Jump Risk in China's Stock Market ⋆

Haigang Zhou [a] John Qi Zhu [b,*]

[a] *Department of Finance, Cleveland State University, Cleveland, OH 44115-2214*

[b] *Antai College of Economics & Management, Shanghai Jiao Tong University, Shanghai 200052, China*

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Abstract

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⋆ Names listed alphabetically.

* Corresponding author. Tel.: 86-21-5230-1042
Email addresses: h.zhou16@csuohio.edu (Haigang Zhou), qizhu@sjtu.edu.cn (John Qi Zhu).

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Abstract

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1 Introduction

Previous theoretical and empirical studies have shown that there are two underlying forces driving the volatilities of financial series: a smooth, continuous component and a discrete, jump component. It is very important to take into account jump risk in the modeling framework for risk management and pricing of exotic and deep out-of-the money options. Using high-frequency returns from China, in this study we examines the impact of jump risk in pricing individual stocks, as well as the gains from explicitly utilizing the jump component in forecasting the volatilities of various equity and bond portfolios.

The fact that jump components of realized volatilities play an important role in many financial variables has led to a flurry of empirical research on the statistical and economic importance of jump risk in realized volatilities and how jump risks can be used to forecast realized volatilities (See for example, Ait-Sahalia, 2004; Andersen, Benzoni, and Lund, 2002; Eraker, 2004; Eraker, Johannes, and Polson, 2003; Maheu and McCurdy, 2004). Among them, Dunham and Friesen (2007) examine the relative importance of jump risk using tick-by-tick data of the S&P 100 Index constituents, three U.S. equity indexes and three U.S. Treasury securities over the period 1999 through 2005. They find that jump risk accounts for 15 % to 25% of the total risk, and the size of jump beta is about 36% of the size of the continuous beta. Andersen, Bollerslev, and Diebold (2007) investigate the dynamics and comparative magnitude of jumps on a decade of five-minute high frequency returns for the DM/$ exchange rates, the S&P 500 market index, and the thirty-year U.S. Treasury yield. They incorporate the jump components in the volatility forecast model and demonstrate significant gains in the forecast accuracy across various prediction horizons. However, scant empirical research along this line has extended beyond the U.S. financial markets.

This study is believed to be the first empirical attempt to (1) examine the jump risk of daily stock returns with assessments of the relative contribution of jump risk to systematic risk in individual stocks and (2) explore the potential benefits in terms of volatility forecast accuracy by explicitly differentiating the jump and continuous sample path components in the Chinese financial markets. With the accelerating pace of financial development in China and financial integration in the rest of the world, financial products are growing exponentially, both in quantity and in complexity. However, the empirical measurement and assessment of risks, or volatilities, associated with these financial products are still unknown to most domestic and foreign investors. Understanding the characteristics of jump risk in various financial assets and portfolios is useful for several reasons. In option pricing, the continuous Brownian part and a discontinuous jump part have different requirements and possibilities in hedging; in portfolio allocation, the demand for different classes of assets can be optimized, subject to risks being continuous or jump. In risk management, the identified jump risk helps better assess value-at-risk and other tail statistics over short horizons; in mutual funds management, the ability to disentangle jumps from volatility is critical to managing the exposure to unexpected events in China. Also, for the policy makers, understanding jump risk has important regulation and policy implication, given the current debate on developing a stock index future/option market in China.

This study demonstrate that jump risk is an important pricing factor for individual stock returns. When jumps occur, it is about one-third to one-half of the size of the daily return. Besides, jump risk accounts for about one-third of the total risk in individual stocks and in stock and bond indexes. For every percentage point increase in market jump returns beyond current expectations, the return on an average SSE 50 Index constituent drop is, on average, 0.6298%, while for every percentage point that continuous return increases, the average SSE 50 Index constituent return increases by 1.0079%.

The results of this study also indicate that accounting for jump components in the SSE B Share Index improves the performance of volatility forecasting models. However, the potential benefit of separately measuring the continuous and jump components of the realized volatility is not immediately evident from a volatility forecasting perspective for the A Share and Government Bond markets.

The results are equally important for both diversified and non-diversified portfolios in China. Jump risk is an important pricing factor of daily returns, although it plays a limited role in forecasting realized volatilities.

The study proceeds as follows. In Section 2 the statistical procedures used to estimate jump risk and to decompose total risk and systematic risk into continuous and jump components are presented. Data and the sampling process are described in Section 3. In Section 4 the empirical findings are presented, while Section 5 offers concluding remarks.

2 Methodology

2.1 Estimation of jump risk from high-frequency data

Let $p(t)$ denotes the log price of an asset at time t [1]. The continuous-time jump diffusion process can be expressed as a stochastic differential equation:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), \qquad 0 \leq t \leq T, \tag{1}$$

where $\mu(t)$ is a continuous and locally bounded variation process, $\sigma(t)$ is a stochastic volatility process, $W(t)$ is a standard Brownian motion, and $q(t)$ is a counting process. $dq(t) = 1$ when a jump occurs at time t and $dq(t) = 0$ otherwise. $\kappa(t)$ refers to the size of the jump when a jump occurs. The quadratic variation for the

[1] The discussion in this section is largely drawn from Andersen, Bollerslev, and Diebold (2007), Dunham and Friesen (2007), and Tauchen and Zhou (2006).

cumulative return process, $r(t) \equiv p(t) - p(0)$ is given by:

$$[r, r]_t = \int_{s=0}^{t} \sigma^2(s)ds + \sum_{0<s\leq t} \kappa^2(s). \tag{2}$$

Let the discretely sampled Δ-period returns be denoted by $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$. Following previous studies (See for example, Andersen, Bollerslev, and Diebold, 2007; Dunham and Friesen, 2007; Tauchen and Zhou, 2006), the daily realized volatility is defined as the summation of the corresponding $1/\Delta$ high-frequency intradaily squared returns,

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r^2_{t+j\Delta,\Delta}. \tag{3}$$

As shown in Andersen, Bollerslev, Diebold, and Labys (2003), the realized volatility converges uniformly in probability to the increment of the quadratic variation process when the sampling frequency of the underlying returns increases. That is,

$$RV_{t+1}(\Delta) \to \int_{s=0}^{t} \sigma^2(s)ds + \sum_{o<s\leq t} \kappa^2(s). \tag{4}$$

