Information about price and volatility jumps inferred from option prices

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Abstract

Option 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 decades, stock market jumps have presented a great challenge to financial models and option pricing. From empirical studies, it is clear that stock market returns do not simply follow a normal distribution. Researchers have made efforts to build more accurate models to describe the largest market movements. First, Merton (1976) evaluates options when there is a jump in underlying asset returns. Since then, researchers have considered jumps in prices. Duffie, Pan and Singleton (2000) propose an option pricing method for a general affine jump-diffusion model. They illustrate that simultaneous jumps in price and volatility are able to describe the implied volatility smirk. Eraker, Johannes and Polson (2003) estimate the stochastic volatility model and find strong evidence for jumps in both price and volatility (see also Chernov, Gallant, Ghysels, and Tauchen, 2003). These papers show that jumps in prices are important, but the importance of jumps in volatility is less clear. Additionally, if there is no risk premium in affine models, then it is assumed that all price jump risks are diversifiable. However, some research shows that there exist idiosyncratic jumps and systematic jumps whose risk is not diversifiable (Bollerslev, Law and Tauchen 2008). Therefore, the associated risk premia are important in option pricing models.

Researchers have found interesting results about associated jump risk premia. Pan (2002) used the generalized method of moments to estimate the parameters of affine jump-diffusion models. She identifies jumps in price and estimates the price jump risk premium. Broadie, Chernov and Johannes (2007) use S&P 500 futures and option prices from 1987 to 2003. They estimate the affine jump-diffusion model under real-world and risk-neutral measurements and indicate that the risk premia associated with jumps may improve option pricing models. As jumps are not hedgeable as diffusive elements, the existence of jump risk premia has an important consequence. Facing an unhedgable jump risk, investors will request a premium to compensate their investment risk. In Broadie, Chernov and Johannes' research, the estimated price jump risk premium is about 3%.

Carr and Wu (2009) use the difference between the realized variance and the variance swap rate to measure the variance risk premium. They find the variance risk premium is negative for S&P 500 indexes and Dow Jones Industrial Average. This shows that investors are averse an increase in volatility and are willing to pay a premium to hedge against it. Further, Bollerslev and Todorov (2011) propose new extreme value approximations to estimate the expected jump tails under real and risk-neutral measures. Their findings suggest that the historical equity and variance risk premia may be explained by the compensation for jump tail risk.

So far, affine models with compound Poisson jumps have been widely used to describe the return and volatility processes in financial markets. However, Todorov and Tauchen (2011) use VIX and S&P 500 futures contracts to test the activity level of returns and the VIX process. They conclude that a jump-diffusion is suitable for the S&P 500 return process, while the VIX index needs a pure-jump process to capture the frequent jumps in VIX. In their research, the VIX index is used as a proxy for volatility level. The advantage of using VIX data is that they are calculated from traded option prices with various strike prices. The option prices are sensitive to volatility, and the VIX provides more information than does 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 is not an instantaneous volatility measure. In fact, VIX is a biased estimate of instantaneous volatility. An alternative is to use option prices directly to investigate jumps and associated risk premia. We consider the affine jump-diffusion models to extract information from option prices.

In another field, researchers have proposed non-parametric methods to detect jumps in price. By using high frequency data, more information can be obtained from these methods. First, Barndorff-Nielsen and Shephard (2006) propose a method to identify days when jumps occur. Andersen, Bollerslev and Dobrev (2007), hereafter ABD, propose a method to detect multiple jumps over a given trading period and show the timing of jumps.

However, little attention is paid to finding evidence for jumps in volatility from the information on jumps in market prices. We use a jump test to detect jumps in futures and option prices and use the detection of these 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 option prices. Consequently, the ABD jump test is used to identify jumps in futures and option prices.

Interestingly, we fail to find strong evidence for jumps in volatility by this method. In all of the jumps we detect in option prices only 1% are cases of call jumps and put jumps in the same direction. Additionally, this small percentage of jumps may result from data issues. This negative result leads us to two possible explanations: first, jumps in price and jumps in volatility occur contemporaneously and jumps in price have a larger effect than the corresponding jumps in volatility; second, there are no jumps in volatility.

To compare these explanations, the ABD test is used to detect jumps in simulated futures and option prices, 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. Based on a comparison between empirical and model-based results, we try to determine which model best describes the observed jump patterns. Our estimates of variances of price jump size and mean volatility jump size are smaller than previous estimates (Eraker, Johannes and Polson, 2003; Chernov, Gallant, Ghysels and Tauchen, 2003; Eraker, 2004). Overall, our findings support that there are jumps in price and a price jump risk premium; secondly that jumps in price and jumps in volatility not occur independently. Finally, the price jump risk premium is a more important factor than 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.

$$dp = \mu dt + \sigma dW + J dN \quad , \tag{1}$$

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

$$RV_d = \sum_{j=1}^{m} r_{d,j}^2 \tag{2}$$

and

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

Andersen and Bollerslev (1998), Comte and Renault (1998) and Barndorff-Nielsen and Shephard (2001, 2004) show 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:

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

2.2 Detecting Index Jumps

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

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

$$\left| r_{d,j} \right| > z_m \sqrt{BV_d / m} \ , \tag{6}$$

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-minute 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

$$\left| r_{d,j} \right| > z_m \sqrt{f_j BV_d} \ , \tag{7}$$

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 Option 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 detect jumps in option 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 option prices. When the underlying asset price S follows a geometric Brownian process,

$$\frac{dS}{S} = \mu dt + \sigma dW \ , \tag{8}$$

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

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

There will then be intraday variation in the volatility of call returns, because of the multiplicative term $(S/C)(\partial C/\partial S)$. We therefore expect that there will always be more intraday volatility variation for percentage change of option 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 option 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 be elusive, 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 3.3.1 to 3.3.3.

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	$\dfrac{\text{number of detected J. P.} \neq 0 \mid \text{true J.P.} = 0}{\text{number of true J.P.} = 0}$	$\dfrac{\text{number of detected J. Options} \neq 0 \mid \text{true J.P.} = 0 \ \& \ \text{J.V.} = 0}{\text{number of true J.P.} = 0 \ \& \ \text{J.V.} = 0}$
$1-\beta$	$\dfrac{\text{number of detected J. P.} \neq 0 \mid \text{true J.P.} \neq 0}{\text{number of true J.P.} \neq 0}$	$\dfrac{\text{number of detected J. Options} \neq 0 \mid \text{true J.P.} \neq 0 \ \& \ /\text{or J.V.} \neq 0}{\text{number of true J.P.} \neq 0 \ \& \ /\text{or J.V.} \neq 0}$

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 option prices.

3.1 Affine Stochastic Processes

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

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

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

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 $\bar{\mu}^p = E[\exp(J_t^p) - 1]$ for which $\sum_{s \le t} \exp(J_s^p) - 1 - \lambda^p \bar{\mu}^p t$ 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 variance σ^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 mean μ^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 $N_t^p = N_t^V$. 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 $J_t^p \big| J_t^V \sim N(\mu + \beta J_t^V, \sigma^2)$. 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 et al (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 $\mu - \tilde{\mu}$, $\tilde{\sigma} - \sigma$, $\tilde{\mu}^V - \mu^V$, $\tilde{k} - k$ 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, namely θ, ξ, ρ, λ^P, λ^V and β, 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 et al. (2007).

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

3.3 Results

Below we will verify that it is reasonable to use an ABD jump detection test on index and option prices that follow the stochastic processes described below. In general we will find that the ABD test performs well and should be able to detect jumps if the true price processes follow these theoretical models.

For all the simulations we consider m =144 intraday returns each day, which correspond to a trading day of 504 minutes when the returns are calculated every 3.5 minutes.

3.3.1 Geometric Brownian Motion Model

The effective sizes from the Monte Carlo study of the geometric Brownian motion model with 200,000 simulation days are shown in Table 4. When the annual volatility σ is set to 10%, 14% and 22% different levels for low volatility, full sample, and high volatility periods, as the estimated values in Table 12, the daily effective sizes for options returns are about 0.03% and 0.006% at the 0.01% and 0.001% jump test levels, respectively. The effective sizes of futures are lower but slightly larger than the nominal significance levels of the ABD jump test. This is consistent with Andersen, Bollerslev and Dobrev (2007). The effective size for the call option does not increase when the diffusion term of the call return increases and call prices become more volatile: size does not increase for the more volatile, out-of-the-money option prices. We find that the ABD test offers good performance in terms of effective size.

