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A comparative analysis of housing prices in different cities using the Black–Scholes and Jump Diffusion models

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ABSTRACT

This study investigates the price structure of urban housing markets comparing the Black–Scholes model and Merton's jump diffusion model with the expectation–maximization algorithm. As price jump information is hidden within the price change itself, an appropriate method must be used to deal with the hidden data. We check the validity of models in six cities using interval-ahead Monte Carlo simulations. We find that the jump diffusion model is well suited for analyzing the housing market and price structure in most cases.

1. Introduction

Housing forms a large share of an individual's living expenses, and the purchase of a house is a major financial decision for a household. In continuous-time asset pricing equilibrium models, a stochastic process depicts price movements explaining the mechanism for analyzing and predicting financial products. The Black–Scholes model (BSM) explains fundamental pricing theory and is often used to analyze price changes in the housing market (Szymanoski, 1994; Kau and Keenan, 1995; Ambrose and Buttimer, 2000; Bardhan et al., 2006; Chu, 2010).

External factors such as macroeconomic factors and government policies should be considered in the price structure (McCue and Kling, 1994; Muellbauer and Murphy, 1997; Chang et al., 2012), but the BSM does not consider any external impact on prices. Such price changes can be included in the stochastic process as a jump diffusion process introduced by Merton (1976). Merton's jump diffusion model (JDM) is used to analyze the housing market with a focus on valuing mortgage insurance (Chang et al., 2010; Chen et al., 2010).

Estimating JDM parameters is essential to illustrate the accurate pricing process but is complicated as this model is a mixture of conditional normal distributions and has an infinite sum of Poisson processes. The computational complexity is due to small jumps in the price movement. Large price movements can be identified as jumps, but one cannot determine whether the small price changes are from the geometric Brownian motion or from the jumps.

The expectation–maximization (EM) algorithm, widely used in data science since its introduction (Dempster et al., 1977), is a useful method in such cases. This algorithm allows each mixture to be computed automatically, allowing us to estimate JDM parameters without the approximated model limits assumptions.

Housing price prediction without considering external effects and other corresponding policies may lead to severe misinterpretations and housing policy failure. Although we assume that the housing price is an equilibrium price, the literature on whether

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housing markets are in the state of bubble is relevant (Case and Shiller, 2003; Smith and Smith, 2006; Arce and Lopez-Salido, 2011). We also refer to a detailed analysis on the 2008 financial crisis and its impact on the global economy and interconnected financial systems (Martin, 2010; Levitin and Wachter, 2012; Mcdonald and Stokes, 2013; Moro, 2014; Vidal-Tomas and Alfarano, 2020).

The objective of this paper is to find jump risks and price structure in the housing markets of several cities using JDM. We estimate JDM parameters using the gradient EM (GEM) algorithm, an extension of the basic EM algorithm. To ensure reliability, we apply a Monte Carlo simulation with variance reduction and the interval-ahead forecasting. We find that JDM is more effective in analyzing the market than BSM, though not in all cases.

2. Methodology

We consider a market that trades only in residential houses. Consider a representative house for a single family in a city. Let (Ω, F, P) be a probability space and let $\{F_t : t > 0\}$ be the filtration generated by a Brownian motion W_t and a Poisson process N_t with intensity λ. Let us assume that a Brownian motion W_t, a Poisson process N_t, and a price jump y_t are mutually independent. We define H_t as the price of a house at time $t \in [0, T]$. In BSM, the housing price H_t at time t is modeled by the geometric Brownian motion and can be calculated analytically:

$$H_t = H_0 \exp\left((\mu - \frac{1}{2}\sigma^2)t + \sigma W_t\right), \tag{1}$$

where μ is the (annualized) mean and σ is the standard deviation of the housing price. Using JDM, the housing price is calculated by

$$H_t = H_0 \exp\left((\mu - \frac{1}{2}\sigma^2 - \lambda k)t + \sigma W_t + \sum_{i=1}^{N_t} Y_i\right), \tag{2}$$

where μ is the expected growth rate, σ is the volatility of the Brownian motion part, and H_t is the house price at time t just before the jump. $k = E[y_t - 1] = \exp(\mu_j + \sigma_j^2/2) - 1$, the expected value of a relative price jump $y_t - 1$, is defined from the log-jump size $Y_t = \log y_t \sim N(\mu_j, \sigma_j^2)$. Note that a Poisson process N_t with an intensity λ shows the total number of price jumps in the time interval $(0, t]$.