Following Barndorff-Nielsen and Shephard (2004, 2006), the standardized realized bipower variation is defined as:

$$BV_{t+1}(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} \left|r_{t+j\Delta,\Delta}\right| \left|r_{t+(j-1)\Delta,\Delta}\right|, \tag{5}$$

where $\mu_1^{-2} = \sqrt{2/\pi}$ represents the average absolute value of a random variable that follows a standard normal distribution. As the sampling frequency increases,

$$BV_{t+1}(\Delta) \rightarrow \int_{s=0}^{t} \sigma^2(s)ds. \tag{6}$$

Therefore, as shown in Barndorff-Nielsen and Shephard (2004), the contribution to the quadratic variation process due to the discontinuities (jumps) in the underlying price process may be consistently estimated by:

$$RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \rightarrow \sum_{0,s \leq t} \kappa^2(s). \tag{7}$$

A simple measure of daily volatility due to discontinuities (jumps) suggested by Barndorff-Nielsen and Shephard (2004) and Andersen, Bollerslev, and Diebold (2007) is:

$$\tilde{J}_{t+1} = \max[RV_{t+1} - BV_{t+1}, 0]. \tag{8}$$

2.2 Shrinkage estimation and noise correction

The simple nonparametric jump estimates defined by the difference between the realized volatility and the bipower variation (8) are theoretically appropriate only if the sampled returns are increasingly finer, or $\Delta \rightarrow 0$. The measurement error is inevitable for any empirical implementations with a fixed sampling frequency, or $\Delta > 0$. Although all theoretically infeasible negative estimates of squared jumps have been truncated in (8), the resulting $\tilde{J}^{1/2}$ series still contains a large number of nonzero small positive values. It is unreasonable to reject the possibility that these very small estimates of "jumps" are actually part of the continuous sample path variation process or simply measurement errors due to the finite-sample problem. Therefore, it is desirable to treat only those large values of $RV_t(\Delta) - BV_t(\Delta)$ as the jump component and to distinguish significant jumps from those insignificant ones based on the asymptotic distribution result of the standardized difference between RV_t and BV_t.

Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen and Shephard (2006) show that, in the absence of jumps, the ratio statistic, as defined in Tauchen and Zhou (2006), is:

$$RJ_t = \frac{RV_t - BV_t}{RV_t}, \tag{9}$$

and converges to a standard normal distribution when scaled by its asymptotic variance:

$$ZJ_t = \frac{RJ_t}{\sqrt{(1/m) \times \left[(\pi/2)^2 + \pi - 5\right] \times \max\left(1, TP_t/BV_t^2\right)}} \rightarrow N(0,1). \tag{10}$$

where:

$$TP_t \equiv m \times \mu_{4/3}^{-3} \times \frac{m}{m-2} \sum_{j=3}^{m} \left|r_{t,j-2}\right|^{4/3} \left|r_{t,j-1}\right|^{4/3} \left|r_{t,j}\right|^{4/3} \rightarrow \int_{t-1}^{t} \sigma_s^4 ds, \tag{11}$$

and

$$\mu_k = 2^{k/2} \times \frac{\Gamma\Big[(k+2)/2\Big]}{\Gamma(1/2)}, \qquad k > 0. \tag{12}$$

An abnormally large value of ZJ_t provides statistical evidence in favor of a "significant" jump over the time period $[t, t+1]$.

Based on simulation and Monte Carlo experiments, Tauchen and Zhou (2006) confirm the robustness and satisfactory performance of the ratio-statistics (10) for a wide range of market microstructure contaminants.

Trading days with realizations of ZJ_t in excess of some critical value (Φ_α) are then identified as "significant" jumps. The jump component of the realized volatility on that day is defined as:

$$J_{t,\alpha} = I[ZJ_t > \Phi_\alpha] \cdot (RV_t - BV_t), \tag{13}$$

where $I[\cdot]$ is the indicator function. The continuous sample path component variation is estimated as:

$$C_{t,\alpha} = I[ZJ_t \leq \Phi_\alpha] \cdot RV_t + I[ZJ_t > \Phi_\alpha] \cdot BV_t, \tag{14}$$

such that (13) and (14) sum to the total realized volatility on any given trading day. As long as $\Phi_\alpha > 0$, (13) and (14) ensure that $J_{t,\alpha}$ and $C_{t,\alpha}$ are both nonnegative.

2.3 Decomposition of jumps

Following Dunham and Friesen (2007), if allowance is made for different continuous and jump systematic risks, the returns can be decomposed into four different components[2]:

$$R_{it} = \alpha_t + \beta_{1t}\Big(R_{Mt} - J_{Mt}^{\text{jump}}\Big) + \beta_{2t} J_{Mt}^{\text{jump}} + \Big(J_{it}^{\text{jump}} - \beta_{2i} J_{Mt}^{\text{jump}}\Big) + \varepsilon_{it}. \tag{15}$$

In Equation (15), $J_t^{\text{jump}} = I_t^{\text{sign}} \times \sqrt{I_t^{\text{jump}}(RV_t - BV_t)}$, where I_t^{sign} equals to 1 if R_t is positive and -1 if R_t is negative, and I_t^{jump} equals to 1 if a jump occurs on day t and zero otherwise. Equation (15) decomposes the total return of stock i into four components: continuous systematic return ($\beta_{1t}(R_{Mt} - J_{Mt})$), jump systematic return ($\beta_{2t} J_{Mt}$), jump non-systematic return ($J_{it} - \beta_{2i} J_{Mt}$), and continuous non-systematic return (ε_{it}).

The two-step procedure proposed by Dunham and Friesen (2007) is then used to estimate the systematic and non-systematic jump risks for all individual stocks. First the systematic risk is decomposed into both continuous and jump risks by regressing total returns on continuous market return and market jump:

$$R_{it} = \alpha_t + \beta_{1t}\Big(R_{Mt} - J_{Mt}^{\text{jump}}\Big) + \beta_{2t} J_{Mt}^{\text{jump}} + \eta_{it}. \tag{16}$$

[2] The discussion in this section is largely drawn from Dunham and Friesen (2007).

The non-systematic jump risk is estimated from:

$$\hat{\kappa}_{it} = J_{it}^{\text{jump}} - \hat{\beta}_{2t} J_{Mt}^{\text{jump}}, \tag{17}$$

and the continuous non-systematic risk, e_{it} is estimated from:

$$R_{it} - \left[\hat{\alpha}_t + \hat{\beta}_{1t}\left(R_{Mt} - J_{Mt}^{\text{jump}}\right) + \hat{\beta}_{2t} J_{Mt}^{\text{jump}} + \hat{\kappa}_{it}\right]. \tag{18}$$

2.4 Accounting for jumps in realized volatility modeling and forecasting

The long-memory dependence in financial market volatility has been documented in numerous empirical studies. These observations in turn motivated researchers to estimate long-memory type ARFIMA models for realized volatilities (See Andersen, Bollerslev, Diebold, and Labys (2003), Areal and Taylor (2002) and others). Along this line of modeling technique, this study employs the simple-to-estimate HAR-RV class of volatility models proposed by Corsi (2004). The formulation of the HAR-RV model is an extension of Müller, Dacorogna, Dave, Olsen, and Pictet (1997)'s Heterogeneous AR models. The conditional variance of the discretely sampled returns is parameterized as a linear function of lagged squared returns over the identical return horizon together with the squared returns over longer and/or shorter return horizons.

