jumps Information inferred from options prices

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Abstract

Options prices jump whenever there is a jump in either the price or volatility of the underlying asset. High-frequency jump tests are applied to the prices of both futures contracts and their options in order to infer the properties of price and volatility jumps. The empirical results for FTSE-100 contracts show that jumps in price and jumps in volatility are, firstly, smaller than those assumed or estimated in previous research and, secondly, do not occur independently. The price jump risk premium is shown to be a more important factor than the volatility jump risk premium. Monte Carlo methods confirm that our empirical jump detection methods are reliable for a selection of jump-diffusion processes.

Keywords:price jumps, volatility jumps, high-frequency prices, jump risk premia

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1 Introduction

Over the past few decades, stock market jumps have posed a great challenge to financial models and options pricing models. Empirical studies have clearly shown that stock market returns do not simply follow a normal distribution. Researchers have expended effort to build more accurate models for describing the largest market movements.Merton (1976) evaluated options for jumps in underlying asset returns. Researchers have subsequently considered jumps in prices. Duffie, Pan, and Singleton (2000) proposed an options pricing method for a general affine jump-diffusion model. They showed that simultaneous jumps in price and volatility could describe the implied volatility smirk. Eraker, Johannes, and Polson (2003) constructed stochastic volatility models, and found strong evidence of jumps in both price and volatility (also see Chernov, Gallant, Ghysels, and Tauchen, CGGT, 2003). These papers revealed that jumps in prices were critical, but the importance of jumps in volatility remains unclear. If there is no risk premium in affine models, then it is assumed that all price jump risks are diversifiable. However,research has shown that there exist idiosyncratic jumps and systematic jumps for which risk is non-diversifiable (Bollerslev, Law, and Tauchen, 2008). Therefore, in options pricing models,the associated risk premia are critical.

Researchers have found critical results pertaining to the associated jump risk premia. Pan (2002) used the generalised method of moments to estimate the parameters of affine jump-diffusion models. She identifiedprice jumps, and estimated the price jump risk premium. Broadie, Chernov,and Johannes (2007) usedStandard & Poor (S&P) 500 futures and options prices from 1987 to 2003 toconstructan affine jump-diffusion model;they also considered real-world and risk-neutral measurements, and indicated that the consideration of risk premia associated with jumps may improve options pricing models. Because jumps cannot be hedged as diffusive elements, the existence of jump risk premia has a crucial consequence. Investors facing a jump risk that cannot be hedgedrequest a premium to compensate for their investment risk. Broadie, Chernov,and Johannes (2007)estimated the price jump risk premium to beapproximately 3%.

Carr and Wu (2009) used the difference between the realised variance and the variance swap rate to determine the variance risk premium. They foundanegative variance risk premium for the S&P 500 indices and the Dow Jones Industrial Average,indicating that investors were averse to an increase in volatility, and were willing to pay a premium to hedge against it. Furthermore, Bollerslev and Todorov (2011) proposed new extreme value approximations to estimate the expected jump tails under real and risk-neutral measures. Their findings suggested that the historical equity and variance risk premia may be explained by the compensation for jump tail risk.

Thus far, affine models with compound Poisson jumps have been widely used for describing the return and volatility processes in financial markets. Todorov and Tauchen (2011) usedthe Chicago Board Options Exchange Market Volatility Index (VIX) and S&P 500 futures contracts to test the activity level of returns and the VIX process. They concluded that jumpdiffusion was suitable for the S&P 500 return process, whereas the VIX index required a pure-jump process to capture the frequent jumps in VIX. In their research, the VIX index was used as a proxy for the volatility level. The advantage of using VIX data is that they are calculated from traded options prices with various strike prices. The options prices are sensitive to volatility, and VIX provides more information compared with the underlying asset series (Blair, Poon, and Taylor, 2001). However, the VIX index is a measure of the risk-neutral expectation of future volatility, and it is not an instantaneous volatility measure; VIX is a biased estimate of instantaneous volatility. An alternative is to use options prices directly to investigate jumps and associated risk premia. We consider affine jump-diffusion modelsto extract information from options prices.

In another field, researchers have proposed non-parametric methods for jump detection in prices. For high-frequency data, more information can be obtained using these methods. First, Barndorff-Nielsen and Shephard (2006) proposed a method for identifying days when jumps occur. Andersen, Bollerslev, and Dobrev (ABD; 2007) proposed a method to detect multiple jumps over a given trading period, and to obtain the timing of the jumps.

However, attention to finding evidence for jumps in volatility from information on jumps in market prices has been scant. We use a jump test to detect jumps in futures and options prices, and use the detected jumps to investigate jumps in underlying asset prices, jumps in volatility, and related risk premia. The main idea is that, when there is no contemporaneous volatility jump, a jump in the (underlying asset) *price* induces a jump in the call price in the same direction as the underlying asset price and a jump in the put price in the *opposite* direction. In contrast, a jump in *volatility* induces jumps in the call price and jumps in the put price in the *same direction*, when there is no contemporaneous price jump. Therefore, if there are contemporaneous call jumps and put jumps in the same direction, we regard this as evidence in favour of independent jumps in volatility. We argue that the assumptions of the ABD test are equally applicable to futures and options prices. Consequently, the ABD jump test is used to identify jumps in futures and options prices.

However, using this method,we fail to find strong evidence for jumps in volatility. In all the jumps detected in options prices,the cases of call jumps and put jumps being in the same direction account for only 1%. In addition, this small percentage of jumps may have resulted from errors in the data. This negative result leadsto two possible explanations: Either jumps in price and jumps in volatility occur contemporaneously, and jumps in price have a greater effecton the directions of options jumps than the corresponding jumps in volatility,or there are no jumps in volatility.

To evaluate these explanations, the ABD test is used to detect jumps in simulated futures and options prices by using affine jump-diffusion models with five scenarios: no price jump and no volatility jump; only price jumps; only volatility jumps; independent price jumps and volatility jumps; and contemporaneous price jumps and volatility jumps. From a comparison between empirical and model-based results, we determine the model that best describes the observed jump patterns. Our estimates of the variances of the price jump size and mean volatility jump size are fewer than previous estimates (Eraker, Johannes, and Polson, 2003; CGGT, 2003; Eraker, 2004). Overall, our findings suggest that there are price jumps and a price jump risk premium, that jumps in the price and jumps in volatility are not mutuallyindependent,and that the price jump risk premium is a more critical factorcompared with the volatility jump risk premium.

2 Detecting Jumps

2.1 Price Variation

We assume the price of an asset follows a semi-martingale process in continuous time. The logarithm of the asset price, denoted p_t, then follows a standard jump-diffusion process, which can be represented by the stochastic differential equation.

$$dp = \mu dt + \sigma dW + JdN , \tag{1}$$

where the drift rate μ_t has locally bounded variation, the volatility process σ_t is positive and caglad[1], W_t is a standard Wiener process, N_t counts jumps and J_t represents the size of any jump at time *t*. The return during an interval of Δ time units, from time $t - \Delta$ until time *t* equals $p_t - p_{t-\Delta}$.

We let one time unit equal the duration of trading at a market for one day, from the open until the close, and divide it into m time steps. We define a set of m intraday returns for day *d* by $r_{d,j} = p_{d+j/m} - p_{d+(j-1)/m}$. The realized variance and the realized bipower variation for day d are respectively defined by

$RV_d = \sum_{j=1}^{m} r_{d,j}^2$(2) and

$$BV_d = \frac{\pi m}{2(m-1)} \sum_{j=2}^{m} |r_{d,j}||r_{d,j-1}|. \tag{3}$$

Andersen and Bollerslev (1998), Comte and Renault (1998) and Barndorff-Nielsen and Shephard (2001, 2004) showed that these quantities converge as $m \to \infty$. The realized bipower variation converges to the integrated variance,

$$BV_d \to \int_d^{d+1} \sigma_s^2 ds, \tag{4}$$

while the realized variance converges to the quadratic variation, which equals the integrated variance plus the sum of the squared jumps:

$$RV_d \to \int_d^{d+1} \sigma_s^2 ds + \sum_{d \le s < d+1} J_s^2. \tag{5}$$

2.2 Detecting Index Jumps

Intuitively, a return contains a jump if the return is large compared with the variation expected when the price follows a diffusion process. A simple implementation of the test

[1] A cadlag function, a function defined on real numbers, is right-continuous with left limits everywhere.

methodology developed by Andersen, Bollerslev, and Dobrev (2007) identifies an index return as containing a jump whenever

$$|r_{d,j}| > z_m\sqrt{BV_d/m}, \quad (6)$$

with z_m determined by the significance level of the hypothesis test and the standard normal distribution. This test procedure assumes it is appropriate to estimate the integrated variance of an intraday return as the daily variation divided by m, i.e. it is assumed that volatility does not change during the day by a substantial amount. ABD try to ensure their evidence for jumps is conclusive by selecting a very low significance level. Let α be the daily Type I error rate, which is the proportion of days without jumps for which the test procedure claims one or more jumps. Then each of the m intraday returns should be tested with a significance level α_m satisfying $(1-\alpha_m)^m = 1-\alpha$. ABD choose $\alpha = 10^{-5}$ and test 195 two-min returns each day, and thus Z_m =5.45.

As there are well-documented intraday patterns in volatility, it is natural to modify (6) to identify a jump within a return whenever

$$|r_{d,j}| > z_m\sqrt{f_j BV_d}, \quad (7)$$

with f_j an estimate of the proportion of the day's variance which occurs during intraday period *j*. The ABD test will detect jumps which are sufficiently large. The test will, however, fail to detect relatively small jumps and thus it may detect only a small fraction of the jumps in a price process (Taylor, 2010).

2.3 Detecting Jumps in Options Prices

The price of an option follows a semi-martingale process whenever the price of the underlying asset has the semi-martingale property. Consequently, it is tempting to detectjumps in options prices using the methods which have already been successfully applied to index levels.

A simple example shows, however, that extra care may be required if the ABD test is applied to options prices. When the underlying asset price S follows a geometric Brownian process,

$$\frac{dS}{S} = \mu dt + \sigma dW, \quad (8)$$

by Ito's lemma the call price C follows the diffusion process

$$\frac{dC}{C} = \frac{1}{C}\left(\frac{\partial C}{\partial t} + \frac{\partial C}{\partial S}\mu S + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 C}{\partial S^2}\right) dt + \sigma \frac{S}{C}\frac{\partial C}{\partial S} dW. \tag{9}$$

There will then be intraday variation in the volatility of call returns, because of the multiplicative term$\frac{S}{C}\frac{\partial C}{\partial S}$. We therefore expect that there will always be more intraday volatility variation for percentage change of options prices than for that of the underlying asset. We use Monte Carlo methods in Section 3 to decide if the ABD methodology remains viable when it is applied to options prices.

2.4 Detecting Jumps in Volatility

The general jump-diffusion specification given by (1) permits jumps in both prices and the volatility component σ_t. Our empirical results are for an underlying asset which is a futures contract on a stock index. Assuming efficient markets, a jump in the futures price (without a contemporaneous volatility jump) will induce all call prices to jump in the same direction as the futures price and all put prices to jump in the opposite direction. In contrast, a jump in the volatility (without a contemporaneous futures jump) will induce all call and all put prices to jump in the same direction. Although theoretical predictions are less precise when both the futures price and the volatility jump at the same time, call and put prices will only move in the same direction when the volatility jump is large relative to the jump in the futures price.

Whenever the ABD test detects contemporaneous jumps in call and put prices in the same direction we will regard this as evidence in favour of a volatility jump. Such evidence may beelusive, however, because contemporaneous jumps in the futures price may hide the impact of volatility jumps.

3 Monte Carlo Results

We use Monte Carlo methods to assess the effective size and power of the ABD test for a selection of stochastic processes. The processes are defined in Sections 3.1 to 3.2 and the results are discussed in Sections 3.3.