3.3.2 Stochastic Volatility Model

In this section, the affine Jump-diffusion models are simulated. The parameters are shown in Table 12 A-C. Table 5 presents the effective sizes of the SV model for the index and for options across various moneyness levels. We can see that all the effective sizes in full sample period are slightly higher than for constant volatility (Table 4) but they remain within acceptable levels.

In Table 6, the effective sizes of the SVJP model are often less than the set significance levels. The effective powers of the index tests and of the option tests are low and almost the same. This implies that only a small fraction of the jumps are identified.[2] Additionally, the number of correctly asserted jumps in the index is almost equal to the number of detected jumps in the options.

Table 7 shows the performance of an ABD test in the SVJV model. The effective sizes for the tests for options and futures are higher than these in other Tables. However, the test has low effective power. The out-of-the-money options are sensitive to jumps in volatility and their effective power is relatively high.

Compared with Table 8, Table 9 illustrates that the ABD jump test has slightly better performance for the SVCJ model than for the SVIJ model. The contemporaneous jumps magnify spikes in futures returns and increase the magnitudes of option returns. Therefore, the ABD test is better able to detect contemporaneous jumps. Generally, the effective sizes of the two models are less than the assumed levels.

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[2] The effective power of test detects about 0.8% of the index jump at the 0.001% level. As λ =2,300, one simulated jumps is then detected every 14 days which is similar to the frequency reported by Andersen, Bollerslev and Dobrev (2007).

4 Data

This section explains how to decide optimal sampling frequency and provide data descriptive statistics.

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.[3] 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 8:00 to 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 4 January 2005 to 31 December 2009, a total of 1,262 trading days.

Three time series of option prices are studied: 1) Matm- At-the-money option prices with a monthly cycle of expiration dates, 2) Motm- out-of-the-money option prices with a monthly cycle of expiration dates, 3) Qatm- At-the-money option 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.[4] 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 option prices. The data with serious violations[5] are deleted. For example, the call prices are highly volatile within one hour around the 7 July 2005

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[3] I thank Xiaoquan Liu for providing some of this data.

[4] Options do not always become more liquidity the closer to maturity. For example, when the closest-to-maturity options expire within few days, investors may switch to invest on other maturity options.

[5] A serious violation of put-call parity is defined as an unusual spike in the prices of calls or puts, larger than $\frac{1}{3}$ of the daily call or put price range.

London bombings event. For each series of option prices, there are 808 daily samples available, as shown in Table 1. The sample period is divided into the low volatility 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:

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 option 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 minutes. To illustrate why we avoid at 13:30 and 15:00, Figure 1.A. presents the monthly out-of-the-money option prices with 0.25-minute frequency on 13 January 2006. It is obvious that the spikes in put prices at 13:30 and 15:00 violate put-call parity. Figure 1.D. shows the option prices with 5-minute frequency from 8:10 to 16:30 and shows that the spikes are then selected. In contrast, Figure 1.C. presents the option prices with 3.5-minute frequency with a sample period from 8:06 to 16:30. No time interval with the 3.5-minute frequency ends at exactly 13:30 or 15:00 and there are no spikes shown. After using a 3.5-minute frequency instead of 5-minute frequency, we can reduce the number of unsatisfactory days 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.[6] The steps of the first three frequencies – 0.25-, 0.5-, and 1-minute- – include 13:30 and 15:00, while the steps of the other frequencies are not at these specific times. The mean realized variances across

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[6] 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 T days.

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 mean realized variance of calls and puts decreases and converges to a stable value generally at a 3.5-minute frequency. The mean realized variances of calls and puts with 3.5-minute frequency during the period 18:06~18:30 are 0.0964 and 0.0797, which are less than their counterparties during 18:10~16:30 (see Figure 3.A): 0.1174 and 0.0872 of call and put with 2-minute frequency, 0.1118 and 0.0868 of call and put with 5-minute frequency, respectively. This suggests that a 3.5-minute frequency is optimal. As Figure 2.D shows, the futures mean realized variances are almost the same across frequencies.

Figure 4 shows and defines the 3.5-minute frequency variance proportions of futures and option prices. The timings of spikes are similar between futures and option 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. For instance, Gilbert, Kogan, Lochstoer and Ozyildirim (2011) find that the U.S. Index of Leading 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 returns r_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 returns r_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).

In the call and put panels, it is shown that the distribution of z_d also has a near 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 JB normality 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.

4.3 Data Results

To ensure the evidence for jumps is highly probable, we select low daily significance levels, α, from a high of 1% down to a low of 0.001%. In Table 11, we observe that the number of detected jumps in futures almost doubles as the significance level is multiplied by 10. Moreover, the number of detected jumps in options is greater than the number of detected jumps in futures. This might imply that there are additional factors, other than simply jumps in price, that drive the jumps in option prices. However, we see late that this effect occurs when simulating index prices with stochastic volatility and jumps in price.

We break down the jumps into eight jump combinations indicating which kind(s) of price jump occur at the same time. For example, the C jump combination denotes the detected jumps in

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[7] The Jarque and Bera test statistic is, $JB = \frac{N}{6}[\hat{S}^2 + \frac{(\hat{k}-3)^2}{4}]$, 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 the JB statistic is less than the significance level. When the null is true, the asymptotic distribution of JB is $\chi^2(2)$.

call prices and no detected jumps in any other price. The CP jump combination denotes the contemporaneous detected jumps in call and put but no detected jumps in futures. The FC jump combination means contemporaneous detected jumps in futures and call prices but no detected jumps in put. The P+ and P－ jump combinations are the detected positive and negative jumps in put prices. As the volatility jump size increases, the number of positive detected put jumps increases. The FCP jump combination represents the contemporaneous detected jumps in futures, call and put prices. The most common combination is FCP, which accounts for 25% of the combinations. This percentage increases as the impact of jumps in price increases. The percentages of C, P and CP jump combinations are about 22%, 25% and 11%, respectively. As the impact of jumps in volatility increases, these percentages increase. This will be illustrated later in Sections 5.2.2 and 5.2.3.

Panel B 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, and this means that the impact of jumps on price dominates over that of jumps in volatility, or that there is no jump in volatility. In the CP jump combinations, there are less than 1% of cases when calls and puts jump together and jump in the same direction. In the example shown in Figure 5.A, the detected call jump and put jump are both negative at the 0.1% significance level at 14:52 on 15 September, 2006. Generally, in Figure 5.C, the call price changes is positively related to futures price changes, while put changes is negatively to future changes. The symbols around (-3,8) and (-3,10) show the double upward increases of call and put prices, while future price decreases by 3. The two symbols around (0,-8) show that the both call and put prices decrease, while future price changes is about zero. Even though these changes of call and put prices are in the same direction, this may result from a data problem. For instance, an unreasonable ask- or bid-price leads to a large price change followed by an almost equivalent opposite price change within a short period of time. Therefore, this evidence is not strong or sound enough to show the existence of an independent jump in volatility.

We consider three extensions to confirm that our results are robust. We consider at-the-money options with monthly and quarterly maturities as well as 5-minute frequency data. The sample period is divided into low and high volatility periods. Table 11 shows the empirical results of detected jumps for these extensions. The numbers of detected out-of-the-money option jumps are larger than these for at-the-money, as shown in A1 and A2 Panels. This implies that the out-of-the-money option is more sensitive to the impact of events or news announcements. In the case that at-the-money option and futures expire quarterly, only few detected jumps of calls and puts are in the same direction.

For different variance proportions in different periods, the detected jumps may be different from period to period. Compared with low volatility period, the high volatility period has relatively high percentages of CP and FCP jump combinations and relatively low percentage of C and P jump combinations. Generally, the percentages of P+ and FCP(－－+) are close to those of P－ and FCP(++－). The number of detected jumps in futures almost doubles as the significance level is multiplied by 10. These characteristics of empirical results from 3.5-minute are similar to those from 5-minute frequency data. Generally, we detected more jumps from 3.5-minute frequency data. We simulate model-based results with 3.5-minute frequency in the next section.

For the FCP jump combinations, the directions of futures jumps and call jumps are always the same, while the directions of put jumps are always opposite to those of futures. There are two possible explanations: first, jumps in the (underlying asset) price exist, while jumps in volatility do not; another explanation is that the jumps in price and jumps in volatility occur contemporaneously and the impact of jumps in price on options dominates over that of jumps in volatility. The results for CP and FCP jump combinations do not show strong support for the existence of jumps in volatility.