For BSM, we can find parameters using maximum likelihood estimation (MLE). However, for JDM, we cannot distinguish between the price movement from jumps or from the Wiener process. The EM algorithm is one way to MLE with incomplete data (i.e., data are omitted or censored). This problem can be addressed in our case because price movement due to jumps being not explicitly distinguishable compared to GBM. A solution from the EM algorithm converges to the local maximum or saddle point. Instead of using the original EM algorithm, we use GEM (Lange, 1995; Chen et al., 2010) because it uses up to the second derivatives.

Let $Y = (Y_1, Y_2, \dots, Y_T)$ be the observed data and $Z = (Z_1, Z_2, \dots, Z_T)$ be the hidden data. Let $X = (Y, Z)$ be the complete data. After choosing the initial parameter $\theta^{(0)}$, the EM algorithm repeats the following two steps until the nth parameter reaches a preset threshold.

1. **E-step**
   Given Y and nth parameter estimates $\theta^{(n)}$, we obtain the probability density function for the complete data X:

   $$f(X|Y;\theta^{(n)})$$

   then calculate the Q-function

   $$Q(\theta|\theta^{(n)}) := E_{X|Y,\theta^{(n)}}[\log f(X|\theta)]$$

2. **M-step**
   We maximize the Q-function with respect to θ: $\theta^{(n+1)} = \arg\max_\theta Q(\theta|\theta^{(n)})$.

Unfortunately, there is no agreement on when to stop iterations and how to set an initial parameter. Ibrahim et al. (2008) discuss the selection of a threshold to stop repetitions, and Karlis and Xekalaki (2003) suggest how to choose an initial parameter for simple mixtures. Although these papers give us intuition to perform the EM algorithm, the main concern is on the computational complexity of adding infinite terms. We, therefore, replace infinite summations with 50 summations because each term rapidly goes to 0 (Honoré, 1998; Duncan et al., 2009). To briefly explain practical implications, we first take an initial parameter μ, σ as the parameter using the MLE in BSM. For other parameters μ_j, σ_j, and λ, we place an arbitrary number and run the EM algorithm until we get real-value numbers by trial and error.

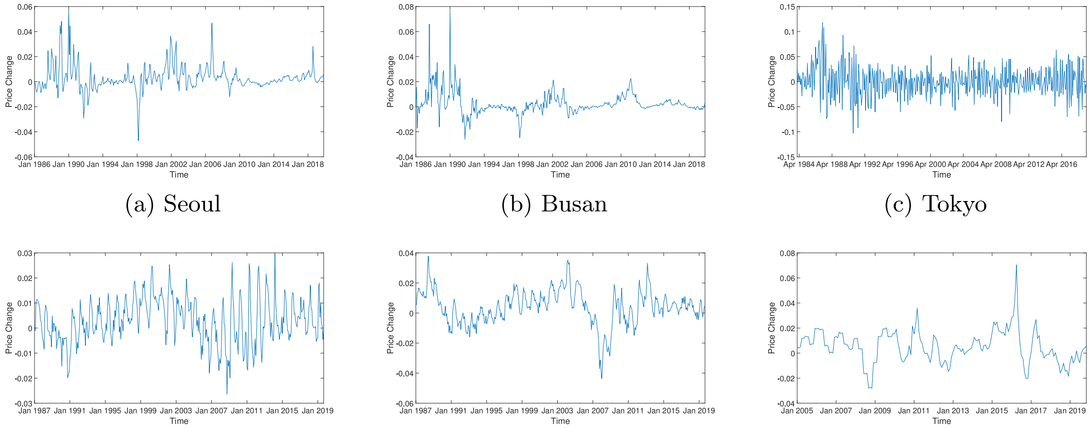
Here we use the L^∞-norm as an error measure ϵ for the EM algorithm (Abbi et al., 2008). For the nth parameter $\theta^{(n)}$,

$$\epsilon_{(n)} := max\left|\theta^{(n)} - \theta^{(n-1)}\right|.$$

And we iterate the EM algorithm for a predetermined threshold 10^{-4} until the following condition does not hold:

$$\epsilon_{(n)} \geq 10^{-4} \text{ when iteration} \leq 100{,}000.$$

Duncan et al. (2009) consider the BSM and JDM simultaneously when deriving the formula to apply the EM algorithm. In contrast, Chen et al. (2010) assume that JDM is appropriate for analyzing data and estimating corresponding parameters using



(a) Seoul (b) Busan (c) Tokyo

(d) Boston (e) Los Angeles (f) Vancouver

Fig. 1. Log-price change in housing markets.