Effective *size* is defined as the proportion of simulated periods containing no price jumps for which the test falsely claims a price jump has occurred. Effective *power* is the proportion containing a price jump for which the test correctly asserts a jump has occurred. A jump in volatility, J.V., leads to a jump in option returns, while a jump in (underlying asset) price, J.P., causes both a jump in the asset return and a jump in the option return. The step effective size, α_m, and effective power, $1-\beta$, of the ABD test for price and option are listed as follow:

	(underlying asset) Price	Options
α_m	$\frac{\text{number of detected J.P.} \neq 0 \mid \text{true J.P.} = 0}{\text{number of true J.P.} = 0}$	$\frac{\text{number of detected J.Options} \neq 0 \mid \text{true J.P.} = 0 \ \& \ J.V. = 0}{\text{number of true J.P.} = 0 \ \& \ J.V. = 0}$
$1-\beta$	$\frac{number\ of\ detected\ J.P. \neq 0 \mid \text{true J.P.} \neq 0}{\text{number of true J.P.} \neq 0}$	$\frac{\text{number of detected J.Options} \neq 0 \mid \text{true J.P.} \neq 0 \ \&/or\ J.V. \neq 0}{\text{number of true J.P.} \neq 0 \ \&/or\ J.V. \neq 0}$

When *m* prices a day are simulated, the estimated size $\hat{\alpha}_m$ is converted to the equivalent daily figure $\hat{\alpha}$ given by: $(1-\hat{\alpha}_m)^m = 1-\hat{\alpha}$. All these definitions are identical for simulated underlying asset prices and options prices.

3.1 Affine Stochastic Processes

The general form of the simulated affine stochastic processes for the logarithms of prices is as follows:

$$dp = (r + \gamma - 0.5V)dt + \sqrt{V}dW + J^p dN^p - \lambda^p \bar{\mu}^p dt, \tag{10}$$

$$dV = \kappa(\theta - V)dt + \xi\sqrt{V}dZ + J^V dN^V \tag{11}$$

with correlation ρ between the Wiener processes W_t and Z_t. The two jump processes, N_t^p and N_t^V, are Poisson processes which are independent of the Wiener processes. The four constants in (10) are the risk-free rate r, the equity risk premium γ, the price jump intensity λ^p and the drift compensator $\bar{\mu}^p = E\left[\exp\left(J_t^p\right) - 1\right]$ for which $\sum_{s \le t} \exp\left(J_s^p\right) - 1 - \lambda^p \bar{\mu}^p t$ is a martingale process.

We consider seven special cases:

1. Geometric Brownian motion, when V_t is constant and the jump components are removed.
2. The jump-diffusion model of Merton (1976), for which V_t is again constant.
3. The stochastic volatility model of Heston (1993), defined by removing both jump components. The variance V_t of this SV model mean-reverts towards the level θ at a rate determined by$k$.
4. The SVJP model which includes jumps in prices alone, as in Bates (1996). The jumps are normally distributed, with mean μ and varianceσ^2.
5. The SVJV model which has jumps in volatility alone. These jumps follow a Poisson process with intensity λ^V and their sizes are exponentially distributed with meanμ^V. This model, like Cases 6 and 7, is a special case of a general specification in Duffie, Pan, and Singleton (2000).
6. The SVIJ model containing independent jump processes, with intensities and jump size distributions as for Cases 4 and 5.
7. The SVCJ model having contemporaneous jumps in price and volatility, so$N_t^p = N_t^{\mathrm{V}}$. The volatility jump properties remain as for Cases 5 and 6, but the conditional means of the price jumps are now a linear function of the volatility jumps; the conditional distributions are defined by$J_t^p \,|\, J_t^V \sim N(\mu + \beta J_t^V, \sigma^2)$. The drift compensator is$\bar{\mu}^p = \exp(\mu + 0.5\sigma^2) - 1$ for Cases 4 and 6, and it equals $\bar{\mu}^p = (\exp(\mu + 0.5\sigma^2) - 1)/(1 - \beta\mu^V)$ for Case 7.

3.2 Risk-Neutral Affine Processes

The simulated prices of options are obtained by assuming the risk-neutral dynamics of the underlying asset have the same affine structure as the real-world processes defined above. As in Broadie, Chernov, and Johannes (2007), four risk premia terms are created by changing the real-world parameters $\mu, \sigma, \mu^V, \kappa$ to risk-neutral parameters$\tilde{\mu}, \tilde{\sigma}, \tilde{\mu}^V, \tilde{\kappa}$. The differences$\mu - \tilde{\mu}$, $\tilde{\sigma} - \sigma$,$\tilde{\mu}^V - \mu^V$,$\tilde{\kappa} - \kappa$ are respectively labelled the risk premia for the mean price jump, the volatility of price jumps, the mean volatility jump and the diffusive volatility. The first two differences together are referred as price jump risk premia. All the remaining parameters, namelyθ, ξ,ρ,λ^P,λ^V andβ, are identical for the real-world and risk-neutral simulations. The jump timing risk is not considered, under assumptions also made by Pan (2002) and Broadie, Chernov, and Johannes (2007).

Exact options prices can be obtained by inverting characteristic functions.We use Duffie, Pan, and Singleton (2000) asset pricing formula to calculate options prices.

3.3 Results

This section verifies that it is reasonable to applythe ABD jump detection test on index and options pricesafter the following stochastic processes. The ABD test is usually effective, and it iscapable of detecting jumps if the true price processes follow these theoretical models.

In all of the simulations, we consider that m=144;for a trading day of 504 min,this value corresponds to the calculation of returns every 3.5 min.

3.3.1 Geometric Brownian motion model

The effective sizesobtained from a Monte Carlo study of the geometric Brownian motion modelfor200,000 simulation days are listed in Table 4. When theannualvolatility σ is set to 10%, 14%, and 22%,different levels for low volatility, full sample, and high volatility periods, respectively, as shown by the estimated values listed in Table 9, the daily effective sizes ofthe options returns are approximately 0.03% and 0.006% at the 0.01% and 0.001% jump test levels, respectively. The effective sizes of futures are low, but slightly larger than the nominal significance levels of the ABD jump test. This is consistent with the estimates made by Andersen, Bollerslev, and Dobrev (2007). The effective size of the call option does not increase when the diffusion term of the call return increases and the call prices become more volatile.Specifically, the effective sizedoes not increase for more volatile, out-of-the-money options prices. Regarding the effective size, the ABD test offersa good performance across periods.

3.3.2 Stochastic volatility model

This section presents a discussion on the simulation of the affine jump-diffusion models. The parameters considered in the simulationare shown in panel A of Table 9. Panel Aof Table 5presents the effective sizes of the SV model for the index and for options across various moneyness levels. All the effective sizes in the full sample period are slightly greater than those for constant volatility (Table 4), which remain within acceptable levels.

In panel B of Table 5, the effective sizes for the SVJP model are shown to be often less than the set significance levels. The effective powers of the index tests and options tests are low and almost identical, implying that only a small fraction of the jumps were identified.[2]In addition, the number of correctly asserted jumps in the index is nearly equal to the number of detected jumps in the options.

Panel C of Table5 shows the performance of the ABD test for the SVJV model. The effective sizes of the options and futures obtained from the tests are higher than those presented in the other tables. However, the test has a low effective power. The out-of-the-money options are sensitive to jumps in volatility, and their effective power is relatively high.

A comparison ofpanel A of Table 6 with panel D of Table 5 shows that the ABD jump test performs slightly better for the SVCJ model compared with the performanceof the SVIJ model. The contemporaneous jumps magnify spikes in futures returns, and increase the magnitudes of options returns. Therefore, the ABD test can detect contemporaneous jumps. The effective sizes of the two models are typically less than the assumed levels.

4 Data

This section provides an explanation into how the optimal sampling frequency is determined and how data descriptive statistics are provided.

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[2]Theeffective power of the test is such that the test detects approximately 0.8% of the index jump at the 0.001% level. Because λ=2,300, one simulated jump is detected every 14 days, which is similar to the frequency reported by Andersen, Bollerslev, and Dobrev (2007).

4.1 The Sampling-Frequency of Data

The data consists of FTSE 100 high-frequency option observations and futures prices and are collected from Euronext. The maturity date of options is the third Friday of the month. The maturity date of futures is the third Friday of each quarter. The trading hours of options are from 8:00to 16:30, while for futures they are from 8:00 to 17:30. For reasons given latter, our sampling hour is from 8:06 to 16:30 and the sampling period is from January 4, 2005 to December 31, 2009, a total of 1,262 trading days.

Three time series of options prices are studied: 1) Matm- At-the-money options prices with amonthly cycle of expiration dates, 2) Motm- out-of-the-money options prices with a monthly cycle of expiration dates, 3) Qatm- At-the-money options prices with a quarterly cycle of expiration date. At-the-money is defined by a daily fixed strike price which is the closest to the daily mid-index range. The option expiry date is changed at 5 trading days to maturity.

The days without ask and bid prices or with missing data are deleted. Generally, a longer maturity option has lower liquidity.[3] The options with quarterly changed expiration have more missing data than the options with monthly changed expiration. There are more violations of put-call parity in the out-of-the-money options prices. The data with seriousviolations[4] are deleted. For example, the call prices are highly volatile within one hour around the July 7, 2005 London bombings event. For each series of options prices, there are 808 daily samples available, as shown in Table 1. The sample period is divided into the lowvolatility period from Jan. 2005 to Jun. 2007 and the high volatility period from Jul. 2007 to Dec. 2009. There are 369 and 439 sample days in the low and high volatility periods, respectively.

To choose the sample period and frequency, we take into account the following aspects:

[3]The liquidity of options does not always increase with closeness to maturity. For example, when the closest-to-maturity options expire within a few days, investors may switch to invest in other maturity options.
[4] A serious violation of put-call parity is defined as an unusual spike in the prices of calls or puts, larger than one-third of the daily call or put price range.

1. To obtain more information, it is better to extract the data from as wide a period of trading time as possible.
2. The futures and options prices should be extracted from the same period of time.
3. In option data, we avoid time intervals which end at specific times, especially 13:30 and 15:00. As this technique reduces noise and realized variance, we can more accurately detect jumps.

After considering the above principles, we extract all the data during the intraday period between 8:06 and 16:30, a total of 504 min. To illustrate why we avoid at 13:30 and 15:00, Figure 1A presents the monthly out-of-the-money options prices with 0.25-min frequency on January 13, 2006. It is obvious that the spikes in put prices at 13:30 and 15:00 violate put-call parity. Figure 1D shows the options prices with 5-min frequency from 8:10 to 16:30 and shows that the spikes are then selected. In contrast, Figure 1C presents the options prices with 3.5-min frequency with a sample period from 8:06 to 16:30. No time interval with the 3.5-min frequency ends at exactly 13:30 or 15:00 and there are no spikes shown. After using a 3.5-min frequency instead of 5-min frequency, we can reduce the number of unsatisfactorydays containing unusual price spikes within the selected data from fifty-four to fifteen out of the 808 sample days.

Figure 2 illustrates the relationship between frequency and mean realized variance.[5] The steps of the first three frequencies – 0.25-, 0.5-, and 1-min – include 13:30 and 15:00, while the steps of the other frequencies are not at these specific times. The mean realized variances across various frequencies are used to find the best trade-off point that maximises the benefit from obtaining additional information through more frequent sampling and minimises the costs of microstructure noise and bid-ask bounce effects. As frequency decreases, the meanrealized variance of calls and puts decreases and converges to a stable value generally at a 3.5-min frequency. The mean realized variancesof calls and puts with 3.5-min frequency during the period between 8:06 and 18:30 are 0.0964 and 0.0797, which are less than their counterparties during the period between 8:10 and 16:30(see Figure 3A): 0.1174 and 0.0872 of call and put with 2-min frequency, 0.1118 and 0.0868 of call and put with 5-min frequency,

[5] The mean realized variance is defined as $\frac{1}{T}\sum_{d=1}^{T}\sum_{j=1}^{m} r_{d,j}^{2}$ when m intraday returns $r_{d,j}$are available for each of the Tdays.

respectively. This suggests that a 3.5-min frequency is optimal. As Figure 2D shows, the futures mean realized variances are almost the same across frequencies.

Figure 4 shows and defines the 3.5-min frequency variance proportions of futures and optionsprices. The timings of spikes are similar between futures and options prices. There are spikes at the beginning and end of the trading period and there are high values at 13:30 and 15:00. Dealers are more active at the beginning of the futures and option markets and the major peak at 13:30 reflects the announcement of the most important US macro news at 8:30 local time. Also the variance proportions are generally higher after the US markets open at 14:30. These results are consistent with the findings of Areal and Taylor (2002) for FTSE 100 futures returns. The peak at 15:00 may reflect the announcement of US macro news as well.[6] For instance, Gilbert, Kogan, Lochstoer, and Ozyildirim (2012) found that the U.S. Index ofLeading Economic Indicators announced at 10:00, corresponding to 15:00 local time, causes temporary and significant mispricing of the S&P 500 index and Treasury bonds.

