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JUMP DIFFUSION MODELS FOR JAPANESE STOCK MARKET

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ABSTRACT

In classical Black-Scholes framework Geometric Brownian motion is used to model the return of assets. In this model the return distribution should be normal. However many empirical studies showed that distributions of assets return have higher peak and longer tail, and sometimes asymmetry compared with normal distributions. One of the causes of such phenomena is jumps in diffusion processes. A typical jump diffusion process consists of Brownian motion plus compound Poisson process, which has been applied to financial date in recent years. Among others we focus on Kou's jump diffusion model in this paper and apply it to Japanese stock market. We examine the performance of this mode by simulation study as well as by comparing option prices derived from Kou's model and Black-Scholes model. Reference S.G.Kou. "A Jump-Diffusion Models for Option Pricing" Management Science, Vol.48, No.8, August 2002.

1 INTRODUCTION

The Black-Scholes(BS) model has been widely and successfully used to model the return of asset and to price financial options. Despite of its success the basic assumptions of this model, that is, Brownian motion and normal distribution are not always supported by empirical studies. Those studies showed the two empirical phenomena: (1) the asymmetric leptokurtic features, (2) the volatility smile. The first means that the return distribution is skewed to the left and has a higher peak and two heavier tails than those of normal distribution, and the second means that if the BS model is correct, then the implied volatility should be flat. But the graph of the observed implied volatility curve often looks like the smile of the Cheshire cat. Many models were proposed to explain the two empirical phenomena. For example popular ones are normal jump diffusion model(Merton(1976)), stochastic volatility models(Heston(1993)), ARCH-GARCH models(Duan(1993)), etc. For other papers see references in Kou(2002)). Among others we focus on a double exponential jump diffusion model proposed by Kou(2002) in this paper. Kou's model is very simple. The logarithm of the asset price is assumed to follow a Brownian motion plus a compound Poisson process with jump sizes double exponentially distributed. This model has the following advantages: (1) it can explain the two empirical phenomena, that is asymmetric leptokurtic feature and the volatility smile, (2) it leads to analytical solutions to many option-pricing problems. Despite of these advantages there are not many empirical studies based on this model partly because probability distribution function derived from this model is rather complicated and difficult to be estimated. However we employ this model to analyze Japanese stock market.

The plan of this paper is as follows. In Section 2 we test the normality assumption of the return distribution by Lilliefors test and Anderson-Darling test in the subsection 2.1, and we introduce Lee and Wee test which is a test to the adequacy of pure jump diffusion model (with no jumps) and we apply Lee and Wee test to real Japanese stock data in the subsection 2.3. In Section 3 we introduce Kou's model and its theoretical background in the subsection 3.1, and apply it to Japanese stock data to calculate option-prices in the subsection 3.2. In Section 4 we compare pure- and jump-diffusion models by observing volatility smile and other statistics and conclude this paper.

2 SEARCH FOR STOCK PRICE PROCESS

It has been observed that structural changes often occur in financial time series data due to the policy changes and social events (See Lee, Ha, Na and Na(2003), Lee and Na(2004), Lee, Tokutsu and Maekawa(2004)). In particular, if there is such a structural change, it is well known that a pure diffusion model does not provide a better fit to the financial data such as stock returns and interest rates. For this reason, jump diffusion models and Levy processes have recently applied to financial time series data. See Barndorff-Nielsen, Mikosch and Resnick(2001), Kou(2002), Shoutens(2003) and Cont and Tankov(2004). In this section, using the empirical process method of Lee and Wee(2004), we conduct the statistical test for the adequacy of modeling the empirically observed data by a pure diffusion process.

