9.87	8.70	12.33	11.23	8.89	10.89	10.42	8.10
Variance	27.78	30.78	37.94	26.52	29.14	35.80	27.70	26.70	36.83	26.25	26.91	36.72	26.41	25.91	37.11
Stochastic		S			F			F			F			x	
Dominance*		S			S			S			S			S	

Table 3 (continued). Comparison of Investor Performance
Means and Variances of Investment Returns for Fully Informed (I), Partially Informed (II) and Uninformed Investors (III) for Different Thresholds and Holding Periods (in Percent)
(1000 Replications)

60 month															
Mean	14.94	12.18	8.00	13.05	11.00	11.34	11.57	12.20	10.24	13.91	10.72	10.94	16.16	11.23	10.57
Variance	30.59	32.68	40.24	28.92	32.56	38.93	28.04	31.54	36.89	28.92	30.98	40.36	28.69	28.71	38.58
Stochastic		F			F			S			F			F	
Dominance*		S			S			S			S			S	
72 month															
Mean	15.37	13.60	10.47	15.30	13.02	12.66	15.24	15.53	11.30	14.63	12.53	13.40	14.93	11.97	11.54
Variance	33.23	35.12	39.69	31.60	33.28	39.68	30.85	32.96	40.44	30.35	32.10	36.90	29.82	30.45	39.78
Stochastic		F			F			F			F			F	
Dominance*		F			S			S			S			S	
84 month															
Mean	15.69	14.90	11.65	17.47	15.34	13.05	17.46	14.26	12.18	18.20	14.31	11.41	16.54	14.24	12.50
Variance	35.86	35.68	40.13	34.97	35.56	41.04	32.58	34.53	40.56	32.48	33.69	41.34	32.80	36.11	41.39
Stochastic		F			F			F			F			F	
Dominance*		S			S			F			S			S	

* In the stochastic dominance test, F indicates first order stochastic dominance by the better informed investor, S indicates second-order stochastic dominance, and X indicates no dominance. The first row represents a comparison of investor I with investor III; and second row represents a comparison of investor I with investor II. All tables for stochastic dominance are based upon Anderson (1996) using ten categories.

Figure 1.
Singapore Condominium Prices*
1990 – 2000



	Model 1	Model 2	Model 3
Constant	0.0723 (20.269)	0.0895 (24.044)	0.0783 (29.837)
γ	-0.0012 (6.710)**	-0.0011 (7.504)	-0.0010 (4.209)
λ	0.78	0.72	1
ρ	0.55	0	0
σ_μ^2	0.0077	0.0133	0.0009
σ_η^2	0.0054	0.0016	0
log L	23743.95	22498.75	7678.98