4.2 Descriptive Statistics

The futures panel in Table 2 shows that the intraday returns $r_{d,j}$ have a fat-tail distribution, whose kurtosis is higher than for daily returnsr_d. The standardized daily return $z_d = (r_d - \bar{r})/\hat{\sigma}_d$ approximately follows a normal distribution, $N(0,1)$and where $\hat{\sigma}_d^2 = \sum_{j=1}^{m} r_{d,j}^2$ is the realized variance on day$d$. The kurtosis of $z_d$is less than that of daily returnsr_d.

The mean of daily futures volatility $\hat{\sigma}_d$ is 0.0088, corresponding to an annual volatility of 13.97%. Moreover, the daily volatility series has a fat right tail. Referring to the realized logarithmic standard deviation, $\log(\hat{\sigma}_d)$, the skewness is reduced to 0.34, compared to 1.57 for the realized volatility $\hat{\sigma}_d$. This is similar to the result of Andersen, Bollerslev, Diebold, and Ebens (2001).

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[6]Deleze and Hussain (2013) showed most of the U.S. macro announcements to be either at 13:30 or 15:00 Greenwich Mean Time.

In the call and put panels, it is shown that the distribution of z_d also is near to a normal distribution. The p-values for the Jarque and Bera test are 47%, $\geq 50\%$ and 6% for futures, calls and puts, respectively. Referring next to JBnormality test,[7]for $\log(\hat{\sigma}_d)$ the p-value for calls and puts are larger than those of $\hat{\sigma}_d$. In Table 3, the p-values of the test across futures and options for individual contracts are generally larger than 5%, which shows the distribution of the logarithm of realized volatility is generally near to a normal distribution.

4.3Empirical Results

To ensure that the evidence for the existence of jumps is highly probable, we chose low daily significance levels (α) from 1% to 0.001%. Table 7 shows that the number of detected jumps in futures almost doubles when the significance level is multiplied by 10. Moreover, the number of detected jumps in options is greater than that in futures, implying that factors other than jumps in price drive the jumps in options prices. Section 5.2.2 shows that this doubling of detected jumps occurs when index prices are simulated with stochastic volatility and jumps in price.

We divide the jumps into eight jump combinations.This classificationindicatesthetypes of price jumps occurringconcurrently. For example, the C jump combination consists ofonly the detected jumps in call prices. The CP jump combination contains only the contemporaneous detected jumps in call and put. The FC jump combination involvesonly the contemporaneous detected jumps in futures and call prices. The P+ and P– jump combinationsconsistsof the detected positive and negativejumpsin put prices, respectively.The number of positive detected put jumps increases with the volatility jump size.The FCP jump combination represents the contemporaneous detected jumps in futures, calland put prices. The most common combination is FCP, which accounts for 25% of the combinations. This percentage increaseswiththe impact of the jumps in price. The percentages of C, Pand CP jump

[7] The Jarque and Bera test statistic is$JB = \frac{N}{6}\left[\hat{S}^2 + \frac{(\hat{k}-3)^2}{4}\right]$, where $N$is the sample size, $\hat{S}$is the sample skewness, and $\hat{k}$ is the sample kurtosis. The null hypothesis that a series has a normal distribution is rejected if the p-value of theJB statistic is less than the significance level. When the null is true, the asymptotic distribution of $JB$is$\chi^2(2)$.

combinations are approximately 22%, 25%and 11%, respectively. These percentages increases with the impact of the jumps in volatility, as shown in Sections 5.2.2 and 5.2.3.

Panel Bof Table 7 shows the direction of jumps for the CP and FCP jump combinations. In almost all cases, the directions of call jumps and put jumps are different, implying that the impact of jumps in price dominated over that of jumps in volatility, or that there is no jump in volatility. In the CP jump combinations, less than 1% of cases are ones in which call jumps and put jumpsoccurr contemporaneouslyand in the same direction. In the example shown in Figure 5A, the detected call jump and put jump are both negative at the 0.1% significance level at 14:52 on September 15, 2006. Although these changes inthe call and put prices occurin the same direction, they may result from a data problem. For instance, an unreasonable ask or bidprice leads to a large price change, followed by an almost equivalent opposite price change within a short period. Therefore, this evidence is neithersufficiently strong nor sufficiently sound to show the existence of an independent jump in volatility.

We consider three extensions to confirm the robustness of our results. We consider at-the-money options with monthly and quarterly maturities as well as 5-min frequency data. The sample period is divided into low- and high-volatility periods. Table 8shows the empirical results for the detected jumps for these extensions. The numbers of detected jumps for the out-of-the-money option are larger than those for at-the-money options, as shown in panels A1 and A2. This implies that the out-of-the-money option is more sensitive to the impact of events or news announcements. When the at-the-money option and futures expire quarterly, only few detected call and put jumps are in the same direction.

Whenthe variance proportions differ in various periods, the detected jumps may differ by period.Compared with the low-volatility period, the high-volatility period has relatively high percentages of the CP and FCP jump combinations, and relatively lowpercentages of the C and P jump combinations.The percentages of P+ and FCP(－－+) are usually close to those of P– and FCP(++－). The number of detected jumps in futures nearly doubledwhen the significance level is multiplied by 10. These characteristics ofthe empirical results for the3.5-min frequency data are similar to those for the 5-min frequency data,and we typically detect more jumps for the 3.5-min frequency data.We simulate the model-based results with the 3.5-min frequency data, and this simulation is discussed in the following section.

For the FCP jump combinations, the directions of futures jumps and call jumps are always the same, whereas the directions of put jumps are always opposite to those of futures jumps. There are two possible explanations for this observation: First, jumps in the (underlying asset) price exists, whereas jumps in volatility does not.Another explanation is that jumps in price and in volatility occurrconcurrently, and the impact of jumps in price on options dominats over that of jumps in volatility. The results for the CP and FCP jump combinations do not strongly support the existence of jumps in volatility.

5 Model-Based Results

The results obtained from the empirical data show no evidence for the existence of independent volatility jumps. Afterward, we attempt to recreate the observed jump statistics by using possible theoretical models. The main purpose is to examinewhether the observed patterns can be explained by contemporaneous jumps in price and volatility or simply by jumps in price.

An ABD test is conducted to detect jumps in theoretical futures and options pricesobtained from simulated affine jump-diffusion models. Section 5.1 provides an explanation into the selected parameters of the different models. Section 5.2 presentsadditional information gleaned from a comparison between the empirical results and the model-based results.

5.1 Parameter Selection for Models

Previous researchers have used various econometric methods to estimate the parameters of affine jump-diffusion models. Eraker, Johannes,and Polson (2003) performed likelihood-based estimation with Markov chain Monte Carlo methods.[8]CGGT (2003) used an efficient

[8]From the detected jumps, we extract information on the range of jump combinations. It is computationally difficult to apply these methods to obtain a reasonable range of jump combinations.

method of moments. Pan (2002) used an implied-state generalised method of moments. Broadie, Chernov,and Johannes (2007) minimisedthe differences between model-based and market-based implied volatility. In this study, we aim to minimise the differences between empirical results and model-based results for the detected jump numbers and the percentages of jump combinations. A deep out-of-the-money option is used to isolate the jump risk and to estimate the parameters of the affine jump-diffusion stochastic volatility models by Bates (2000), Pan (2002) and Eraker (2004). For high liquidity and similarity of empirical results with other sets of options, we focuss on the results for the out-of-the-money option with monthly expiration. Therefore, in the simulations, we allow the expiration time to decrease repeatedly from 25 to 6 trading days.[9]

Table 9 lists the values of the estimated and selected parametersfor different periods. The parameters $V_0, \tilde{k}, \theta,$ and $\xi$are the medians of monthly estimated parametersby minimising the squared errors between the theoretical prices by Duffie, Pan, and Singleton (2000)and the 7-min frequency out-of-money option prices during the period between 8:06 and 16:30.Our estimated parameters are relatively close to those obtained by Pan (2002), as shown inpanel B of Table 9.

Panel A lists the values of parameters used to simulate the model-based results presented in Tables 10–13. Our annual equity risk premium is set to approximately6%, 12% and 18%over periods, similar to the study by Pan(2002).[10] The diffusive volatility annualised risk premium$\eta_v = \tilde{k} - k$is set as -0.25, similar to the value set in the estimation by Chernov and Ghysels (2000). In the SVCJ model forthe full sample period, k and $\tilde{k}$ are 7.25 and 7, respectively;these values corresponds to half-life values of 24.1(=$252 \times \ln(2)/k$) and 25 trading days, respectively. The initial variance levels (V_0)are 0.01, 0.02and 0.05, corresponding to 10%, 14% and 22% annual volatility for the different periods. The daily initial futures are set as S_0=5475. The riskrate is the three-month Euro interest rate, which is

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[9] Following Dumas, Fleming, and Whaley (1998), we exclude options with a maturity time of less than 6 days. Because the time premium of options with short maturity is relatively small, options prices are sensitive to non-synchronous options prices and other measurement errors.

[10] Our estimatedprice jump risk premium is similar to thatby Pan(2002), in whose study the jump risk premiumranged from approximately 13% to 21%, as the volatilities ranged from approximately 10% to 22%. Broadie, Chernov, and Johannes (2007) usedthe S&P 500 futures options from 1987 to 2003. They estimated the SVJ mean price jump risk premiumto be in the approximate range of 3% to 6%, and the SVCJ mean price jump risk premiumto range from 2% to 4%.

approximately 0.5% to 5.3% during the sample period. Consequently, we set the risk-freerate as *r*=3%.

The jump-related parameters are selected to fit the ideal simulation results for the jump combination. In our simulation involving the SVCJ model, to ensure thatthe percentages of P+ and FCP(－－+) are close to those of P– and FCP(++－), we set$\rho$to be equal to -0.01, which is different from the value used in the estimations of Eraker (2004) (-0.46) and Pan (2002) (approximately -0.5). The regression slope between jump sizes, β, is approximately -0.06, similar to the value obtained byEraker (2004) and Eraker, Johannes, and Polson (2003). The standard deviations of the price jump sizes, σ, and the mean of the volatility jump size, μ^V, in our simulation are smaller than our estimations as well as the values obtained by Pan(2002), Eraker,Johannes, and Polson (2003), CGGT (2003), Eraker (2004) and Wang (2009). The annual jumpintensity in our simulation ranges from 2,000 to 3,000, which is apparently larger than that estimated in previous studies.

5.2 Model Results

For this section, we compare the model-based results with empirical results, and discuss information on jumps in price, jumps in volatility, and related risk premia.

5.2.1 Stochastic volatility

In this model, there is no jump component in the return and variance processes. Panel Aof Table 10 shows that the ABD test falsely claimedapproximately 12 futures and 13 options jumps every 808 days at the 1% daily significance level. The directions of all the call jumps and put jumps in the FCP jump combinationdiffer, but the small number of jumps observed eliminats this model as a candidate model that describes futures observations satisfactorily.

5.2.2 Stochastic volatility with jump in price

In this model, there are jump components only in the return process. In panel B3 of Table 10, there is no price risk premium. The number of detected jumps in options is less than that observed empirically. The percentages of F, FC, and FP jump combinations are relatively high. As expected, whenonly prices can jump, in most cases, jumps in futures and in options occur concurrently. The percentage of CP jump combinations is close to zero, which is not the case for the empirical results. The percentages of C and P jump combinations arelow. In a few cases, the observed jumps in options do not occur contemporaneouslywith jumps in futures.

If the average magnitudes of risk-neutral price jumps are larger than those of real-world price jumps,accordingly, the CP(+ −) and CP(− +) jump combinationsare expected to be large.Panel B2 of Table 10shows that,if we consider the price jump risk premia ($\mu - \tilde{\mu} > 0$and$\tilde{\sigma} - \sigma > 0$), the percentages of C, P, and CP jump combinations increase to a relatively reasonable level, suggesting that jumps in price and price jump risk premia are critical for explaining the range of jump combinations. However, the percentage of F jump combinationsis lower than that obtained from the empirical results, whereas the percentage of FCP jump combination is higher than that obtained from the empirical results.

By considering Pan's parameter estimates, we attempt to determine the parameter estimates that canyield the observed results. Panel B4 shows the simulation results for the parameters estimated by Pan (2002). The jump intensity may clearly have been underestimated, because the numbers of detected jumps are noticeably low. In addition, the jump size forprice may have been overestimated, because the percentage of the FCP jump combination is high, and the number of detected jumps does not doublewhen the significance level is multiplied by 10. This relationshipis further illustratedin Case 3 of Table 13.