2.1 Testing For Normality

In this section we test the normality of return distribution by using two tests, that is, Lilliefors test (abbreviated L-test hereafter) and Anderson-Darling test (abbreviated AD test hereafter). The definitions of these tests are as follows. Let N denote the sample size then L-test is defined by

$$L = \max\{L', L''\}.$$

Where

$$L' = \max_{i=1,\dots,n}\{i/n - p_i\},$$
$$L'' = \max_{i=1,\dots,n}\{p_i - (i-1)/n\}.$$

AD test is define by

$$A^2 = -N - S,$$
$$S = \frac{1}{N}\cdot\sum_{i=1}^{N}(2i-1)\left[\log\Phi_i + \log(1-\Phi_{N+1-i})\right].$$

Where pi is $p_i = \Phi([x_i - \bar{x}]/s)$ and Φ is the standard normal distribution function.

By conducting these tests to all of 214 time series of stock prices the normality assumption of the return distributions are not accepted by both of the tests. It is said that the AD-test is more sensitive to the heavy tail feature than the L-test.

2.2 Test based on the empirical process method

In this section we briefly describe the methodology of Lee and Wee(2004) statistical test for diffusion processes. Let $\{X_t; t \geq 0\}$ be a stochastic process. We consider the following hypothesis test:

$$\begin{aligned} &H_0 : \{X_t\} \text{ follows} \\ &\qquad dX_t = a(X_t;\theta)dt + \sigma dW_t,\ t \geq 0 \ \text{ vs.} \qquad (1) \\ &H_1 : \text{not } H_0, \end{aligned}$$

where θ is a p-dimensional unknown parameters, σ is a constant, a is a real valued function, and $\{W_t; t \geq 0\}$ is a standard Wiener process.
Suppose that $\{X_t\}$ is actual market data observed at discrete times $t_i = ih_n, i = 1, 2, \cdots, n$, where $\{h_n\}$ is a sequence of positive real numbers such that $h_n \to 0$ and $nh_n \to \infty$ We can rewrite (1) as

$$\begin{aligned} X_{t_i} - X_{t_{i-1}} &= h_n a(X_{t_{i-1}};\theta) \\ &\quad + \int_{t_{i-1}}^{t_i}\big(a(X_{t_i};\theta) - a(X_{t_{i-1}};\theta)\big)ds + \int_{t_{i-1}}^{t_i} dW_t \\ &\simeq h_n a(X_{t_{i-1}};\theta) + \sigma\sqrt{h_n}r_i, \end{aligned} \qquad (2)$$

where r_i are iid standard normal r.v.'s.

Let $\hat{\theta}_n$ be a consistent estimator of θ such that $\sqrt{nh_n}(\hat{\theta}_n - \theta)$ is asymptotically normal (see Lee and Wee(2004) for details). Define the residuals

$$\hat{r_i} = \{X_{t_i} - X_{t_{i-1}} - h_n a(X_{t_{i-1}}; \hat{\theta}_n)\}^2 / (\hat{\sigma}_n \sqrt{h_n}), \quad (3)$$

where

$$\hat{\sigma}_n = \frac{1}{nh_n} \sum_{i=1}^{n} \{X_{t_i} - X_{t_{i-1}} - h_n a(X_{t_{i-1}}; \hat{\theta}_n)\}^2, \quad (4)$$

which is a constant estimator of σ^2.

The residual empirical process is defined by

$$Y_n(x) = \frac{1}{\sqrt{n_h}} \sum_{i=1}^{n_h} \{1_{\{\eta_{ni} \le x\}} - \Phi(x)\}, \quad x \in R, \quad (5)$$

where n_h is the largest integer that does not exceed nh_n.

By putting $\eta_{ni} = (W_{t_i} - W_{t_{i-1}})/\sqrt{h_n}$, Lee and Wee(2004) has shown that the following equation can be obtained

$$Y_n(x) = \frac{1}{\sqrt{n_h}} \sum_{i=1}^{n_h} \{1_{\{\eta_{ni} \le x\}} - \Phi(x) + \xi_n(x)\}, \quad x \in R, \quad (6)$$

where $\sup_x |\xi_n(x)| = o_P(1)$ Hence, using $Y_n(\phi^{-1}(u))$ instead of $Y_n(x)$, where $0 \le u \le 1$, the limiting distribution of $Y_n(\phi^{-1}(u))$ converges weakly to a Brownian bridge $W^o(u)$.