GEM. Using the likelihood ratio test, they verify whether the assumption of jumps is proper or not. In this research, we estimate parameters by MLE, assuming BSM is true, and by GEM, assuming JDM is true. We then verify which method is appropriate using a simulation. For the derivation, see Chen et al. (2010) and the supplementary material.

Given the nth parameter estimates $\theta^{(n)} = (\mu_{(n)}, \sigma^2{}_{(n)}, \mu_{j\,(n)}, \sigma_j{}^2{}_{(n)}, \lambda_{(n)})$, we get the formula

$$\theta^{(n+1)} = \theta^{(n)} - \mathcal{H}(\theta^{(n)}|\theta^{(n)})^{-1}\nabla(\theta^{(n)}|\theta^{(n)}), \tag{3}$$

where $\mathcal{H}(\theta|\theta^{(n)}) = \frac{\partial^2 Q(\theta|\theta^{(n)})}{\partial\theta\partial\theta^T}$ the Hessian matrix, and $\nabla(\theta|\theta^{(n)}) = \frac{\partial Q(\theta|\theta^{(n)})}{\partial\theta}$ the first derivative of Q-function.

3. Data

Residential property price indices (RPPIs) summarize the price change for dwellings. There are four main approaches to calculate RPPI (Eurostat, 2013). In this paper, we use the repeat sales method, widely used by the Standard and Poor's CoreLogic Case–Shiller Home Price Index (Case–Shiller Index) and the U.S. Federal Housing Finance Agency House Price Index (FHFA Index). The repeat sales method tracks the repeated transaction price using three price levels (low, middle, and high) in the specified locality to measure monthly housing price for a single entity. It assumes constant-quality so that repairing costs are not considered. The major difference between the Case–Shiller and FHFA indices is that the former is value-weighted while the latter is equally weighted. We follow the former[1] because many national financial institutions that announce housing prices use the value-weighted repeat sales methodology.

We collect index data for six cities. Data from January 1987 to October 2019 for Los Angeles and Boston in the United States are collected from S&P Dow Jones Index. Single-family housing price data for Tokyo, Japan from April 1984 to August 2019 are obtained from the Bank for International Settlements. Housing purchase price composite index data from January 1986 to December 2019 for Seoul and Busan, Korea are collected from KB Commercial Bank, as their statistics are preferred by practitioners and researchers. Lastly, MLS home price index data from January 2005 to December 2019 for Vancouver, Canada, which describes housing price for a single family, are obtained from the Canadian Real Estate Association. We show the log-price change in Fig. 1, which shows that it is difficult to specify the jump effects and internal variations. Price indices are not seasonally adjusted because we are interested in modeling the transaction price through asset pricing methods.

4. Discussions

To select the most suitable model, we divide the data into training and testing sets in the ratio of 80:20 as this is a commonly-used rule-of-thumb ratios[2] in simulation studies. We estimate five parameters of JDM using the GEM algorithm and two BSM parameters using the MLE from the training data. We then forecast the interval-ahead price using a Monte Carlo simulation (Tashman, 2000; Stock and Watson, 2002).

After fixing a forecast interval and starting at the last price of the training data, we simulate the price one forecast interval later, 100,000 times, including the antithetic sampling. We then simulate the price from the real price, which is 1 month after the

[1] One may use the US housing price data from other sources like the Zillow index. Unlike the Case–Schiller index, the Zillow index only uses the 35th to 65th percentile (mid tier) of home values as a single family index, and provides seasonally adjusted prices. We have applied the proposed method to the seasonally adjusted CS and Zillow indices for comparison and obtained similar results for LA and Boston.