5 Model-Based Results

The results from the empirical data show no evidence for the existence of independent volatility jumps. Next, we will try to recreate the observed jump statistics by using possible theoretical models. The main aim is to see if the observed patterns can be explained by contemporaneous jumps in price and volatility or simply by jumps in price.

In this section, an ABD test is used to detect jumps in theoretical futures, and option prices from simulated affine jump-diffusion models. Section 5.1 explains the selected parameters of the different models. Section 5.2 shows further information from a comparison between empirical results and model-based results.

5.1 Parameter Selection for Models

Affine Jump-Diffusion Models

Previous researchers use various econometric methods to estimate the parameters. Eraker, Johannes and Polson (2003) use a likelihood-based estimation with Markov Chain Monte Carlo (MCMC) methods.[8] Chernov, Gallant, Ghysels and Tauchen (2003) use an efficient method of moments. Pan (2002) uses an implied-state generalized method of moments. Broadie, Chernov and Johannes (2007) minimize the difference between model-based and market-based implied volatility. In this paper, we aim to minimize the difference between empirical results and model-based results in terms of detected jump numbers and the percentages of jump combinations. A deep out-of-the-money option is used to isolate jump risk and to estimate the parameters of 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 focus on the results from the out-of-the-money option with monthly expiration. Therefore, in the simulations, we let the time to expiration repeatedly decrease from 25 to 6 trading days.[9]

Table 12 lists the values of estimated and selected parameters in different periods. The parameters $V_0, \tilde{k}, \theta$ and ξ are the medians of monthly estimated parameters by minimizing squared errors between Duffie, Pan, and Singleton (2000) theoretical prices and the 7-minute frequency out-of-money options prices during the period between 8:06 and 16:30. Our estimated parameters are close to Pan (2002), see Panel D.

[8] In the research, we extract information from detected jumps in terms of the range of jump combinations. It is computational difficult to apply MCMC to obtain a reasonable range of jump combinations.
[9] Following Dumas, Fleming and Whaley (1998), we exclude options with less than 6 days to maturity. Because the time premium of options with short maturity is relatively small, option prices are sensitive to nonsynchronous option prices and other measurement errors.

Panels A-C list the values of parameters applied to simulate model-based results in Tables 13-18. Our annual equity risk premium is set about 6%, 12%, and 18% in three different periods, which is similar to Pan(2002).[10] The diffusive volatility annualised risk premium $\eta_v = \tilde{k} - k$ is set as -0.25, similar to the estimation of Chernov and Ghysels (2000). In SVCJ model of full sample period, k and $\tilde{k}$ are 7.25 and 7, respectively, corresponding to half-life values of 24.1 ($= 252 * \ln(2) / k$) and 25 trading days. The initial variance levels, V_0, are 0.01, 0.02, and 0.05, corresponding to 10%, 14%, and 22% annual volatility for different periods. The daily initial futures are set as S_0 =5475. The risk-rate rate refers to the three-month Euro-currency interest rate, which is about 0.5% to 5.3% during the sample period. Consequently, we set the risk-free as r =3%.

The jump related parameters are selected to fit the best simulation results in terms of jump combination. In our simulation SVCJ model, to keep the percentages of P+ and FCP(－－+) are close to those of P－ and FCP(++－), we set ρ equal to -0.01, which is different from the estimations of Eraker (2004) (-0.46), Pan (2002) (around -0.5). The regression slope between jump sizes, β, is about -0.06, similar to previous researches, Eraker (2004), Eraker, Johanner and Polson (2003). The standard deviations of price jump sizes, σ, and means volatility jump size, μ^V, in our simulation are smaller than our estimations and previous researches, Pan(2002), Eraket et al. (2003), Chernov et al. (2003), Eraker (2004), and Wang (2009). The jump intensities in our simulation are from 2,000 to 3,000 jumps per year which is obviously larger than previous researches.

5.2 Model Results

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

[10] Our estimated price jump risk premia is similar to the results of Pan(2002), in which the jump risk premia is about from 13% to 21%, as the volatilities is about from 10% to 22%. Broadie, Chernov and Johannes (2007) use S&P 500 futures options from 1987 to 2003. They estimate the SVJ mean price jump risk premia about 3% to 6% and the SVCJ mean price jump risk premia is 2% to 4%.

5.2.1 Stochastic Volatility (SV)

In this model, there is no jump component in the return and variance processes. Table 13 shows that the ABD test falsely claims about 12 futures and 13 option jumps per 808 days at the 1% daily significance level. All the directions of call jump and put jump are different in FCP jump combination but the small number of jumps observed rules this out as a possible model.

5.2.2 Stochastic Volatility with Jump in Price (SVJP)

In this model, there are jump components only in the return process. In Table 14. Panel A3, there is no price risk premium. It shows that the number of detected jumps in options is less than observed empirically. Its percentage of F, FC and FP jump combinations is relatively high. As you would expect, as only prices can jump, in most cases, jumps in futures and jumps in options occur together. Interestingly, the percentage of CP jump combinations is close to zero, which was not the case with the empirical results. The percentage of C and P jump combinations is low. In a few cases, observed jumps in options do not occur with jumps in futures.

Considering the price risk premium, the average magnitudes of risk-neutral price jumps are larger than these of real-world price jumps. In return, it is expected to increase the CP(+−) and CP(−+) jump combinations. Tables 14 Panels A2, B2 and C2 illustrate that if we consider the price jumps 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 result. It suggests that jumps in price and price jump risk premiums are important to explain the range of jump combinations. However, the percentage of F jump combinations is lower than empirical results, while the percentage of FCP jump combination is higher than empirical results.

Considering Pan's parameter estimates, we attempt to find the parameter estimates that can recreate the observed results. Panel A4 shows the simulation results with the estimated parameters by Pan (2002). It illustrates that jump intensity may be under-estimated, for the number of detected jumps is noticeably low. Additionally, the jump size of price may be over-estimated, for the percentage of FCP jump combination is high and the number of detected jumps does not increase twice as the significance level is multiplied by 10. This will be further illustrated in Table 18 case 3.

5.2.3 Stochastic Volatility with Jumps in Volatility (SVJV)

In this model, there are jump components only in the variance process, so all of the jumps should be observed in the option prices. In Table 15.A3, the volatility jump risk premium is not considered. As expected, the results show that the numbers of detected jumps in options are much greater than those in futures. For the leverage effect and volatility jump effect, the numbers of detected jumps for puts are much greater than those for calls. The leverage effect describes a negatively skewed futures return distribution. The volatility jump sizes leads to: first, positive jumps in options and secondly, the fat tails of futures return and in return the jumps in options. The mixed effect results in both the directions of call jumps and put jumps are positive in the CP combinations; the percentage of P+ jump combinations is obviously higher than that of P－. These results reflect there being only positive jumps in volatility in the model. This clearly is not a viable model for the time period we consider.

Considering the volatility risk premium, the average magnitudes of risk-neutral volatility jumps are larger than these of real-world volatility jumps. In our simulation, the volatility risk premium is small. Table 15.A2 shows the results as the jump volatility risk premium is considered in which the number of Put options jumps is slightly increase. Overall, the relatively large percentages of P+ and CP(++) jump combination observed rule this out as a possible model. This suggests that the volatility jump risk premium is not an important factor.

5.2.4 Stochastic Volatility with Independent Jumps in price and in volatility (SVIJ)

As with the volatility jump only model, we do not expect that this model will be able to explain the results as independent jumps will lead to call and put prices jumping in the same direction. In Table 16 Panels A2, B2 and C2, the percentage of P and F jump combinations are less than the empirical results, while the FCP jump combination is higher than the empirical results. This suggests that jumps in price and in volatility are not occurring independently.

5.2.5 Stochastic Volatility with Contemporaneous Jumps in price and in volatility (SVCJ)

We start by considering our estimated parameters in Table 12.D and then we attempt to find simulation results with estimated parameters from affine jump-diffusion models of Duffie, Pan and Singleton (2000). Table 17.A6 shows the simulation results from our estimation parameters. The number of detected jumps is obviously low and this shows that jump intensity may be under-estimated. Moreover, the mean jump size of volatility may be over-estimated, for the directions of call jumps and put jumps are almost the same in CP jump combinations. Recall, that in the empirical findings this very rarely, if ever, occurred. Finally, unlike empirical results, the number of detected jumps in futures does not increase twice as the significance level is multiplied by 10.

Table 17.A5 presents the model results with no price jump premium and no volatility jump risk premium. The number of jumps in futures is close to empirical results, while the number of jumps in options is not as high as that in the empirical results. Note that increasing the jump sizes of volatility in real and risk-neutral worlds leads to the number of positive detected put jumps increasing and the number of detected call jumps decreasing, so this is not a possibility (see Table 18 Case 5).