Now we can apply the above result to the Kolmogorov-Smirnov test to perform a goodness of fit test against diffusion models with jumps.

$$KS_n := \sup_{0 \le u \le 1} |Y_n(\phi^{-1}(u))| \to \sup_{0 \le u \le 1} |W^0(u)| \quad (7)$$

If the test statistics KS_n is large, we reject the null hypothesis H_0. We apply Lee and Wee(2004) test to a geometric Brownian motion in below.

2.3 Empirical Study Using Japanese Stock Data

In this section, we check the validity of a diffusion process for the Nikkei 225 component stocks. In doing this, we use the individual stocks with more than 1000 observations in the Nikkei 225 component stocks and conduct the Lee and Wee(2004) test.

Let us assume that stock price processes follow the geometric Brownian motion

$$\frac{dX_t}{X_t} = \mu dt + \sigma dW_t, \quad t \ge 0. \quad (8)$$

Now, using Ito Formula and the notation of eq (2), we can obtain

$$\log X_t - \log X_{t_{i-1}} \simeq (\mu - \frac{\sigma^2}{2}) h_h + \sigma \sqrt{h_n} r_i. \quad (9)$$

Then the residuals can be computed from

$$\hat{r_i} = \{\log X_{t_i} - \log X_{t_{i-1}} - (\hat{\mu} - \frac{\hat{\sigma}^2}{2}) h_h\} / (\hat{\sigma} \sqrt{h_n}) \quad (10)$$

Performing the following test

$$H_0 : \text{stock returns follow (9) vs.}$$
$$H_1 : \text{not } H_0,$$

all the null hypothesis for all of the 214 individual stocks were rejected. This result implies that stock price processes do not follow the geometric Brownian motion. Rather, it is appropriate to consider an alternative model for these stock price processes. To look at the shape of an empirical distribution, we choose a stock, which is used in Section below, from the Nikkei 225 component stocks and plot the empirical returns with a normal density in Figure 1. Similarly, Figure 2 shows log returns and log density to take a closer look at the tail behavior. As can be seen from these figures, the actual returns show higher peak around the center compared with the normal density. In general, it is known that the distribution of empirical returns has two characteristics; fat tail (or excess kurtosis) and asymmetry. In particular, we can mention the existence of jumps in price processes as one of reasons why fat tail distribution can be observed. As an alternative model which can capture two such characteristics and provide analytical formulas for prices of options, we employ a jump diffusion model proposed by Kou(2002). The model consists of two parts: (1) a geometric Brownian motion. (2) a compound Poisson process with jump sizes following a double exponential distribution. Using the approximate density of returns given by Kou's model, we show the goodness of fit of the density to actual returns along with the normal density in Figure 3. We can see that the density given by Kou's model shows better fit than the normal around the center and in tails(see Figure 4).

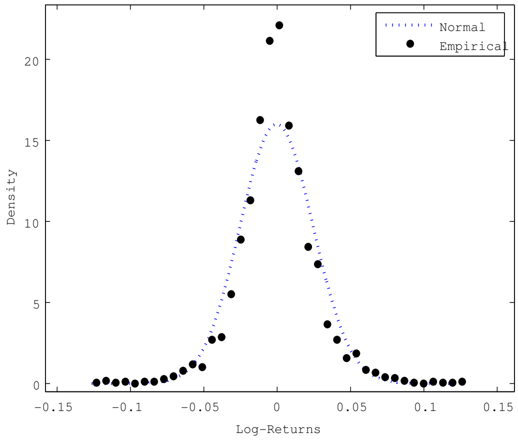

Figure 1: Empirical and Normal densities for Mitsubishi Chemical Co.