A typical HAR-RV model, following Andersen, Bollerslev, and Diebold (2007), for the one-day-ahead forecast of daily realized volatility can be expressed as:

$$RV_{t+1} = \beta_0 + \beta_D RV_t + \beta_W RV_{t-4,t} + \beta_M RV_{t-21,t} + \varepsilon_{t+1}, \tag{19}$$

where $RV_{t-4,t}$ (or $RV_{t-21,t}$) are the 5 (or 22) day moving average of the realized volatilities up to the day of t. It is also straightforward to incorporate realized volatilities over other horizons as additional explanatory variables into the regression, but the daily, weekly, and monthly measures offer the natural economic interpretation to the above model. The HAR-RV one-day-ahead volatility forecast model can be extended to longer horizons. Given the non-parametric measurement of the jump component defined in (8), this study uses the explanatory power of $\tilde{J}$ in the forecast model of realized volatilities. The forecast model (19), as shown in Andersen, Bollerslev, and Diebold (2007), thus becomes:

$$RV_{t,t+k} = \beta_0 + \beta_D RV_t + \beta_W RV_{t-4,t} + \beta_M RV_{t-21,t} + \beta_J \tilde{J}_t + \varepsilon_{t,t+h}. \tag{20}$$

The error term ε_t will be serially correlated up to order $k-1$ with observation every period and $k > 1$. Therefore, in the results this study relies on the Newey-West heteroskedasticity consistent covariance matrix estimator to obtain the corresponding standard errors of the estimates. In addition 5, 10, and 44 lags areused for the daily ($k = 1$), weekly ($k = 5$), and monthly ($k = 22$) regression estimations, respectively.

In order to consider the practical use of volatility models and forecasts, we employ a nonlinear HAR-RV-J model, proposed by Andersen, Bollerslev, and Diebold

(2007), that involves standard deviations instead of variances is uded as follows:

$$(RV_{t,t+k})^{1/2} = \beta_0 + \beta_D RV_t^{1/2} + \beta_W (RV_{t-4,t})^{1/2} + \beta_M (RV_{t-21,t})^{1/2} + \beta_J \tilde{J}_t^{1/2} + \varepsilon_{t,t+k}. \tag{21}$$

Next, building on the explicit decomposition of daily realized volatility into a significant jump component and a corresponding continuous component in (13) and (14), the HAR-RV-J model is further extended to include the continuous sample path variability and jump variation as explanatory variables on the right side of the regression.

Similar to the definition of $RV_{t,t+k}$, $J_{t,t+k}$ and $C_{t,t+k}$ are defined as the moving averages of k days jump and continuous sample path variability measures, respectively. Following Andersen, Bollerslev, and Diebold (2007), the new HAR-RV-CJ model is expressed as

$$RV_{t,t+k} = \beta_0 + \beta_{CD} C_t + \beta_{CW} C_{t-4,t} + \beta_{CM} C_{t-21,t} + \beta_{JD} J_t + \beta_{JW} J_{t-4,t} + \beta_{JM} J_{t-21,t} + \varepsilon_{t,t+k}. \tag{22}$$

The non-linear HAR-RV-CJ model can also be expressed in standard deviation forms as:

$$\begin{aligned} RV_{t,t+k}^{1/2} = {} & \beta_0 + \beta_{CD} C_t^{1/2} + \beta_{CW} (C_{t-4,t})^{1/2} + \beta_{CM} (C_{t-21,t})^{1/2} \\ & \beta_{JD} J_t^{1/2} + \beta_{JW} (J_{t-4,t})^{1/2} + \beta_{JM} (J_{t-21,t})^{1/2} + \varepsilon_{t,t+k}. \end{aligned} \tag{23}$$

3 Data

The sample includes 47 of the 50 constituents of the Shanghai Stock Exchange (SSE) 50 Index and SSE Composite Index, Shanghai A Share Index, Shanghai B Share index, and the Government Bond Index. Three firms, Aluminum Corporation of China Limited, China Shenhua Energy Company Limited, and PetroChina Company limited, are excluded from the sample because only limited data is available. Five-minutes and daily price data are collected from The Analyst, who developed highly regarded technical analysis software in China.

The SSE 50 Index contains the 50 stocks with the largest capitalization and with the highest liquidity. The 50 stocks only represent 5.52% of the total number of listed stocks on the Shanghai Stock Exchange. However, it represents 65.82% of the total market capitalization and 41.51% of the tradable market capitalization [3] .

Visual investigation of the quotes reveals that there are a large number of erroneous quotes for January 06, 2004 when the data first became available, for December 30, 2006, for January 16, 2007, and for November 2006. The above sample periods are excluded from thisstudy.

Following Dunham and Friesen (2007), the sandwich filter method is used to eliminate quotations that are 10% or further away in absolute value of the surrounding quotes.

[3] Source: http://www.sse.com.cn/.

4 Empirical results

4.1 Summary statistics

In Table 1 the summary statistics for total risk and of the continuous and jump components are shown. Not surprising, the average SSE 50 stock is about twice as risky as a stock index and about 20 times riskier than the government bond index. It indicates that investing in equity index portfolios can eliminate about half of the risks in individual stocks. For both individual stocks and indexes, continuous risk account for the majority of total risk. For an average stock, continuous risk contributes about 90% of the total risk. Comparatively, jump risk contributes a higher percentage to the total risk in individual stocks than in stock indexes. For individual stocks, the average correlation between the continuous and jump components of the total risk is 0.0349. The correlation for stock indexes ranges from 0.0149 for the SSE 50 index to 0.1203 for A shares. There is a negative correlation between the continuous and jump components of risk for the government bond index.

Insert Table 1 about here.

Total risks are lower than the sum of continuous and jump risks due to the "diversification" effect, partially attributed to the low or even negative correlations between continuous and jump risks. For example, for an average SSE 50 stocks, the sum of continuous and jump risks is 3.45 percent compared to 2.7891 percent for the total risk.

Table 2 reports the summary statistics for jump risk, for both individual stocks and indexes on all sample days (Panel A), on days with high volatility defined to be days on which an asset's realized volatility is above its median realized volatility over the entire sample period (Panel B), and on days when market jumps occur (Panel C).