In Table 17.A4 only volatility jump risk premium is considered, the results is similar to A5 results without any premium considered. Note that increasing the volatility jump risk premium leads to the relatively high percentages of P+ and CP++, so this is not a possibility (see Table 18 Case 8). In A3, when price jump risk premium is considered, the number of CP(+ −) and CP(−+) jump combination increase, the CP, FC and FP jump combinations go to reasonable levels. Compared with Panel A4, Panel A3 demonstrates that the number of option jumps and the range of jump combinations are relatively reasonable. This suggests that price jump risk premium is a more important factor than volatility jump risk premium.

Finally, Table 17.A2 shows the results when both price jump risk premium and volatility jump risk premium are considered. This model provides more reasonable results than SVJV and SVIJ. It suggests that jumps in price and price jumps premium are both important factors and that jumps in price and in volatility not occur independently. The expected jumps per year are more than 2,000 in our sample periods, which is higher than the estimated value 1.7 of CGGT (2003) and our estimation 0.38 (see Table 12.D). Our selected price jump sizes have a normal distribution with mean -1.1e-4 and standard deviation 15.2e-4 for all sample period. The average magnitude of price jump size is smaller than those of CGGT (2003) and our estimations. The selected average volatility jumps, 0.04e-4, is smaller than that of CGGT (2003) 181e-4 and our estimations. The selected annual price jump risk premium is 11.4% which is close to that of Pan(2002).

5.3 SVCJ Model Results with estimated parameters

Table 17.A6 shows that the model-based simulation results with estimated parameters are obviously different from empirical results. This section may explain the difference. In Table 18, we constrain the one or two selected parameters equal to our estimated parameters in each Cases1-8. Other parameters are the same as the estimated values in Table 12.A. We compare the results in each case with model result, which is with parameters in Table 12.A.

Case 1: the decrease of correlation ρ between Weiner processes leads to the increase of positive detected call jump number and the decrease of detected put jump number.

Case 2: the decrease of mean price jumps in real and risk-neutral worlds causes more negative detected jumps in futures, negative detected jumps in call and positive detected jumps in put.

Case 3: it illustrates results of the increase of standard deviation of jump, σ , in real and risk-neutral worlds. The large price jumps lead to, first high percentage FCP jump combination and the percentages of FCP(－－+) jump combinations is still close to that of FCP(++－); second, the number of detected jumps does not increase twice as the significance level is multiplied by 10.

Case 4: it shows the result of the decrease of correlation between volatility jumps and price jumps, β . The percentages of P+ and FCP(－－+) jump combinations slightly increase.

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

Case 6: the decrease of mean risk-neutral price jumps leads to more positive detected put jumps. Different from Case 2 result , the result in this case shows the number of detected futures jumps is unchanged and detected options jump number decreases.

Case 7: the increase of risk-neutral standard deviation of price jumps leads the increase of price jump size in risk-neutral world. The number of detected options jumps increases; the percentages of CP+－ and CP－+ jump combinations noticeably increase with small difference between the two combinations.

Case 8: the increase of risk neutral volatility jumps, or volatility jump risk premium, leads to the increase of positive detected options jumps; the percentages of C+, P+ and CP++ jump combinations increase.

It a nutshell, the percentage of P+ jump combination is greater than that of P－ in case 2, 4, 5, 6, and 8, because the risk-neutral return of futures is more fat in left tail. But the two percentages are similar in empirical result. The cases 6 and 7 are related to price jump risk premium, and the case 8 is related to the volatility jump risk premium.

6 Conclusions

We have developed a novel way to show the presence of volatility jumps, by detecting jumps in option prices. Intuitively, if the volatility jumps, and there is no contemporaneous price jump, then we should observe call and put option prices jumping in the same direction. Our empirical results provide no immediate and sound evidence for volatility jumps, as we detect almost no jumps in option prices of the same sign, almost ruling out the idea of independent volatility jumps.

However, it is possible that there are volatility jumps but that they occur contemporaneously with the underlying asset jumps. To test this we consider models where there are only price jumps (SVJP) and models where there are contemporaneous price and volatility jumps (SVCJ). The SVCJ model results show that jumps in price and a price jump risk premium provide a reasonable explanation of the observed jump patterns. Moreover, the SVCJ model results are better than the SVIJ results. This provides support for jumps in price and jumps in volatility not occurring independently. This is consistent with previous research by Todorov and Tauchen

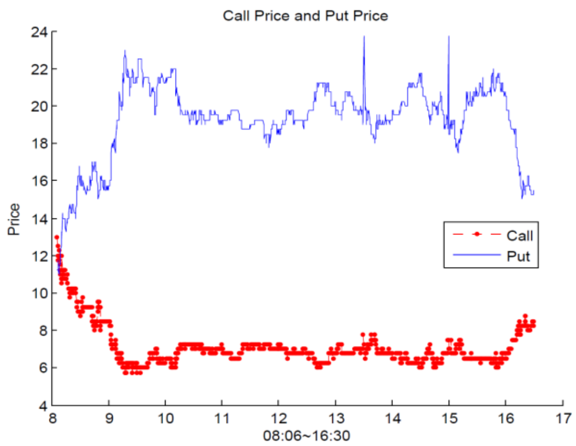
(2010) and Duffie, Pan and Singleton (2000). However, our research shows that the standard deviations of price jump size and mean volatility jump size are far smaller than those in previous research (Eraker, Johannes and Polson, 2003; Chernov, Gallant, Ghysels and Tauchen, 2003; Eraker, 2004).[11] We show the simulations with the estimated parameters from affine jump-diffusion models of Duffie, Pan and Singleton (2000) may not provide good explanation in terms of jump combinations.

Finally, our research offers an intuitive and transparent way to identify jumps and risk premia. It links the research between jump identification and parameter estimation across the widely used models. From the viewpoint of jumps, it shows the importance of jumps and risk premiums. The research shows that jump intensity is higher than in previous research (Eraker, Johannes and Polson, 2003; Chernov, Gallant, Ghysels and Tauchen, 2003; Eraker, 2004). Recently, some researchers have proposed new pure-jump models (Carr and Wu, 2004; Cartea and Howison 2009). It is worth paying more attention to these models.

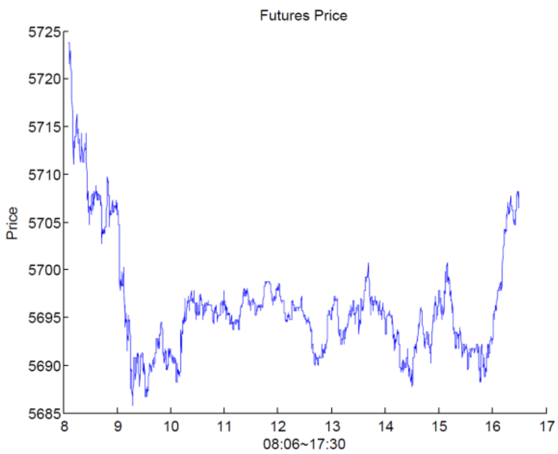
[11] Eraker, Johannes and Polson (2003) adopted S&P 500 index and Nasdaq 100 index from 1980 to 1999; Chernov, Gallant, Ghysels and Tauchen (2003) used Dow Jones industrial average (DJIA) index from 1953 to 1999; Eraker (2004) used S&P 500 index from 1987 to 1996.