5.2.3 Stochastic volatility with jumps in volatility

In this model, there are jump components only in the variance process, and therefore, all jumps should be observed in the options prices. Inpanel A3 of Table 11, the volatility jump risk premium is not considered. As expected, the results reveal that the numbers of detected jumps in options are substantially greater than those in futures. The directions of both call jumps and put jumps are positive in the CP combinations,and the percentage of P+ jump combinations isapparently higher than that of P– jump combinations.These results reflect theexistence of only positive jumps in volatility in the model,and therefore,this model isclearly not viable for the period we consider.

If there existsthe volatility risk premium, the average magnitudes of risk-neutral volatility jumps are larger than those of real-world volatility jumps. In our simulation, the volatility risk premium is small. Panel A2 of Table 11 shows the results obtained by considering the jump volatility risk premium;specifically, the number of put options jumps is shown to have increased slightly. Overall, the relatively large percentages of P+ and CP(++) jump combinations observed eliminate this modelas a possible model.

5.2.4 Stochastic volatility with independent jumps in price and in volatility

Similar to the case of the model considering only volatility jumps, we do not expect this model to explain the empirical results,becauseindependent jumps imply that thejumps in the call and put prices occur in the same direction.In panel B2 of Table 11, the percentages of P and F jump combinations are less than those obtained from the empirical results, whereas the percentage of FCP jump combinationsis higher than that determined from the empirical results. This observation suggests that jumps in price and in volatility do not occur independently.

5.2.5 Stochastic volatility with contemporaneous jumps in price and in volatility

We begin by considering ourestimatedparametersinpanel B of Table 9,and then attempt to obtainthesimulation results by usingthe parameters estimated from the affine jump-diffusion models by Duffie, Pan,and Singleton (2000).Panel A6 of Table 12 shows the simulation results obtained usingour estimated parameters.The numbers of detected jumps areapparently low,indicating that the jump intensity may have been underestimated. Moreover, the mean jump size of volatility may have been overestimated, because the directions of call jumps and put jumps are nearly identical in the CP jump combinations. In the empirical results, this similarity in directions is rarely observed, if at all. Finally, unlike the empirical results, the number of detected jumps in futures does not doublewhen the significance level is multiplied by 10.

Panel A5 of Table 12 shows the model results with no price jump premium and no volatility jump risk premium. The number of jumps in futures is close to that determined from the empirical results, whereas that of jumps in options is not as high as that obtained from the empirical results.The increaseinthe jump sizes of volatility in real- and risk-neutral worlds leads toan increase in the number of positive detected put jumpsand a decrease in the number of detected call jumps, and therefore, this model is not viable (see Case 5 of Table 13).

To obtain the results shown in panel A4 of Table 12, only the volatility jump risk premium is considered, andthe results are similar to the panel A5 results (which are obtained without considering any premium).An increase in volatility jump risk premium leads to relatively high percentages of P+ and CP++;therefore, this model is not viable (see Case 8 of Table 13). In A3, when the price jump risk premium is considered, the number of CP(+−) and CP(−+) jump combinations increases, and the number of CP, FC, and FP jump combinations reaches reasonable levels. Compared with panel A4, the number of options jumps and the range of jump combinations are relatively reasonable in panel A3, suggesting that the price jump risk premium is a more critical factorcompared with the volatility jump risk premium.

Finally, panel A2 of Table 12 shows the results obtainedwhen both price jump risk premium and volatility jump risk premium are considered. This model provides more reasonable results compared with SVJV and SVIJ, suggesting that jumps in price and price jump premiumare both critical factors, and that jumps in price and in volatility donot occur independently. The number of expected jumps per yearexceeds 2,000 in our sample periods, which is higher than the value of 1.7, asestimated byCGGT (2003), and our estimation of 0.38 (see panel B of Table 9). Our selected price jump sizes exhibitsa normal distribution, with a mean of -1.1e-4 and a standard deviation of 15.2e-4 for the full sample period. The average price jump size is smaller than those of CGGT (2003) and our estimations. The selected average volatility jump (i.e. 0.04e-4)is smaller than that of CGGT (i.e. 181e-4; 2003) and our estimations. The selected annual price jump risk premium is11.4%, which is close to that by Pan(2002).

5.3 SVCJ Model Results with Estimated Parameters

This section shows the relationship between a change in the selected parameters and a change in the number of jump combinations.Panel A2 of Table 13 shows the SVCJ model results for the simulation parameters presented in panel A of Table 9. We change one or two selected parameters,and observe the jump combinations in Cases1–8.

Case 1: A decrease inthe correlation ρ between Weiner processes leads to an increase inthe number of positive detected call jumps and a decrease inthe number of detected put jumps.

Case 2: A decrease inthe mean price jump in the real and risk-neutral worldsleads toa larger number of negative detected jumps in futures, negative detected call jumps, and positive detected put jumps.

Case 3: This casedemonstrates the results of an increase inthe standard deviation of jumps, σ, inthe real and risk-neutral worlds.A large price jump leads toa high percentageof FCP jump combinations.The number of detected jumps does not doublewhen the significance level is multiplied by 10.

Case 4: This case shows the result of a decrease inthecorrelation between volatility jumps and price jumps, β .The percentages of P+ and FCP(－－+) jump combinations increaseslightly.

Case 5: An increase in volatility jump size in the real- and risk-neutral worlds results in more positive detected put jumps and fewer detected futures jumps and call jumps. The percentages of P+ and FCP(－－+) jump combinations are higher than those of P– and FCP(++－).

Case 6: A decrease inthemean risk-neutral price jump leads to more positive detected put jumps. Unlikein Case 2, in this case, the number of detected futures jumps is unchanged, and the number of detected options jumps decreases.

Case 7: An increase inthe risk-neutral standard deviation of price jumps leads to an increase in price jump size in the risk-neutral world. The number of detected optionsjumps increases,and the percentages of CP+－ and CP–+ jump combinations increase markedly, with a small difference between the percentages of the two combinations.

Case 8: An increase in risk-neutral volatility jumps, or in the volatility jump risk premium, leads to an increase inpositivedetected options jumps; the percentages of C+, P+, and CP++ jump combinations increase.

In brief, the percentage of P+ jump combinations is greater than that of P–jump combinations in Cases2, 4, 5, 6and 8,because the risk-neutral return of futures is fatter in the left tail. The percentages of the P+ and P– jump combinations determined from the empirical results are similar. Furthermore,Cases 6 and 7 are related to the price jump risk premium, and Case 8 is related to the volatility jump risk premium.

6 Conclusions

We develope a novel methodfor identifying the presence of volatility jumps; that is, by detecting jumps in options prices. Intuitively, if there are volatility jumps, and there is no contemporaneous price jump, then the call and put options pricesshowing jumps in the same direction should be observed. Our empirical results donot provide any evidence for volatility jumps, and we barely detectedany jumps of the same sign in options prices, almost ruling out the idea of independent volatility jumps.

However, volatility jumps may have occurred contemporaneously with underlying asset jumps. To test this possibility, we consider models involving only price jumps (SVJP) and thoseinvolving contemporaneous price and volatility jumps (SVCJ). The SVCJ model results revealthat jumps in price and the price jump risk premium provide a reasonable explanation of the observed jump patterns. Moreover, the SVCJ model results are superior to the SVIJ model results,suggestingthat jumps in price and in volatility donot occur independently. This is consistent with the results obtained by Todorov and Tauchen (2010) and Duffie, Pan,and Singleton (2000). However, our results reveal that the standard deviations of the price jump size and mean volatility jump size were far smaller than those obtained in previous studies(Eraker, Johannes, and Polson, 2003; CGGT, 2003; Eraker, 2004).[11] Weshow that the

[11]Eraker, Johannes, and Polson (2003) adopted S&P 500 index and Nasdaq 100 index from 1980 to 1999; CGGT (2003) used Dow Jones industrial average (DJIA) index from 1953 to 1999; Eraker (2004) used S&P 500 index from 1987 to 1996.

simulations performed with the parameters estimated from the affine jump-diffusion models by Duffie, Pan,and Singleton (2000) may not provide an explanation for jump combinations.

Finally, for our study, wedevelope an intuitive and transparent methodfor identifying jumps and risk premia.It links jump identification and parameter estimation by using widely used models. From the viewpoint of jumps, it shows the importance of jumps and risk premia.We find that the jump intensity is higher than that determined in previous studies (Eraker, Johannes, and Polson, 2003; CGGT, 2003; Eraker, 2004). Researchers have recently proposed novel pure-jump models (Carr and Wu, 2004; Cartea and Howison, 2009), which should be investigated in greater detail.

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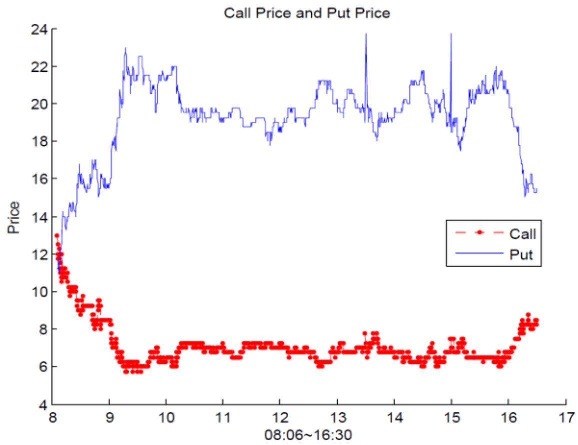
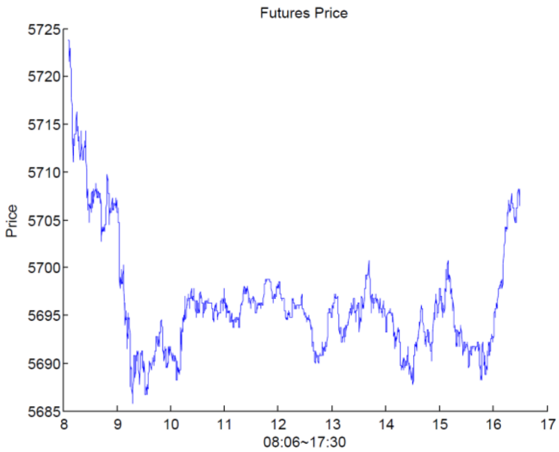
Figures

A. 0.25-min frequency



B. Futures 0.25-min frequency



C. 3.5-min frequency

D. 5-min frequency

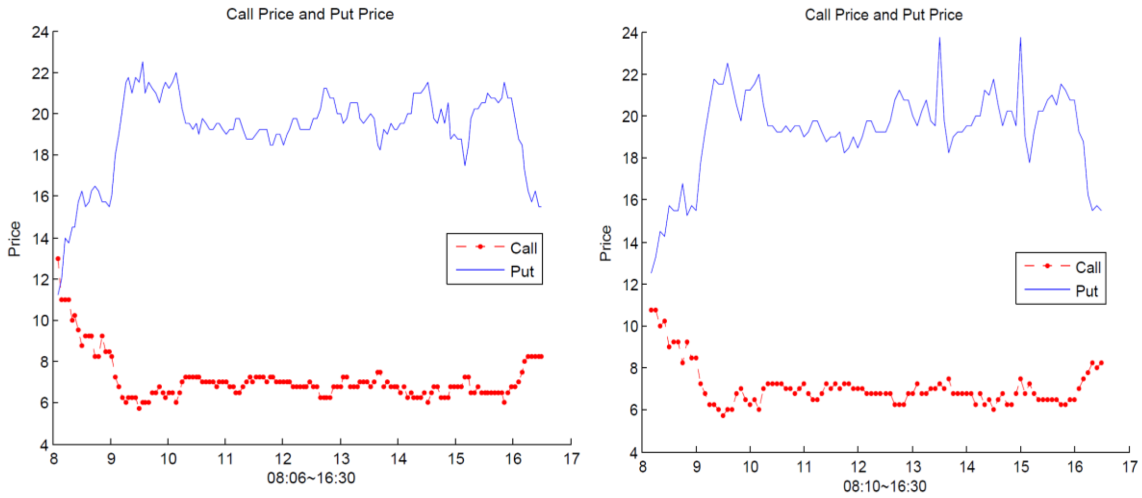


Figure 1 The Motmoptions prices on January 13, 2006

Motm: out-of-the-money calls (puts) with the strike price, which is ATM strike price plus (minus) 50, and monthly changed expiration date.