Insert Table 2 about here.

The results in Panel A indicate that a jump is more likely to occur for an individual stock than on a stock index and the average absolute jump size for an individual stock is approximately three times that of an index. For individual stocks, a jump occurs, on average, once every month (8.6% of the trading days). The SSE Composite, A- and B-share, and 50 indexes generate fewer than 8 jumps (3% of the trading days) a year. In contrary, the Government Bond index yields 90 jumps a year. The average jump size of a stock is 2.8 times of that of the average jump for the stock indexes and is 21 times of that of the government bond index. Jumps occur much more often on the government bond index (90 times a year), although the average jump size is much smaller (5% of the size of a jump on a stock). **It indicates that jumps can either significantly increase or significantly decrease daily returns.** About 15% of an individual stocks' total risk can be attributed to jump risk, measured by the variance of jump returns, ranging from 3% to 80%. For indexes, the contribution of jump risk to total risk ranges from 1.08% for the B Share Index to 14.42% for the Government Bond Index.

In Panel B significant jumps that occur on days of high realized volatilities are examined. Jumps occur slightly more frequently and jump returns are higher than unconditional jump returns (Panel A). Compared to unconditional jumps, the size of jump returns relative to the absolute daily return is lower, although the portion of total variance attributed to jump variance does not change.

The summary and distribution properties of jumps conditional on the occurrence of market jumps are reported in Panel C. Jumps of the Composite index are highly correlated with those of the A Share Index, but not with those of the B Share Index. Jumps of B Share Index occur 5.5% on the days when market jumps occur, compared to 94% for the A Share Index. Market jump is defined as a jump in the SSE Composite Index. Jumps occur on an SSE 50 stock about 22% of the time when a market jump occurs. The relative magnitude of absolute jump returns increased to about 60%. When the market jump occurs, 18% for the market risk is attributed to jump risks, indicating that jump risk is an important factor driving total risks.

Insert Table 3 about here.

Table 3 summarizes moment statistics of the daily realized volatility and its jump component for a cross section of individual stocks consisting of the Shanghai Stock Exchange 50 Index and four representative indices in the Shanghai Stock Exchange[4]. Panel A reports the cross-sectional averages of relevant statistics calculated for each individual stock. The descriptive statistics reported in Panel B through E depict the time-series characteristics of the daily realized volatility and its jump component for four selected indices.

Several common features emerge immediately. First it is evident that daily realized volatilities for indices are much smaller in magnitude than those for individual stocks in the sample. This is consistent with the empirical evidence about total risk and jump risk that was documented in Table 1. Secondly, a very large positive skewness in daily realized volatilities and their jump components for all the indices under study is observed, indicating a small number of events occasionally arriving at the market with some tremendous disturbing impacts on the evaluations of the underlying asset prices in the portfolios. Finally, the last column of Table 3 reports the Ljung-Box test statistics for serial correlation for up to 10th order for each of the variables in the row [5]. Daily realized volatility and the jump component of the

[4] In what follows, we focus on Shanghai Stock Exchange A Share Index, B Share Index, Government Bond Index, and Shanghai Stock Exchange 50 Index. The Shanghai Stock Exchange Composite Index is omitted largely due to its significant similarity in the performance to the A Share Index. As a matter of fact, the constituent stocks in the A Share Index overwhelmingly dominate the Composite Index, which is a weighted average of market cap across A Share and B Share stocks by design. With a rapid expansion of the A share market cap relative to the B share's, it is not surprising to observe the performance of the Composite Index increasingly converge to the performance of the A Share Index.

[5] In Panel A, the cross-sectional sample mean of Ljung-Box statistics for each individual stocks are reported instead.

realized volatility, measured as $\tilde{J}$, exhibit high degrees of serial correlation. However, it is equally noteworthy that, in Panel B through E, Ljung-Box statistics for the jump component, $\tilde{J}$ and $\tilde{J}^{1/2}$, across all four indices are remarkably lower than the corresponding test statistics for the realized volatility, RV and $RV^{1/2}$. This indicates the statistically significant dynamic dependence observed in the overall quadratic variation largely originates from the dynamic dependence in the continuous sample path price movement, rather than the discontinuous sample path price process, or jumps. This conjuncture is also confirmed at individual stock level, as the last column of Panel A shows, where BV and $BV^{1/2}$ are the bi-power variation measures for the continuous sample path.

Figure 1 provides visual observations of the daily realized volatility and its jump component for the selected indices for the Shanghai Stock Exchange and readily confirms the conclusions from previous tables.

The top left graph in each panel plots the daily realized volatility in standard deviation form, or $RV^{1/2}$. As is evident from the tables, the sizes of daily realized volatilities are comparable across the three stock indices in panel (a), (b), and (d), while the government bond index has much smaller daily fluctuations in panel (c).

Insert Figure 1 about here.

The top right graph in each panel shows the jump components, defined as $\tilde{J}^{1/2}$. For three stock indices, the jump components of daily realized volatilities exhibit simultaneous spikes concentrating on three specific periods of time; July to September of 2005, June to August of 2006, and an episode from January to the end of our sample period in 2007. Correspondingly, similar patterns are found in the overall realized volatility, indicating that many realized volatilities are directly linked to jumps in the underlying equity price process. However, the fluctuations of the jump components for the government bond index in panel (c) are more tranquil compared to the stock indices and show little synchronization with the equity market.

The bottom left graphs in all panels show the ZJ_t statistic defined in (10). It distinguishes statistically significant jump components from those jump estimates occurring concurrently with large continuous variations, and therefore likely due to measurement errors or market microstructure contaminants. The horizontal line indicates the critical value that identifies significant jumps corresponding to $\alpha = 0.99$. We now know, among three episodes having clustered spikes in daily realized volatility, two of them are indeed due to sudden increases in jump components. The other one, occurred in 2006, mainly results from concurrent increases in volatilities of continuous sample path since we barely observe statistically significant jumps in the year of 2006 for three stock indices. Interestingly, the frequency of statistically significant jumps for the government bond index are markedly higher than those for stock indices, although the size of these significant jumps in the bond market is, relatively, much smaller. This phenomenon is evident from bottom right graphs and consistent with the numerical illustrations in Table 2.

Insert Figure 2 about here.