Figures

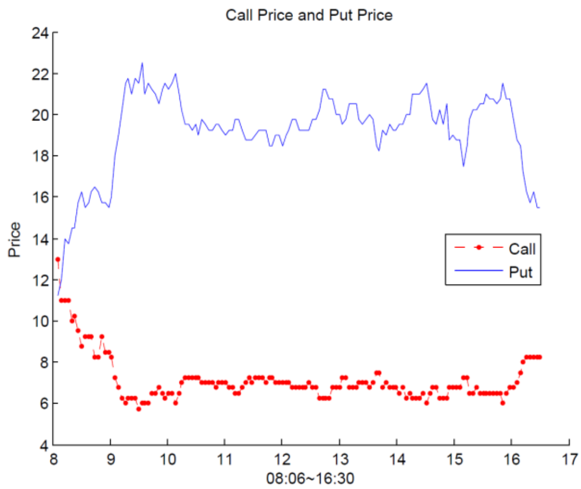
A. 0.25-minute frequency



B. Futures 0.25-minute frequency



C. 3.5-minute frequency



D. 5-minute frequency

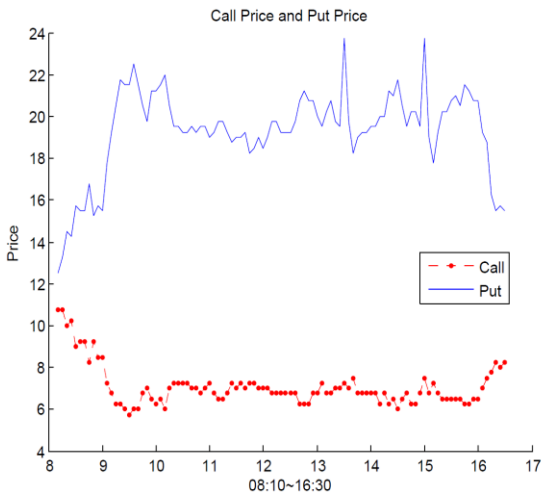


Figure 1 The Motm option prices on 13 January, 2006

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

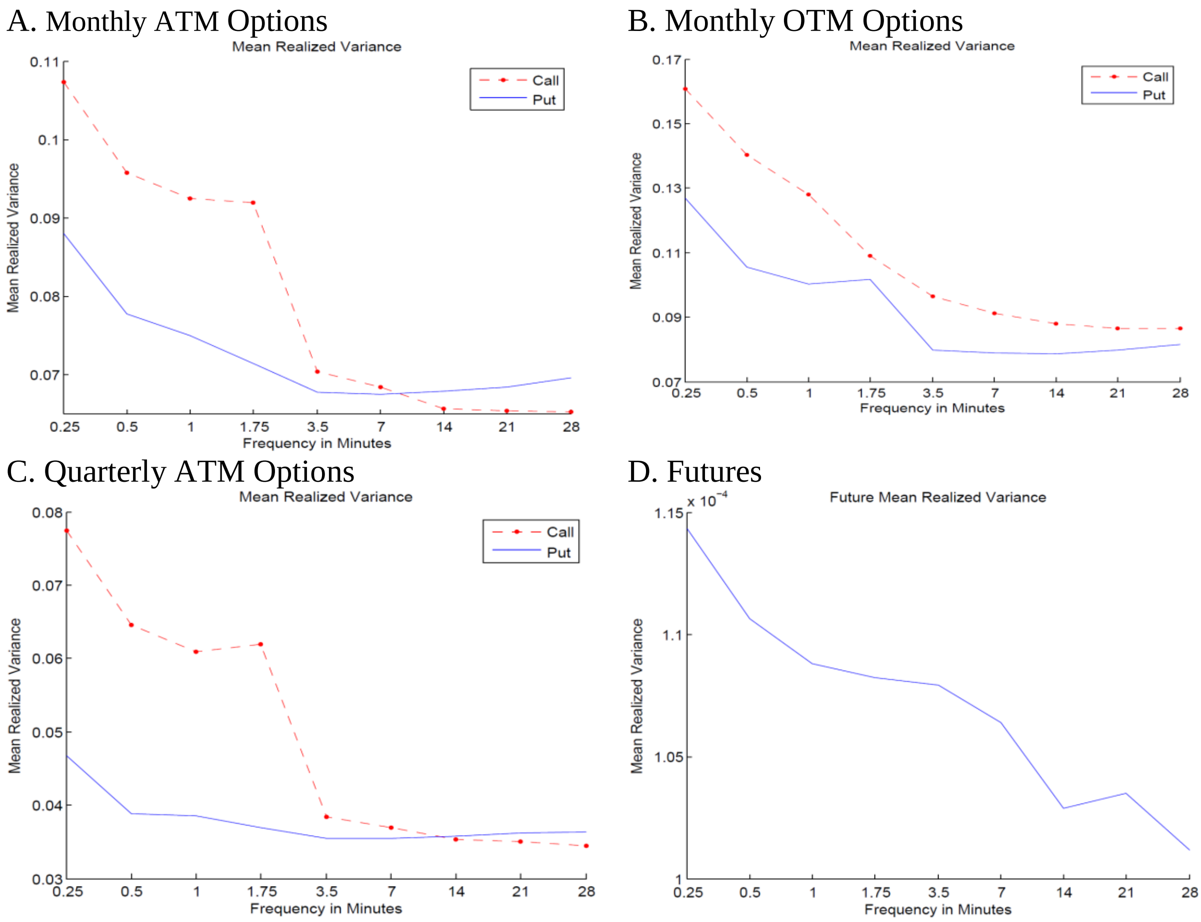


Figure 2 The mean realized variance during the period 8:06~16:30

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 C are 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.

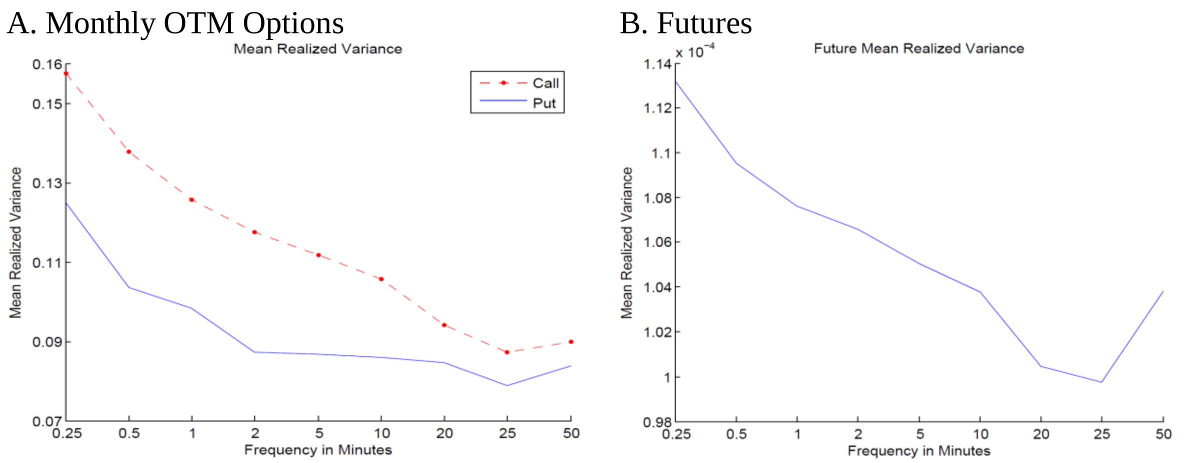
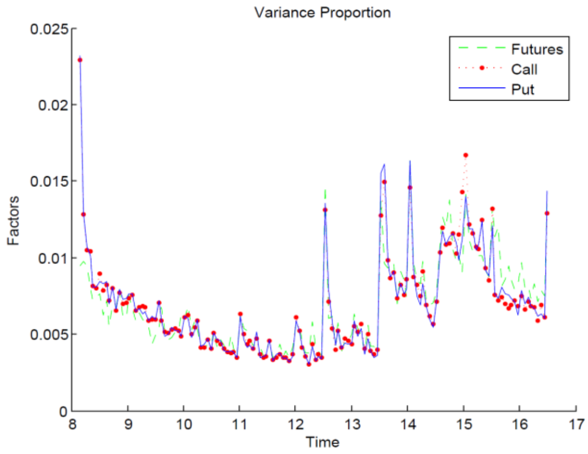


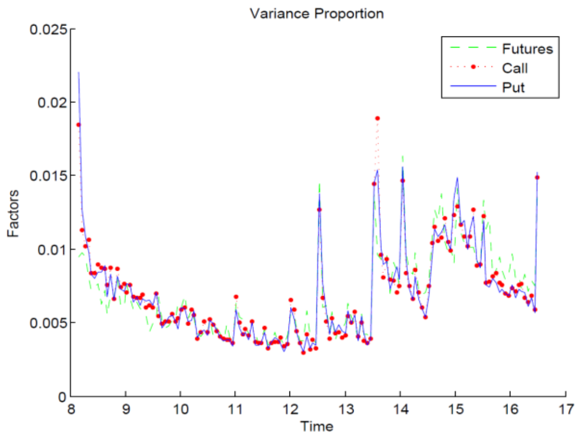
Figure 3 The mean realized variance during the period 8:10~16:30

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

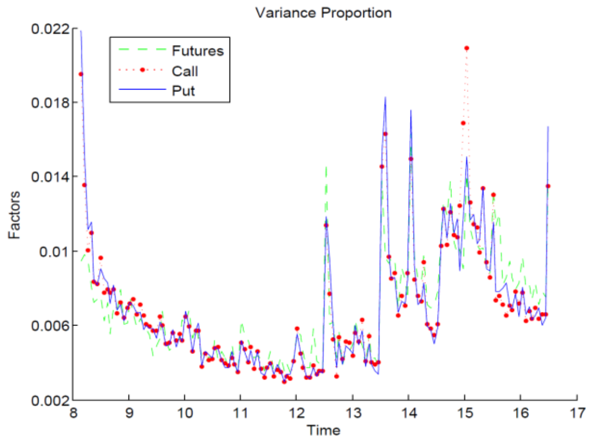


Figure 4 The variance proportions of 3.5-minute frequency data during the period 8:06~16:30

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.