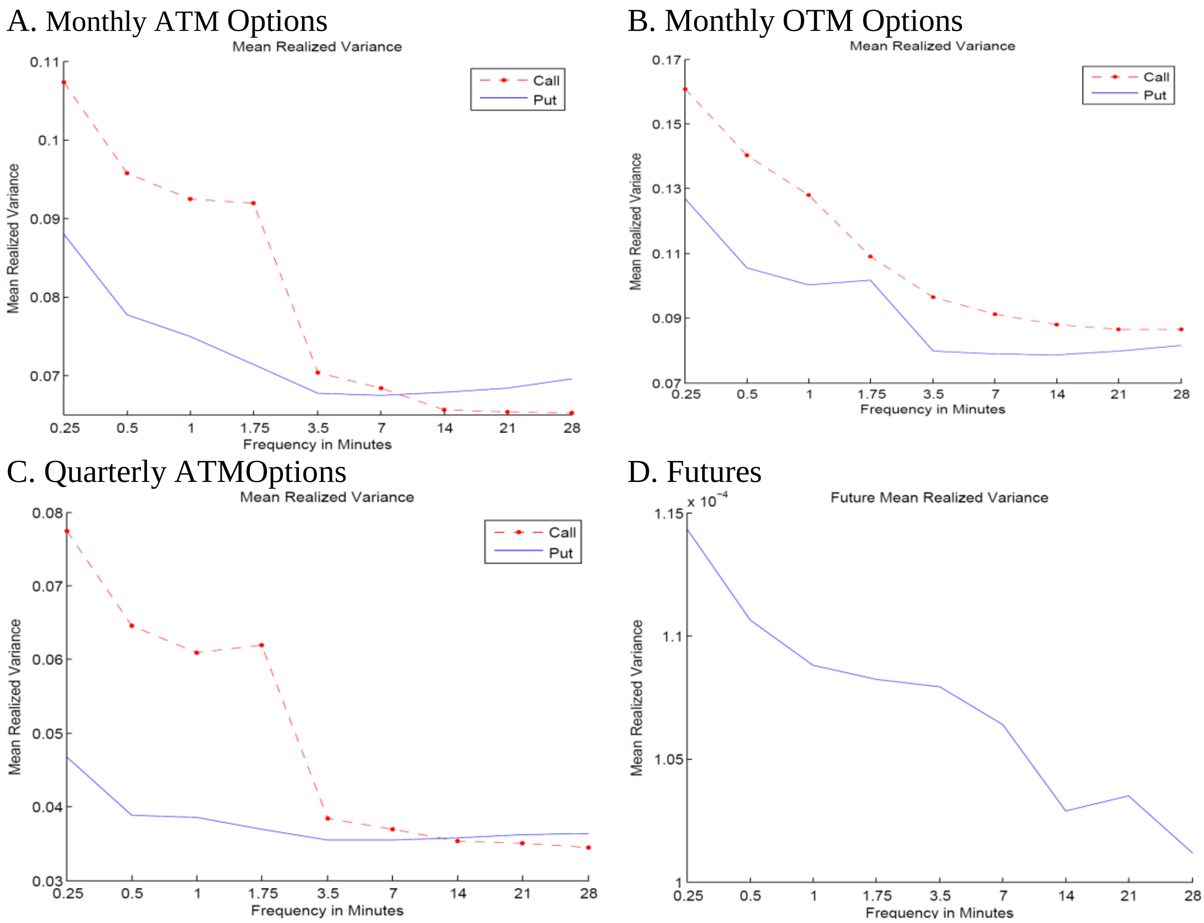


Figure 2 The mean realized variance during the period between 8:06 and 16:30

Motm: out-of-the-money calls (puts) with the strike price, which is ATM strike price plus (minus) 50.The options prices in Panels A and B are with monthly changed expiration date and in Panel Care with quarterly changed expiration date.The dot-dashed line denotes the mean realized variance of call prices. The solid denotes the mean realized variance of put or futures prices.

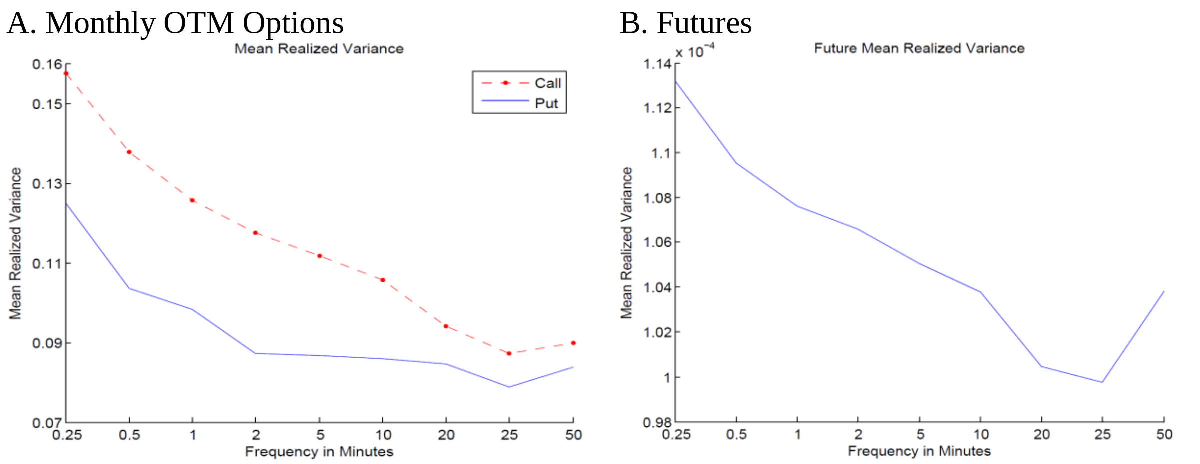
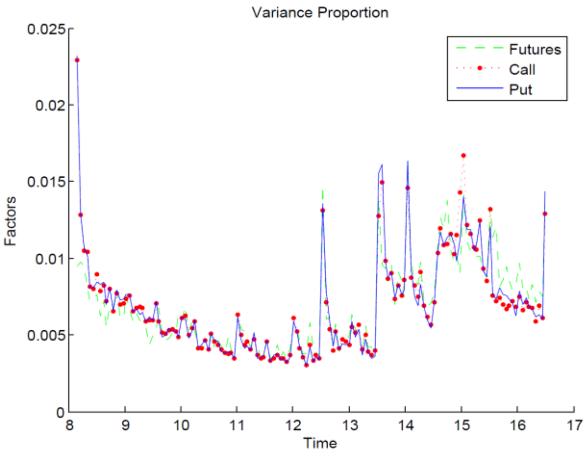


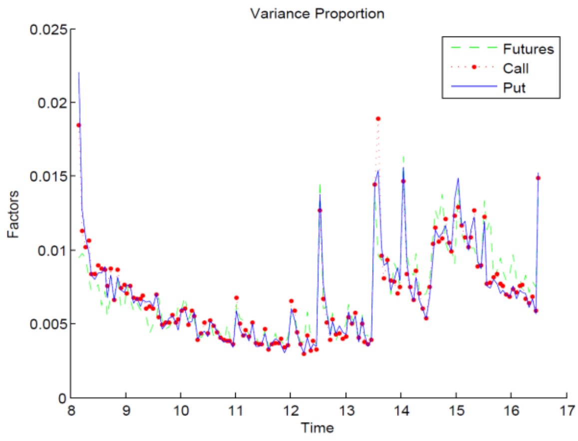
Figure 3 The mean realized variance during the periodbetween 8:10 and 16:30

The options prices are out-of-the-money calls (puts) with the strike price, which is ATM strike price plus (minus) 50, and with monthly changed expiration date. The dot-dashed line denotes the mean realized variance of call prices. The solid denotes the mean realized variance of put or futures prices.

A. Monthly ATM



B. Monthly OTM



C. Quarterly ATM

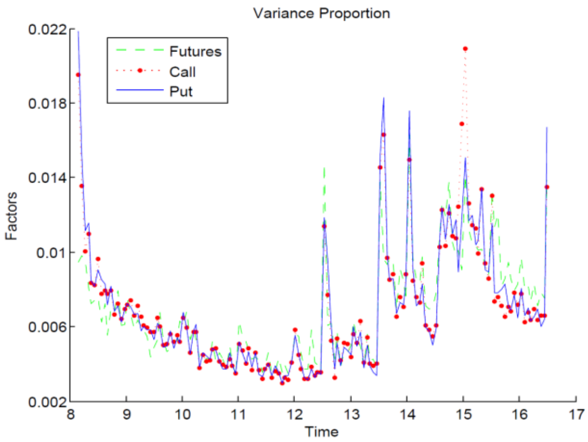


Figure 4 The variance proportions of 3.5-min frequency data during the period between 8:06 and 16:30

The variance proportion f_j at the j-th intraday period is defined by Taylor and Xu (1997) and calculated from intraday returns $r_{d,j}$ as: $f_j = \frac{\sum_{d=1}^{T} r_{d,j}^2}{\sum_{d=1}^{T}\sum_{j=1}^{m} r_{d,j}^2}$. The dashed line denotes the variance proportion of futures; the dot-dashed line denotes that of call prices; the solid denotes that of put prices.

A. B.

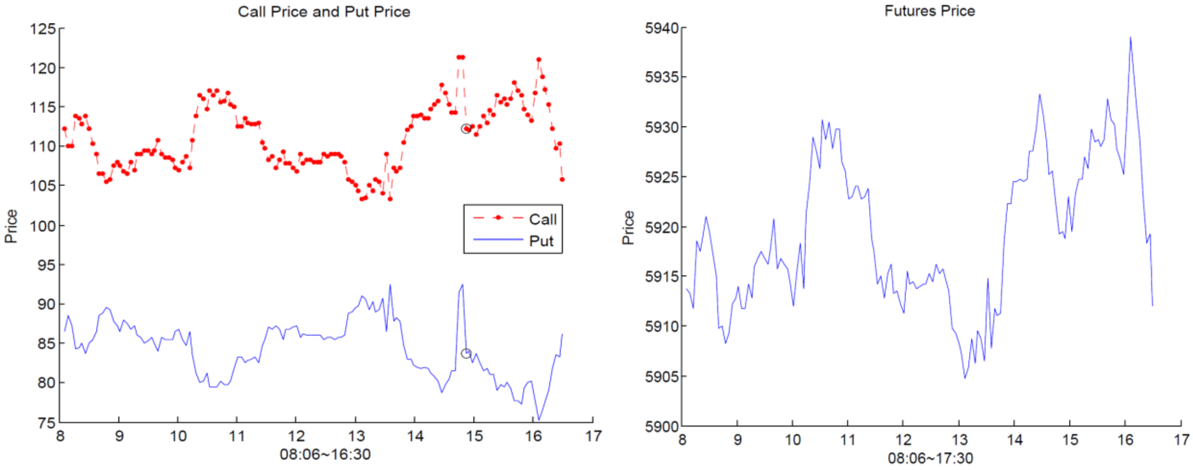


Figure 5 Futures and monthly at-the-money options prices with 3.5-min frequency on September 15, 2006

Note: In figure A, the small circle denotes the detected jump

Tables

Table 1 Days included in and excluded from samples

		Matm	Motm	Qatm	Futures
Original sample size	2005	243	243	243	251
	2006	154	154	154	252
	2007	238	238	238	253
	2008	225	225	225	253
	2009	247	247	247	253
Not enough ask and bid prices	2005	32	32	32	10
	2006	19	19	19	17
	2007	69	66	62	2
	2008	37	35	45	1
	2009	9	8	13	2
Violation of put-call parity or large price spike at beginning or end of day	2005	8	4	8	0
	2006	10	3	9	0
	2007	11	11	14	0
	2008	5	5	6	0
	2009	3	1	4	0
Sample days in full sample period			808		
Sample days in low volatility period			369		
Sample days in high volatility period			439		

Matm: at-the-money options prices monthly changes in expiration dates on the third Monday.

Motm: out-of-the-money calls (puts), with the strike price, equal to the ATM strike price plus (minus) 50, and monthly changes in expiration date.The calls (puts) is with aboutmoneyness,$K/S_0$of 1.01(0.99), at beginning of day.

Qatm: at-the-money option with quarterly changes in expiration date on the third Monday of the third month.

The unsatisfactory sample days include the days when there are missing data over twenty minutes, serious violations of put-call parity condition, and/or large price spikes at the beginning or end of the day in futures or options prices.