In Figure 2 is ploted the smoothed jump intensities and jump sizes for each of four indices to illustrate the complex dynamic dependence in the significant jump time series. This figure graphs the exponentially smoothed average monthly jump intensities (solid line) to the left scale and sizes of the significant jumps based on $\alpha = 0.99$ (dash line) to the right scale. The jump sizes are expressed in standard deviation form of (13), or $J_{t,0.99}^{1/2}$. The top left panel for the A Share Index and the bottom right panel for the SSE 50 Index share a similar pattern of temporal dependence in the jump arrival processes and jump sizes, while the other stock index for B Shares in the top right panel suggests a sharp increase in jump intensities and sizes in 2007. In contrast, the government bond index in the bottom left panel appears to have a systematic rising trend in both the jump intensities and sizes over the sample period.

4.2 Decomposition of systematic risk and total risk

In Panel A of Table 4, the systematic risk of a stock is decomposedalso into jump and continuous systematic risk according to Equation (15). The total return beta, proxy of the systematic risk, is estimated from regressing daily individual stock returns on those of the SSE Composite Index. The average systematic risk, measured by total return beta is 1.0062, indicating the systematic risk of an average stock in the SSE 50 index is similar to that of the market. Based on the official definition provided by the Shanghai Stock Exchange, the constituents of the SSE 50 index are the "50 largest stocks of good liquidity and representativeness from the Shanghai security market by scientific and objective method". Previous studies have documented that companies of the highest capitalization are most influential in the Shanghai security market.

Insert Table 4 about here.

Panel A of Table 4 shows that jump risk is an important pricing factor for daily returns. For every percentage point increase in market jump returns beyond current expectations, the return on an average SSE 50 Index stock drops on average of 0.6298%, while for every percentage point that continuous return increases, the average SSE 50 Index constituent return increases by 1.0097%. The result is different from that reported in Dunham and Friesen (2007) on the U.S. stock market. They find that the size of jump beta is 36% of the size of the continuous beta.

Pane B of Table 4 provides information on the importance of each factor in explaining the volatility of daily SSE 50 Index returns. It reports the percentages of total risk, measured by the variance of daily returns, attributed to four components: (1) systematic jump risk ($= \beta_{2i}^2 \sigma_{M,jump}^2 \equiv \beta_{2i}^2 \operatorname{Var}(RJ_{Mt})$), (2) systematic continuous risk ($= \beta_{1i}^2 \sigma_{M,cont}^2 \equiv \beta_{1i}^2 \operatorname{Var}(R_{Mt} - RJ_{Mt})$), (3) nonsystematic jump risk ($= \sigma_{\hat{K}_{it}}^2 \equiv \operatorname{Var}(\hat{K}_{it})$), and (4) nonsystematic continuous risk ($= \sigma_{\hat{e}_{it}}^2 \equiv \operatorname{Var}(\hat{e}_{it})$). On average, the systematic continuous risk is 37% of the total risk and the non-systematic continuous risk accounts for 63% of the total risk. The majority of the total risk is attributed to the continuous risk. The systematic and nonsystematic jump risk attribute equally to the total risk at 0.15% each.[6] The low contribution of jump risk to total risk is due to the low correlation between market jumps and jumps of individual stocks. As shown in Table 2, on average a jump occurs on an individual SSE 50 stock about 22% of the time when a market jump occurs.

The results illustrate that it is equally important to study the jump risk for both diversified and non-diversified portfolios. The results are qualitatively similar to those reported by Dunham and Friesen (2007) for U.S. stock markets.

4.3 Accounting for jumps in realized volatility modeling and forecasting

Turning to the empirical estimates of (20) and (21), the results are shown for four selected indices in panel A through D in Table 5. The first three columns report coefficient estimates from the linear HAR-RV-J model and the last three columns for the nonlinear model. Across the four indices, estimates of β_D remain significant, regardless of the model specifications and forecast horizon, confirming the highly persistent volatility dependence in the Shanghai Stock Exchange's equity and bond markets. Interestingly, as to the estimates of β_W, they appear to be important and significant in the B share and the government bond market over various forecast horizons, but powerless in the A share stock market. However, the estimates of β_M

[6] The average percentage contributions of different components do not add up to 100% because the covariance among different risk components has been ignored.

exactly reverse the above conclusion for β_W; they are economically and statistically significant for the A Share Index and SSE 50 Index, but not for the B Share Index and the Government Bond Index across various forecast horizons.

Insert Table 5 about here.

The estimates of β_J, characterizing the relative impact of the lagged jump component on the realization of the current daily volatility, are systematically negative and statistically insignificant at conventional levels across all markets, except for the B Share Index . The insignificance of β_Js is not surprising based on the visual observation of the $\tilde{J}$ series in Figure 3. Although $\tilde{J}$, depicted in the top right graphs, seems to track the variability of realized volatilities in the left graphs, the statistical tests in the bottom left graphs indicate variations in the continuous sample path have captured most of the variations in overall realized volatilities leaving a relatively small portion to be explained by the jump components. Among the four selected indices, $\tilde{J}$ plays a relatively important role in forecasting the realized volatilities of the B Share Index where the jump component significantly increases the following day's realized volatility over various forecast horizons. For instance, a one unit increase in daily realized volatility will, on average, increase the daily realized volatility on the following day by $0.252+0.401/5-0.016/22 = 0.3315$ for days when $\tilde{J} = 0$ in the first column of Panel B. In contrast, if part of the realized volatility is due to the jump component, the increase in realized volatility on the following day will further rise by another 2.972 times the jump component. The induced realized volatilities on the next day can be 10 times different in magnitude between a day when a one unit increase in realized volatility exclusively comes from the jump component and a day when the same one unit increase in realized volatility is purely due to the variation in the continuous sample path. For the A Share Index, Government Bond Index, and SSE 50 Index, jump components play a minor role that generally dampens the future realized volatility once jumps occur. This particular finding is consistent with regression results in Andersen, Bollerslev, and Diebold (2007), who implement the test on the high frequency data for the US market.

The benefit of using high frequency data in modeling and forecasting volatility is most evident when the R^2 of the HAR-RV-J models is compared to the R^2 of the HAR-RV models. In HAR-RV models, the jump component is absent and the realized volatilities on the right side, but not the left side of equation (22), are replaced by the corresponding lagged squared daily, weekly, and monthly returns. Large gains in forecast accuracy through the use of realized volatility, together with the separate jump components, highlight the added value of high frequency data in forecasting the realized volatilities over various forecast horizons. However, the importance of the jump component as an explanatory variable in the volatility forecast regressions is indeed limited for the Chinese market.