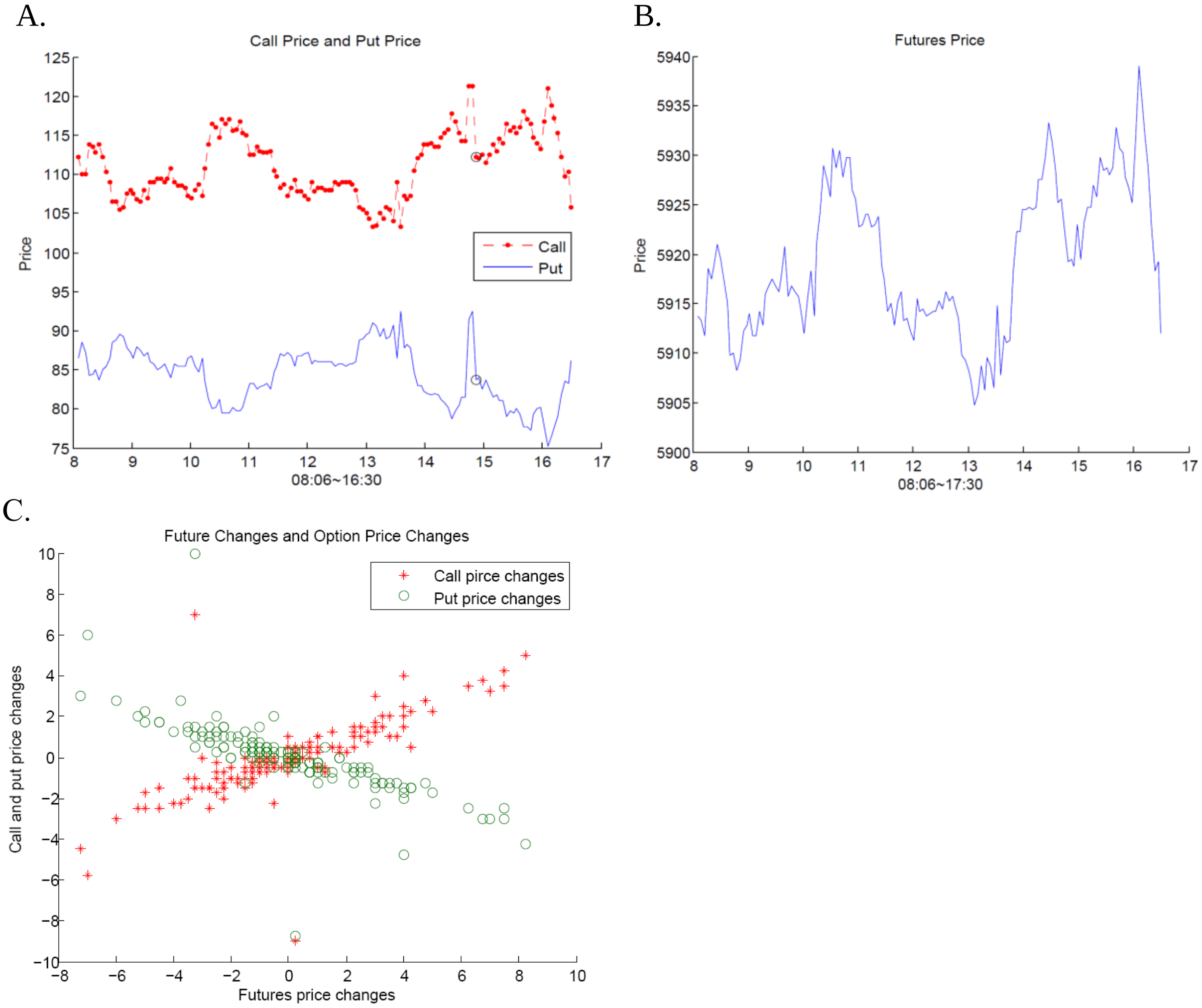


Figure 5 Futures and monthly at-the-money option prices with 3.5 minute frequency on 15 September 2006

Note: In 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 option 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 about 1.01/0.99 moneyness, K/S_0, 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 option prices. The low volatility period is from Jan 2005 to Jun 2007 and the high volatility period is from July 2007 to Dec 2009.

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

Contract		Mean	Median	Std. Dev.	Kurtosis	Skew.	p -value
Futures	$r_{d,j}$	1.5E-06	0	0.0009	13.4752	-0.0715	$\leq$ 0.10%
	r_d	0.0002	0.0004	0.0100	9.6519	0.2400	$\leq$ 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	$\leq$ 0.10%
	$\log(\hat{\sigma}_d)$	-4.9094	-4.9717	0.5745	2.3035	0.3442	$\leq$ 0.10%
Call	$r_{d,j}$	-1.7E-04	0	0.0257	11.8632	-0.0593	$\leq$ 0.10%
	r_d	-0.0235	-0.0091	0.3061	4.2628	-0.1845	$\leq$ 0.10%
	z_d	-0.0514	-0.0363	0.9705	2.8565	0.0325	$\geq$ 50.00%
	$\hat{\sigma}_d$	0.2916	0.2669	0.1068	4.9449	1.2479	$\leq$ 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	$\leq$ 0.10%
	r_d	-0.0317	-0.0477	0.2952	4.2423	0.2142	$\leq$ 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	$\leq$ 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-minute 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		1	.1	.01	.001	1	.1	.01	.001
K/S_0	e.s. (%)	e.s. (%)	e.s. (%)	e.s. (%)	$\frac{S}{C}\frac{\partial C}{\partial S}$	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 200,000 days. There are 144 steps per day. K is the strike price. 'e.s.' denotes daily effective size.

Table 5 The effective size of the ABD test for the SV model

Price	α Moneyness (K/S_0)	1% Eff. size	0.1% Eff. size	0.01% Eff. size	0.001% Eff. size
A. full sample period					
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. low volatility period					
Index		1.73	0.25	0.037	0.0075
	1.02	1.99	0.49	0.223	0.1379
Call	1	1.67	0.24	0.031	0.0060
	0.98	1.94	0.29	0.045	0.0095
	1.02	1.91	0.28	0.049	0.0110
Put	1	1.60	0.21	0.034	0.0055
	0.98	2.70	0.91	0.520	0.3529
C. high volatility period					
Index		1.35	0.17	0.025	0.0035
	1.02	1.55	0.21	0.029	0.0035
Call	1	1.57	0.21	0.028	0.0040
	0.98	1.58	0.21	0.026	0.0050
	1.02	1.62	0.21	0.033	0.0055
Put	1	1.58	0.20	0.031	0.0055
	0.98	1.56	0.20	0.029	0.0055

Note: the unit is percentage. Time to maturity repeatedly decreases from 25 to 6 days, total 200,000 days. There are no jumps. ‘Eff. size’ denotes daily effective size.

