**Modeling the dynamics of Chinese spot interest rates**

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**Abstract**

Using the daily data of Chinese 7-day repo rates from January 1, 1997 to December 31, 2008, this paper tests a variety of popular spot rate models, including single-factor diffusion, GARCH, Markov regime-switching and jump-diffusion models. We document that Chinese spot rates are subject to both market forces and administrative forces. GARCH, regime-switching and jump-diffusion models capture some important features of the dynamics of Chinese spot rates, but all models under study are overwhelmingly rejected. We further explore possible sources of model misspecification using diagnostic tests.

*JEL classification:* E4; C5; G1
*Keywords:* Spot rate models; Term structure of interest rates; Market segmentation; Nonparametric specification tests

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## 1. Introduction

The spot rate is the yield on a zero-coupon bond with zero maturity and is the most important factor of the term structure of interest rates. A vast literature has been devoted to modeling the dynamics of spot rates in mature markets. These include, among many others, Chan, Karolyi, Longstaff and Sanders (CKLS, 1992), Ait-Sahalia (1996, 1999), Gray (1996), Stanton (1997), Brenner, Harjes and Kroner (1996), Andersen and Lund (1997), Ahn and Gao (1999), Conley, Hansen, Luttmer and Scheinkman (1997), Chapman and Pearson (2000), Dai and Singleton (2000), Elerian, Chib and Shephard (2001), Ang and Bekaert (2002), Das (2002), Durham (2003), Jones (2003), Johannes (2004), Hong, Li and Zhao (2004) and Hong and Li (2005). These studies document some important features of spot interest rates in mature markets, particularly the U.S. markets. For example, there exists significant mean reversion when using one-factor diffusion models for the U.S. interest rates, although whether there exists a nonlinear drift is inconclusive. Ait-Sahalia (1996), Stanton (1997), Conley et al. (1997), Ahn and Gao (1999) report the evidence of nonlinear drifts, whereas Chapman and Pearson (2000), Hong et al. (2004) cast doubts on it. Chan et al. (1992) and Hong et al. (2004) document that the interest rate volatility tends to be higher when the interest rate level is higher, which is called the "level effect" and often is characterized by a Constant Elasticity Variance (CEV) specification. Moreover, Brenner et al. (1996) and Andersen and Lund (1997) find that it is important to capture the conditional heteroskedasticity of interest rates via stochastic volatility/GARCH models. Gray (1996), Ang and Bekaert (2002), Das (2002) and Johannes (2004), Kanas (2008), Jiang and Yan (2008) find that that regime-switching and jump models help capture volatility clustering and especially the excess kurtosis and heavy tails of spot interest rates. Once stochastic volatility/GARCH, regime switching, or jump effects are introduced, the importance of modeling mean reversion in drift diminishes substantially. A sophisticated specification for the drift usually provides little help to the overall goodness of fit of spot rate models (Durham, 2003).

While the spot rate dynamics have been extensively examined in mature markets, such as the U.S. markets, there has been little study of spot interest rates in China and other emerging markets.[1] This is perhaps due to the relatively short history of the Chinese bond markets and the strict regulation of Chinese interest rates. However, understanding the dynamics of Chinese spot rates is important for developing efficient financial markets, determining effective interest rate policy and piloting optimal investments. Moreover, knowledge of Chinese interest rate dynamics aids in the determination of security prices, the prediction of interest rate changes and the choice of hedging strategies. Generally, in an emerging market such as China, the spot rate plays a role similar to the fed fund rate in the U.S. and it is a fundamental instrument in developing bond markets and other fixed-income markets.

It is undoubted that Chinese spot rates are quite heavily managed by the authorities. It is often argued that Chinese spot rates are strongly subject to administrative control by the government, their mechanism is quite different from that of other developed markets, and the models popular in U.S. markets do not work for the Chinese market. On the other hand, the degree of marketization in China has been gradually improving. Chinese spot rates are becoming increasingly market oriented. It is very interesting to study the dynamics of such heavily managed but gradually reformed spot rates as well as the similarities and differences between Chinese spot rates and U.S. spot rates. In particular, we are interested in whether Chinese spot rates are subject to both market forces and administrative forces, which is evidence of a transition economy. On the one hand, we examine whether Chinese spot rates share similar dynamic features to U.S. spot rates and whether the models that can capture

[1] Fan and Zhang (2007) is one of the few literatures that explore market segmentation in the two Chinese repo markets, i.e., the interbank repo market and the exchange repo market.

important features of U.S. interest rate dynamics can also characterize important features of Chinese spot rates. This is a test of the degree of marketization in China using spot rate data. If Chinese spot rates share important features with U.S. spot rates, it indicates the development of Chinese fixed-income markets towards market orientation. On the other hand, we would like to test whether Chinese spot rates are also subject to external impacts. We consider two types of external events that have significant impact on the dynamics of Chinese spot rates in this paper. One is the set of administrative events including the institutional change in 1999 and interest rate policy changes[2]. The other is the spillover effect from Chinese stock market IPOs[3].

Spot rate models are widely used in risk management and the pricing of fixed-income securities. Different information of spot rate models is used for different applications. For example, the marginal distribution is important when we forecast the distribution and calculate the VAR, while the model dynamics are used more when we price fixed-income securities. It is important to know whether a complicated model improves the marginal distribution when we calculate the VAR and whether it improves the model dynamics when we price the fixed-income securities. The model specification test in this paper provides useful information regarding the improvement of more complicated models on marginal distribution and model dynamics, and could therefore be used to select the most appropriate spot rate model.

In this paper, we provide the first comprehensive empirical study on the dynamics of Chinese spot rates. We consider a wide variety of spot rate models, including single-factor diffusion, GARCH, Markov regime-switching and jump-diffusion models, and we examine how well they can capture important features of Chinese spot rates. We use a nonparametric test proposed by Hong and Li (2005) and Hong, Li and Zhao (2007) to test the adequacy of

[2] Fan and Johansson (2009) show that Chinese bond yields are influenced by the monetary policy decisions.
[3] Li and Zou (2008) show that the correlation between Chinese's T-bond and stock returns is affected by the policy and information shocks.

these models for Chinese spot rates. We introduce dummy variables to account for external impacts, which include the impact of administrative events including institutional change and interest rate policy changes, and the spillover from stock market IPOs. We find that there are both similarities and differences between the dynamics of Chinese spot rates and U.S. spot rates. The spot rate models popular in the U.S. could also successfully capture some important features of Chinese spot rates. This is evidence of the development of Chinese fixed-income markets towards a market orientation. However, the models considered in this paper are all rejected and thus misspecified. We have not yet found a correct model that could be used to capture Chinese spot rates. We also find that Chinese spot rates are subject to external impacts. Chinese spot rates are subject to both market and administrative forces. The separate specifications show that GARCH models reduce specification errors in both the marginal distribution and model dynamics. Regime-switching and jump models mainly reduce the specification errors in the marginal distribution, but they do not help much in reducing the misspecification of model dynamics.

In Section 2, we review the history of the Chinese interest rate liberalization and describe the data on Chinese spot rates. In Section 3, we introduce a wide variety of spot rate models and the nonparametric tests by Hong and Li (2005) and Hong et al. (2007). In Section 4, we report the empirical results. Section 5 concludes the paper.

## 2. Interest rate liberalization in China and proxy for Chinese spot rates

### *2.1. Interest rate liberalization in China*

China regulated savings rates until the mid-1980s. Due to the short history of the Chinese market economy and the main focus on developing the stock market, the Chinese bond market and interest rate liberalization are underdeveloped. Chinese spot interest rate is determined in two main markets, i.e., the interbank borrowing/offering market and the bond repurchase market. Chinese interbank borrowing/offering markets appeared in the 1980s at different locations over China and were united into a single market in January 1996 with "CHIBOR" as its uniformed rates. CHIBOR mainly consists of short-term interest rates, with four months as the longest maturity. On January 4, 2007, the Chinese interbank borrowing/offering center located in Shanghai began to report the Shanghai interbank offered rate, which is called SHIBOR. CHIBOR and SHIBOR mainly characterize the Chinese short-term interest rates.

Chinese collateralized bond repurchase began in 1991 at four stock exchanges, i.e., the Shanghai Stock Exchange, the Wuhan Stock Trading Center, the Tianjin Stock Trading Center, and the STAQ system (the later three have been closed). In 1997, to prevent banks from stock markets, the Chinese central bank, the People's Bank of China, prohibited all commercial banks from the collateralized bond repurchase on stock exchanges and opened another bond repurchase sub-market in the interbank market. This leads to two independent and segmented bond repurchase markets in China, i.e., the OTC market at interbank markets and the electronic market at stock exchanges. These two markets are artificially segmented, with different prices for the same bond.

The long-term interest rates are determined by the Chinese long-term bond market. There are also two segmented long-term bond markets, the OTC bond market at the interbank market and the electronic market at stock exchanges. The interest rates of middle maturities are controlled tightly by the Chinese central bank. They do not change every day to reflect market information but remain unchanged for a relatively long period. They change only when the Chinese government uses them as instruments of interest rate policy.

There are two main deficiencies of the current interest rate mechanism in China that hinder the play of its fundamental roles in Chinese economy. First, there exist two independent bond markets that share similar functions and trade the same products, i.e., the interbank OTC market and the exchange electronic market. Since they are artificially segmented, the same bond has different prices at these two markets, resulting in two different interest rates between the interbank market and the exchange market. The difference in the interest rate levels of two segmented markets reflects different expectations of investors. It is very difficult, if not impossible, to develop derivative markets without a uniform market interest rate. Second, the deposit rates in China are still regulated by the Chinese central bank. They cannot be changed by commercial banks to reflect market information. Therefore, there is a large gap between the regulated deposit rates and the market interest rates, and serious problems and arbitrage opportunities may arise. (Lin and Zheng, 2004 ).

The Chinese government has recently proposed several reforms on interest rate liberalization. It issues bonds at both the interbank market and the exchange market. Eligible banks were allowed to be the bid-ask quoters in 2001. Some security companies and trust companies are also allowed to issue securities on the interbank market. Another kind of repo transaction, called the buyout repurchase, was also introduced in 2005.

The Chinese government also begins to issue bonds systematically from long maturities to short maturities. By issuing and trading bonds with different maturities, an integrated bond market can be developed to provide a robust benchmark for pricing and hedging. Furthermore, the Chinese government has a plan to gradually deregulate deposit rates and to eventually liberalize them. It also seeks to introduce other financial instruments, such as Stock Index Futures and Bond Futures. In all, although the liberalization of Chinese interest rates is still far from complete, it has been steadily advancing. Table 1 summarizes the major characteristics of Chinese interest rate liberalization, including its history and recent developments.

[TABLE 1 HERE]

*2.2. Proxy for Chinese spot rates*

To investigate the dynamics of Chinese spot rates, we shall use the Chinese collateralized 7-day repo rates as the proxy for Chinese spot rates.[4] We use the average of two segmented collateralized 7-day repo rates (one in the OTC market and the other in the exchange market) as the proxy. Table 2 reports the trading volumes of collateralized 1-day repo, 7-day repo, 14-day repo and 1-month repo, which could represent Chinese spot rate during the sample period. It also reports the trading volume of the Chinese interbank offered rate. These data are obtained from the WIND dataset and the *Chinese Financial Industry Annual Report*. The trading of the repo is much more active than that of the interbank offered rate[5]. The trading of the 7-day repo is the most active among all repos before 2005, which makes it the best proxy for Chinese spot interest rates. We use the daily data of 7-day repo rates from January 1, 1997 to December 31, 2008 with a total of 2,986 observations. We transform the original data to eliminate the impact of holidays on the repurchase time; i.e.,

$$r_t = \frac{\tilde{r}_t \times 7}{\tau} \tag{1}$$

where $r_t$ is the transformed 7-day repo rate used for the test, $\tilde{r}_t$ is the listed 7-day repo rate, and $\tau$ is the number of exact repurchase days.