[2] This 80:20 ratio is based on the Pareto Principle. More theoretical approach can be found in Amari et al. (1997), Guyon (1997) and Efron and Tibshirani (1997).

Table 1
Estimated parameters for housing markets.
Sources: KB Bank (Korea), BIS (Japan), CREA (Canada), S&P Global (US). Data cover the period 1986:1–2019:12 (Korea), 1984:4–2019:8 (Japan), 2005:1–2019:12 (Canada), and 1987:1–2019:10 (US).

City (training data[a]/total data)	Model	μ	σ	μ_j	σ_j	λ
Seoul, Korea (326/408)	JDM	0.037465	0.013382	0.0059207	0.013885	5.4914
	BSM	0.0375	0.0383	–	–	–
Busan, Korea (326/408)	JDM	0.034495	0.020583	0.018259	0.0054716	1.7446
	BSM	0.0346	0.0347	–	–	–
Tokyo, Japan (340/425)	JDM	0.0062499	0.067934	0.0005078	0.025458	10.317
	BSM	0.0063	0.1063	–	–	–
Vancouver, Canada (144/180)	JDM	0.085348	0.029724	−0.0026565	0.015685	4.7414
	BSM	0.0854	0.0458	–	–	–
Los Angeles, United States (315/394)	JDM	0.044678	0.037479	−0.015535	0.012962	1.2172
	BSM	0.0447	0.0435	–	–	–
Boston, United States (315/394)	JDM	0.04257	0.0050749	−0.004397	0.0015148	21.532
	BSM	0.0311	0.0323	–	–	–

[a]Parameters are estimated from 80% of total data and initial price is set as 100.

Table 2
Interval-ahead simulation result for housing markets.

City (testing data)	Model	6 month		12 month		24 month	
		MSE	MAE	MSE	MAE	MSE	MAE
Seoul (82 months)	JDM	11	10	14*	12*	9	12*
	BSM	9	10	6	8	11	8
Busan (82 months)	JDM	20*	20*	20*	20*	20*	20*
	BSM	0	0	0	0	0	0
Tokyo (85 months)	JDM	10	10	5	7	12*	6
	BSM	10	10	15*	13*	8	14*
Vancouver (36 months)	JDM	14*	14*	11	15*	12*	15*
	BSM	6	6	9	5	8	5
Los angeles (79 months)	JDM	11	11	15*	13*	14*	11
	BSM	9	9	5	7	6	9
Boston (79 months)	JDM	20*	20*	20*	20*	20*	20*
	BSM	0	0	0	0	0	0

Notes: The table shows the number of better predicted models out of 20 seeds, and * indicates the fitted model to the data.

beginning price at the previous step. These steps are repeated until we reach the end of the testing data. Finally, we compare the mean squared error (MSE) and the mean absolute error (MAE) of each model, selecting the one with the least errors. For observed data Y and predicted data $\hat{Y}$, MSE and MAE are defined as: $\text{MSE} = E[(Y-\hat{Y})^2]$ and $\text{MAE} = E[|Y-\hat{Y}|]$.

In Table 1, we show the number of the price data and the size of the training data used after modifying the beginning housing price to 100. We have 408 months' data for Seoul and estimate parameters from 326 months' (80%) data. We further apply the method to all other cities.

The validity of the model is not guaranteed using only one measure, as the housing price is time-dependent. Therefore, we calculate several measures using different random number generators[3] to check for consistency. We verify which model is suitable in Table 2 with 6 -, 12 -, and 24-month forecast intervals and 20 different seeds.

Typically one calculates the model accuracy with confidence intervals assuming normal approximation. A typical way to obtain robustness is to repeat the simulation with different random seeds and compute the average performance. Instead of showing summary statistics calculated from normal approximations, we abridged the number of more effective models from the 20 seeds and place * against the more accurate models.

The advantage of our implications is that we considerably explain housing prices and include external shocks in the simple price model. Seoul, Busan, Vancouver, Los Angeles, and Boston are better analyzed using JDM, although the results occasionally vary with time intervals and measures.