<u>Insert Table 6 about here.</u>

An extension of the HAR-RV-J model explicitly decomposes the explanatory variable on the right side into continuous sample path variability and the jump variation, as in (22) and (23). The measurement and separation of C_t and J_t build on the nonparametric estimation and construction of test statistic ZJ_t described in (10), (13), and (14). In the following estimations, the significant jump series depicted in the bottom right graph of each panel in Figure 1 is utilized. The first three columns in Table 6 report coefficient estimates from the linear HAR-RV-CJ model for four selected indices. Most of the estimates for jump coefficients, β_{JD}, β_{JW}, and β_{JM}, are insignificant, except for the B Share Index. The evidence that most of the continuous coefficient estimates, β_{CD}, β_{CW}, and β_{CM}, appear to be significant indicates that the predictability of realized volatility is almost exclusively due to the continuous sample path components. However, the importance of jump component to forecast the realized volatility is noteworthy again in the B Share market. Measurements of daily and monthly-averaged jump components exert economically large and statistically significant impacts on the realized volatility over various forecast horizons. These same qualitative results carry over to the nonlinear HAR-RV-CJ models reported in the next three columns of Table 6.

Insert Figure 3 about here.

To further illustrate the predictability of the HAR-RV-CJ model, in Figure 3 the daily, weekly, and monthly realized volatility is plotted in standard deviation form (solid line to the left scale) together with their corresponding forecasts (dash line to the right scale) obtained from the nonlinear HAR-RV-CJ model in the last three columns in Table 6 for each index. Across all of the markets and forecast horizons, there is evidently a close coherence between the different pairs of realizations and forecasts.

The results from Table 5 and Table 6 suggest that accounting for jump components in the B Share Index improves the performance of volatility forecasting models. However, the potential benefit of separately measuring the continuous and jump components of the realized volatility is not immediately evident from a volatility forecasting perspective for the A Share and the Government Bond markets. Further work along these lines may construct models for the jump component, J_t, and the continuous sample path component, C_t, separately. Then the individual models of J_t and C_t can either construct out-of-sample forecasts for each component or combine together to forecast the overall realized volatility $RV_t = J_t + C_t$.

5 Conclusion

Theoretical and empirical studies have shown that there are two underlying forces driving the realized volatilities of a financial series: a smooth, continuous component and a discrete, jump component. The importance of empirically disentangling continuous sample path variability from the discontinuous jump part has been emphasized from an asset pricing perspective in various contexts, such as option pricing, portfolio allocation, and risk management.

In this study we implement a non-parametric procedure recently developed separately by Andersen, Bollerslev, and Diebold (2007), Tauchen and Zhou (2006), and Barndorff-Nielsen and Shephard (2004) was used to measure the continuous sample path variation and the discontinuous jump part for a sample of fifty Chinese stocks and four stock and one government bond indexes. Using high-frequency five-minute stock returns, the distributional properties of jump risk are estimated and examined. The empirical results suggest that statistically significant jumps occur, on average, for individual stocks about once every month (8.6% of trading days). Indexes of equity portfolios generate fewer than eight significant jumps per year, while an index of government bonds yields ninety significant jumps. Despite of the relatively low frequency of jump occurrences over the sample period for individual stocks and equity portfolios, the jump returns are sizeable, relative to the daily return, accounting for 30% to 50% of changes in total returns. We further observe stronger own dynamic dependence in realized volatilities across different asset portfolios than that in their jump components.

When applying the canonical capital asset pricing approach to decomposing the total systematic risk into jump and continuous risks, market systematic jump risks are revealed as an important pricing factor for daily returns. The absolute magnitude of jump beta is, on average, similar to that of the absolute magnitude for continuous beta across firms. Very low contributions of systematic or non-systematic jump risk to the total risks across individual stocks over the sample period are found. The co-existence of the two phenomenon is an indication that discontinuities or jump components in the stochastic process of asset pricing are indeed statistically rare events, but have tremendous impacts on the prices of underlying assets in Chinese markets. Understanding and measuring the catastrophic feature of jump risks is particularly important and critical to the practice of risk management relies on the accurate assessment of such unlikely, though foreseeable, risks in the market.

In estimating a simple linear volatility forecasting model that includes the continuous sample path and jump variability measures, it is found that most predictive power comes from the continuous part for equity portfolios denominated in domestic currency and the government bond portfolio. Accounting for jump components does improve the performance of volatility forecasting for the equity portfolio denominated in US dollars.

The empirical results presented here add to the recent discussion of developing an option market and improving the the effectiveness of risk management for China. Both tasks critically hinge on better understanding, measurement, and assessment of the market risks or realized volatilities across time. As a first pass, separating the continuous sample path variation from the discontinuous part should shed additional light on the risk analysis and volatility forecasting for Chinese stock markets.

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Table 1
Summary Statistics for Realized Volatility and Jumps

Jump returns equal to $RJ_{t,\alpha} = sign(R_t)\sqrt{(RV_t - BV_t) \times I[ZJ_t > \Phi_\alpha]}$, where R_t denotes daily returns, and $I[ZJ_t > \Phi_\alpha] = 1$ if $ZJ_t > \Phi_\alpha$ and equals to 0 otherwise. The daily continuous return is equal to the total daily return minus the jump return. Total risk is defined as the sample variance of daily returns. Continuous and jump risk are defined as the sample variance of daily continuous and jump returns, respectively, using returns on all days in the sample period. All numbers are multiplied by 100 except correlation coefficients.

	Cross-sectional Distribution for SSE 50 firms				Sample Means for Indices				
	Mean	Median	Min	Max	Composite	A Shares	B Shares	Govt Bond	50 Index
Total risk	2.7891	2.6007	1.8411	5.2381	1.3977	1.3967	2.001	0.1404	1.3167
Continuous risk	2.4422	2.3984	1.7757	3.7069	1.3673	1.3646	1.976	0.1348	1.2991
Jump risk	1.01	0.6656	0.4453	4.6817	0.1765	0.1756	0.208	0.0533	0.1672
Corr(jump, cont)	0.0349	0.0391	-0.075	0.1533	0.1099	0.1203	0.0679	-0.0918	0.0419

Table 2
Distributional properties of jump risks

Jump frequency is the fraction of days on which a jump occurs. Statistics for the rest of the variables are calculated for jump days only, and thus conditional on a jump occurring. Jump return is defined as $RJ_{t,\alpha} = sign(R_t)\sqrt{(RV_t - BV_t) \times I[ZJ_t > \Phi_\alpha]}$, where R_t denotes daily returns, and $I[ZJ_t > \Phi_\alpha] = 1$ if $ZJ_t > \Phi_\alpha$ and equals to 0 otherwise. Jump variance is the variance of jump returns, and total variance is the variance of daily returns. Panel A includes all jumps; Panel B includes jumps that occur on days of high realized volatility defined to be days on which an asset's realized volatility is above its median realized volatility over the entire sample period; Panel C includes jumps that occur on days of having an identified jump in the composite index daily 5-min return series. All numbers are multiplied by 100 except jump frequency and ratio of jump and total variance.