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

Price	Moneyness (K/S_0) α	1% Eff. size	1% Eff. power	0.1% Eff. size	0.1% Eff. power	0.01% Eff. size	0.01% Eff. power	0.001% Eff. size	0.001% Eff. power
A. full sample period									
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
B. low volatility period									
Index		0.78	5.53	0.10	3.16	0.016	1.86	0.0032	1.14
	1.02	1.22	3.83	0.38	2.06	0.226	1.17	0.1642	0.70
Call	1	0.76	4.71	0.10	2.62	0.012	1.52	0.0016	0.93
	0.98	0.91	5.54	0.11	3.20	0.018	1.91	0.0016	1.19
	1.02	0.89	5.12	0.12	2.91	0.020	1.73	0.0026	1.07
Put	1	0.78	4.32	0.09	2.37	0.014	1.36	0.0021	0.82
	0.98	1.78	2.84	0.66	1.48	0.407	0.82	0.2885	0.48
C. high volatility period									
Index		0.53	2.76	0.06	1.43	0.007	0.80	0.0005	0.49
	1.02	0.65	2.75	0.07	1.43	0.007	0.80	0.0011	0.49
Call	1	0.66	2.80	0.08	1.46	0.009	0.82	0.0011	0.50
	0.98	0.68	2.82	0.07	1.47	0.010	0.83	0.0027	0.51
	1.02	0.67	2.64	0.07	1.38	0.015	0.78	0.0016	0.47
Put	1	0.66	2.56	0.07	1.34	0.011	0.75	0.0016	0.46
	0.98	0.64	2.46	0.07	1.28	0.011	0.71	0.0016	0.43

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 effective size and effective power of the ABD test for the SVJV 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		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
B. low volatility period									
Index		20.09	-	7.89	-	3.403	-	1.5755	-
	1.02	16.33	1.68	6.02	0.95	2.397	0.58	1.0479	0.38
Call	1	16.44	1.58	6.07	0.88	2.427	0.54	1.0625	0.35
	0.98	16.56	1.49	6.11	0.82	2.460	0.50	1.0793	0.32
	1.02	12.37	6.25	4.18	4.20	1.612	2.96	0.6960	2.14
Put	1	12.24	6.48	4.12	4.37	1.575	3.09	0.6865	2.25
	0.98	12.09	6.71	4.06	4.56	1.555	3.24	0.6739	2.36
C. high volatility period									
Index		15.74	-	5.34	-	1.903	-	0.7780	-
	1.02	13.65	0.47	4.47	0.22	1.531	0.11	0.5956	0.06
Call	1	13.71	0.45	4.50	0.20	1.540	0.10	0.6032	0.05
	0.98	13.77	0.44	4.52	0.20	1.551	0.09	0.6118	0.05
	1.02	9.25	3.62	2.64	2.29	0.826	1.52	0.2928	1.05
Put	1	9.34	3.53	2.66	2.23	0.839	1.48	0.2972	1.02
	0.98	9.41	3.46	2.69	2.17	0.848	1.44	0.3026	0.99

Note: the unit is percentage. The simulation includes 100,000 days. ‘Eff. size’ denotes daily effective size. ‘Eff. power’ denotes effective power.

Table 8 The effective size and effective power of the ABD test for the SVIJ model

Price	Moneyness (K/S_0)	1% Eff. size	1% Eff. power	0.1% Eff. size	0.1% Eff. power	0.01% Eff. size	0.01% Eff. power	0.001% Eff. size	0.001% Eff. power
A. full sample period									
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
B. low volatility period									
Index		0.77	4.75	0.09	2.62	0.016	1.50	0.0032	0.90
	1.02	0.76	2.08	0.10	1.12	0.020	0.63	0.0073	0.37
Call	1	0.79	2.23	0.10	1.22	0.016	0.69	0.0022	0.42
	0.98	0.86	2.31	0.10	1.27	0.017	0.73	0.0028	0.44
	1.02	0.84	2.17	0.10	1.17	0.017	0.66	0.0028	0.40
Put	1	0.80	2.00	0.09	1.06	0.012	0.60	0.0017	0.36
	0.98	0.85	1.76	0.13	0.91	0.033	0.50	0.0151	0.29
C. high volatility period									
Index		0.50	2.77	0.06	1.42	0.008	0.80	0.0011	0.48
	1.02	0.62	1.42	0.06	0.73	0.008	0.41	0.0018	0.25
Call	1	0.64	1.43	0.06	0.74	0.008	0.42	0.0018	0.25
	0.98	0.64	1.44	0.06	0.75	0.009	0.42	0.0018	0.25
	1.02	0.64	1.36	0.08	0.70	0.013	0.39	0.0018	0.24
Put	1	0.63	1.33	0.07	0.68	0.013	0.38	0.0006	0.23
	0.98	0.63	1.29	0.07	0.66	0.012	0.37	0.0012	0.22

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

Table 9 The effective size and effective power of the ABD test for the SVCJ model

Price	Moneyness (K/S_0) α	1% Eff. size	1% Eff. power	0.1% Eff. size	0.1% Eff. power	0.01% Eff. size	0.01% Eff. power	0.001% Eff. size	0.001% 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 10 The jumps in futures and monthly out-of-the-money option prices

Panel A

α (%)	Number of Det. Jump F	C	P	Number of Jump Combination C	P +	P −	CP	F	FC	FP	FCP	Total number of J. Comb.
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
				Percentage of Jump Combination (%)								
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 number of detected jumps and the number of jump combinations across different significance levels. In the second column F denotes the number of detected jumps in futures. In the third column C denotes the number of detected jumps in call. The fifth column C denotes the number of detected jumps in call and no jumps in futures or put prices. The sixth column P+ denotes the number of positive detected jumps in put and no jumps in any other price. The seventh column P− denotes the number of negative detected jumps in put and no jumps in any other price. The eighth column CP shows the number of the contemporaneous detected jumps in call and in put. The ninth column F denotes the number of detected jumps in futures and no jumps in any other price. The tenth column FC denotes the number of contemporaneous jumps in futures and call price. The eleventh column FP denotes the number of contemporaneous jumps in futures and put. The twelfth column FCP shows the number of contemporaneous jumps in futures, call and put prices. The 5th-8th rows show the percentage of jump combination which is the number of specific jump combinations divided by total number of jump combinations.

Panel B The components of the CP and FCP jump combinations

α (%)	Number of Jump Combination CP +−	CP −+	Sub-total	CP ++	CP −−	Sub-total	Number of Jump Combination FCP ++−	FCP −−+	Others FCP	Total no. J. Comb.
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
	Percentage of Jump Combination						Percentage of Jump Combination			
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 number of jump combination across different significance levels. The second four rows are the percentage of jump combination which is the number of specific jump combinations divided by total number 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 subtotal 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 11 The empirical results of the detected jumps in futures and option prices

α (%)	# of Det. Jump per 808 days F	C	P	Percentage of Jump Combination C	P +	P —	CP	F	FC	FP	FCP	Percentage of J. Comb. CP +—	CP —+	CP + +	CP — —
Panel A. Full sample period from 2005 to 2009															
A1. 3.5- minute frequency futures and option prices with monthly out-of-the-money option 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- minute frequency futures and option prices with monthly at-the-money option 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- minute frequency futures and option prices with quarterly at-the-money option 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- minute frequency futures and option prices with monthly out-of-the-money option 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- minute frequency futures and option prices with monthly out-of-the-money option 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- minute frequency futures and option prices with monthly out-of-the-money option 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- minute frequency futures and option prices with monthly out-of-the-money option 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- minute frequency futures and option prices with monthly out-of-the-money option 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 12 The selected and estimated parameters of affine jump-diffusion models

Panel A full sample period

Parameters	SV	SVJP	SVJV	SVIJ	SVCJ
V_0	0.022	0.021	0.022	0.022	0.020
γ	0.5%	11.9%	0.5%	14.3%	11.9%
k	4.65	6.25	7.15	7.25	7.25
θ	0.020	0.007	0.003	0.004	0.004
ξ	0.51	0.50	0.47	0.45	0.45
ρ	-0.01	-0.01	-0.01	-0.01	-0.01
λ^P	-	2300	-	2300	2300
λ^V	-	-	2300	2300	2300
μ (e-4)	-	-0.6	-	-0.6	-0.6
σ (e-4)	-	13.4	-	13.8	12.95
β	-	-	-	-	-0.06
μ^V (e-4)	-	-	1600	1	0.02
$\tilde{k}$	4.4	6.0	6.9	7.0	7.0
$\tilde{\mu}$ (e-4)	-	-1.1	-	-1.2	-1.1
$\tilde{\sigma}$ (e-4)	-	15.8	-	16.0	15.2
$\tilde{\mu}^V$ (e-4)	-	-	1608	2	0.04
Annual price jump risk premium	-	11.4%	-	13.7%	11.4%

Panel B low volatility period

Parameters	SV	SVJP	SVJV	SVIJ	SVCJ
V_0	0.012	0.010	0.012	0.010	0.010
γ	0.3%	6.2%	0.3%	8.2%	6.2%
k	6.55	6.45	7.25	7.25	7.25
θ	0.011	0.004	0.002	0.002	0.004
ξ	0.52	0.50	0.47	0.45	0.45
ρ	-0.01	-0.01	-0.01	-0.01	-0.01
λ^P	-	2000	-	2000	2000
λ^V	-	-	2000	2000	2000
μ (e-4)	-	-0.01	-	-0.01	-0.01
σ (e-4)	-	9.9	-	9.65	9.8
β	-	-	-	-	-0.06
μ^V (e-4)	-	-	0.206	1e-4	0.01
$\tilde{k}$	6.3	6.2	7.0	7.0	7.0
$\tilde{\mu}$ (e-4)	-	-0.31	-	-0.41	-0.31
$\tilde{\sigma}$ (e-4)	-	12.9	-	12.15	12.7
$\tilde{\mu}^V$ (e-4)	-	-	2068	2	0.02
Annual price jump risk premium	-	5.9%	-	7.9%	5.9%