Table 2 The descriptive statistics of futures and monthly out-of-the-money options returns

Contract		Mean	Median	Std. Dev.	Kurtosis	Skew.	p-value
Futures	$r_{d,j}$	1.5E-06	0	0.0009	13.4752	-0.0715	≤0.10%
	r_d	0.0002	0.0004	0.0100	9.6519	0.2400	≤0.10%
	Z_d	0.0468	0.0638	0.9874	2.9305	-0.0977	47.12%
	$\hat{\sigma}_d$	0.0088	0.0069	0.0056	5.8006	1.5725	≤0.10%
	$\log(\hat{\sigma}_d)$	-4.9094	-4.9717	0.5745	2.3035	0.3442	≤0.10%
Call	$r_{d,j}$	-1.7E-04	0	0.0257	11.8632	-0.0593	≤0.10%
	r_d	-0.0235	-0.0091	0.3061	4.2628	-0.1845	≤0.10%
	Z_d	-0.0514	-0.0363	0.9705	2.8565	0.0325	≥50.00%
	$\hat{\sigma}_d$	0.2916	0.2669	0.1068	4.9449	1.2479	≤0.10%
	$\log(\hat{\sigma}_d)$	-1.2923	-1.3207	0.3416	2.8329	0.2848	0.63%
Put	$r_{d,j}$	-2.0E-04	0	0.0233	12.1799	0.0441	≤0.10%
	r_d	-0.0317	-0.0477	0.2952	4.2423	0.2142	≤0.10%
	Z_d	-0.1361	-0.1679	1.0346	2.8245	0.1906	6.38%
	$\hat{\sigma}_d$	0.2663	0.2470	0.0938	4.4386	1.1007	≤0.10%
	$\log(\hat{\sigma}_d)$	-1.3798	-1.3982	0.3335	2.6631	0.2359	0.73%

Table 3 The p-value of the JB normal test for the logarithm of each realized volatility across each quarter

$\log(\hat{\sigma}_d)$	05				06				07				08				09			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Futures	36	12	50	9	44	1	17	32	7	41	6	50	10	40	50	50	50	50	2	32
Calls	9	12	16	50	10	50	9	26	3	2	50	7	50	3	6	50	14	21	50	7
Puts	15	9	17	50	13	6	50	50	3	1	50	5	50	2	12	50	11	14	50	20

The unit is percentage. The $r_{d,j}$ denotes the 3.5-min frequency return series; r_d denotes daily return series; Z_d denotes daily standardized returns, $Z_d = (r_d - \bar{r})/\hat{\sigma}_d$; $\hat{\sigma}_d$ denotes realized volatility; $\log(\hat{\sigma}_d)$ denotes logarithm of realized volatility. The last column is the p-value of the JB normality test. The null hypothesis that a series has normal distribution is rejected if the p-value of the JB statistic is less than the significance level. The p-value of the JB statistic is in a range of [0.001, 0.5] in matlab jbtest code. When the p-value shows 50%, it means more than or equal to 50%.

Table 4 The effective size of the ABD test for the geometric Brownian motion model

	Det. jump in Index				Call					Put			
α(%)	1	.1	.01	.001	$\frac{S}{C}\frac{\partial C}{\partial S}$	1	.1	.01	.001	1	.1	.01	.001
K/S_0	e.s. (%)	e.s. (%)	e.s. (%)	e.s. (%)		e.s. (%)	e.s. (%)	e.s. (%)	e.s. (%)	e.s. (%)	e.s. (%)	e.s. (%)	e.s. (%)
A. full sample period													
	1.27	0.15	0.018	0.0025									
1.02					43	1.54	0.20	0.027	0.0055	1.64	0.23	0.032	0.0075
1					37	1.59	0.21	0.029	0.0055	1.60	0.22	0.033	0.0065
0.98					29	1.63	0.22	0.028	0.0055	1.57	0.21	0.030	0.0055
B. low volatility period													
	1.27	0.15	0.018	0.0025									
1.02					62	1.53	0.20	0.026	0.0060	1.64	0.23	0.032	0.0075
1					49	1.60	0.21	0.029	0.0055	1.60	0.22	0.033	0.0060
0.98					36	1.64	0.22	0.028	0.0060	1.55	0.20	0.029	0.0055
C. high volatility period													
	1.27	0.15	0.018	0.0025									
1.02					25	1.56	0.21	0.027	0.0055	1.63	0.23	0.032	0.0075
1					23	1.59	0.21	0.029	0.0055	1.61	0.22	0.032	0.0065
0.98					20	1.62	0.22	0.029	0.0050	1.58	0.21	0.032	0.0060

Note: Annual volatility is equal to 14%, 10%, and 22% in Panel A, B and C panels, respectively. Time to maturity repeatedly decreases from 25 to 6 days, total 200,000simulation days. There are 144 steps per day. $K$is the strike price. 'e.s.' denotes daily effective size.

Table 5 The effective size and effective power of the ABD test for the SV,SVJP, SVJV, and SVIJ models in full sample period

Price	α	1%		0.1%		0.01%		0.001%	
	Moneyness (K/S_0)	Eff. size	Eff. power	Eff. size	Eff. power	Eff. size	Eff. power	Eff. size	Eff. power
A. SVmodel									
Index		1.51	-	0.19	-	0.031	-	0.0055	-
	1.02	1.58	-	0.23	-	0.043	-	0.0150	-
Call	1	1.65	-	0.23	-	0.035	-	0.0040	-
	0.98	1.75	-	0.24	-	0.035	-	0.0050	-
	1.02	1.73	-	0.25	-	0.038	-	0.0095	-
Put	1	1.64	-	0.21	-	0.032	-	0.0065	-
	0.98	1.63	-	0.23	-	0.056	-	0.0195	-
B. SVJP model									
Index		0.63	4.32	0.07	2.36	0.012	1.36	0.0021	0.82
	1.02	0.70	3.83	0.08	2.08	0.013	1.18	0.0032	0.71
Call	1	0.71	4.17	0.08	2.29	0.011	1.32	0.0027	0.80
	0.98	0.76	4.34	0.08	2.40	0.012	1.39	0.0027	0.84
	1.02	0.76	4.03	0.10	2.20	0.014	1.26	0.0027	0.77
Put	1	0.74	3.69	0.09	1.99	0.014	1.13	0.0021	0.68
	0.98	0.76	3.20	0.09	1.69	0.013	0.95	0.0048	0.56
C. SVJV model									
Index		17.89	-	6.43	-	2.597	-	1.1524	-
	1.02	14.56	1.18	4.96	0.64	1.901	0.36	0.7884	0.22
Call	1	14.66	1.11	5.01	0.59	1.918	0.33	0.7980	0.20
	0.98	14.77	1.05	5.06	0.55	1.943	0.30	0.8064	0.18
	1.02	11.28	4.30	3.57	2.72	1.296	1.81	0.5185	1.25
Put	1	11.14	4.48	3.51	2.85	1.281	1.91	0.5122	1.33
	0.98	10.99	4.66	3.46	2.99	1.255	2.02	0.4984	1.40
D. SVIJ model									
Index		0.58	4.24	0.06	2.30	0.010	1.32	0.0011	0.78
	1.02	0.66	2.05	0.07	1.11	0.011	0.63	0.0017	0.38
Call	1	0.67	2.12	0.07	1.14	0.010	0.66	0.0011	0.39
	0.98	0.70	2.15	0.07	1.16	0.010	0.67	0.0017	0.40
	1.02	0.71	2.02	0.08	1.09	0.012	0.62	0.0011	0.37
Put	1	0.69	1.94	0.07	1.04	0.011	0.59	0.0006	0.35
	0.98	0.67	1.83	0.07	0.97	0.009	0.54	0.0006	0.32

Note: the unit is percentage. The simulation includes 200,000 days. 'Eff. size' denotes daily effective size. 'Eff. power' denotes effective power.

Table 6 The effective size and effective power of the ABD test for the SVCJ model

	α	1%		0.1%		0.01%		0.001%	
Price	Moneyness (K/S_0)	Eff. size	Eff. power	Eff. size	Eff. power	Eff. size	Eff. power	Eff. size	Eff. power
A. full sample period									
Index		0.60	4.88	0.06	2.78	0.011	1.65	0.0021	1.02
	1.02	0.69	4.23	0.10	2.34	0.022	1.37	0.0085	0.85
Call	1	0.72	4.60	0.09	2.59	0.010	1.54	0.0011	0.96
	0.98	0.76	4.81	0.09	2.74	0.010	1.64	0.0011	1.03
	1.02	0.72	4.72	0.08	2.68	0.016	1.60	0.0027	1.00
Put	1	0.70	4.45	0.08	2.50	0.012	1.48	0.0021	0.92
	0.98	0.71	4.01	0.09	2.22	0.017	1.28	0.0059	0.79
B. low volatility period									
Index		0.72	6.05	0.08	3.53	0.016	2.15	0.0042	1.36
	1.02	1.15	4.27	0.35	2.34	0.188	1.35	0.1320	0.83
Call	1	0.76	5.36	0.10	3.09	0.012	1.84	0.0011	1.15
	0.98	0.85	5.95	0.11	3.49	0.018	2.12	0.0037	1.35
	1.02	0.84	5.81	0.11	3.39	0.020	2.07	0.0053	1.31
Put	1	0.77	5.02	0.08	2.85	0.014	1.70	0.0021	1.05
	0.98	1.69	3.84	0.68	2.09	0.403	1.20	0.2833	0.72
C. high volatility period									
Index		0.51	3.16	0.06	1.69	0.006	0.97	0.0011	0.59
	1.02	0.62	3.04	0.07	1.62	0.010	0.93	0.0016	0.57
Call	1	0.64	3.10	0.07	1.67	0.011	0.95	0.0011	0.59
	0.98	0.66	3.14	0.07	1.69	0.012	0.97	0.0016	0.60
	1.02	0.65	3.10	0.08	1.67	0.010	0.95	0.0005	0.58
Put	1	0.64	3.05	0.08	1.63	0.008	0.93	0.0005	0.56
	0.98	0.62	2.97	0.08	1.58	0.008	0.90	0.0011	0.54

Note: the unit is percentage. The simulation includes 200,000 days. ‘Eff. size’ denotes daily effective size. ‘Eff. power’ denotes effective power.

Table 7 The jumps in futures and monthly out-of-the-money options prices

Panel A

α (%)	Numbers of Det. Jumps F	C	P	Numbers of Jump Combinations C	P +	P −	CP	F	FC	FP	FCP	Total # of JumpCombina-tions
1	307	431	423	144	70	73	74	65	35	28	178	667
0.1	150	217	228	74	41	41	36	21	19	22	88	342
0.01	79	128	127	47	22	24	21	10	9	9	51	193
0.001	45	65	90	22	21	19	15	6	4	11	24	122
				Percentages of Jump Combinations(%)								
1				22	10	11	11	10	5	4	27	
0.1				22	12	12	11	6	6	6	26	
0.01				24	11	12	11	5	5	5	26	
0.001				18	17	16	12	5	3	9	20	

Note: the first 4 rows show the numbers of detected jumps and the numbers of jump combinations across different significance levels. In the second column F denotes the numbers of detected jumps in futures. In the third column C denotes the number of detected jumps in call. The fifth column C denotes the numbers of detected jumps in call and no jumps in futures or put prices. The sixth column P+ denotes the numbers of positive detected jumps in put and no jumps in any other price. The seventh column P－ denotes the numbers of negative detected jumps in put and no jumps in any other price. The eighth column CP shows the numbers of the contemporaneous detected jumps in call and in put. The ninth column F denotes the numbers of detected jumps in futures and no jumps in any other price. The tenth column FC denotes the numbers of contemporaneous jumps in futures and call price. The eleventh column FP denotes the numbers of contemporaneous jumps in futures and put. The twelfth column FCP shows the numbers of contemporaneous jumps in futures, call and put prices. The 5th-8th rows show the percentages of jump combinations which are the numbers of specific jump combinations divided by total numbers of jump combinations.