Housing markets in Seoul and Busan are well explained by JDM. The average jump frequency $\lambda\Delta t$ is $5.49 \times 1/12 = 0.45$ for Seoul and 0.14 for Busan per year. Notably, housing markets in Seoul and Busan have experienced "positive" jumps on average, which means external factors including government policies increase housing prices. These two major Korean cities have experienced rapid economic growth from the 1960s to the 1990s, and the government has announced many policies to control housing prices.

[3] Seed $0, 1000, \ldots, 19000$ by the Mersenne Twister on MATLAB R2020b.

However, most price stabilizing policies have been ineffective in lowering the price; instead, they acted as boosters (Kim and Cho, 2010).

Vancouver's housing market is also suited to JDM. The average jump frequency is once in 3 years, and the average price jumps size is negative. The trend of rapid inflated housing price can be explained by high drifts in the estimated parameters, and negative shocks (negative price jumps) are incorporated in the equilibrium model. This is consistent with previous studies of the Vancouver housing market that analyze the reasons for rapid price rise (Moos and Skaburskis, 2010; Grigoryeva and Ley, 2019).

The simulation result for Los Angeles is compatible with JDM. Tax regulations and limited housing supply in California are known to increase the price (Quigley and Raphael, 2005). As shown in Table 1, the average jump frequency $\lambda\Delta t$ in Los Angeles is once a decade, and expected price jumps are negative. Note that testing data start from around 2013, after the third wave of quantitative easing by the Federal Reserve due to subprime mortgage crisis around late 2008 (Cukierman, 2019). This financial crisis is incorporated in the expected price jump as a large negative value.

The result of Boston housing market is interesting. The price change is comparatively small (mostly within the range of −0.02 to 0.02) so one may expect that it will be better described by internal variations. Our results shows that there are 1.79 jumps per year on average, and this jump model depicts the data very well.

BSM is appropriate for the housing markets of Tokyo. The Tokyo housing market is a popular subject for real estate economists due to its housing price bubble during 1986–1991 and bubble collapse until 2001. McMillen and Shimizu (2020) decomposed changes in the house price distribution in Tokyo across time into changes due to differences in the explanatory variables and changes due to coefficients changes in quantile regression over time. Tokyo housing prices fluctuate too much and cannot be explained by JDM assuming "instant" and "rare" jumps. Moreover, the implicit assumption of external shocks, incorporated as negative price jumps in JDM, is not well-matched to the recession situation. Long-term negative shocks that may change the market structure could be inappropriate for a JDM analysis.

Although we have analyzed the housing market with the house price index, these indices may not reflect enough all the variables in the housing market. For example, the owners' estimated value of the main residence is a valuable source to study housing market dynamics (Lepinteur and Waltl, 2020), but this is not included in current price indices.

5. Conclusion

We reviewed the EM algorithm and discussed its application to JDM that uses hidden jump data. Several practical considerations, such as selection of initial points, error measures, and stopping criterion, in applying the EM algorithm were proposed. Data related to housing markets were explained and six city housing markets selected. Jump diffusion parameters were estimated by the gradient EM algorithm, and housing prices predicted by the Monte Carlo simulation. We compared the JDM results with typical BSM prediction estimated by the maximum likelihood method and simulated with antithetic sampling.

Our work finds that JDM with EM algorithm is effective in discovering the housing market structure in most cases. This result depicts well the equilibrium housing price structure and jump risks in city housing markets, so it is convenient to use this method to predict a price and corresponding mortgage-related products. It is not effective in some cases, however, because JDM assumes instant and rare external impacts to the price structure, which is not appropriate for analyzing the price data during long recessions.

For future studies, one can think about variations on basic asset pricing models. JDM may be insufficient to cover the price structure; instead, one can use other models that use log-uniform, or double exponential distributions. Research using period decomposition by certain events such as the bubble collapse at Japan or the subprime mortgage crisis can be discussed further, as such events may change entire market structures.

CRediT authorship contribution statement

Sebeom Oh: Writing - original draft, Methodology, Data curation, Visualization. **Hyejin Ku:** Supervision, Conceptualization, Writing - review & editing. **Doobae Jun:** Supervision, Methodology, Investigation, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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This article uses data from the Case–Shiller indices (S&P Global), the data collection from the Bank for International Settlements, the KB commercial Bank, and Canadian Real Estate Association. The results and analyses may not correspond to those of the data producers.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.frl.2021.102241.

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