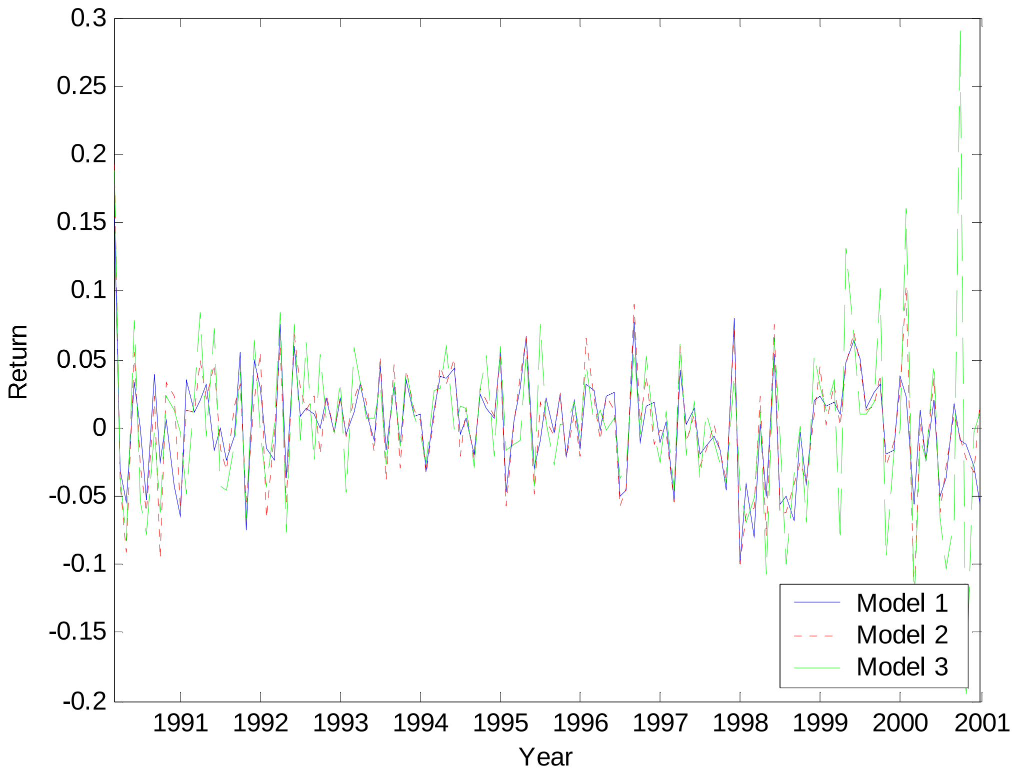
Note: *The figure graphs the monthly index values $I_t = \exp\left[\sum_{j=1}^{t} P_j\right]$ where the values of P are estimated from Models 1, 2, and 3. The index values and their t ratios are presented in Appendix Table A1.

** T ratios in parentheses.

Figure 2.

Monthly Returns to Investment in Singapore Condominiums

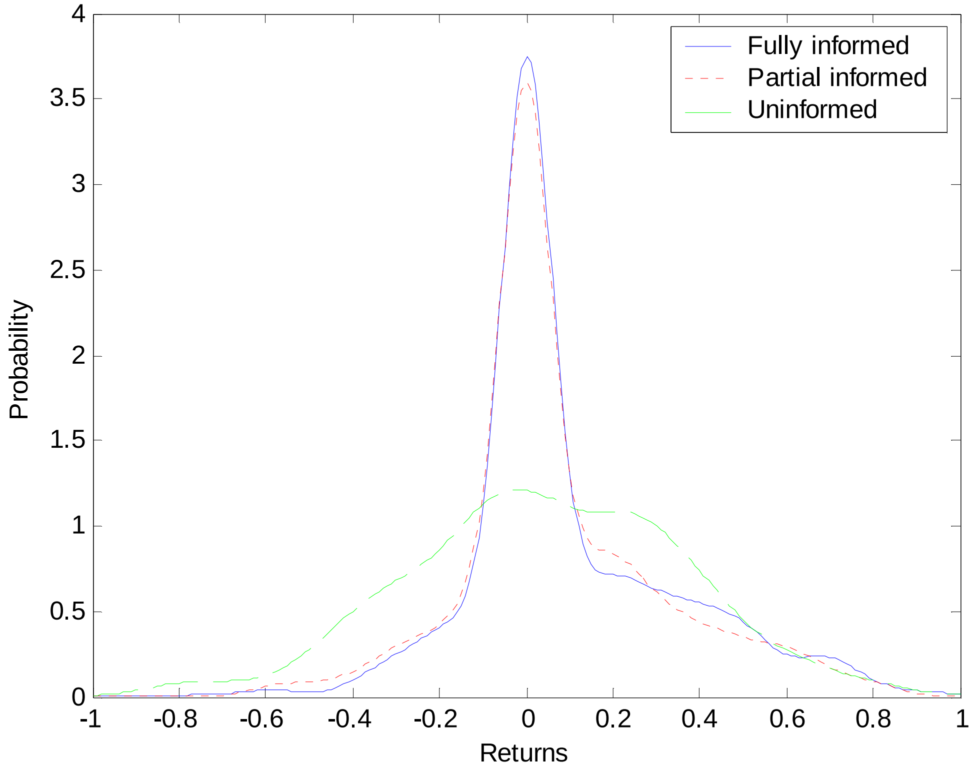
1990 – 2000



	Model 1	Model 2	Model 3
λ	0.78	0.72	1
ρ	0.55	0	0
Average Returns	0.0041	0.0044	0.0045
Standard Deviation	0.0379	0.0453	0.0600

Figure 3.