Panel C high volatility period

Parameters	SV	SVJP	SVJV	SVIJ	SVCJ
V_0	0.059	0.050	0.058	0.050	0.050
γ	1.5%	19.1%	1.5%	22.1%	19.1%
k	3.05	6.25	4.65	5.15	7.05
θ	0.238	0.022	0.010	0.010	0.010
ξ	0.50	0.50	0.50	0.50	0.46
ρ	-0.01	-0.01	-0.01	-0.01	-0.01
λ^P	-	3000	-	3000	3000
λ^V	-	-	3000	3000	3000
μ (e-4)	-	-1	-	-1	-1
σ (e-4)	-	18.2	-	18.3	17.8
β	-	-	-	-	-0.03
μ^V (e-4)	-	-	2850	1	0.2
$\tilde{k}$	2.8	6.0	4.4	4.9	6.8
$\tilde{\mu}$ (e-4)	-	-1.6	-	-1.7	-1.6
$\tilde{\sigma}$ (e-4)	-	21.2	-	21.3	20.7
$\tilde{\mu}^V$ (e-4)	-	-	2858	2	0.4
Annual price jump risk premium	-	17.8%	-	20.8%	17.8%

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

Panel D The comparison of estimated and selected parameters with previous research

	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 (2003), Chernov et al. (2003), Eraker(2004), and Wang (2009). Our estimation parameters are the medians of estimated parameters by minimizing squared pricing error between Duffie, Pan and Singleton (2000) theoretical prices and the 7-min frequency monthly expiration market prices. The simulation parameters are equal to these parameters Panels A-C, which are applied to simulate model-based results in Tables 13-18.

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

Table 13 Stochastic volatility (SV) model

α (%)	# of Det. Jump per 808 days			Percentage of Jump Combination								Percentage of J. Comb.		
	F	C	P	C	P +	P —	CP	F	FC	FP	FCP	FCP ++—	FCP ——+	Others FCP
A. Full sample period														
1	12.3	13.0	13.1	28	15	15	0	15	13	10	4	2	2	0
0.1	1.6	1.8	1.7	30	16	15	0	17	11	9	2	1	1	0
0.01	0.2	0.3	0.3	31	16	14	0	22	6	8	3	1	2	0
0.001	0.04	0.02	0.05	17	17	22	0	35	0	4	4	4	0	0
B. Low volatility period														
1	14.1	12.4	12.5	28	15	15	0	26	9	7	1	0.4	0.6	0
0.1	2.0	1.7	1.7	29	15	15	0	29	7	5	0	0.2	0.3	0
0.01	0.3	0.3	0.3	28	20	16	0	26	6	3	1	0.5	0.0	0
0.001	0.06	0.05	0.09	27	20	23	0	25	0	5	0	0.0	0.0	0
A3. High volatility period														
1	11.0	12.7	12.8	25	13	14	0	4	14	13	17	8	9	0
0.1	1.3	1.7	1.7	29	11	17	0	5	12	12	13	6	8	0
0.01	0.2	0.2	0.3	28	12	17	0	7	9	17	9	5	5	0
0.001	0.03	0.03	0.05	25	10	30	0	15	0	10	10	5	5	0

Note: 200,000 simulation days.

Table 14 Stochastic volatility with jump in price (SVJP) model

α (%)	# of Det. Jump per 808 days F	C	P	Percentage of Jump Combination C	P +	P —	CP	F	FC	FP	FCP	Percentage of J. Comb. 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	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
A3. 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
A4. Result with estimated parameters from Pan(2002) in Table 12 D															
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
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	351	559	517	23	9	10	10	0.9	4	3	41	4.8	5.1	0.0	0.0
0.1	196	351	318	25	9	10	12	0.4	4	2	37	5.9	5.9	0.0	0.0
0.01	115	226	202	28	10	11	12	0.3	3	2	33	6.3	6.2	0.0	0.0
0.001	71	150	132	29	10	11	13	0.3	3	2	32	6.3	6.7	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	259	397	388	19	9	8	11	0.2	2	2	49	5.1	6.3	0.0	0.0
0.1	133	218	213	20	10	9	12	0.1	2	1	46	5.2	7.1	0.0	0.0
0.01	74	129	125	21	10	9	14	0.0	1	1	43	5.9	8.1	0.0	0.0
0.001	45	81	77	22	10	9	14	0.1	1	1	42	5.8	8.7	0.0	0.0

Note: the Panel A4 is from 60,000 simulation days and others are from 30,000 simulation days.

Table 15 Stochastic volatility with jump in volatility (SVJV) model

α (%)	# of Det. Jump per 808 days F	C	P	Percentage of Jump Combination C	P +	P —	CP	F	FC	FP	FCP	Percentage of J. Comb. 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	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. 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
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	180	236	513	9	57	0.8	6	4	8	3	13	0.0	0.0	5.5	0.0
0.1	67	106	311	9	67	0.4	5	3	6	2	7	0.0	0.0	5.4	0.0
0.01	29	54	210	8	74	0.2	5	2	4	1	4	0.0	0.0	5.4	0.0
0.001	13	30	149	8	79	0.2	5	2	2	1	2	0.0	0.0	5.2	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	137	151	399	6	64	0.8	2	3	10	2	13	0.0	0.0	1.5	0.0
0.1	43	52	224	6	76	0.5	1	2	7	1	6	0.0	0.0	1.4	0.0
0.01	14	20	142	5	85	0.4	1	1	4	1	3	0.0	0.0	1.3	0.0
0.001	5	8	95	4	90	0.1	1	1	2	1	2	0.0	0.0	1.1	0.0

Note: 30,000 simulation days.

Table 16 Stochastic volatility with independent jumps in price and in volatility (SVIJ) model

α (%)	# of Det. Jump per 808 days			Percentage of Jump Combination								Percentage of J. Comb.			
	F	C	P	C	P +	P —	CP	F	FC	FP	FCP	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	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
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	326	533	515	19	8	8	15	0.2	2	1	47	7.4	7.2	0.0	0.0
0.1	178	323	310	21	9	9	17	0.1	1	1	43	8.3	8.5	0.0	0.0
0.01	103	202	191	22	9	9	18	0.1	1	1	40	9.0	9.1	0.0	0.0
0.001	61	131	123	23	9	9	20	0.0	1	0	37	10.1	10.1	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	258	394	384	18	9	8	12	0.1	2	1	51	5.4	6.3	0.0	0.0
0.1	129	212	209	19	9	9	14	0.0	1	1	46	5.7	7.8	0.0	0.0
0.01	71	122	120	20	10	9	15	0.0	1	1	44	6.1	8.5	0.0	0.0
0.001	42	75	73	21	11	9	15	0.0	1	1	43	6.9	7.7	0.0	0.0

Note: 30,000 simulation days.

Table 17 Stochastic volatility with contemporaneous jumps in price and in volatility (SVCJ) model

α (%)	# of Det. Jump per 808 days F	C	P	Percentage of Jump Combination C	P +	P —	CP	F	FC	FP	FCP	Percentage of J. Comb. 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: $\tilde{\mu}^V = \mu^V = 0.02e\text{-}4$															
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: $\tilde{\mu} = \mu = -0.6e\text{-}4$, $\tilde{\sigma} = \sigma = 12.95e\text{-}4$															
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 from Table 12.D															
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 from 100,000 simulation days and others are from 30,000 simulation days.

Table 18 The results of different selected parameters of SVCJ model

# of Det. Jump/ 808 days				Percentage of Jump Combination													
α (%)	F	C	P	C +	C −	P +	P −	CP +−	CP −+	CP ++	F +	F −	FC	FP	FCP ++−	FCP −−+	FCP +++
A1. empirical result of full sample period																	
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 Table 12A																	
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. ρ decreases 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. μ decreases to -36.5e-4; $\tilde{\mu} = \mu$ - 0.5e-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. σ increases 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^V increases 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: 10,000 simulation days. Cases 1-8 are based on the parameters in Table 12 A and the above specific constraint.

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