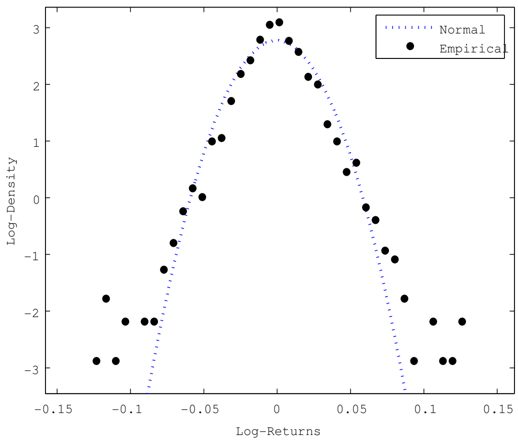

Figure 2: Log-densities of Empirical and Normal for Mitsubishi Chemical Co.

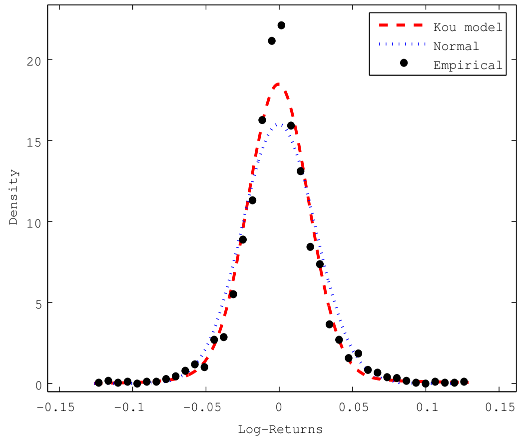

Figure 3: The densities of Empirical, Kou model and Normal for Mitsubishi Chemical Co.

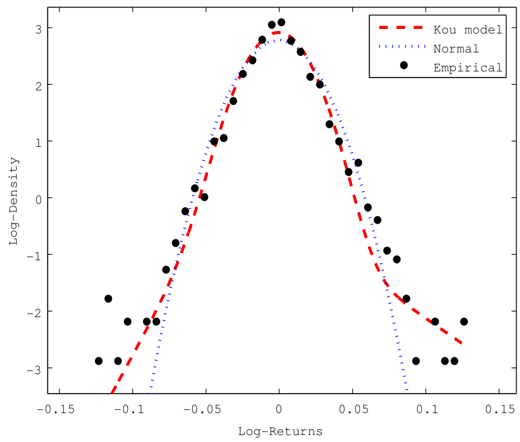

Figure 4: The log-densities of Empirical, Kou model and Normal for Mitsubishi Chemical Co.

3 THEORETICAL BACKGROUND

In this section we illustrate theoretical background of Kou's jump diffusion model.

3.1 Model Specification

Under probability measure $\mathbf{P}$ we assume that underlying asset price process $S(t)$ follows

$$\frac{dS(t)}{S(t-)} = \mu dt + \sigma dW(t) + d\left(\sum_{i=1}^{N(t)}(V_i - 1)\right), \quad (11)$$

where $W(t)$ is standard Brownian motion, $N(t)$ is a Poisson process with intensity λ and $\{V_i\}\mathcal{Y}$ is a i.i.d. nonnegative stochastic sequence. Again $\Upsilon = \log(V)$ is an asymmetric double exponential distribution with density

$$f_\Upsilon(y) = p \cdot \eta_1 e^{-\eta_1 y} 1_{\{y \geq 0\}} + q \cdot \eta_2 e^{\eta_2 y} 1_{\{y<0\}}, \quad \eta_1 > 1, \eta_2 > 0,$$

where $p, q \geq 0$, $p+q = 1$ are up-move jump and down-move jump respectively. Put another way,

$$\log(V) = \Upsilon \stackrel{d}{=} \begin{cases} \xi^+, & \text{with probability } p \\ -\xi^-, & \text{with probability } q \end{cases} \quad (12)$$

where ξ^+ and ξ^- is exponential random variable with mean $1/\eta_1$ and $1/\eta_2$. Note that $\stackrel{d}{=}$ denotes identically distributed. In this model we assume that stochastic element $N(t)$, $W(t)$, Υ_S are independent. For notational convenience and explicit solution for option price we assume that drift term μ and diffusion term σ are constants and restrict ourselves to one dimensional case. However these assumptions are easily generalized to more complex case.