Distribution of Investor Returns for Fully Informed, Partially Informed and Uninformed Investor with 0 per cent Investment Rule (1000 replications)



	Mean Return	Standard Deviation
Fully Informed	9.98%	24.56%
Partially Informed	7.98%	24.44%
Uninformed	4.89%	32.29%

Appendix Table A1. Parameter Estimates for Coefficients

	Model 1 Spatially Correlation and Mean Reversion	Model 2 Mean Reversion	Model 3 Graphed in Figure 1 Random Walk
Constant	0.0723	0.0885	0.0783
	(20.2685)	(24.0443)	(29.8365)
Feb,1990	0.1558	0.1951	0.1903
	(1.0329)	(1.4461)	(0.7027)
Mar,1990	0.1209	0.1502	0.1501
	(0.8252)	(1.1889)	(0.5804)
Apr,1990	0.0713	0.0647	0.0732
	(0.5057)	(0.5397)	(0.2912)
May,1990	0.1063	0.1219	0.1534
	(0.7670)	(1.0476)	(0.6255)
Jun,1990	0.1078	0.0952	0.1007
	(0.7579)	(0.7824)	(0.3975)
Jul,1990	0.0549	0.0333	0.0221
	(0.3770)	(0.2651)	(0.0841)
Aug,1990	0.0971	0.0592	0.0235
	(0.6488)	(0.4568)	(0.0882)
Sep,1990	0.0787	-0.0286	-0.0308
	(0.5245)	(0.2327)	(0.1197)
Oct,1990	0.0922	0.0127	0.0003
	(0.6301)	(0.1034)	(0.0012)
Nov,1990	0.0498	0.0355	0.0127
	(0.3309)	(0.2742)	(0.0477)
Dec,1990	-0.0107	-0.0185	0.0129
	(0.0745)	(0.1546)	(0.0513)
Jan,1991	0.0256	-0.0048	-0.0341
	(0.1662)	(0.0360)	(0.1257)
Feb,1991	0.0451	0.0154	-0.0012
	(0.3126)	(0.1258)	(0.0048)
Mar,1991	0.0606	0.0605	0.0793
	(0.4353)	(0.5163)	(0.3228)
Apr,1991	0.0979	0.0879	0.0779
	(0.7135)	(0.7690)	(0.3229)
May,1991	0.0851	0.1380	0.1540
	(0.6160)	(1.1978)	(0.6336)