[TABLE 2 HERE]

Figure 1 plots the level and change series of the transformed daily 7-day repo rates, as well as their histograms. There is persistent volatility clustering, and the volatility was generally higher at the higher interest rate level before 1999; i.e., there exists a "level effect."

[4] In empirical studies of spot rate models in mature markets, yields on different short-term debts are used as proxies of spot rates. These include 1-month T-bill rates used by Gray (1996), Chan et al. (1992) and Hong et al. (2004), 3-month T-bill rates used by Stanton (1997) and Andersen and Lund (1997), 7-day Eurodollar rates used by Ait-Sahalia (1996) and Hong and Li (2005), and the Fed fund rates used by Conley et al. (1997) and Das (2002).

[5] There are other reasons that make the Chinese repo rate a better reflection of market forces than the Chinese interbank borrowing/offering rate. The members that are eligible to trade in repo market are much more extensive than interbank borrowing/offering market. A financial institution has to be authorized by Chinese central bank to trade in the interbank offered rate market, while it only needs to file in the central bank to trade in the repo market. In 2007, there are 274 members in Chinese interbank offered rate market, while there are more than 800 members in Chinese repo market. The security companies, funds, financial companies and other nonfinancial institutions could only trade in the repo market. Moreover, repo is a kind of collateralized borrowing and has less credit risk than the interbank offered rate. The transaction of the interbank offered rate is private and the counterparties have to undertake all risks, while repo is through the official trustee and settlement system. Dai and Liang (2006) find that CHIBOR is Granger caused by the repo rate but not vice versa. This suggests that repo rate is more efficient in incorporating new market information.

There appeared an institutional change in repo rate behavior following 1999. Before 1999, the Chinese IPO price was no more than 15 times earnings per share. The Chinese Securities Law exercised on July 1, 1999, however, reformed the IPO pricing mechanism, requiring that the IPO price be based on the market value. This reform had a significant impact on the repo market.

Another important administrative event that would affect the dynamics of Chinese spot rates is the change in interest rate policy. Table 3 reports the history of Chinese interest rate policy changes during the sample period, including the changes in the savings rate, the lending rate, the statuary deposit reserve rate and the excess deposit reserve rate. Chinese spot rates seem to be more volatile during the period when the central bank frequently changes the interest rate. For example, the Chinese central bank changed the interest rate six times during the period of 1997 and 2000, while changed the interest rate only once between 2000 and 2005. Chinese spot rates are more volatile between 1997 and 2000 than between 2000 and 2005.

[TABLE 3 HERE]

The marginal distribution of the interest rate level is skewed to the right, with a long right tail. The repo rates show frequent jump behaviors, which are quite different from mature markets where the interest rates generally change steadily. This is mainly due to the arbitrage of large institutions in Chinese IPOs. Before 1999, the return from subscribing new shares on the primary market and selling it immediately on the secondary markets could be as high as 100% in the Chinese stock market. Then, when there was an IPO on the primary market, investors would demand a large amount of money for a few days at a rate as high as 24%, which would result in a sudden jump in the repo rate. After the IPO, the spot rate would fall immediately. Other possible reasons for the extreme interest rate observations include liquidity shocks and interventions of the Chinese central bank.

Nevertheless, IPO is the main reason for frequent large changes in Chinese spot rates[6]. The mean 7-day repo rate for the days with an IPO is 4.49% and the mean 7-day repo rate for the days without an IPO is only 2.98%. The difference is 1.51%, which is significant at the 1% level.

[FIGURE 1 HERE]

## 3. Spot rate models

We examine whether popular spot rate models that have been used to capture the dynamics of spot rates in mature markets can also be used to characterize Chinese spot rates. The models to be examined include single-factor diffusion, GARCH, regime-switching, and jump-diffusion models.

### *3.1. Single factor diffusion models*

Single-factor diffusion models have been widely used in the pricing of fixed-income securities. Specifically,

$$dr_t = \mu(r_t,\theta)dt + \sigma(r_t,\theta)dW_t, \tag{2}$$

where $\mu(r_t, \theta)$ and $\sigma(r_t, \theta)$ are the drift and diffusion functions, $W_t$ is a standard Brownian motion. Here, $\mu(r_t, \theta)$ and $\sigma(r_t, \theta)$ completely determine the model transition density, which captures the full dynamics of $r_t$.

Table 4(a) lists all single-factor diffusion models examined in this paper. We consider a variety of discretized single-factor diffusion models, which are nested by the Ait-Sahalia (1996) nonlinear drift model,

$$\begin{cases} \Delta r_t = \alpha_{-1} r_{t-1}^{-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2 + \sigma r_{t-1}^{\rho} z_t, \\ \{z_t\} \sim iid.N(0,1), \end{cases} \tag{3}$$

where $\Delta r_t = r_t - r_{t-1}$. Discretizations are approximations of continuous-time models.

6 We retrieve the total size of IPOs and the amount of short-term money used to subscribe these shares from WIND. The total size of IPOs in the Chinese stock market between 1997 and 2008 is 1157.83 billion RMB, and around 185700 billion RMB short-term money is used to subscribe these shares. Such a large amount of short-term money demand will definitely affect the repo market.

Nevertheless, Bandi (2002) documents that the error introduced by discretization is of second-order importance if changes are measured over very short periods. Stanton (1997) and Das (2002) also document that the discretization bias for daily data is not substantial. To examine different model specifications, we allow the drift function to have a zero, linear, and nonlinear specifications and allow the diffusion function to be a constant or to depend on the interest rate level, which is referred to as the "level effect." The diffusion specification $\sigma r_{t-1}^{\rho}$ is called the Constant Elasticity Variance (CEV).

*3.2. GARCH models*

Table 4(b) lists the GARCH models we would like to test. We consider six GARCH models, including three drift specifications (zero, linear and nonlinear) and two volatility specifications (pure GARCH and combined CEV-GARCH). These models are nested by the following specification:

$$\begin{cases} \Delta r_t = \alpha_{-1} r_{t-1}^{-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2 + \sigma r_{t-1}^{\rho} \sqrt{h_t} z_t, \\ h_t = \beta_0 + h_{t-1}(\beta_2 + \beta_1 r_{t-2}^{2\rho} z_{t-1}^2), \\ \{z_t\} \sim iid.N(0,1). \end{cases} \tag{4}$$

For identification, we set $\sigma = 1$ in all GARCH models.

*3.3. Markov regime-switching models*

Table 4(c) lists a variety of regime-switching models, all of which are nested by the following specification:

$$\begin{cases} \Delta r_t = \alpha_{-1}(s_t) r_{t-1}^{-1} + \alpha_0(s_t) + \alpha_1(s_t) r_{t-1} + \alpha_2(s_t) r_{t-1}^2 + \sigma(s_t) r_{t-1}^{\rho(s_t)} \sqrt{h_t} z_t, \\ h_t = \beta_0 + \beta_1 E[e(r_{t-1}, s_{t-1} \mid r_{t-2}, s_{t-2})]^2 + \beta_2 h_{t-1}, \\ e(r_{t-1}, s_{t-1} \mid r_{t-2}, s_{t-2}) = [\Delta r_{t-1} - E(\Delta r_{t-1} \mid r_{t-2}, s_{t-2})] / \sigma(s_{t-1}), \\ \{z_t\} \sim iid.N(0,1), \end{cases} \tag{5}$$

where $s_t$ =1 (or 2) means the first (or second) regime. Following Ang and Bekaert (2002), the transition probability of $\{s_t\}$ is assumed to depend on the one-lagged spot rate level,

$$\Pr(s_t = l \mid s_{t-1} = l) = \frac{1}{1+\exp(-c_l - d_l r_{t-1})}, \quad l = 1,2 \tag{6}$$

We consider three specifications for the drift function, zero, linear and nonlinear drifts, and three specifications for the diffusion function, CEV, GARCH and CEV-GARCH. Similarly, for identification, we set the diffusion constant $\sigma(s_t) = 1$ for $s_t = 1$.

*3.4. Jump-diffusion models*

We consider a class of discretized jump-diffusion models listed in Table 4(d). We consider zero, linear and nonlinear drift specifications. For volatility, we consider CEV, GARCH and combined CEV-GARCH specifications. These nine models are nested by the following specification:

$$\begin{cases} \Delta r_t = \alpha_{-1} r_{t-1}^{-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2 + \sigma r_{t-1}^{\rho} \sqrt{h_t} z_t + J(\psi, \gamma^2)\pi(q_t), \\ h_t = \beta_0 + \beta_1 [\Delta r_{t-1} - E(\Delta r_{t-1} \mid r_{t-2})]^2 + \beta_2 h_{t-1}, \\ \{z_t\} \sim iid.N(0,1), \\ \{\pi(q_t)\} \sim Bernoulli(q_t), \\ J \sim N(\psi, \gamma^2), \end{cases} \tag{7}$$

where $J$ is a random jump size and $q_t$ is the jump probability with

$$q_t = \frac{1}{1+\exp(-c - d r_{t-1})}. \tag{8}$$

For identification, we set $\sigma = 1$ in all GARCH and CEV-GARCH specifications.

[TABLE 4 HERE]

Chinese spot rates are also subject to external influences. We consider two kinds of external influence in this paper. One is the administrative events, including institutional change in 1999 and interest-rate policy changes. The other is spillover from Chinese stock market IPOs. We introduce three sets of dummy variables in the drift, volatility, elasticity and jump probability parameters to account for these external impacts. For example, the dummy variables for institutional change in 1999 $\alpha_{ID}$ (drift dummy), $\sigma_{ID}$ (volatility dummy), $\rho_{ID}$ (elasticity dummy) and $c_{ID}$ (jump probability dummy) are one before 1999 and zero after

1999.

To evaluate the relative performance of spot rate models, we use a robust nonparametric test proposed by Hong and Li (2005) and Hong et al. (2007). The basic ideas are as follows. Supposing that we have a random sample $\{r_t\}_{t=1}^{n}$ of size *n*, Hong and Li (2005) consider generalized residuals $\{Z_t(\theta)\}_{t=1}^{n}$ by the following probability integral transform,

$$Z_t(\theta) \equiv \int_{-\infty}^{r_t} p(r,t|I_{t-1},\theta)dr,\ t=1,2,...,n\,, \tag{9}$$

where $p(r,t\,|\,I_{t-1},\theta)$ is the model-implied conditional density function. The generalized residuals $\{Z_t \equiv Z_t(\theta)\}_{t=1}^{n}$ is i.i.d. U[0,1] under the correct model specification. Intuitively, the i.i.d. U[0,1] property captures two important aspects of model specification: i.i.d. characterizes the correct specification of model dynamics, and U[0,1] characterizes the correct specification of the model's marginal distribution. In empirical test, we employ the statistics $\hat{W}(p)$ proposed in Hong and Li (2005) for the specification test and M*(m,l)* proposed in Hong and Li (2005) and Hong et al. (2007) to check the possible sources of model misspecification. Hong and Li (2005) and Hong et al. (2007) show that both $\hat{W}(p)$ and M*(m,l)* $\rightarrow$ N(0,1) under the correct model specification and $\rightarrow\infty$ under model misspecification.[7]

## 4. Empirical results

### *4.1. Model estimation*

We now use the Maximum Likelihood Estimation method to estimate various spot rate models. Table 5 to Table 8 report the parameter estimates for discretized single-factor diffusion, GARCH, regime-switching and jump-diffusion models respectively. These estimations reveal some important stylized facts of Chinese spot rates.

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7 The introductions of two tests are not reported for brevity and available upon request. Readers could also refer to Hong and Li (2005) and Hong et al. (2007) for detailed description of these test statistics.