Given a solution of SDE(11), then we obtain asset price dynamics

$$S(t) = S(0) \exp\left\{\left(\mu - \frac{1}{2}\sigma^2\right) t + \sigma W(t)\right\} \prod_{i=1}^{N(t)} V_i, \quad (13)$$

where $\mathrm{E}(\Upsilon) = \frac{p}{\eta_1} - \frac{q}{\eta_2}$, $\mathrm{Var}(\Upsilon) = pq(\frac{1}{\eta_1} + \frac{1}{\eta_2})^2 + (\frac{p}{\eta_1^2} + \frac{q}{\eta_2^2})$ and

$$\begin{aligned}\mathrm{E}(V) &= \mathrm{E}(e^\Upsilon) \\ &= q\frac{\eta_2}{\eta_2 + 1} + p\frac{\eta_1}{\eta_1 - 1}, \quad \eta_1 > 1, \quad \eta_2 > 0.\end{aligned}$$

Again $\eta_1 > 1$ guarantees $\mathrm{E}(V) < \infty$ and $\mathrm{E}(S(t)) < \infty$. This means that average rate of up-jump does not exceed 100%.

Rate of return on Δt is given by (13) and

$$\begin{aligned}\frac{\Delta S(t)}{S(t)} =& \frac{S(t+\Delta t)}{S(t)} - 1 \\ =& \exp\left\{\left(\mu - \frac{1}{2}\sigma^2\right)\Delta t\right. \\ &+ \sigma(W(t+\Delta t) - W(t)) \\ &\left.+ \sum_{i=N(t)+1}^{N(t+\Delta t)} \Upsilon_i\right\} - 1.\end{aligned}$$

If Δt is sufficiently small, by omitting higher order term than Δt and using expansion $e^x \approx 1 + x + x^2/2$, one can approximate rate of return to the distribution

$$\frac{\Delta S(t)}{S(t)} \approx \mu\Delta t + \sigma Z\sqrt{\Delta t} + B \cdot \Upsilon$$

where Z and B are random variable of standard normal and binomial respectively, and $\mathbf{P}(B = 1) = \lambda\Delta t$, $\mathbf{P}(B = 0) = 1 - \lambda\Delta t$ and Υ is given by (12). The density function is

$$\begin{aligned}g(x) =& \frac{1 - \lambda\Delta t}{\sigma\sqrt{\Delta t}}\phi\left(\frac{x - \mu\Delta t}{\sigma\sqrt{\Delta t}}\right) \\ &+ \lambda\Delta t\left\{p\eta_1 e^{(\sigma^2\eta_1^2\Delta t)/2} e^{-(x-\mu\Delta t)\eta_1}\right. \\ &\times \Phi\left(\frac{x - \mu\Delta t - \sigma^2\eta_1\Delta t}{\sigma\sqrt{\Delta t}}\right) \\ &+ q\eta_2 e^{(\sigma^2\eta_2^2\Delta t)/2} e^{-(x-\mu\Delta t)\eta_2} \\ &\left.\times \Phi\left(-\frac{x - \mu\Delta t + \sigma^2\eta_2\Delta t}{\sigma\sqrt{\Delta t}}\right)\right\} \quad (14)\end{aligned}$$

where $\phi(\cdot)$ is density function of standard normal and $\Phi(\cdot)$ is its distribution function.

3.2 Option Pricing

In this subsection we demonstrate Kou's formula of option pricing for European call. For obtaining option price we need to consider the sum of normal and double exponential distributions. Fortunately we can compute explicitly the distribution by using Hh function. Hh function is a special function of mathematical physics, for more detail see Abramowitz and Stegun (1972, p. 691).