Jun,1991	0.0866	0.1258	0.1131
	(0.6260)	(1.0934)	(0.4689)
Jul,1991	0.0635	0.0956	0.0690
	(0.4563)	(0.8233)	(0.2856)
Aug,1991	0.0576	0.1110	0.0562
	(0.4118)	(0.9482)	(0.2301)
Sep,1991	0.1152	0.1448	0.0982
	(0.8251)	(1.2364)	(0.4003)
Oct,1991	0.0402	0.0895	0.0313
	(0.2874)	(0.7597)	(0.1276)
Nov,1991	0.0922	0.1114	0.0974
	(0.6649)	(0.9552)	(0.3994)
Dec,1991	0.1292	0.1741	0.1016
	(0.9205)	(1.4721)	(0.4149)
Jan,1992	0.1140	0.1077	0.0585
	(0.8000)	(0.8965)	(0.2364)
Feb,1992	0.0888	0.1028	0.0592
	(0.6337)	(0.8692)	(0.2394)
Mar,1992	0.1637	0.1610	0.1419
	(1.1530)	(1.3559)	(0.5726)
Apr,1992	0.1323	0.1128	0.0714
	(0.9497)	(0.9653)	(0.2921)
May,1992	0.1975	0.1861	0.1522
	(1.4453)	(1.6271)	(0.6310)
Jun,1992	0.2065	0.2154	0.1430
	(1.5159)	(1.8875)	(0.5954)
Jul,1992	0.2251	0.2323	0.2091
	(1.6548)	(2.0379)	(0.8695)
Aug,1992	0.2325	0.2529	0.1822
	(1.7074)	(2.2157)	(0.7585)
Sep,1992	0.2328	0.2342	0.2371
	(1.7160)	(2.0608)	(0.9908)
Oct,1992	0.2574	0.2616	0.2457
	(1.9007)	(2.3065)	(1.0279)
Nov,1992	0.2562	0.2602	0.2438
	(1.8904)	(2.2918)	(1.0197)
Dec,1992	0.2791	0.2842	0.2801
	(2.0575)	(2.4990)	(1.1714)
Jan,1993	0.2819	0.2863	0.2415

	(2.0776)	(2.5166)	(1.0103)
Feb,1993	0.2889	0.3026	0.2952
	(2.1311)	(2.6637)	(1.2357)
Mar,1993	0.3233	0.3378	0.3305
	(2.3950)	(2.9889)	(1.3842)
Apr,1993	0.3376	0.3589	0.3399
	(2.5014)	(3.1782)	(1.4239)
May,1993	0.3318	0.3445	0.3500
	(2.4590)	(3.0512)	(1.4663)
Jun,1993	0.3777	0.3978	0.3825
	(2.7987)	(3.5245)	(1.6025)
Jul,1993	0.3657	0.3636	0.3595
	(2.7068)	(3.2151)	(1.5059)
Aug,1993	0.3945	0.4094	0.3912
	(2.9205)	(3.6196)	(1.6379)
Sep,1993	0.3830	0.3795	0.3775
	(2.8342)	(3.3547)	(1.5810)
Oct,1993	0.4218	0.4256	0.4251
	(3.1221)	(3.7618)	(1.7804)
Nov,1993	0.4328	0.4413	0.4360
	(3.2014)	(3.8999)	(1.8260)
Dec,1993	0.4460	0.4507	0.4346
	(3.2970)	(3.9801)	(1.8200)
Jan,1994	0.4185	0.4209	0.4130
	(3.0941)	(3.7171)	(1.7293)
Feb,1994	0.4345	0.4335	0.4449
	(3.2099)	(3.8250)	(1.8630)
Mar,1994	0.4671	0.4734	0.4690
	(3.4597)	(4.1892)	(1.9649)
Apr,1994	0.5101	0.5121	0.5358
	(3.7785)	(4.5339)	(2.2449)
May,1994	0.5586	0.5687	0.5398
	(4.1432)	(5.0423)	(2.2619)
Jun,1994	0.5590	0.5525	0.5596
	(4.1409)	(4.8913)	(2.3445)
Jul,1994	0.5671	0.5683	0.5756
	(4.2007)	(5.0288)	(2.4114)
Aug,1994	0.5489	0.5454	0.5479
	(4.0663)	(4.8276)	(2.2956)