	Cross-sectional Distribution for SSE 50 firms				Sample Mean				
	Mean	Median	Min	Max	Composite	A Shares	B Shares	Govt Bond	50 Index
Panel A: All Days									
Jump frequency	8.65%	8.50%	2.96%	19.67%	2.00%	2.00%	2.78%	35.26%	1.49%
Jump size	0.8258	0.8072	0.5662	1.0854	0.2531	0.2532	0.2309	0.0458	0.2350
Absolute jump size	1.0081	0.9904	0.6831	1.4322	0.3625	0.3625	0.3689	0.0474	0.3478
Absolute daily return	1.8621	1.8377	1.2688	2.9456	1.0348	1.0344	1.3046	0.0892	0.9772
Jump variance	0.0202	0.0044	0.002	0.2189	0.0003	0.0003	0.0004	0.0000	0.0003
Total variance	0.0832	0.0674	0.0339	0.2741	0.0195	0.0195	0.0400	0.0002	0.0173
Jump/Total	14.20%	7.55%	3.00%	79.88%	1.59%	1.58%	1.08%	14.42%	1.61%
Panel B: Jumps on days of high volatility									
Jump frequency	6.78%	6.38%	1.54%	16.95%	2.23%	2.23%	3.12%	30.29%	1.38%
Jump size	1.0189	1.0114	0.6823	1.4162	0.3704	0.3704	0.3273	0.0594	0.3353
Absolute jump size	1.2983	1.2775	0.8861	1.9141	0.5124	0.5121	0.5504	0.0624	0.4834
Absolute daily return	2.591	2.5358	1.8141	4.2401	1.3688	1.3668	1.8429	0.1223	1.2900
Jump variance	0.0379	0.0063	0.0029	0.4354	0.0005	0.0005	0.0008	0.0000	0.0005
Total variance	0.1427	0.1087	0.0584	0.5307	0.0313	0.0311	0.0703	0.0003	0.0273
Jump/Total	13.77%	6.48%	2.88%	82.05%	1.70%	1.70%	1.13%	14.23%	1.68%
Panel C: Jumps on days when market jumps occur									
Jump frequency	21.79%	22.22%	0.00%	50.00%	100.00%	94.44%	5.56%	27.78%	11.11%
Jump size	1.0477	0.9917	0.1943	2.4892	0.8469	0.8298	0.1885	0.0438	0.6591
Absolute jump size	1.1446	1.0951	0.4931	2.4892	0.8469	0.8351	0.3438	0.0438	0.6773
Absolute daily return	1.8404	1.9273	0.1	3.7468	1.4196	1.4343	1.6377	0.0656	1.3256
Jump variance	0.0058	0.0064	0	0.0131	0.0076	0.0076	0.0000	0.0000	0.0028
Total variance	0.0655	0.066	0	0.1617	0.0426	0.0428	0.0511	0.0001	0.0413
Jump/Total	10.77%	8.66%	0.00%	94.90%	17.86%	17.78%	0.00%	40.78%	6.72%

Table 3
Summary statistics of daily realized volatilities and jumps for stocks and indices

RV is the realized volatility measure, BV is the bi-power variation measure, and $\tilde{J}$ is the positively truncated simple measure of daily volatility due to jumps, defined as $\tilde{J}_t = \max[RV_t - BV_t, 0]$. Except for Skewness, kurtosis, and Ljung-Box statistics, all numbers are multiplied by 100. The column labeled LB_{10} gives the Ljung-Box test statistic for up to tenth order serial correlation.

	Mean	Std	Skew	Kurt	Min	Max	LB_{10}
Panel A: Average statistics of Shanghai Stock Exchange Constituents							
RV	0.107	0.5367	7.2058	123.4084	0.0486	0.2894	729.9598
$RV^{1/2}$	2.7283	1.5007	4.3026	78.9397	1.9305	4.1672	1206.192
BV	0.0821	0.0107	5.0884	45.8009	0.0736	0.0443	843.2683
$BV^{1/2}$	2.5334	0.1233	4.3026	78.9397	2.4569	1.8089	1435.531
Panel B: Shanghai Stock Exchange A Share Index							
RV	0.0182	0.0256	5.8404	62.070	0.0012	0.3870	1157.54
$RV^{1/2}$	1.1886	0.6400	21.368	10.531	0.3481	6.2211	2281.87
$\tilde{J}$	0.0016	0.0037	5.2775	39.603	0.0000	0.0411	137.05
$\tilde{J}^{1/2}$	0.2532	0.3053	1.836	7.6966	0.0000	2.0278	211.37
Panel C: Shanghai Stock Exchange B Share Index							
RV	0.0204	0.0489	7.1998	70.169	0.0003	0.6845	1875.00
$RV^{1/2}$	1.1304	0.8756	3.2557	18.169	0.1811	8.2735	2885.62
$\tilde{J}$	0.0015	0.0051	9.3362	121.450	0.0000	0.0872	276.91
$\tilde{J}^{1/2}$	0.2309	0.3104	2.9742	17.368	0.0000	2.9531	231.85
Panel D: Shanghai Stock Exchange Government Bond Index							
RV	0.0001	0.0002	5.6816	41.537	0.0000	0.0021	206.23
$RV^{1/2}$	0.0849	0.0545	3.1951	16.079	0.0287	0.4565	473.51
$\tilde{J}$	0.0000	0.0001	9.8931	120.726	0.0000	0.0020	46.16
$\tilde{J}^{1/2}$	0.0458	0.0407	4.5138	32.897	0.0000	0.4428	146.55
Panel E: Shanghai Stock Exchange 50 Index							
RV	0.0180	0.0264	6.7201	76.905	0.0015	0.4118	1104.65
$RV^{1/2}$	1.1809	0.6346	2.3507	12.678	0.3929	6.4169	2224.99
$\tilde{J}$	0.0014	0.0032	5.5664	45.099	0.0000	0.0353	93.36
$\tilde{J}^{1/2}$	0.2350	0.2888	1.7965	7.6163	0.0000	1.8783	135.33

Table 4

Decomposing jump risk into systematic and nonsystematic components

Jumps for individual equities are decomposed into their systematic and non-systematic jump components. Daily returns calculated from 5-min returns are used. The total return for stock i is regressed on the market continuous return and market jump return according to the specification: $R_{it} = \alpha_{it}+\beta_{1i}(R_{Mt}-J_{Mt})+\beta_{2i}J_{Mt}+\eta_{it}$. The first row reports β from the standard CAPM specification: $R_{it} = \alpha_{it}+\beta R_{Mt}+\varepsilon_{it}$. The non-systematic jump is estimated as $\hat{K}_{it} = J_{it} - \hat{\beta}_{2i}J_{Mt}$. Total risk is defined as the variance of total daily return. Systematic continuous (jump) risk is equal to the squared continuous (jump) beta, β_{1i} (β_{2i}), times the variance of continuous (jump) market returns. Non-systematic jump risk is defined as the sample variance of $\hat{K}_{it}$. Non-systematic continuous risk is the sample variance of residuals from regression $R_{it} = \alpha_{it} + \beta_{1i}(R_{Mt} - J_{Mt}) + \beta_{2i}J_{Mt} + \hat{K}_{it} + e_{it}$. The average percentage contributions of different components do not add up to 100% because we ignore the covariance among different risk components in our estimation.