For a probability $\mathbf{P}$ we define

$$\Upsilon(\mu, \sigma, \lambda, p, \eta_1, \eta_2; a, T) := \mathbf{P}\{Z(T) \geq a\},$$

where $Z(t) = \mu t + \sigma W(t) + \sum_{i=1}^{N(t)} \varUpsilon_i$, $\varUpsilon$ follows double exponential distribution with density $f_\varUpsilon(y) \sim p \cdot \eta_1 e^{-\eta_1 y} \mathbf{1}_{\{y \geq 0\}} + q \cdot \eta_2 e^{y \eta_2} \mathbf{1}_{\{y<0\}}$ and $N(t)$ is a Poisson process with intensity λ. This Υ is the formula for European call option, which given by the sum of Hh function. As for the explicit form of Υ, see Theorem B.1 in Kou (2002) Appendix B.

Theorem 1 *The European call price is given by*

$$\begin{aligned} \psi_c(0) =& S(0)\Upsilon(r + \frac{1}{2}\sigma^2 - \lambda\zeta, \\ & \sigma, \tilde{\lambda}, \tilde{p}, \tilde{\eta_1}, \tilde{\eta_2}; \log(K/S(0)), T) \\ & - Ke^{-rT}\Upsilon(r - \frac{1}{2}\sigma^2 - \lambda\zeta, \\ & \sigma, \lambda, p, \eta_1, \eta_2; \log(K/S(0)), T), \end{aligned} \tag{15}$$

where

$$\begin{aligned} \tilde{p} &= \frac{p}{1+\zeta} \cdot \frac{\eta_1}{\eta_1 - 1}, \quad \tilde{\eta_1} = \eta_1 - 1, \\ \tilde{\eta_2} &= \eta_2 + 1, \quad \tilde{\lambda} = \lambda(\zeta + 1), \\ \zeta &= \frac{p\eta_1}{\eta_1 - 1} + \frac{q\eta_2}{\eta_2 + 1} - 1. \end{aligned}$$

Note that when substituting Φ for Υ the equation (15) seems like Black-Scholes formula for European call. For the proof of Theorem 1, see Theorem 3 in Kou and Wang (2004).

4 COMPARISON OF OPTION PRICE

In this section we compare option prices derived from BS formula and Kou's formula (15) as well as implied volatility derived from BS model and Kou's model by using 214 series with more than 1000 observations out of Nikkei 225 from 1 June 1992 to 31 December 2002.

4.1 Option Pricing: Kou v.s. BS

We estimated parameters of Kou's density function (14) by MLE and substituted the estimators to (15) to obtain the European call option prices for each stock. We also calculated the option price for each stock by BS formula and computed the differences between these two prices in terms of mean root differences defined by

$$D_p = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(BS_i - KOU_i)^2} \tag{16}$$

where N denote the sample size, and BS and KOU are respectively denote the option price obtained by BS formula and Kou's formula.The distance measured by D_p in (16) showed that BS model and Kou's model are not uniformly closed and we can not see which model is better performed. To see this we substituted the option price calculated by Kou's formula into the BS formula

$$\begin{aligned} H(t, S_t) = & S_t\Phi[d_1(t, S_t)] \\ & - e^{-r(T-t)}K\Phi N[d_2(t, S_t)]. \end{aligned}$$

Where Φ denotes the distribution function of the standard normal distribution and d_1, d_2 are defined by

$$\begin{aligned} d_1(t, S_t) =& \frac{1}{\sigma\sqrt{T-t}} \\ & \times \left\{ \ln\left(\frac{S_t}{K}\right) + \left(r + \frac{1}{2}\sigma\right)(T-t) \right\}, \\ d_2(t, S_t) =& d_1(t, s) - \sigma\sqrt{T-t}. \end{aligned}$$

Figure 5 shows the implied volatility surface with three components: the implied volatility, time to the maturity, and the strike price. As an example we present the figure of the implied volatility surface of Mitsubishi Chemical Co. (Code: 4010). As is seen the volatility smile is symmetric in both side of the "at the money" point. In other stock data similar volatility smile were observed. This observational results implied that the real Nikkei data do not satisfied the normality assumption premised in BS model. Furthermore we compared the following two kind of volatilities:

(a) Implied volatility derived from BS formula based on real stock data,

(b) Implied volatility derived from BS formula based on calculated option price by Kou's formula.