(1) There exists significant mean reversion in Chinese spot rates. For example, the estimates of the drift parameters in Vasicek, CIR and CKLS models in Table 5 all show significant mean reversion. However, the contribution of a nonlinear drift specification over a linear drift specification is limited. In Table 5, the log-likelihood value increases from 12064.11 to 12148.09 by introducing a linear drift in the pure CEV, and only slightly increases to 12162.40 if we use a nonlinear drift.

(2) There exists significant conditional heteroskedasticity in Chinese spot rates, which can be captured by the GARCH effect or the level effect. The log-likelihood values of GARCH models are higher than those of single-factor diffusion models. All GARCH parameter estimates are significant. Combining both the GARCH effect and the level effect, however, does not significantly improve the goodness of fit.

(3) Regime-switching and jump help capture volatility clustering and especially the excess kurtosis and heavy tails of Chinese interest rates. The log-likelihood values of regime-switching models and jump-diffusion models are higher than those of GARCH models. In Table 7, both regimes show mean reversion for the linear drift models, with higher and lower long-run means, respectively[8]. For the linear drift CEV model, the higher long-run mean is 2.61%, and the lower long-run mean is 1.58%. For the linear drift GARCH model, the higher long-run mean is 8.37%, and the lower long run mean is 1.90%. The linear drift model combining CEV and GARCH has a higher long-run mean of 2.95% and a lower-long run mean of 1.60%. In Table 8, the parameter estimates of jump probability are overwhelmingly significant under the GARCH and CEV-GARCH specifications. The mean jump size $\psi$ is negative for CEV specifications but is positive for the GARCH and CEV-GARCH specifications. The jump volatility parameter estimates $\gamma$ in all specifications remain stable at about 1.10%.

[8] It should be noted that $-\alpha_0/\alpha_1$ are used here to calculate the long-run mean. However, since the CEV specification affects the mean, and since it may be difficult to find an analytical expression for the marginal mean of the CEV models, $-\alpha_0/\alpha_1$ might not exactly refer to the mean. We use these only for descriptive analysis.

(4) Chinese spot rates behave significantly differently before and after 1999, when a structural break occurred. The level/volatility of interest rates and the jump probability are significantly higher before 1999. However, the level effect, namely the dependence of the interest rate volatility on the interest rate level, becomes stronger after 1999. Most of the dummy variables for IPO and interest rate policy changes are significant, implying that the IPO events and interest rate policy changes also have significant impact on the dynamics of Chinese spot rates.

[TABLE 5 HERE]

[TABLE 6 HERE]

[TABLE 7 HERE]

[TABLE 8 HERE]

Table 9 summarizes the significant similarities and differences between the dynamics of Chinese spot rates and the U.S spot rates. There exist significant mean reversion and conditional heteroskedasticity in both the Chinese and U.S. spot rates. Regime switching and jump help capture volatility clustering and especially the excess kurtosis and heavy tails of both the Chinese and the U.S. interest rates. On the other hand, there are also significant differences between the dynamics of Chinese spot rates and those of U.S. spot rates. Chinese spot rates are much more volatile and much more shocked by external events such as institutional change, interest rate policy changes and IPOs. The elasticity parameter estimate is close to 0.5 for Chinese spot rates and is 1.5 in CKLS (1992) for U.S. spot rates. For GARCH models, mean reversion is significant when the GARCH effect is included for Chinese spot rates, but it is insignificant for U.S. spot rates. For Markov regime-switching models, there exist significant differences in the estimation results of elasticity, mean reversion, volatility ratios, and the relative performance of the level effect and the GARCH effect. For jump-diffusion models, there also exist significant differences in the estimation results of elasticity and jump size.

[TABLE 9 HERE]

*4.2. Portmanteau specification testing*

Table 10 reports the $\hat{W}(p)$ statistics with lag order $p=1,5,10$ for the spot rate models. These specification tests reveal some important findings in modeling Chinese spot rates.

(1) A linear drift is significant for simple models such as single-factor diffusion models and GARCH models. For example, introducing the linear drift substantially reduces the $\hat{W}(p)$ value for GARCH models in Panel (b). However, it becomes insignificant when more complicated models such as regime-switching models and jump-diffusion models are introduced. The contribution of nonlinear drift over linear drift is not robust, either.

(2) The level effect or GARCH effect can capture the volatility clustering of interest rates. However, their relative performance is different under different model specifications. CEV models perform better for regime-switching models, while GARCH models perform better for jump-diffusion models. There is little improvement in combining both effects.

(3) Introducing the GARCH/level effect, the regime-switching effect and the jump effect can improve the performance of various models for Chinese spot rates. In Panel (a), the $\hat{W}(p)$ statistics range from 254.44 to 1028.56, suggesting that all eight single-factor diffusion models are firmly rejected at any reasonable significance level. In Panel (b), the $\hat{W}(p)$ statistics for GARCH models range from 178.94 to 594.25 and are significantly smaller than those of single factor diffusion models. This highlights the effectiveness of the GARCH specification in modeling Chinese spot rates. In Panel (c), the $\hat{W}(p)$ statistics for Markov regime-switching models are from 13.77 to 78.54 and are much smaller than those of GARCH models. Panel (d) reports the $\hat{W}(p)$ statistics for jump-diffusion models, which

range from 32.94 to 125.78. Regime-switching models and jump-diffusion models are the two best classes of models to characterize Chinese spot rates, particularly in capturing the extreme observations. However, they are all rejected by the $\hat{W}\left(p\right)$ tests at any reasonable significance level, suggesting that they are still grossly misspecified.

[TABLE 10 HERE]

*4.3. Separate inference*

The results of the portmanteau tests suggest that introducing GARCH, regime switching and jump effectively reduce the specification errors of Chinese spot rate models, but all of them are still strongly rejected. Therefore, it may be interesting to examine the possible source of model misspecification. For this purpose, we first check the model marginal distribution and then check model dynamics.

The model marginal distribution is characterized by the U[0,1] property of generalized residuals. If the model could characterize the marginal distribution adequately, the histogram of generalized residuals would be horizontal. Figure 2 plots the histograms of generalized residuals for different models. Panel (a) plots the histograms of generalized residuals for single-factor diffusion models, which are far from being uniform, with a high peak around 0.5. This implies that these diffusion models are inadequate in capturing excess kurtosis. Panel (b) plots the histograms of generalized residuals for GARCH models. The peak is much lower than that of single-factor diffusion models. This reflects the improvement in the marginal distribution specification by introducing GARCH effects, which can capture some extreme changes. However, the histograms of generalized residuals for GARCH models are still different from the uniform distribution.

Panels (c) and (d) plot the histograms of generalized residuals for regime-switching models and jump-diffusion models, respectively. These histograms are very similar to the uniform distribution. These results suggest that regime switching and jump diffusion could effectively model the marginal distribution of Chinese spot rates, particularly the heavy tails.

[FIGURE 2 HERE]

Next, we examine the model dynamics by checking the i.i.d. property of their generalized residuals. We compare the M*(m,l)* values of different models to examine the source of dynamic misspecification. Table 11 reports the M*(m,l)* values of spot rate models for *(m,l)* = (1,1), (1,2), (2,1), (2,2), (3,3) and (4,4). Approximately, M(1,1) checks autocorrelations in level, M(1,2) checks the ARCH-in-mean effect, M(2,1) checks the leverage effect, and M (2,2), M(3,3) and M(4,4) check autocorrelations in higher-order moments. The results suggest that GARCH models reduce the M*(m,l)* values in almost all dimensions, while regime-switching and jump models only reduce the M*(m,l)* values in some dimensions. For example, they do not help reduce the autocorrelations in level measured by M(1,1).

[TABLE 11 HERE]

In summary, our separate inference reveals some important findings in the marginal distribution and model dynamics of Chinese spot rates. GARCH models reduce specification errors in both marginal distribution and model dynamics. Regime-switching and jump models mainly reduce the specification errors in the marginal distribution, but they do not help much in reducing the misspecification of model dynamics.

*4.4. What can we learn from empirical results*

The above estimation and specification test results provide useful information for understanding and modeling Chinese spot rates. The estimation results suggest that Chinese spot rates are subject to both market forces and administrative forces, which is a special phenomenon of a transition economy. On the one hand, Chinese spot rates are endogenously stochastic and share important features with U.S. spot rates. Chinese spot rates are gradually becoming market-oriented. On the other hand, administrative events also significantly affect

Chinese spot rates. The institutional change and interest rate policy changes have a significant impact on Chinese spot rates. Furthermore, there is a spillover from the Chinese stock market to the Chinese spot rate market. These results give us ideas on how to combine market and administrative forces to understand the dynamics of asset prices in emerging markets.

The specification test results show that different model specifications capture different features of Chinese spot rates. The improvement of more complicated models is not unanimous. This has useful implications for practical applications. For example, when we forecast the marginal distribution and calculate the VAR of fixed-income securities, we need to use the models that could characterize the marginal distribution correctly, such as regime-switching and jump-diffusion models. On the other hand, when we price complicated fixed-income securities, such as interest rate derivatives that mainly depend on the model dynamics of Chinese spot rates, GARCH models are possibly a better choice than regime-switching and jump-diffusion models since regime-switching and jump-diffusion models do not reduce the specification errors in model dynamics very much but are much more difficult to implement.

The specification test results show that all models are misspecified. This also provides open discussions on how to reach a correct model. Some discussions are worthwhile here. We consider two types of external events that have significant impact on the dynamics of Chinese spot rates using dummy variables. One is administrative events, including the institutional change in 1999 and interest rate policy changes. The other is the spillover effect from Chinese stock market IPOs. The use of dummy variables could not fully capture the administrative effect. The use of one dummy for the interest rate policy change does not consider the magnitude of impact by different interest rate policy changes, either. The results in our paper show the existence of administrative impact. The exact magnitudes of these impacts are still open questions and for future study. In addition to the official policy changes, the Chinese government also affects Chinese spot rates using implicit administrative approaches, such as open speeches, the replacement of CEOs of state-owned commercial banks, and administrative orders. These factors are implicit and difficult to combine into spot rate models by only using dummy variables. Furthermore, the model parameters possibly change due to gradual institutional changes, which cannot be detected by the models with constant coefficients. One possible way is to use the models with smooth transition parameters[9].

**5. Conclusion**

Using a daily sample of the Chinese 7-day spot interest rates, we estimate and test a variety of spot rate models, which include discretized single-factor diffusion models, GARCH models, Markov regime-switching models and jump-diffusion models. We document that introducing GARCH effects significantly improves the goodness of fit. Regime switching and jump effects help capturing volatility clustering and especially the excess kurtosis and heavy tails of Chinese spot interest rates. We also document that Chinese spot rates are significantly affected by external shocks including institutional changes, interest rate policy changes, and stock market IPOs. Chinese spot rates are subject to both market and administrative forces.

Although GARCH, regime-switching and jumps are important for modeling Chinese spot rate dynamics, they are still grossly misspecified. There is a long way to go before we reach a correct specification for Chinese spot rate dynamics. We further explore possible sources of model misspecification by examining the marginal distribution and model dynamics separately. We find that GARCH models reduce specification errors in both marginal distribution and model dynamics. Regime-switching and jump models mainly reduce the specification errors in the marginal distribution, but they do not help much in

[9] See van Dijk, Teräsvirta and Franses (2002).

reducing the misspecification of model dynamics. This may have useful implications for future modeling of Chinese spot rates.