Sep,1994	0.5732	0.5746	0.5768
	(4.2448)	(5.0857)	(2.4163)
Oct,1994	0.5910	0.5984	0.6327
	(4.3742)	(5.2896)	(2.6499)
Nov,1994	0.6011	0.6107	0.6156
	(4.4524)	(5.4064)	(2.5792)
Dec,1994	0.6528	0.6602	0.6721
	(4.8308)	(5.8353)	(2.8154)
Jan,1995	0.6076	0.6040	0.6571
	(4.4900)	(5.3301)	(2.7521)
Feb,1995	0.6137	0.6096	0.6462
	(4.5219)	(5.3602)	(2.7053)
Mar,1995	0.6394	0.6437	0.6337
	(4.7338)	(5.7066)	(2.6557)
Apr,1995	0.7110	0.7134	0.6945
	(5.2592)	(6.3037)	(2.9086)
May,1995	0.6854	0.6679	0.6552
	(5.0720)	(5.9184)	(2.7451)
Jun,1995	0.6780	0.6880	0.7327
	(5.0134)	(6.0811)	(3.0690)
Jul,1995	0.6978	0.6919	0.7352
	(5.1572)	(6.1082)	(3.0790)
Aug,1995	0.6941	0.6859	0.7085
	(5.1364)	(6.0623)	(2.9673)
Sep,1995	0.7189	0.7107	0.7105
	(5.3085)	(6.2658)	(2.9737)
Oct,1995	0.6993	0.6899	0.7134
	(5.1713)	(6.0904)	(2.9871)
Nov,1995	0.7206	0.7010	0.7343
	(5.3237)	(6.1835)	(3.0742)
Dec,1995	0.7027	0.6778	0.7253
	(5.1972)	(5.9881)	(3.0372)
Jan,1996	0.7360	0.7458	0.7737
	(5.4448)	(6.5930)	(3.2396)
Feb,1996	0.7720	0.7750	0.7839
	(5.7070)	(6.8448)	(3.2828)
Mar,1996	0.7654	0.7606	0.7922
	(5.6618)	(6.7207)	(3.3174)
Apr,1996	0.7904	0.7854	0.7922

	(5.8594)	(6.9563)	(3.3185)
May,1996	0.8211	0.8034	0.8044
	(6.0808)	(7.1100)	(3.3687)
Jun,1996	0.7718	0.7466	0.7678
	(5.6650)	(6.5290)	(3.2046)
Jul,1996	0.7267	0.7025	0.7386
	(5.3541)	(6.1729)	(3.0833)
Aug,1996	0.8052	0.7931	0.7982
	(5.9092)	(6.9342)	(3.3272)
Sep,1996	0.7960	0.7977	0.7950
	(5.8311)	(6.9524)	(3.3125)
Oct,1996	0.8109	0.8351	0.8471
	(5.9378)	(7.2746)	(3.5233)
Nov,1996	0.8323	0.8263	0.8449
	(6.0937)	(7.1921)	(3.5162)
Dec,1996	0.8234	0.8265	0.8216
	(6.0273)	(7.2052)	(3.4217)
Jan,1997	0.8294	0.8244	0.8342
	(6.0645)	(7.1604)	(3.4711)
Feb,1997	0.7814	0.7749	0.7928
	(5.7195)	(6.7468)	(3.2998)
Mar,1997	0.8192	0.8300	0.8522
	(6.0178)	(7.2674)	(3.5523)
Apr,1997	0.8267	0.8233	0.8377
	(6.0753)	(7.2133)	(3.4920)
May,1997	0.8430	0.8347	0.8581
	(6.2181)	(7.3594)	(3.5849)
Jun,1997	0.8249	0.8086	0.8208
	(6.0618)	(7.0740)	(3.4205)
Jul,1997	0.8150	0.7962	0.8350
	(6.0277)	(7.0124)	(3.4871)
Aug,1997	0.8123	0.8022	0.8281
	(5.9580)	(7.0087)	(3.4502)
Sep,1997	0.7973	0.7862	0.8038
	(5.8366)	(6.8454)	(3.3434)
Oct,1997	0.7525	0.7490	0.7653
	(5.5050)	(6.5162)	(3.1824)
Nov,1997	0.8333	0.8238	0.8049
	(6.0622)	(7.1098)	(3.3305)