Panel B The components of the CP and FCP jump combinations

α (%)	Numbers of Jump Combinations CP +−	CP −+	Sub-total	CP ++	CP −−	Sub-total	Numbers of Jump Combinations FCP ++−	FCP −−+	Others FCP	Total # J. Combina-tions
1	33	38	71	2	1	3	79	99	0	667
0.1	16	18	34	1	1	2	45	43	0	342
0.01	11	9	18	0	1	1	24	27	0	193
0.001	10	5	15	0	0	0	10	14	0	122
	Percentages of Jump Combinations						Percentages of Jump Combination s			
1	4.9	5.7	10.6	0.3	0.1	0.4	11.8	14.8	0	
0.1	4.7	5.3	9.9	0.3	0.3	0.6	13.2	12.6	0	
0.01	5.7	4.7	9.3	0.0	0.5	0.5	12.4	14.0	0	
0.001	8.2	4.1	12.3	0.0	0.0	0.0	8.2	11.5	0	

Note: the first four rows are the numbers of jump combination across different significance levels. The second four rows are the percentages of jump combinations which are the numbers of specific jump combinations divided by total numbers of jump combinations. In the second column CP(+－) denotes positive detected jumps in call but negative detected jumps in put. In the third column CP(－+) denotes negative detected jumps in call but positive detected jumps in put. The forth column shows the subtotals of CP(++) and CP(－+). In the fifth column CP(++) denotes positive detected jumps in call and positive detected jumps in put which occur at the same time. The seventh column shows the subtotal of CP(++) and CP(－－). The eighth column FCP(++－) denotes both positive detected jumps in futures and in call but negative detected jumps in put. The ninth column FCP(－－+) denotes both negative detected jumps in futures and in call but positive detected jumps in put.

Table 8 Theempirical results of the detected jumps in futures and options prices

α (%)	# of Det. Jumps per 808 days			Percentages of Jump Combinations								Percentages of Jump Combinations			
	F	C	P	C	P +	P —	CP	F	FC	FP	FCP	CP +—	CP —+	CP + +	CP — —
Panel A. Full sample period from 2005 to 2009															
A1. 3.5- min frequency futures and options prices with monthly out-of-the-money options prices															
1	306	431	423	22	10	11	11	10	5	4	27	4.9	5.7	0.3	0.1
0.1	150	217	228	22	12	12	11	6	6	6	26	4.7	5.3	0.3	0.3
0.01	79	128	127	24	11	12	11	5	5	5	26	5.7	4.7	0.0	0.5
0.001	45	65	90	18	17	16	12	5	3	9	20	8.2	4.1	0.0	0.0
A2. 3.5- min frequency futures and options prices with monthly at-the-money options prices															
1	306	402	392	18	8	8	13	10	5	5	33	5.8	7.0	0.2	0.3
0.1	150	192	194	15	13	6	14	11	6	3	32	7.0	5.9	0.3	0.3
0.01	79	112	112	17	9	8	16	8	3	4	35	6.4	9.6	0.0	0.0
0.001	45	71	70	18	8	9	19	4	6	5	31	9.3	9.3	0.0	0.0
A3. 3.5- min frequency futures and options prices with quarterly at-the-money options prices															
1	306	403	447	17	12	10	14	10	4	6	28	6.0	7.6	0.0	0.2
0.1	150	206	220	17	14	8	15	10	5	4	28	7.5	7.2	0.0	0.3
0.01	79	116	131	16	13	12	15	7	4	3	31	6.2	8.4	0.0	0.0
0.001	45	76	82	18	11	13	18	4	5	5	28	9.0	9.0	0.0	0.0
A3. 5- minfrequency futures and options prices with monthly out-of-the-money options prices															
1	205	364	356	27	11	15	12	7	5	4	20	6.3	5.4	0.3	0.2
0.1	101	180	184	22	12	15	16	6	7	4	19	6.4	8.1	0.7	0.4
0.01	50	105	103	28	13	15	14	7	4	2	16	8.9	4.7	0.6	0.0
0.001	33	74	55	36	9	12	13	8	5	4	13	4.5	7.3	0.9	0.0
Panel B.Low-volatility period from Jan. 2005 to Jun. 2007															
B1. 3.5- min frequency futures and options prices with monthly out-of-the-money options prices															
1	324	528	519	27	13	14	8	6	7	6	19	3.6	4.1	0.3	0.3
0.1	149	252	250	31	14	15	6	7	5	6	17	2.5	3.0	0.0	0.0
0.01	61	136	145	33	17	15	9	3	3	8	12	4.6	4.6	0.0	0.0
0.001	39	74	94	31	22	15	6	4	1	9	12	4.4	1.5	0.0	0.0
B2. 5- min frequency futures and options prices with monthly out-of-the-money options prices															
1	206	381	342	31	14	12	8	7	5	3	20	4.4	3.7	0.4	0.0
0.1	81	208	184	34	13	16	12	1	6	3	15	5.6	5.6	0.7	0.0
0.01	35	120	107	38	16	16	11	2	2	0	14	3.5	5.9	1.2	0.0
0.001	20	85	79	40	19	17	10	2	2	0	11	1.6	6.3	1.6	0.0
Panel C.High-volatility period from Jul. 2007 to Dec. 2009															
C1. 3.5- min frequency futures and options prices with monthly out-of-the-money options prices															
1	252	364	396	15	10	9	20	9	2	5	31	8.2	11.3	0.0	0.0
0.1	123	180	204	15	11	12	17	9	2	3	30	6.6	10.6	0.0	0.0
0.01	59	92	107	20	19	8	13	8	1	4	25	6.0	7.2	0.0	0.0
0.001	29	39	70	17	17	20	11	0	0	17	17	2.2	8.7	0.0	0.0
C2. 5- min frequency futures and options prices with monthly out-of-the-money options prices															
1	166	374	322	29	10	8	21	7	1	2	23	10.1	9.8	0.0	0.7
0.1	85	193	171	28	13	9	20	6	4	2	19	10.7	9.4	0.0	0.0
0.01	48	107	105	26	12	11	21	5	2	5	19	10.6	10.6	0.0	0.0
0.001	28	59	63	21	8	13	27	6	2	6	17	10.4	16.7	0.0	0.0

The second, third and fourth columns show the number of detected jumps per 808 days.

Table 9 The estimated and selected parameters of affine jump-diffusion models

Panel A

Period	Full sample period					Low volatility	High volatility
Parameters	SV	SVJP	SVJV	SVIJ	SVCJ	SVCJ	SVCJ
V_0	0.022	0.021	0.022	0.022	0.020	0.010	0.050
γ	0.5%	11.9%	0.5%	14.3%	11.9%	6.2%	19.1%
k	4.65	6.25	7.15	7.25	7.25	7.25	7.05
θ	0.020	0.007	0.003	0.004	0.004	0.004	0.010
ξ	0.51	0.50	0.47	0.45	0.45	0.45	0.46
ρ	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
λ^p	-	2300	-	2300	2300	2000	3000
λ^V	-	-	2300	2300	2300	2000	3000
μ(e-4)	-	-0.6	-	-0.6	-0.6	-0.01	-1
σ(e-4)	-	13.4	-	13.8	12.95	9.8	17.8
β	-	-	-	-	-0.06	-0.06	-0.03
μ^V(e-4)	-	-	1600	1	0.02	0.01	0.2
$\tilde{k}$	4.4	6.0	6.9	7.0	7.0	7.0	6.8
$\tilde{\mu}$(e-4)	-	-1.1	-	-1.2	-1.1	-0.31	-1.6
$\tilde{\sigma}$(e-4)	-	15.8	-	16.0	15.2	12.7	20.7
$\tilde{\mu}^V$(e-4)	-	-	1608	2	0.04	0.02	0.4
Annual price jump risk premium	-	11.4%	-	13.7%	11.4%	5.9%	17.8%

Note: price jump risk premium is $\lambda^P(\bar{\mu}^P - \tilde{\bar{\mu}}^P)$

Panel B The comparison of estimated and selected parameters with previous studies

	Time unit	period	$\tilde{k}$	θ	ξ	ρ	$\tilde{\mu}$ (e-2)	$\tilde{\sigma}$ (e-2)	$\tilde{\mu}^V$ (e-4)	β	λ
Pan	year		7.1	0.013	0.28	-0.52	-0.3	3.25	-	-	27.1
Wang	year		1.6	0.044	0.367	-0.64	-13.3	2.19	680	-0.47	0.25
CGGT*	year		3.6	0.206	0.272	-0.46	-1.52	1.73	181	-0.87	1.7
Our estimation and simulation:											
Estimation	year	Full	7.0	0.004	0.45	-0.60	-0.37	1.77	319	-0.11	0.38
		Low	7.0	0.004	0.45	-0.65	-0.24	2.63	1584	-0.11	0.16
		High	6.8	0.010	0.46	-0.52	-0.37	1.66	83	-0.08	1.28
Simulation	year	Full	7.0	0.004	0.45	-0.01	-0.0110	0.152	0.04	-0.06	2300
		Low	7.0	0.004	0.45	-0.01	-0.0031	0.125	0.20	-0.06	2000
		High	6.8	0.010	0.46	-0.01	-0.0160	0.207	0.40	-0.03	3000
EJP*	day		0.026	0.54 e-4	0.08 e-2	-0.48	-1.75	2.89	1.48	-0.60	0.006
Eraker	day		0.023	1.353 e-4	0.163 e-2	-0.58	-6.1	3.63	1.63	-0.69	0.002

The parameters are estimated with daily or yearly time unit by Pan (2002),Eraker, Johannes, and Polson (EJP; 2003), CGGT (2003), Eraker(2004), and Wang (2009).Our estimationparametersarethe medians of estimated parameters by minimizing squared pricing error between theoretical prices by Duffie, Pan, and Singleton (2000) and the 7-min frequency market prices. The simulation parameters are equal to these parameters Panels A, which are applied to simulate model-based results in Tables 10-13.

*: the parameters of CGGT (2003) and EJP (2003) are estimated from P measure; others are under Q measure.

Table 10 Stochastic volatility (SV) model and Stochastic volatility with jump in price(SVJP) model in full sample period

α (%)	# of Det. Jumps per 808 days			Percentages of Jump Combinations								Percentages of Jump Combinations			
	F	C	P	C	P +	P —	CP	F	FC	FP	FCP	CP +—	CP —+	CP + +	CP — —
A. SVmodel result															
1	12.3	13.0	13.1	28	15	15	0	15	13	10	4	0.0	0.0	0.0	0.0
0.1	1.6	1.8	1.7	30	16	15	0	17	11	9	2	0.0	0.0	0.0	0.0
0.01	0.2	0.3	0.3	31	16	14	0	22	6	8	3	0.0	0.0	0.0	0.0
0.001	0.04	0.02	0.05	17	17	22	0	35	0	4	4	0.0	0.0	0.0	0.0
B1. empirical result															
1	306	431	423	22	10	11	11	10	5	4	27	4.9	5.7	0.3	0.1
0.1	150	217	228	22	12	12	11	6	6	6	26	4.7	5.3	0.3	0.3
0.01	79	128	127	24	11	12	11	5	5	5	26	5.7	4.7	0.0	0.5
0.001	45	65	90	18	17	16	12	5	3	9	20	8.2	4.1	0.0	0.0
B2. SVJP model result															
1	310	448	425	20	8	9	8	0.5	4	3	47	3.5	4.3	0.0	0.0
0.1	165	257	248	22	10	10	9	0.3	4	3	43	4.2	4.8	0.0	0.0
0.01	96	157	149	23	10	10	10	0.2	3	3	41	4.2	5.5	0.0	0.0
0.001	57	99	94	24	12	9	11	0.2	3	2	38	4.5	6.1	0.0	0.0
B3. SVJP model result with constraint: no price jump risk premium: $\tilde{\mu} = \mu$ = -0.6e-4, $\tilde{\sigma} = \sigma$ =13.4e-4															
1	310	275	263	10	5	5	0.3	6	16	13	44	0.1	0.1	0.0	0.0
0.1	165	144	138	10	5	4	0.2	8	16	13	43	0.1	0.1	0.0	0.0
0.01	96	82	78	11	5	4	0.4	8	16	15	41	0.2	0.2	0.0	0.0
0.001	57	49	46	11	5	4	0.3	10	16	13	40	0.1	0.2	0.0	0.0
B4. Result with estimated parameters from Pan(2002) in panel B of Table 9															
1	91	92	89	5	1.9	1.9	0	1.4	4	2	83	0.0	0.0	0.0	0.0
0.1	81	82	79	2	0.3	0.3	0	0.4	2	0	95	0.0	0.0	0.0	0.0
0.01	79	79	77	1	0.1	0.1	0	0.1	2	0	97	0.0	0.0	0.0	0.0
0.001	78	78	76	1	0.1	0.0	0	0.0	2	0	97	0.0	0.0	0.0	0.0

Note: the PanelsA and B4 are the simulation results from 200,000 and 60,000 simulation days, respectively, and others are from 30,000 simulation days.