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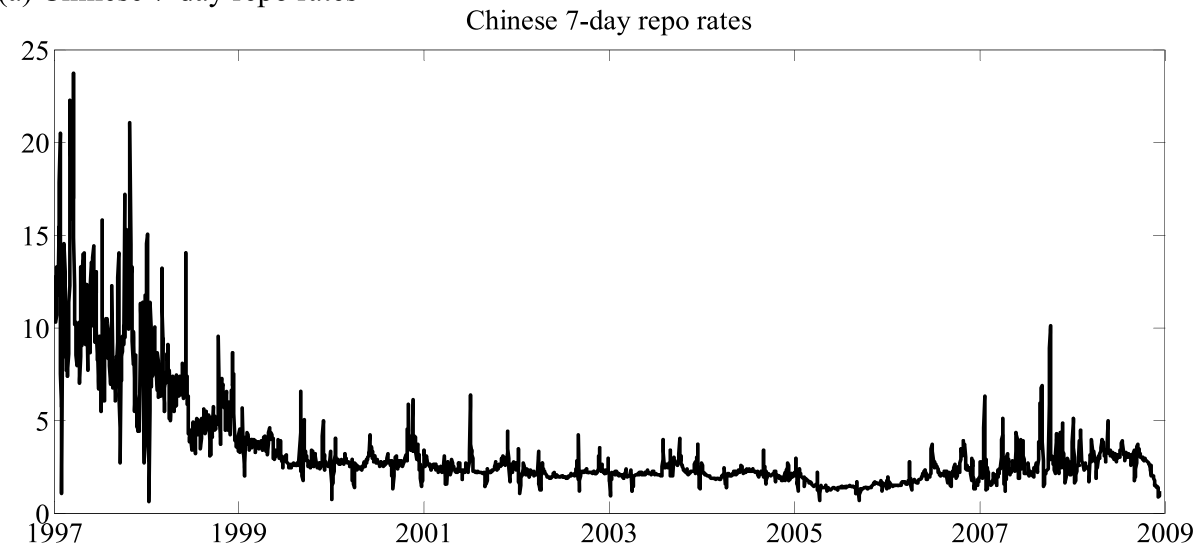
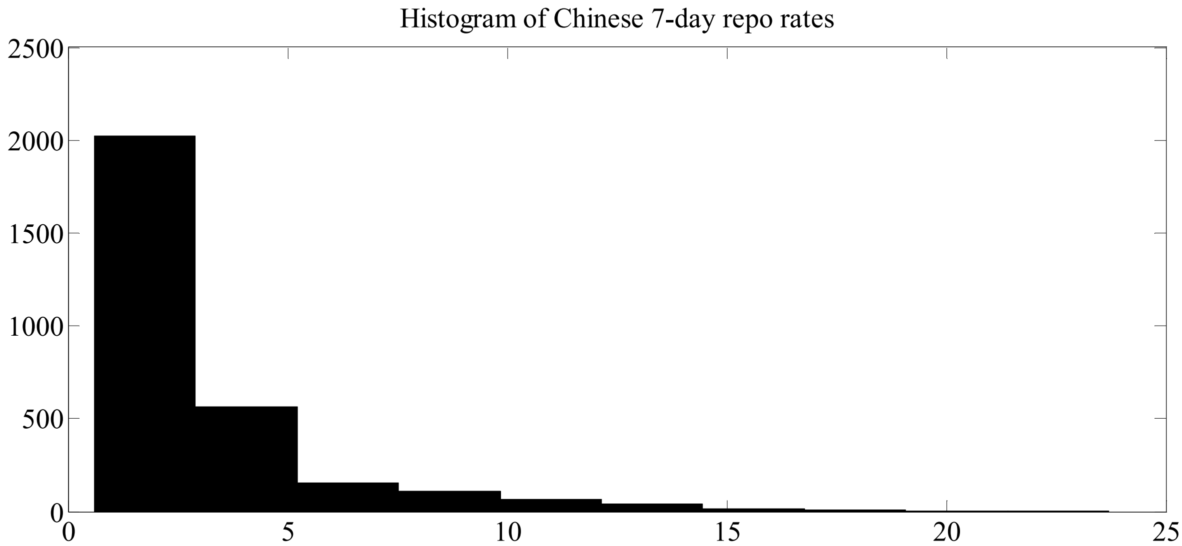
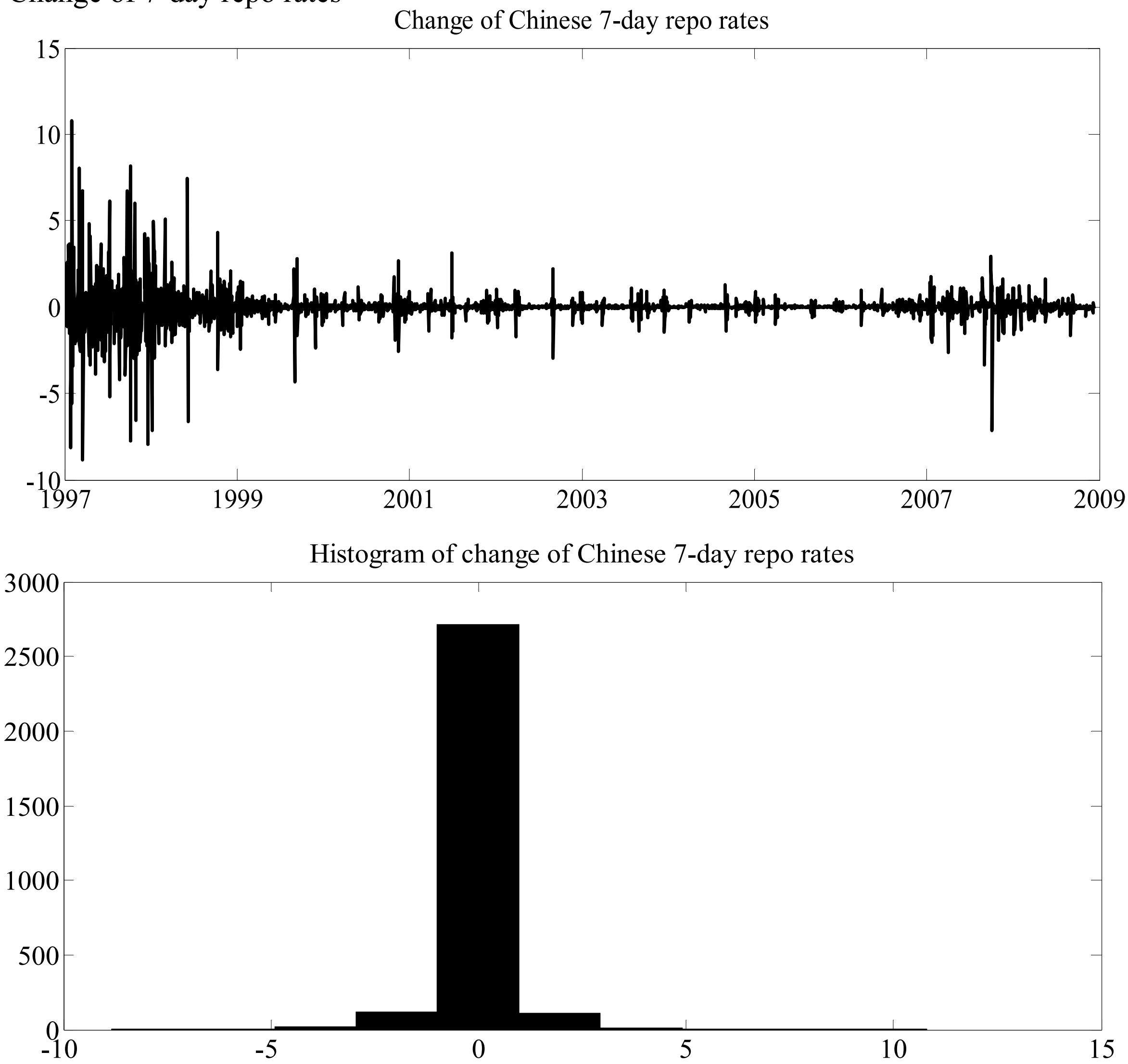
Figure 1. Chinese daily 7-day repo rates between Jan. 1, 1997 and Dec. 31, 2008. This figure plots the level and change series of daily 7-day repo rates, as well as their histograms.

(a) Chinese 7-day repo rates



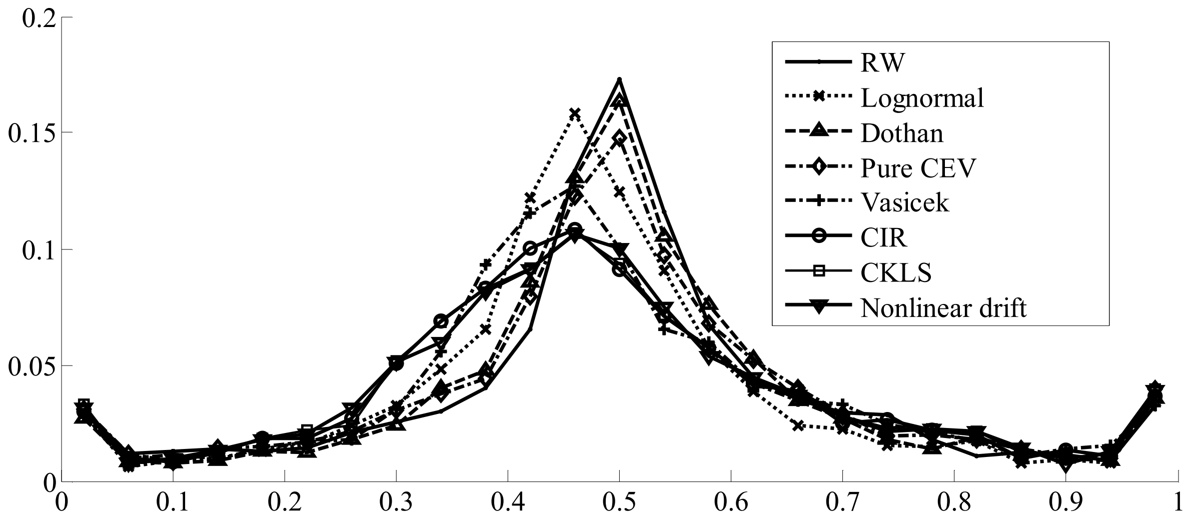
(b) Change of 7-day repo rates



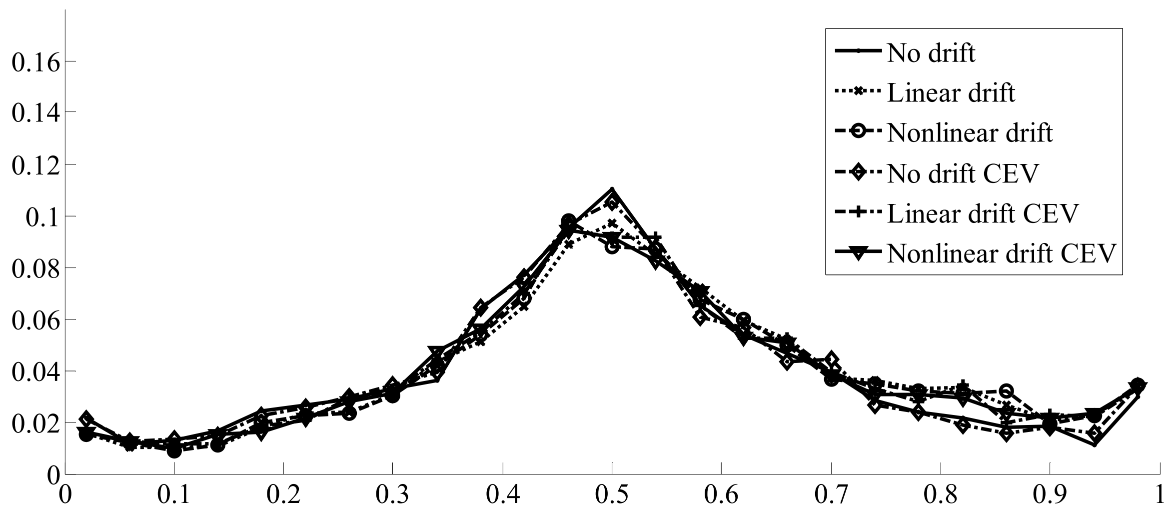

Notes: (1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2,986 observations;
(2) Panel (a) plots the level series, and Panel (b) plots the change series.