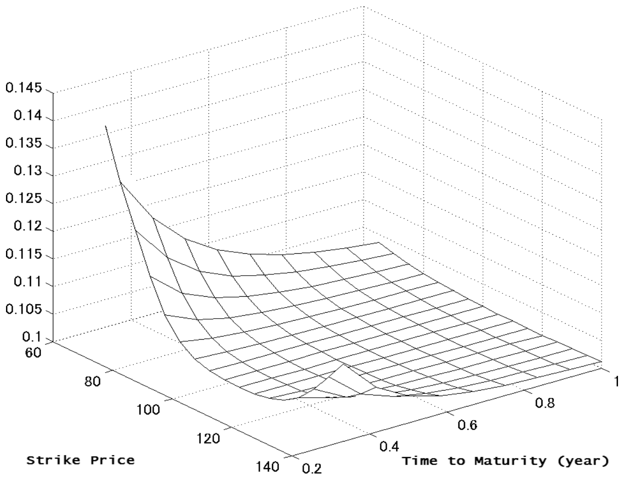

Figure 5: Implied Volatility Surface (Mitsubishi Chemical Co.)

If the difference between the return distribution and the normality become larger, D_p and/or D_v would also become larger. Therefore the difference measured by AD and/or L and D_p and/or D_v may have positive correlation (or at least non-zero correlation). To see this we calculated the three kind coefficient of correlation (Peason, Spearman, Kendall) between AD-test, L-test, D_p, and D_v, where D_p denotes the differences between option prices from BS and Kou's formulae, and D_v denotes the differences between volatilities from BS model and Kou's model measured by

$$D_v = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Vol(BS)_i - Vol(KOU)_i)^2},$$

where $Vol(BS)$ and $Vol(KOU)$ respectively denotes the implied volatility defined by (a) and (b) above. These results are shown in Table 2-4. All of the three coefficient of correlation showed that the null of no correlation was rejected. These tables showed that the correlation between D_p and D_v have slightly higher correlation to AD-test compared with L-test. This might reflect that L-test is more sensitive to heavy tail properties than AD-test.

Finally we compared the three prices: the market price (MP), theoretical prices derived by BS and Kou's models. We used the market prices of European call option for Nikkei 225 from September 10, 1999 to December 12, 2002 with various strike prices and times to maturity. The relative differences of theoretical and market prices divided by market prices are shown in the figures 6-8. In each figure the vertical axis denotes the difference between the two prices and horizontal axes denote strike price and time to maturity. Figures 6 and 7 show the differences between the market price and theoretical price by Kou's mode and the differences between the market price and theoretical price by BS model. Figure 8 shows the differences between two theoretical prices by BS and Kou's model. These figures show that the calculated prices by Kou's model are much closer to the real data than calculated prices by BS model. To see this we calculated two measures of distance, i.e., average relative percentage error(ARPE) and weighted average relative percentage error(WARPE) defined by

$$\text{ARPE} = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{\hat{C}_i - C_i}{C_i}\right|,$$

$$\text{WARPE} = \sum_{i=1}^{M}\left|\frac{\hat{C}_i - C_i}{C_i}\right| w_i,\ w_i = \frac{V_i}{\sum_{i=1}^{M} V_i},$$

where M is the number of options, and $C_i, \hat{C}_i$ and V_i denote market price, model price, and the volume on the ith option trade, respectively. Table 1 shows the results: From our data analysis it seems that Kou's model is fitted well to Japanese stock data than Black-Scholes model.