Table 11 Stochastic volatility with jump in volatility (SVJV) model and Stochastic volatility with independent jumps in price and in volatility (SVIJ) model in full sample period

α (%)	# of Det. Jumps per 808 days			Percentages of Jump Combinations								Percentage of Jumps Combinations			
	F	C	P	C	P +	P —	CP	F	FC	FP	FCP	CP +—	CP —+	CP ++	CP ——
A1. empirical result															
1	306	431	423	22	10	11	11	10	5	4	27	4.9	5.7	0.3	0.1
0.1	150	217	228	22	12	12	11	6	6	6	26	4.7	5.3	0.3	0.3
0.01	79	128	127	24	11	12	11	5	5	5	26	5.7	4.7	0.0	0.5
0.001	45	65	90	18	17	16	12	5	3	9	20	8.2	4.1	0.0	0.0
A2. SVJV model result															
1	159	203	417	11	55	0.8	4	4	8	3	15	0.0	0.0	4.0	0.0
0.1	54	85	237	11	66	0.5	4	3	6	2	8	0.0	0.0	4.1	0.0
0.01	21	40	150	10	74	0.4	4	3	4	1	4	0.0	0.0	4.0	0.0
0.001	9	21	101	9	79	0.1	4	2	3	1	2	0.0	0.0	3.8	0.0
A3. SVJV model result with constraint: no volatility price jump risk premium: $\tilde{\mu}^V = \mu^V$ =0.16															
1	159	202	416	11	55	0.8	4	4	8	3	15	0.0	0.0	3.9	0.0
0.1	54	84	235	11	66	0.6	4	3	6	2	8	0.0	0.0	3.9	0.0
0.01	21	39	147	10	74	0.3	4	2	4	1	4	0.0	0.0	3.9	0.0
0.001	9	21	99	9	79	0.1	4	2	3	1	2	0.0	0.0	3.6	0.0
B2. SVIJ model result															
1	309	437	430	17	8	8	9	0.2	2	2	53	4.5	5.0	0.0	0.0
0.1	163	250	245	19	9	9	11	0.1	2	2	49	4.8	5.8	0.0	0.0
0.01	93	151	146	20	9	8	13	0.0	2	1	47	5.6	6.9	0.0	0.0
0.001	56	94	91	22	10	9	12	0.0	1	1	44	5.4	6.5	0.0	0.0

Note: the simulation results are from 30,000 simulation days.

Table 12 Stochastic volatility with contemporaneous jumps in price and in volatility (SVCJ) model

α (%)	# of Det. Jumps per 808 days F	C	P	Percentages of Jump Combinations C	P +	P —	CP	F	FC	FP	FCP	Percentages of Jump Combinations CP +—	CP —+	CP + +	CP — —
A1. empirical result of full sample period															
1	306	431	423	22	10	11	11	10	5	4	27	4.9	5.7	0.3	0.1
0.1	150	217	228	22	12	12	11	6	6	6	26	4.7	5.3	0.3	0.3
0.01	79	128	127	24	11	12	11	5	5	5	26	5.7	4.7	0.0	0.5
0.001	45	65	90	18	17	16	12	5	3	9	20	8.2	4.1	0.0	0.0
A2. model result															
1	306	441	426	19	9	9	8	0.4	4	3	49	3.6	4.7	0.0	0.0
0.1	163	257	245	21	9	9	10	0.1	3	2	44	4.3	5.7	0.0	0.0
0.01	93	156	148	23	11	10	10	0.1	3	2	42	4.6	5.4	0.0	0.0
0.001	56	99	94	24	11	10	11	0.2	3	2	39	5.2	5.8	0.0	0.0
A3. constraint: only consider price jump risk premium: $\tilde{\mu}^V = \mu^V$ =0.02e-4															
1	306	441	425	19	9	9	8	0.4	4	3	48	3.6	4.6	0.0	0.0
0.1	163	257	245	21	9	9	10	0.1	3	2	44	4.3	5.7	0.0	0.0
0.01	93	156	148	23	11	10	10	0.1	3	2	42	4.6	5.4	0.0	0.0
0.001	56	99	94	24	11	10	11	0.2	3	2	38	5.3	5.8	0.0	0.0
A4. constraint: only consider volatility jump risk premium: $\tilde{\mu} = \mu = -0.6$e-4, $\tilde{\sigma} = \sigma$ =12.95e-4															
1	305	274	266	10	5	5	0.2	5	15	13	47	0.1	0.1	0.0	0.0
0.1	163	147	139	11	5	5	0.2	7	15	12	45	0.1	0.1	0.0	0.0
0.01	93	83	78	11	5	5	0.3	7	16	13	42	0.1	0.1	0.0	0.0
0.001	56	50	46	11	4	5	0.3	8	16	13	42	0.2	0.2	0.0	0.0
A5. constraint: no price jump risk premium and no volatility jump risk premium															
1	305	274	266	10	5	5	0.2	5	15	13	47	0.1	0.1	0.0	0.0
0.1	163	147	139	11	5	5	0.2	7	15	12	45	0.1	0.1	0.0	0.0
0.01	93	83	78	11	5	5	0.3	7	16	13	42	0.1	0.1	0.0	0.0
0.001	56	50	46	11	4	5	0.3	8	16	13	42	0.2	0.2	0.0	0.0
A6. result with our estimated parameters frompanel Bof Table 9															
1	13	14	15	26	14	16	1	13	13	11	7	0.0	0.1	0.6	0.0
0.1	2	3	3	23	14	13	4	13	9	9	15	0.0	0.0	3.6	0.0
0.01	1	1	1	14	8	3	11	7	8	10	38	0.0	0.0	11.2	0.0
0.001	1	1	1	4	4	0	18	2	7	14	51	0.0	0.0	18.2	0.0
B1. empirical result of low volatility period															
1	324	528	519	27	13	14	8	6	7	6	19	3.6	4.1	0.3	0.3
0.1	149	252	250	31	14	15	6	7	5	6	17	2.5	3.0	0.0	0.0
0.01	61	136	145	33	17	15	9	3	3	8	12	4.6	4.6	0.0	0.0
0.001	39	74	94	31	22	15	6	4	1	9	12	4.4	1.5	0.0	0.0
B2. model result															
1	333	556	523	22	9	9	12	0.6	3	2	42	5.6	5.7	0.0	0.0
0.1	187	349	322	25	10	10	14	0.2	3	1	38	6.6	6.4	0.0	0.0
0.01	110	223	203	26	10	10	15	0.1	2	1	35	6.9	7.1	0.0	0.0
0.001	68	149	133	28	11	10	16	0.2	2	1	32	7.7	7.2	0.0	0.0
C1. empirical result of high volatility period															
1	252	364	396	15	10	9	20	9	2	5	31	8.2	11.3	0.0	0.0
0.1	123	180	204	15	11	12	17	9	2	3	30	6.6	10.6	0.0	0.0
0.01	59	92	107	20	19	8	13	8	1	4	25	6.0	7.2	0.0	0.0
0.001	29	39	70	17	17	20	11	0	0	17	17	2.2	8.7	0.0	0.0
C2. model result															
1	242	371	366	18	9	8	12	0.5	2	1	49	5.3	6.0	0.0	0.0
0.1	121	203	197	20	10	8	14	0.2	1	1	45	6.0	6.7	0.0	0.0
0.01	66	117	115	21	11	9	14	0.2	1	1	43	6.0	7.2	0.0	0.0
0.001	40	71	70	20	12	8	16	0.2	1	1	43	7.0	7.5	0.0	0.0

Note: the Panel A6 is the simulation result from 100,000 simulation days and others are from 30,000 simulation days.

Table 13 The results of different selected parameters of SVCJ model in full sample period

α (%)	# of Det. Jumps/ 808 days F	C	P	Percentages of Jump Combinations C +	C −	P +	P −	CP +−	CP −+	CP ++	F +	F −	FC	FP	FCP ++−	FCP −−+	FCP +++
A1. empirical result																	
1	306	431	423	10	12	10	11	5	6	0.3	5	5	5	4	12	15	0.0
.1	150	217	228	10	12	12	12	5	5	0.3	2	4	6	6	13	13	0.0
.01	79	128	127	13	11	11	12	6	5	0.0	3	2	5	5	12	14	0.0
.001	45	65	90	8	10	17	16	8	4	0.0	5	0	3	9	8	11	0.0
A2. model result with parameters in panel A of Table 9																	
1	306	441	426	9	11	9	9	4	5	0.0	0.2	0.2	4	3	22	26	0.0
.1	163	257	245	10	12	9	9	4	6	0.0	0.1	0.1	3	2	20	24	0.0
.01	93	156	148	11	13	11	10	5	5	0.0	0.1	0.0	3	2	19	23	0.0
.001	56	99	94	10	14	11	10	5	6	0.0	0.1	0.1	3	2	17	21	0.0
Case 1. ρdecreases to -0.6																	
1	304	680	274	22	29	1	1	2	1	0.0	0	0	9	0	15	19	0.0
.1	166	431	146	25	32	1	1	1	2	0.0	0	0	9	0	12	16	0.0
.01	94	279	81	26	37	1	0	2	2	0.0	0	0	9	0	10	14	0.0
.001	55	191	48	28	39	1	1	1	2	0.0	0	0	8	0	8	12	0.0
Case 2. μdecreases to -36.5e-4;$\tilde{\mu} = \mu - 0.5$e-4																	
1	2573	3317	3238	0	10	8	0	0	11	0.0	0	0	1	1	0.0	10.9	0.0
.1	1760	2485	2395	0	14	10	0	0	13	0.0	0	0	1	1	0.0	13.3	0.0
.01	1198	1833	1746	0	16	12	0	0	15	0.0	0	0	1	1	0.0	14.7	0.0
.001	804	1340	1268	0	18	14	0	0	17	0.0	0	0	1	1	0.0	16.7	0.0
Case 3. σincreases to 174.75e-4; $\tilde{\sigma} = \sigma$ +2.25e-4																	
1	5027	5028	5028	0	0	0	1	0	0	0.0	0	0	1	1	48	48	0.0
.1	4760	4763	4761	0	1	0	1	0	0	0.0	0	0	1	1	48	48	0.0
.01	4526	4526	4526	0	1	1	1	0	0	0.0	0	0	1	1	47	48	0.0
.001	4314	4315	4314	1	1	1	1	0	0	0.0	0	0	1	1	47	47	0.0
Case 4. β decreases to -0.11																	
1	302	436	425	9	11	9	9	4	4	0.0	0	0	3	3	21	27	0.0
.1	162	259	243	10	13	10	8	4	6	0.0	0	0	3	2	19	24	0.0
.01	92	156	149	10	13	11	9	5	6	0.0	0	0	3	2	18	23	0.0
.001	58	100	95	11	13	12	9	5	6	0.0	0	0	2	2	17	24	0.0
Case 5. μ^Vincreases to 318.98e-4; $\tilde{\mu}^V = \mu^V$ +0.02e-4																	
1	283	152	1021	1	2	71	0	0	0	0.0	0	0	3	15	2	6	0.0
.1	141	53	751	1	1	80	0	0	0	0.0	0	0	1	13	1	3	0.0
.01	80	22	574	0	0	85	0	0	0	0.0	0	0	1	11	0	2	0.0
.001	51	10	450	0	0	88	0	0	0	0.0	0	0	0	10	0	1	0.0
Case 6. $\tilde{\mu}$ decreases to -37e-4																	
1	302	291	335	18	1	25	1	0.8	0.6	0.2	4	5	12	13	8	12	0.0
.1	162	152	181	19	0	27	0	0.3	0.5	0.3	5	6	12	13	7	11	0.0
.01	92	86	107	19	0	29	0	0.2	0.3	0.3	5	6	11	13	6	10	0.0
.001	58	50	66	18	0	29	0	0.4	0.2	0.3	5	6	12	14	6	9	0.0
Case 7. $\tilde{\sigma}$ increases to 177e-4																	
1	302	5029	5024	1	1	1	1	43	47	0.0	0	0	0	0	3	3	0.0
.1	163	4766	4765	1	1	1	1	44	48	0.0	0	0	0	0	1	2	0.0
.01	92	4526	4522	1	1	1	1	44	49	0.0	0	0	0	0	1	1	0.0
.001	58	4311	4309	1	2	1	1	44	49	0.0	0	0	0	0	1	1	0.0
Case 8. $\tilde{\mu}^V$increases to 319e-4																	
1	302	215	326	13	3	28	2	4	3	2.3	14	16	5	8	1	1	0.0
.1	162	92	170	13	1	33	1	2	2	2.3	15	18	4	7	0	1	0.0
.01	92	48	101	14	1	37	1	1	1	2.1	16	18	4	6	0	1	0.0
.001	58	26	64	13	0	39	0	0	1	1.8	15	19	3	6	0	0	0.0

Note: the simulation results are from 10,000 simulation days.