Figure 2. Histograms of generalized residuals. This figure plots the histograms of generalized residuals of discrete-time spot rate models.

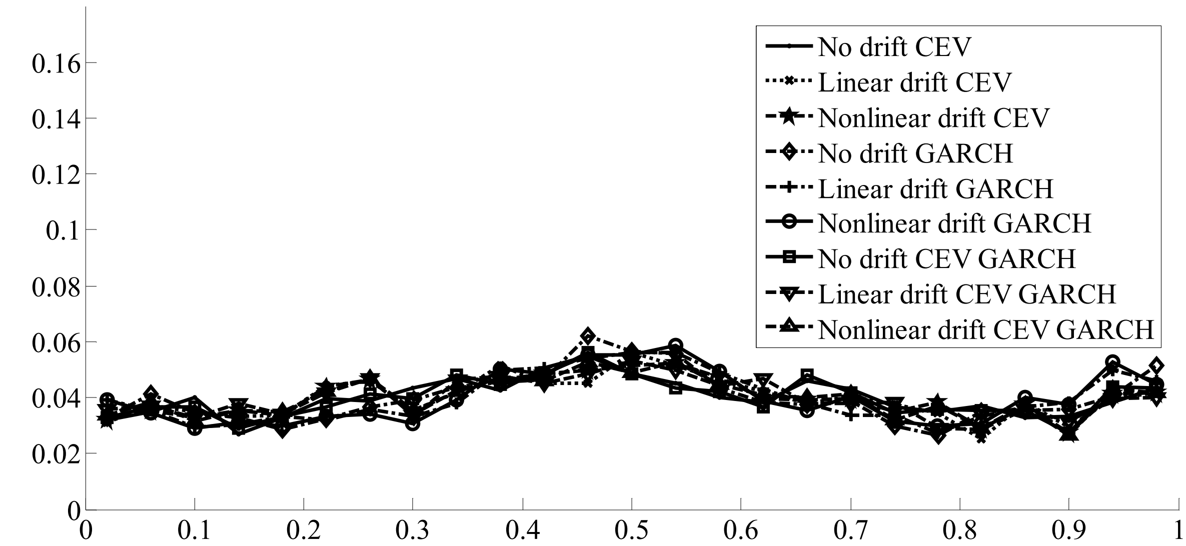
(a) Single factor diffusion models



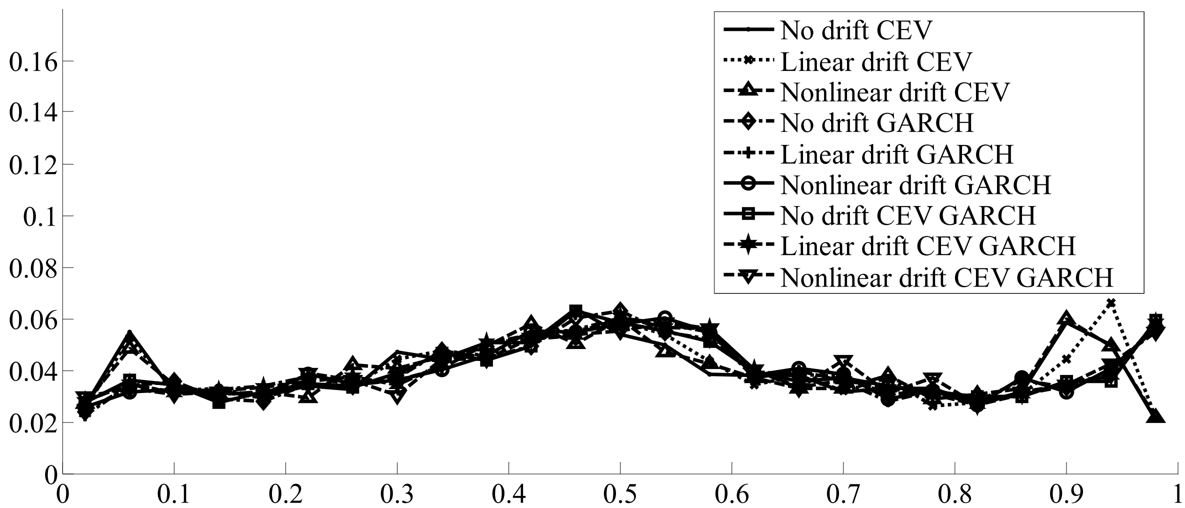

(b) GARCH models



(c) Regime-switching models




(d) Jump-diffusion models




Notes: (1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2986 observations;

(2) Panel (a), (b), (c), (d) plot the histograms of generalized residuals for single-factor diffusion, GARCH, Markov regime-switching and jump-diffusion models, respectively.

Table 1. Characteristics of Chinese interest rate liberalization. This table summarizes the history and recent reforms of Chinese interest rate liberalization.

<table>
<tr><td rowspan="4">History:<br>● Market segmentation;<br>● Strict regulation</td><td rowspan="2">Short term</td><td>Interbank offered rate</td></tr>
<tr><td>Collateralized repurchase: Two segmented sub-markets<br>● Interbank repurchase market<br>● Exchange repurchase market: serious impact by IPO.</td></tr>
<tr><td>Middle term</td><td>Saving rates strictly regulated by Chinese central bank</td></tr>
<tr><td>Long term</td><td>Two segmented sub-markets:<br>● Interbank long term bond market<br>● Exchange long term bond market</td></tr>
<tr><td>Reforms:<br>● In a stable process</td><td colspan="2">● Issue bonds at both interbank market and exchange market;<br>● Permit some eligible securities and trust companies to join the issuing;<br>● Propose the market maker system in 2001 for the secondary market;<br>● Issue bonds systematically ranging from long term to short term;<br>● Introduce buyout repurchase transaction in 2005;<br>● Report SHIBOR since 2007.<br>● Propose many other instruments, such as Stock Index Futures and Bond Futures.</td></tr>
</table>

Notes: This table outlines the history and recent reforms of Chinese interest rate liberalization between Jan.1, 1997 and Dec. 31, 2008.

Table 2. Summary of Chinese short-tem money trading. This table reports the yearly trading volume of Chinese short-term money market between 1997 and 2008.

| Year | Collateralized repo 1-day repo (Billion RMB) | 7-day repo (Billion RMB) | 14-day repo (Billion RMB) | 1-month repo (Billion RMB) | Interbank offered rate All (Billion RMB) |
|---|---|---|---|---|---|
| 1997 | 0 | 89.40 | 25.37 | 24.94 | |
| 1998 | 0 | 168.29 | 13.72 | 22.44 | |
| 1999 | 0 | 619.64 | 146.17 | 129.37 | 646.92 |
| 2000 | 0.68 | 1654.42 | 303.91 | 158.33 | 672.81 |
| 2001 | 3.19 | 3650.32 | 609.22 | 240.18 | 808.20 |
| 2002 | 256.41 | 9291.20 | 1347.72 | 370.97 | 201.52 |
| 2003 | 3615.31 | 9257.76 | 1764.23 | 582.71 | 641.89 |
| 2004 | 3618.86 | 6891.69 | 1524.40 | 746.30 | 283.34 |
| 2005 | 7356.31 | 7038.23 | 1710.11 | 583.42 | 223.03 |
| 2006 | 13682.64 | 10229.62 | 2369.69 | 382.34 | 625.31 |
| 2007 | 23019.30 | 15854.11 | 3848.37 | 493.52 | 8030.47 |
| 2008 | 36005.08 | 15026.3 | 3641.30 | 735.03 | 10651.37 |

Notes: (1) The trading volume of repo market is the trading volume in both exchange markets and interbank markets;

(2) The trading volume for the interbank offered rate market is the trading volume of interbank offered rate with maturities ranging from 1 day, 7 days, 14 days, 1 month to 4 months.

Table 3. History of Chinese interest rate policy changes. This table reports the history of Chinese interest rate policy changes between Jan. 1, 1997 and Dec. 31, 2008.

| Date | 1-year savings rate (%) | 1-year lending rate (%) | Statuary deposit reserve rate (%) | Excess deposit reserve rate (%) |
|---|---|---|---|---|
| 1997-10-23 | 5.67 | 7.65 | 7.56 | 7.02 |
| 1998-03-21 | | | 5.22 | 5.22 |
| 1998-03-25 | 5.22 | 7.02 | | |
| 1998-07-01 | 4.77 | 6.57 | 3.51 | 3.51 |
| 1998-12-07 | 3.78 | 6.12 | 3.24 | 3.24 |
| 1999-06-10 | 2.25 | 5.58 | 2.07 | 2.07 |
| 2002-02-21 | 1.98 | 5.04 | 1.89 | 1.89 |
| 2003-12-20 | | | | 1.62 |
| 2004-10-29 | 2.25 | 5.22 | | |
| 2005-03-17 | | | | 0.99 |
| 2006-04-28 | | 5.40 | | |
| 2006-08-19 | 2.52 | 5.58 | | |
| 2007-03-18 | 2.79 | 5.67 | | |
| 2007-05-19 | 3.06 | 5.85 | | |
| 2007-07-21 | 3.33 | 6.03 | | |
| 2007-08-22 | 3.60 | 6.21 | | |
| 2007-09-15 | 3.87 | 6.48 | | |
| 2007-12-21 | 4.14 | 6.57 | | |
| 2008-09-16 | | 6.21 | | |
| 2008-10-09 | 3.87 | | | |
| 2008-10-30 | 3.60 | 6.03 | | |
| 2008-11-27 | 2.52 | 5.04 | 1.62 | 0.72 |
| 2008-12-23 | 2.25 | 4.86 | | |

Notes: The changes of Chinese interest rate policy include changes in the savings rate, the lending rate, the statuary deposit reserve rate and the excess deposit reserve rate.

Table 4. Spot rate models considered for evaluation. This table lists the spot rate models that will be evaluated in paper.