Table 1: Distances from the market price

	BS model	Kou's model	sample size
ARPE	0.3646	0.2895	50955
WARPE	0.5001	0.5041	50955

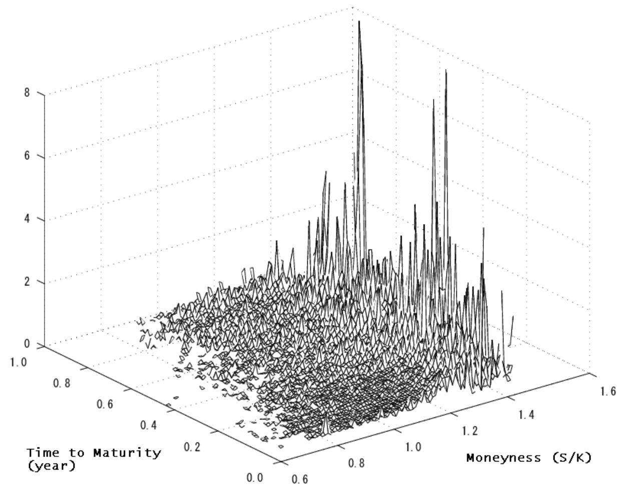

Figure 6: Relative Difference between MP and BS Price

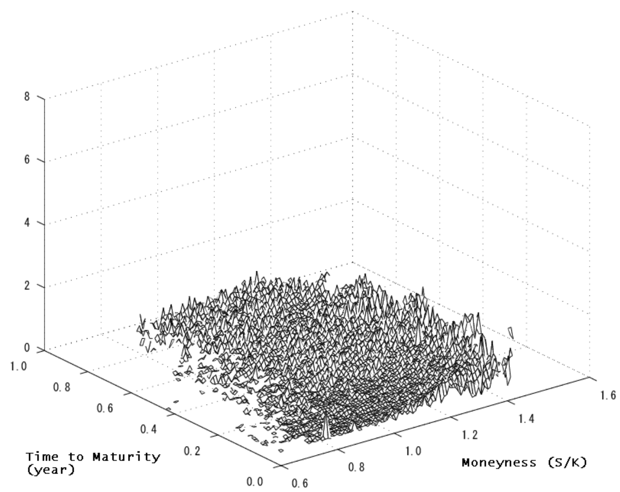

Figure 7: Relative Difference between MP and Kou Price

Table 2: Peason

	AD	L	D_p	D_v
AD	1	0.86781	0.28675	0.28440
L	0.86781	1	0.25351	0.25138
D_p	0.28675	0.25351	1	0.99528
D_v	0.28440	0.25138	0.99528	1

Table 3: Spearman

	AD	L	D_p	D_v
AD	1	0.76253	0.20767	0.21198
L	0.76253	1	0.06511	0.07600
D_p	0.20767	0.06511	1	0.99366
D_v	0.21198	0.07600	0.99366	1

Table 4: Kendall

	AD	L	D_p	D_v
AD	1	0.58928	0.13773	0.14002
L	0.58928	1	0.04300	0.04985
D_p	0.13773	0.04300	1	0.93624
D_v	0.14002	0.04985	0.93624	1

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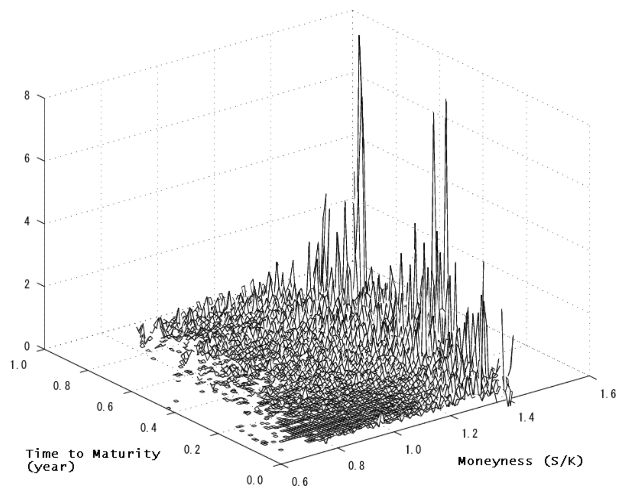

Figure 8: Relative Difference between BS and Kou Price

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