Dec,1997	0.7338	0.7235	0.7599
	(5.3464)	(6.2632)	(3.1583)
Jan,1998	0.6894	0.6579	0.6879
	(4.9434)	(5.5769)	(2.8396)
Feb,1998	0.6089	0.5977	0.6346
	(4.4021)	(5.1125)	(2.6186)
Mar,1998	0.6070	0.6158	0.6404
	(4.4081)	(5.3063)	(2.6553)
Apr,1998	0.5562	0.5361	0.5332
	(4.0845)	(4.6896)	(2.2219)
May,1998	0.6077	0.6102	0.5963
	(4.4521)	(5.3231)	(2.4830)
Jun,1998	0.5513	0.5462	0.5893
	(4.0406)	(4.7686)	(2.4565)
Jul,1998	0.5016	0.4852	0.4900
	(3.6672)	(4.2231)	(2.0423)
Aug,1998	0.4324	0.4433	0.4544
	(3.1531)	(3.8505)	(1.8870)
Sep,1998	0.4279	0.4173	0.4548
	(3.1124)	(3.6074)	(1.8873)
Oct,1998	0.3843	0.3754	0.3837
	(2.8180)	(3.2943)	(1.5995)
Nov,1998	0.4056	0.3871	0.4386
	(2.9822)	(3.3957)	(1.8309)
Dec,1998	0.4267	0.4304	0.4662
	(3.1459)	(3.7891)	(1.9480)
Jan,1999	0.4441	0.4341	0.4804
	(3.2724)	(3.8169)	(2.0048)
Feb,1999	0.4647	0.4674	0.5177
	(3.4311)	(4.1186)	(2.1627)
Mar,1999	0.4715	0.4651	0.4311
	(3.4818)	(4.1004)	(1.8023)
Apr,1999	0.5208	0.5135	0.5649
	(3.8550)	(4.5412)	(2.3637)
May,1999	0.5865	0.5849	0.6322
	(4.3449)	(5.1773)	(2.6460)
Jun,1999	0.6364	0.6299	0.6414
	(4.7103)	(5.5679)	(2.6832)
Jul,1999	0.6522	0.6442	0.6526

	(4.8237)	(5.6924)	(2.7291)
Aug,1999	0.6785	0.6601	0.6705
	(5.0168)	(5.8284)	(2.8037)
Sep,1999	0.7098	0.6989	0.7720
	(5.2428)	(6.1627)	(3.2269)
Oct,1999	0.6892	0.6702	0.6753
	(5.0844)	(5.8988)	(2.8215)
Nov,1999	0.6741	0.6609	0.6578
	(4.9755)	(5.8231)	(2.7504)
Dec,1999	0.7126	0.6892	0.6564
	(5.2601)	(6.0719)	(2.7431)
Jan,2000	0.7398	0.7964	0.8203
	(5.4596)	(7.0242)	(3.4278)
Feb,2000	0.6888	0.6739	0.6945
	(5.0800)	(5.9308)	(2.8994)
Mar,2000	0.6989	0.6741	0.6833
	(5.1530)	(5.9307)	(2.8506)
Apr,2000	0.6763	0.6530	0.6605
	(4.9850)	(5.7416)	(2.7525)
May,2000	0.6927	0.6864	0.7060
	(5.1093)	(6.0394)	(2.9456)
Jun,2000	0.6436	0.6261	0.6414
	(4.7392)	(5.4978)	(2.6707)
Jul,2000	0.6122	0.6027	0.5442
	(4.5082)	(5.2867)	(2.2664)
Aug,2000	0.6352	0.6191	0.4823
	(4.6749)	(5.4318)	(2.0103)
Sep,2000	0.6253	0.6112	0.7734
	(4.6049)	(5.3657)	(3.2213)
Oct,2000	0.6148	0.5902	0.5754
	(4.5153)	(5.1643)	(2.3908)
Nov,2000	0.5879	0.5592	0.5738
	(4.1855)	(4.6844)	(2.3322)
Dec,2000	0.5345	0.5794	0.5876
	(2.9333)	(3.6423)	(1.8693)