| Model | Mean | Volatility |
|---|---|---|
| (a) Discretized single factor diffusion models | | |
| Random walk | $\alpha_0$ | $\sigma$ |
| Lognormal | $\alpha_1 r_{t-1}$ | $\sigma r_{t-1}$ |
| Dothan | 0 | $\sigma r_{t-1}$ |
| Pure CEV | 0 | $\sigma r_{t-1}^{\rho}$ |
| Vasicek | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma$ |
| CIR | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma r_{t-1}^{0.5}$ |
| CKLS | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma r_{t-1}^{\rho}$ |
| Nonlinear drift | $\alpha_{-1} / r_{t-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2$ | $\sigma r_{t-1}^{\rho}$ |
| (b) GARCH models | | |
| No drift GARCH | 0 | $\sigma \sqrt{h_t}$ |
| Linear drift GARCH | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma \sqrt{h_t}$ |
| Nonlinear drift GARCH, | $\alpha_{-1} / r_{t-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2$ | $\sigma \sqrt{h_t}$ |
| No drift CEV-GARCH | 0 | $\sigma r_{t-1}^{\rho} \sqrt{h_t}$ |
| Linear drift CEV-GARCH | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma r_{t-1}^{\rho} \sqrt{h_t}$ |
| Nonlinear drift CEV GARCH | $\alpha_{-1} / r_{t-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2$ | $\sigma r_{t-1}^{\rho} \sqrt{h_t}$ |
| (c) Markov regime-switching models | | |
| No drift RS CEV | 0 | $\sigma(s_t) r_{t-1}^{\rho(s_t)}$ |
| Linear drift RS CEV | $\alpha_0(s_t) + \alpha_1(s_t) r_{t-1}$ | $\sigma(s_t) r_{t-1}^{\rho(s_t)}$ |
| Nonlinear drift RS CEV, | $\alpha_{-1}(s_t)/r_{t-1} + \alpha_0(s_t) + \alpha_1(s_t) r_{t-1} + \alpha_2(s_t) r_{t-1}^2$ | $\sigma(s_t) r_{t-1}^{\rho(s_t)}$ |
| No drift RS GARCH | 0 | $\sigma(s_t) \sqrt{h_t}$ |
| Linear drift RS GARCH | $\alpha_0(s_t) + \alpha_1(s_t) r_{t-1}$ | $\sigma(s_t) \sqrt{h_t}$ |
| Nonlinear drift RS GARCH | $\alpha_{-1}(s_t)/r_{t-1} + \alpha_0(s_t) + \alpha_1(s_t) r_{t-1} + \alpha_2(s_t) r_{t-1}^2$ | $\sigma(s_t) \sqrt{h_t}$ |
| No drift RS CEV GARCH | 0 | $\sigma(s_t) r_{t-1}^{\rho(s_t)} \sqrt{h_t}$ |
| Linear drift RS CEV GARCH | $\alpha_0(s_t) + \alpha_1(s_t) r_{t-1}$ | $\sigma(s_t) r_{t-1}^{\rho(s_t)} \sqrt{h_t}$ |
| Nonlinear drift RS CEV GARCH | $\alpha_{-1}(s_t)/r_{t-1} + \alpha_0(s_t) + \alpha_1(s_t) r_{t-1} + \alpha_2(s_t) r_{t-1}^2$ | $\sigma(s_t) r_{t-1}^{\rho(s_t)} \sqrt{h_t}$ |
| (d) Discretized jump-diffusion models | | |
| No drift JD CEV | 0 | $\sigma r_{t-1}^{\rho}$ |
| Linear drift JD CEV | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma r_{t-1}^{\rho}$ |
| Nonlinear drift JD CEV, | $\alpha_{-1} / r_{t-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2$ | $\sigma r_{t-1}^{\rho}$ |
| No drift JD GARCH | 0 | $\sigma \sqrt{h_t}$ |
| Linear drift JD GARCH | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma \sqrt{h_t}$ |
| Nonlinear drift JD GARCH | $\alpha_{-1} / r_{t-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2$ | $\sigma \sqrt{h_t}$ |
| No drift JD CEV GARCH | 0 | $\sigma r_{t-1}^{\rho} \sqrt{h_t}$ |
| Linear drift JD CEV GARCH | $\alpha_0 + \alpha_1 r_{t-1}$ | $\sigma r_{t-1}^{\rho} \sqrt{h_t}$ |
| Nonlinear drift JD CEV GARCH | $\alpha_{-1} / r_{t-1} + \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2$ | $\sigma r_{t-1}^{\rho} \sqrt{h_t}$ |

Notes: panel (a), (b), (c), (d) list eight specifications of discretized single factor diffusion models, six specifications of GARCH models, nine specifications of Markov regime-switching models, and nine specifications of jump-diffusion models that will be evaluated respectively.

Table 5. Parameter estimates for the single-factor diffusion models. This table reports the parameter estimates of single-factor diffusion models and log-likelihood value.

| Parameters | RW | Lognormal | Dothan | PCEV | Vasicek | CIR | CKLS | Nonlinear drift |
|---|---|---|---|---|---|---|---|---|
| $\alpha_{-1}$ | | | | | | | | 3.1E-5*** |
| $\alpha_0$ | -8.0E-05 | 0.0057* | | | 0.0029*** | 0.0026*** | 0.0023*** | -0.0018 |
| $\alpha_1$ | | | | | -0.1293*** | -0.1144*** | -0.1041*** | -0.0473 |
| $\alpha_2$ | | | | | | | | -1.4084*** |
| $\sigma$ | 0.0034*** | 0.1329*** | 0.1330*** | 0.0505*** | 0.0034*** | 0.0198*** | 0.0513*** | 0.0532*** |
| $\rho$ | | | | 0.7478*** | | | 0.7595*** | 0.7720*** |
| $\alpha_{1D}$ | -5.75E-04 | 0.0424 | | | 0.0068*** | 0.0083*** | 0.0067*** | 0.0080*** |
| $\alpha_{2D}$ | 4.09E-05 | 0.0129*** | | | 8.73E-04*** | 7.54E-04*** | 6.93E-04*** | 6.87E-04*** |
| $\alpha_{3D}$ | -1.30E-03 | -0.0543*** | | | -0.0013** | -0.0011 | -0.0011** | -0.0010** |
| $\sigma_{1D}$ | 0.0150*** | 0.5149*** | 0.5170*** | | 0.0143*** | 0.0571*** | | |
| $\sigma_{2D}$ | 0.0021*** | 0.0071 | 0.0081* | | 0.0019*** | 0.0056*** | | |
| $\sigma_{3D}$ | -0.0006 | -0.0412*** | -0.0296 | | -0.0009* | -0.0056** | | |
| $\rho_{1D}$ | | | | -0.4192*** | | | -0.4090*** | -0.4081*** |
| $\rho_{2D}$ | | | | -0.0362*** | | | -0.0392*** | -0.0391*** |
| $\rho_{3D}$ | | | | 0.0699 | | | 0.1038** | 0.0965** |
| Log-likelihood | 11596.85 | 11686.06 | 11676.07 | 12064.11 | 11696.36 | 12007.83 | 12148.09 | 12162.40 |

Notes: (1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2,986 observations;

(2) The models are nested by: $\Delta r_t = \alpha_{-1} r_{t-1}^{-1} + \alpha_0 + \alpha_{1D} + \alpha_{2D} + \alpha_{3D} + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2 + (\sigma + \sigma_{1D} + \sigma_{2D} + \sigma_{3D}) r_{t-1}^{(\rho+\rho_{1D}+\rho_{2D}+\rho_{3D})} z_t$, $\{z_t\} \sim iid.N(0,1)$.

(3) $\alpha_{1D}$, $\sigma_{1D}$, $\rho_{1D}$ are dummy variables for institutional change after 1999; $\alpha_{2D}$, $\sigma_{2D}$, $\rho_{2D}$ are dummy variables for the days with IPO; $\alpha_{3D}$, $\sigma_{3D}$, $\rho_{3D}$ are the dummy variables for the days with interest rate policy changes.

(4) ***, **, * means significance at 1%, 5% and 10% levels, respectively.

Table 6. Parameter estimates for GARCH models. This table reports the parameter estimates of GARCH models and log-likelihood value.

| Parameters | No drift | linear drift | Nonlinear drift | No drift CEV | linear drift CEV | Nonlinear drift CEV |
|---|---|---|---|---|---|---|
| $\alpha_{-1}$ | | | -3.00E-05*** | | | -2.60E-05*** |
| $\alpha_0$ | | 9.38-E04*** | 0.0040*** | | 8.52E-04*** | 0.0037*** |
| $\alpha_1$ | | -0.0510*** | -0.1244*** | | -0.0450*** | -0.1224*** |
| $\alpha_2$ | | | 0.1285 | | | 0.3607 |
| $\rho$ | | | | 0.4078*** | 0.2922*** | 0.2628*** |
| $\beta_0$ | 4.24E-07*** | 5.19E-07*** | 5.51E-07*** | 1.31E-05*** | 5.89E-06*** | 4.77E-06*** |
| $\beta_1$ | 0.5304*** | 0.7031*** | 0.7348*** | 9.0267*** | 5.5715*** | 4.6521*** |
| $\beta_2$ | 0.6087*** | 0.5193*** | 0.4925*** | 0.5870*** | 0.5011*** | 0.4870*** |
| $\alpha_{1D}$ | | 0.0020*** | -7.92E-04* | | 0.0016*** | -8.18E-04* |
| $\alpha_{2D}$ | | 2.40E-04*** | 1.53E-04** | | 2.44E-04*** | 1.77E-04** |
| $\alpha_{3D}$ | | -2.02E-04 | -2.52E-04 | | -2.71E-04 | -2.93E-04 |
| $\sigma_{1D}$ | 0.4586*** | 0.2142*** | 0.2212*** | | 0.0143*** | 0.0571*** |
| $\sigma_{2D}$ | 0.3025*** | 0.2635*** | 0.2729*** | | 0.0019*** | 0.0056*** |
| $\sigma_{3D}$ | 0.7916*** | 0.6755*** | 0.5512*** | | -0.0009* | -0.0056** |
| $\rho_{1D}$ | | | | -0.0695*** | -0.0369** | -0.0451*** |
| $\rho_{2D}$ | | | | -0.0568*** | -0.0520*** | -0.0561*** |
| $\rho_{3D}$ | | | | -0.1168** | -0.1187** | -0.1052** |
| Log-likelihood | 12630.17 | 12758.27 | 12768.70 | 12686.95 | 12783.37 | 12788.41 |

Notes: (1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2,986 observations;

(2) The GARCH models are nested by:
$$\begin{cases} \Delta r_t = \alpha_{-1} r_{t-1}^{-1} + \alpha_0 + \alpha_{1D} + \alpha_{2D} + \alpha_{3D} + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2 + \left(\sigma + \sigma_{1D} + \sigma_{2D} + \sigma_{3D}\right) r_{t-1}^{(\rho+\rho_{1D}+\rho_{2D}+\rho_{3D})} \sqrt{h_t}\, z_t, \\ h_t = \beta_0 + h_{t-1}(\beta_2 + \beta_1 r_{t-2}^{2\rho} z_{t-1}^2), \\ \{z_t\} \sim iid.N(0,1). \end{cases}$$

(3) $\alpha_{1D}$, $\sigma_{1D}$, $\rho_{1D}$ are dummy variables for institutional change after 1999; $\alpha_{2D}$, $\sigma_{2D}$, $\rho_{2D}$ are dummy variables for the days with IPO; $\alpha_{3D}$, $\sigma_{3D}$, $\rho_{3D}$ are the dummy variables for the days with interest rate policy changes.

(4) ***, **, * means significance at 1%, 5% and 10% levels, respectively.

Table 7. Parameter estimates for Markov regime-switching models. This table reports the parameter estimates of Markov regime-switching models and log-likelihood value.

| Parameters | No drift CEV | linear drift CEV | Nonlinear drift CEV | No drift GARCH | linear drift GARCH | Nonlinear drift GARCH | No drift CEV-GARCH | Linear drift CEV-GARCH | nonlinear drift CEV-GARCH |
|---|---|---|---|---|---|---|---|---|---|
| $\alpha_{-1}$ (1) | | | -4.0E-06 | | | -0.0001 | | | 3.30E-05 |
| $\alpha_0$ (1) | | 2.76E-04*** | 5.52-04 | | 0.0016 | 0.0149 | | 0.0030*** | -0.0018 |
| $\alpha_1$ (1) | | -0.0174*** | -0.0115 | | -0.0191 | -0.3830 | | -0.1016*** | 0.1191 |
| $\alpha_2$ (1) | | | -0.3918 | | | 2.3223 | | | -3.3951 |
| $\alpha_{-1}$ (2) | | | 2.2E-05** | | | 1.0E-06 | | | 2.47E-04*** |
| $\alpha_0$ (2) | | 0.0042*** | 0.0012 | | 0.0004*** | 4.00E-05 | | 2.93E-04*** | 0.0007 |
| $\alpha_1$ (2) | | -0.1612*** | -0.0336 | | -0.0211*** | 3.37E-04 | | -0.0183*** | -0.0169 |
| $\alpha_2$ (2) | | | -1.3086 | | | -0.4019*** | | | -0.3036* |
| $\rho$ (1) | 1.4690*** | 1.4428*** | 1.4285*** | 0 | 0 | 0 | 0.7170*** | 0.7730*** | 0.7988*** |
| $\rho$ (2) | 0.7487*** | 0.7833*** | 0.8009*** | 0 | 0 | 0 | 1.4399*** | 1.4323*** | 1.4493*** |
| $\sigma$(1) | 0.1882*** | 0.1677*** | 0.1581*** | 1 | 1 | 1 | 1 | 1 | 1 |
| $\sigma$(2) | 0.0931*** | 0.0996*** | 0.1056*** | 0.1616*** | 0.1711*** | 0.1732*** | 2.2491 | 6.1191*** | 1.7599*** |
| $\beta_0$ | | | | 1.60E-05*** | 1.70E-05*** | 1.50E-06*** | 2.25E-03*** | 3.27E-03** | 5.30E-03 |
| $\beta_1$ | | | | 0.4211*** | 0.4703*** | 0.4587*** | 17.2218** | 21.0723** | 32.4138 |
| $\beta_2$ | | | | 0.5263*** | 0.4878*** | 0.4986*** | 0.6046*** | 0.5732*** | 0.4290* |
| $c$ (1) | -3.1631*** | -3.1990*** | -3.1567*** | 1.3324*** | 0.3117 | 0.2644 | -2.7375*** | -2.7555*** | -2.6819*** |
| $d$ (1) | 20.152*** | 22.718*** | 21.1362*** | -1.7586 | 42.3518* | 43.7184* | 35.3406*** | 36.8582*** | 33.9790*** |
| $c$ (2) | -2.4633*** | -2.5249*** | -2.5189*** | -3.0324*** | -2.9793*** | -3.0016*** | -2.9186*** | -2.9597*** | -2.7436*** |
| $d(2)$ | 25.8657*** | 29.0353*** | 28.3099*** | 19.2201*** | 20.4075*** | 21.2889*** | 11.2106 | 14.1550 | 5.0355 |
| $\alpha_{1D}$ | | 0.0016*** | 0.0027*** | | 0.0002 | 0.0007* | | 0.0017*** | 0.0024*** |
| $\alpha_{2D}$ | | 2.9E-04*** | 2.78E-04*** | | 0.0002*** | 0.0002*** | | 0.0003*** | 0.0003 |
| $\alpha_{3D}$ | | -5.20E-05 | -4.60E-05 | | -1.20E-05 | -1.80E-05 | | -5.70E-05 | -4.90E-05 |
| $\rho_{1D}$ | -0.3814*** | -0.3980*** | -0.4038*** | | | | -0.3125*** | -0.3179*** | -0.3284*** |
| $\rho_{2D}$ | -0.0126 | -0.0180* | -0.0195* | | | | -0.0167 | -0.0150 | -0.0175* |
| $\rho_{3D}$ | 0.1032** | 0.0889 | 0.0942* | | | | 0.0940 | 0.0739 | 0.0826 |
| $\sigma_{1D}$ | | | | 0.0026 | -0.0045 | -0.0208 | | | |
| $\sigma_{2D}$ | | | | 0.0048 | 0.0064 | 0.0086 | | | |
| $\sigma_{3D}$ | | | | 0.0008 | -0.0093 | -0.0067 | | | |
| $c_{1D}$ | -1.3759** | -1.7043** | -1.6646*** | -0.5866 | -0.8591* | -0.9758** | -0.3243 | -0.7401 | -0.4963 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $c_{2D}$ | 0.1075 | 0.1186 | 0.1244 | 0.2856 | 0.2132 | 0.2225 | 0.0156 | 0.0140 | -0.0349 |
| $c_{3D}$ | 1.8754 *** | 1.8508 *** | 1.8413 *** | 1.6120 *** | 1.5943 *** | 1.5838 *** | 1.5552 ** | 1.4387 ** | 1.3760 * |
| Log-likelihood | 13754.09 | 13821.65 | 13827.43 | 13706.93 | 13752.44 | 13758.79 | 13782.31 | 13844.15 | 13855.74 |

Notes:

(1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2,986 observations;

(2) The Markov regime-switching models are nested by:

$$\begin{cases} \Delta r_t = \alpha_{-1}(s_t) r_{t-1}^{-1} + \alpha_0(s_t) + \alpha_{1D} + \alpha_{2D} + \alpha_{3D} + \alpha_1(s_t) r_{t-1} + \alpha_2(s_t) r_{t-1}^2 + \left(\sigma(s_t) + \sigma_{1D} + \sigma_{2D} + \sigma_{3D}\right) r_{t-1}^{\left(\rho(s_t)+\rho_{1D}+\rho_{2D}+\rho_{3D}\right)} \sqrt{h_t} z_t, \\ \Pr\left(s_t = l \mid s_{t-1} = l\right) = \dfrac{1}{1+\exp\left(-c_l - c_{1D} - c_{2D} - c_{3D} - d_l r_{t-1}\right)}, \quad l = 1,2, \\ h_t = \beta_0 + \beta_1 E[e(r_{t-1}, s_{t-1} \mid r_{t-2}, s_{t-2})]^2 + \beta_2 h_{t-1}, \\ e(r_{t-1}, s_{t-1} \mid r_{t-2}, s_{t-2}) = [\Delta r_{t-1} - E(\Delta r_{t-1} \mid r_{t-2}, s_{t-2})] / \left(\sigma(s_{t-1}) + \sigma_{1D} + \sigma_{2D} + \sigma_{3D}\right), \\ \{z_t\} \sim iid.N(0,1). \end{cases}$$

(3) $\alpha_{1D}$, $\sigma_{1D}$, $\rho_{1D}$, $c_{1D}$ are dummy variables for institutional change after 1999; $\alpha_{2D}$, $\sigma_{2D}$, $\rho_{2D}$, $c_{2D}$ are dummy variables for the days with IPO; $\alpha_{3D}$, $\sigma_{3D}$, $\rho_{3D}$, $c_{3D}$ are the dummy variables for the days with interest rate policy changes.

(4) ***, **, * means significance at 1%, 5% and 10% levels, respectively.

Table 8. Parameter estimates for jump-diffusion models. This table reports the parameter estimates of jump-diffusion models and log-likelihood value.

| Parameters | No drift CEV | linear drift CEV | Nonlinear drift CEV | No drift GARCH | linear drift GARCH | Nonlinear drift GARCH | No drift CEV-GARCH | Linear drift CEV-GARCH | nonlinear drift CEV-GARCH |
|---|---|---|---|---|---|---|---|---|---|
| $\alpha_{-1}$ | | | -2.90E-05 | | | 1.0E-06 | | | 7.0E-06 |
| $\alpha_0$ | | $0.0004^{***}$ | $0.0036^{***}$ | | $3.72E-04^{***}$ | 1.60E-05 | | $0.0004^{***}$ | -0.0010 |
| $\alpha_1$ | | $-0.0243^{***}$ | $-0.1071^{***}$ | | $-0.020^{***}$ | $0.0117^{***}$ | | $-0.0201^{***}$ | $0.0548^{***}$ |
| $\alpha_{-2}$ | | | 0.1819 | | | $-0.7124^{**}$ | | | $-1.3002^{***}$ |
| $\rho$ | $2.0362^{***}$ | $1.8123^{***}$ | $1.9082^{***}$ | | | | $0.3017^{***}$ | $0.2971^{***}$ | $0.3479^{***}$ |
| $\sigma$ | $2.2938^{**}$ | $0.9847^{***}$ | $1.3714^{***}$ | | | | | | |
| $\beta_0$ | | | | $6.30E-05^{***}$ | $6.20E-05^{**}$ | $6.60E-05^{***}$ | 8.50E-07 | 8.56E-07 | 1.26E-06 |
| $\beta_1$ | | | | $0.4177^{***}$ | $0.4070^{***}$ | $0.3986^{***}$ | $4.0068^{*}$ | 3.7552 | $5.1807^{*}$ |
| $\beta_2$ | | | | $0.4632^{***}$ | $0.4763^{***}$ | $0.4757^{***}$ | $0.4475^{***}$ | $0.4585^{***}$ | $0.4655^{***}$ |
| $c$ | $1.5864^{***}$ | $1.9493^{***}$ | $1.7999^{***}$ | $4.8507^{***}$ | $4.5403^{***}$ | $4.5777^{***}$ | $4.4271^{***}$ | $4.3212^{***}$ | $4.4087^{***}$ |
| $d$ | $15.2920^{*}$ | 29.7391 | 28.7330 | $-89.5074^{***}$ | $-73.9297^{***}$ | $-78.1359^{***}$ | $-73.9091^{***}$ | $-66.9975^{***}$ | $-74.7071^{***}$ |
| $\psi$ | $-0.0016^{***}$ | $-0.0014^{***}$ | $-0.0017^{***}$ | $0.0027^{***}$ | $0.0034^{***}$ | $0.0018^{*}$ | $0.0014^{*}$ | $0.0017^{**}$ | 0.0001 |
| $\gamma$ | $0.0107^{***}$ | $0.0107^{***}$ | $0.0104^{***}$ | $0.0124^{***}$ | $0.0132^{***}$ | $0.0118^{***}$ | $0.0112^{***}$ | $0.0117^{***}$ | $0.0097^{***}$ |
| $\alpha_{1D}$ | | $0.0019^{***}$ | $0.0031^{***}$ | | $0.0016^{***}$ | $0.0027^{***}$ | | $0.0013^{***}$ | $0.0024^{***}$ |
| $\alpha_{2D}$ | | $0.0003^{***}$ | $0.0002^{***}$ | | $2.15E-04^{***}$ | $0.0002^{***}$ | | $0.0002^{***}$ | $0.0002^{***}$ |
| $\alpha_{3D}$ | | $-1.35E-04^{***}$ | -3.70E-05 | | -3.4E-05 | -3.40E-05 | | -4.9E-05 | -4.80E-05 |
| $\rho_{1D}$ | 0.0766 | -0.0654 | -0.0262 | | | | $-0.4109^{***}$ | $-0.4165^{***}$ | $-0.5023^{***}$ |
| $\rho_{2D}$ | $0.0466^{***}$ | $0.0519^{***}$ | $0.0386^{***}$ | | | | 0.0340 | 0.0318 | $-0.0413^{***}$ |
| $\rho_{3D}$ | $0.2481^{***}$ | $0.4387^{***}$ | $0.8520^{***}$ | | | | 0.1587 | 0.0948 | 0.2644 |
| $\sigma_{1D}$ | | | | $0.1229^{**}$ | 0.0746 | 0.0985 | $-0.7458^{***}$ | $-0.7563^{***}$ | $-0.8179^{***}$ |
| $\sigma_{2D}$ | | | | $0.1075^{**}$ | $0.0977^{*}$ | $0.1288^{**}$ | $0.1640^{**}$ | $0.1670^{*}$ | $0.1235^{***}$ |
| $\sigma_{3D}$ | | | | -0.1570 | $-0.2865^{**}$ | $-0.3133^{**}$ | 0.1974 | -0.1304 | 0.6876 |
| $c_{1D}$ | $-1.4675^{***}$ | -0.5938 | $-0.8770^{*}$ | $2.0615^{***}$ | $1.3521^{**}$ | $1.1692^{*}$ | $1.1046^{*}$ | 0.7988 | 0.6073 |
| $c_{2D}$ | -0.0453 | -0.0774 | -0.0586 | -0.3978 | $-0.5488^{**}$ | $-0.4358^{*}$ | -0.4125 | -0.4007 | -0.4093 |
| $c_{3D}$ | -1.3628 | $-1.5804^{***}$ | $-1.9607^{***}$ | $-1.5838^{**}$ | -1.3141 | $-1.3501^{*}$ | $-1.2207^{*}$ | $-1.2305^{*}$ | $-1.3346^{*}$ |
| Log-likelihood | 13268.87 | 13301.99 | 13315.19 | 13693.95 | 13726.98 | 13731.56 | 13708.21 | 13740.66 | 13752.06 |

Notes:

(1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2986 observations;

(2) The jump-diffusion models are nested by:

$$\begin{cases} \Delta r_t = \alpha_{-1} r_{t-1}^{-1} + \alpha_0 + \alpha_{1D} + \alpha_{2D} + \alpha_{3D} + \alpha_1 r_{t-1} + \alpha_2 r_{t-1}^2 + \left(\sigma + \sigma_{1D} + \sigma_{2D} + \sigma_{3D}\right) r_{t-1}^{(\rho+\rho_{1D}+\rho_{2D}+\rho_{3D})} \sqrt{h_t} z_t + J(\psi, \gamma^2)\pi(q_t), \\ h_t = \beta_0 + \beta_1 [\Delta r_{t-1} - E(\Delta r_{t-1} \mid r_{t-2})]^2 + \beta_2 h_{t-1}, \\ \{z_t\} \sim iid.N(0,1), \\ \{\pi(q_t)\} \sim Bernoulli(q_t), \\ q_t = \dfrac{1}{\exp\left(-c - c_{1D} - c_{2D} - c_{3D} - dr_{t-1}\right)}, \\ J \sim N(\psi, \gamma^2). \end{cases}$$

(3) $\alpha_{1D}$, $\sigma_{1D}$, $\rho_{1D}$, $c_{1D}$ are dummy variables for institutional change after 1999; $\alpha_{2D}$, $\sigma_{2D}$, $\rho_{2D}$, $c_{2D}$ are dummy variables for the days with IPO; $\alpha_{3D}$, $\sigma_{3D}$, $\rho_{3D}$, $c_{3D}$ are the dummy variables for the days with interest rate policy changes.

(4) $^{***}$, $^{**}$, $^{*}$ means significance at 1%, 5% and 10% levels, respectively.

Table 9. Similarities and differences of time series dynamics of Chinese spot rates and U.S. spot rates. This table reports important similarities and differences between the time series dynamics of Chinese spot rates and U.S. spot rates.

<table>
<tr><th rowspan="2">Models</th><th>Similarities</th><th colspan="2">Differences</th></tr>
<tr><th>China/U.S.</th><th>China</th><th>U.S.</th></tr>
<tr><td>Single factor diffusion models</td><td rowspan="4">1. There exists significant mean reversion.<br>2. There exists significant conditional heteroskedasticity, which can be captured by the GARCH effect or the level effect.<br>3. Regime switching and jump help capture volatility clustering and especially the excess kurtosis and heavy tails of interest rate data.</td><td>1. volatile and shocked by the external administrative events including institutional change and interest rate policy change, and stock market event such as IPOs.<br>2. The estimate of elasticity is about 0.7.</td><td>1. stable;<br>2.elasticity estimate: CKLS (1992)-1.5, Hong, Li and Zhao (2004)-0.25;</td></tr>
<tr><td>GARCH models</td><td>Mean reversion is still significant after the introduction of GARCH</td><td>Mean reversion decreases rapidly after the introduction of GARCH</td></tr>
<tr><td>Markov regime switching models</td><td>1.the elasticity for two regimes are 1.4 and 0.8;<br>2. mean reversion is still significant in two regimes；<br>3. the volatility ratios are unstable in two regimes: it is about 2 times for CEV models, 5 times for GARCH models and unstable for CEV-GARCH models;<br>4. The relationship between volatility and level effect is relatively stable: higher volatility is related to stronger level effect;<br>5. CEV models have larger likelihood value than GARCH models</td><td>1. the elasticity for two regimes are 0.8 and 0.1;<br>2. mean reversion is significant in only one regime；<br>3. the volatility ratios are relatively stable in two regimes: for CEV models it is about 30 times, for GARCH models it is about 4 times, for CEV-GARCH models it is about 3 times；<br>4. The relationship between volatility and level effect is relatively unstable: for CEV models, higher volatility is related to a weaker level effect, for CEV-GARCH models higher volatility is related to a stronger level effect;<br>5. GARCH models have larger likelihood value than CEV models.</td></tr>
<tr><td>Jump-diffusion models</td><td>1. The elasticity is more than 1.5 without GARCH effect and decreases to about 0.2 with GARCH effect;<br>2. The jump size is negative for CEV models, and is positive for GARCH and CEV-GARCH;</td><td>1. The elasticity is 0.9 without GARCH effect and decreases to about 0.1 with GARCH effect;<br>2. The jump size for GARCH models is larger than that of CEV models;</td></tr>
</table>

Table 10. $\hat{W}(p)$ stats of discrete spot rate models. This table reports the portmanteau statistic $\hat{W}(p)$ of spot rate models.

(a) Discretized single factor diffusion models

| $p$ | RW | Lognormal | Dothan | PCEV | Vasicek | CIR | CKLS | Nonlinear drift |
|---|---|---|---|---|---|---|---|---|
| 1 | 303.33 | 334.77 | 327.98 | 282.62 | 286.59 | 257.21 | 254.44 | 256.65 |
| 5 | 655.63 | 731.78 | 714.46 | 603.82 | 618.72 | 557.29 | 544.56 | 545.24 |
| 10 | 924.61 | 1028.56 | 1005.04 | 843.55 | 866.41 | 778.59 | 763.08 | 763.17 |

(b) GARCH models

| $p$ | No drift | Linear drift | Nonlinear drift | No drift CEV | linear drift CEV | Nonlinear drift CEV |
|---|---|---|---|---|---|---|
| 1 | 195.82 | 183.30 | 185.72 | 193.47 | 182.93 | 178.94 |
| 5 | 424.14 | 400.99 | 405.17 | 423.10 | 398.68 | 391.13 |
| 10 | 594.25 | 560.51 | 565.51 | 592.30 | 558.24 | 547.67 |

(c) Markov regime-switching models

| $p$ | No drift CEV | Linear drift CEV | Nonlinear drift CEV | No drift GARCH | linear drift GARCH | Nonlinear drift GARCH | No drift CEV-GARCH | Linear drift CEV-GARCH | nonlinear drift CEV-GARCH |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 15.69 | 17.10 | 16.25 | 28.52 | 30.89 | 31.06 | 15.31 | 14.78 | 13.77 |
| 5 | 29.70 | 30.94 | 29.41 | 56.16 | 58.45 | 58.72 | 29.60 | 27.70 | 27.47 |
| 10 | 38.24 | 41.04 | 39.67 | 73.51 | 77.00 | 78.54 | 38.22 | 36.93 | 37.68 |

(d) Jump-diffusion models

| $p$ | No drift CEV | Linear drift CEV | Nonlinear drift CEV | No drift GARCH | linear drift GARCH | Nonlinear drift GARCH | No drift CEV-GARCH | Linear drift CEV-GARCH | nonlinear drift CEV-GARCH |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 69.23 | 69.71 | 67.16 | 37.78 | 39.30 | 37.63 | 33.56 | 35.68 | 32.94 |
| 5 | 110.96 | 110.47 | 106.83 | 77.79 | 81.25 | 75.44 | 71.03 | 75.70 | 66.22 |
| 10 | 125.78 | 125.58 | 121.15 | 103.35 | 109.97 | 102.64 | 94.15 | 101.40 | 88.28 |

Notes: (1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2,986 observations;

(2) The test statistic based on the square Hellinger metric is used in calculating the portmanteau test statistic, which is expected to effectively reduce the impact of outliers;

(3) Upper-tailed N(0,1) critical value (e.g., 1.645 at 5% level) is used for specification tests.

Table 11. M*(m,l)* stats of discrete spot rate models. This table reports the M*(m,l)* stats of discrete spot rate models

| | | M(1,1) | M(1,2) | M(2,1) | M(2,2) | M(3,3) | M(4,4) |
|---|---|---|---|---|---|---|---|
| Discretized Single Factor Diffusion Models | RW | 16.60 | 13.54 | 15.94 | 350.50 | 33.48 | 242.05 |
| | Lognormal | 21.92 | 12.38 | 10.22 | 376.64 | 64.79 | 273.38 |
| | Dothan | 23.13 | 11.03 | 5.22 | 391.31 | 64.75 | 277.22 |
| | PCEV | 19.13 | 8.22 | 9.39 | 337.21 | 53.26 | 243.48 |
| | Vasicek | 38.22 | 20.18 | 98.22 | 343.69 | 17.26 | 280.89 |
| | CIR | 50.00 | 10.88 | 42.44 | 292.48 | 34.00 | 245.34 |
| | CKLS | 36.97 | 9.14 | 30.03 | 294.75 | 39.36 | 243.33 |
| | Nonlinear drift | 32.95 | 10.20 | 29.99 | 299.73 | 36.14 | 241.25 |
| GARCH Models | No drift | 15.97 | 4.36 | 20.02 | 25.60 | 14.40 | 17.54 |
| | Linear drift | 6.76 | 4.30 | 22.69 | 15.26 | 5.88 | 7.80 |
| | Nonlinear drift | 9.31 | 6.35 | 23.44 | 15.87 | 4.87 | 7.43 |
| | No drift CEV | 16.12 | 5.74 | 9.19 | 33.52 | 18.14 | 23.00 |
| | Linear drift CEV | 6.45 | 5.22 | 11.05 | 16.77 | 9.10 | 10.38 |
| | Nonlinear drift CEV | 6.77 | 6.39 | 11.68 | 16.94 | 8.70 | 9.97 |
| Markov Regime-switching Models | No drift CEV | 17.08 | 2.57 | 3.34 | 14.46 | 20.42 | 17.37 |
| | Linear drift CEV | 10.07 | 2.63 | 7.72 | 15.06 | 10.21 | 17.38 |
| | Nonlinear drift CEV | 9.23 | 2.71 | 7.99 | 14.79 | 9.83 | 17.01 |
| | No drift GARCH | 17.99 | 1.16 | 11.36 | 3.62 | 14.35 | 4.17 |
| | Linear drift GARCH | 14.09 | 1.74 | 13.99 | 6.23 | 12.94 | 6.69 |
| | Nonlinear drift GARCH | 13.82 | 2.19 | 13.14 | 6.56 | 12.87 | 6.59 |
| | No drift CEV GARCH | 16.88 | 2.46 | 2.57 | 9.60 | 18.74 | 10.65 |
| | Linear drift CEV GARCH | 11.57 | 2.41 | 5.36 | 9.53 | 12.21 | 10.48 |
| | Nonlinear drift CEV GARCH | 9.67 | 2.80 | 4.89 | 8.99 | 9.77 | 9.41 |
| Jump-diffusion models | No drift CEV | 10.94 | 4.62 | 4.49 | 298.91 | 21.70 | 318.86 |
| | Linear drift CEV | 6.88 | 6.31 | 6.95 | 307.36 | 18.78 | 333.60 |
| | Nonlinear drift CEV | 4.90 | 7.92 | 6.75 | 291.92 | 16.64 | 320.32 |
| | No drift GARCH | 17.35 | 2.36 | 2.16 | 6.61 | 14.75 | 5.41 |
| | Linear drift GARCH | 12.79 | 2.84 | 2.40 | 7.66 | 11.89 | 5.51 |
| | Nonlinear drift GARCH | 10.96 | 3.13 | 3.85 | 6.68 | 10.72 | 5.08 |
| | No drift CEV GARCH | 17.87 | 2.53 | 3.89 | 6.35 | 15.31 | 5.65 |
| | Linear drift CEV GARCH | 13.56 | 3.17 | 3.80 | 7.21 | 12.64 | 5.68 |
| | Nonlinear drift CEV GARCH | 10.81 | 3.91 | 4.94 | 6.13 | 11.71 | 5.41 |

Notes: (1) The sample period is from Jan. 1, 1997 to Dec. 31, 2008 with 2,986 observations;

(2) M(1,1) checks the autocorrelations in level, M(1,2) checks the ARCH-in-mean, M(2,1) checks the leverage effects, and M(2,2), M(3,3) and M(4,4) checks autocorrelations in higher order moments;

(3) A lag truncation order $p = 20$ is used;

(4) Upper-tailed N(0,1) critical value (e.g., 1.645 at 5% level) is used for specification tests.