	Cross-sectional distribution of firms in SSE 50						
	Mean	Min	25 pct	Median	75 pct	Max	Std Dev.
Panel A: Estimated parameter							
Total return beta (β)	1.0062	0.6496	0.922	1.0199	1.118	1.3025	0.1478
Jump beta (β_{2i})	0.6298	-1.4817	0.2277	0.6845	1.1004	2.012	0.7906
Continous beta (β_{1i})	1.0097	0.6415	0.9159	1.0248	1.1205	1.2884	0.1468
Difference ($\beta_{1i} - \beta_{2i}$)	0.3799	-1.0863	-0.0209	0.3217	0.7779	2.4927	0.759
Panel B: Percentage total risk							
Systematic jump risk	0.1496	0	0.0087	0.054	0.1592	1.0518	0.2508
Systematic continous risk	36.5032	16.7965	31.0998	35.6679	42.411	53.8529	8.587
Nonsystematic jump risk	0.1499	0.0003	0.0096	0.0545	0.1614	1.0543	0.2503
Nonsystematic continous risk	63.4872	48.0045	57.0867	63.6162	69.4924	82.715	8.7398

Table 5
Daily, weekly, and monthly volatility forecasting HAR-RV-J regression

$$RV_{t,t+k} = \beta_0 + \beta_D RV_t + \beta_W RV_{t-4,t} + \beta_M RV_{t-21,t} + \beta_J J_t + \varepsilon_{t,t+k}$$
$$RV^{1/2}_{t,t+k} = \beta_0 + \beta_D RV^{1/2}_t + \beta_W RV^{1/2}_{t-4,t} + \beta_M RV^{1/2}_{t-21,t} + \beta_J J^{1/2}_t + \varepsilon_{t,t+k}$$

The table reports the OLS estimates for daily ($k = 1$), overlapping weekly (k=5) and monthly (k=22) HAR-RV-J volatility forecast regressions. The realized volatility and jumps are constructed from five-minute returns from January 2004 to October 2007. The standard errors reported in parenthesis are based on Newey-West/Bartlett correction allowing for serial correlation of up to order 5 (k=1), 10 (k=5), and 44 (k=22), respectively. The last two rows of each panel labeled $R^2_{HAR-RV-J}$ and R^2_{HAR} are for the HAR-RV-J model and a typical HAR model with no jumps and with the realized volatilities on the right side of the regression replaced with the corresponding lagged daily, weekly, and monthly squared returns.

	$RV_{t,t+k}$			$RV^{1/2}_{t,t+k}$		
	k=1	k=5	k=22	k=1	k=5	k=22
Panel A: Shanghai Stock Exchange A share index						
β_D	0.543	0.472	0.186	0.542	0.538	0.273
	(0.127)	(0.065)	(0.021)	(0.076)	(0.046)	(0.032)
β_W	-0.023	-0.096	0.081	0.078	0.006	0.177
	(0.077)	(0.080)	(0.069)	(0.071)	(0.082)	(0.084)
β_M	0.386	0.480	0.435	0.288	0.377	0.347
	(0.105)	(0.088)	(0.126)	(0.071)	(0.084)	(0.144)
β_J	-0.266	0.091	-0.121	-6.085	-3.228	-8.795
	(0.396)	(0.248)	(0.199)	(6.566)	(4.250)	(5.175)
$R^2_{HAR-RV-J}$	0.44	0.58	0.51	0.56	0.69	0.58
R^2_{HAR}	0.29	0.29	0.35	0.33	0.36	0.35
Penel B: Shanghai Stock Exchange B share index						
β_D	0.252	0.373	0.213	0.375	0.493	0.284
	(0.072)	(0.037)	(0.043)	(0.045)	(0.021)	(0.049)
β_W	0.401	0.386	0.364	0.342	0.292	0.304
	(0.171)	(0.162)	(0.132)	(0.093)	(0.099)	(0.129)
β_M	-0.016	-0.025	-0.098	0.056	0.065	0.032
	(0.093)	(0.108)	(0.160)	(0.072)	(0.082)	(0.136)
β_J	2.972	1.178	0.559	27.728	12.531	7.046
	(1.125)	(0.365)	(0.304)	(8.277)	(4.863)	(4.304)
$R^2_{HAR-RV-J}$	0.48	0.68	0.41	0.58	0.71	0.45
R^2_{HAR}	0.42	0.31	0.22	0.42	0.36	0.23

to be continued.

Table 5, continued.

	$RV_{t,t+k}$			$RV^{1/2}_{t,t+k}$		
	k=1	k=5	k=22	k=1	k=5	k=22
Panel C: Shanghai Stock Exchange Government Bond Index						
β_D	0.343	0.321	0.143	0.362	0.414	0.218
	(0.114)	(0.040)	(0.036)	(0.073)	(0.036)	(0.042)
β_W	0.161	0.214	0.191	0.188	0.192	0.188
	(0.097)	(0.092)	(0.091)	(0.066)	(0.074)	(0.106)
β_M	0.241	0.155	0.01	0.185	0.159	0.046
	(0.144)	(0.094)	(0.132)	(0.082)	(0.083)	(0.150)
β_J	-0.313	-0.089	-0.048	-75.522	-15.431	-15.16
	(0.141)	(0.053)	(0.049)	(26.920)	(11.502)	(16.879)
$R^2_{HAR-RV-J}$	0.11	0.38	0.19	0.19	0.42	0.22
R^2_{HAR-RV}	0.14	0.2	0.13	0.13	0.15	0.11
Panel D: Shanghai Stock Exchange 50 index						
β_D	0.601	0.493	0.184	0.573	0.556	0.279
	(0.145)	(0.072)	(0.021)	(0.085)	(0.050)	(0.033)
β_W	-0.023	-0.099	0.041	0.101	0.021	0.126
	(0.087)	(0.085)	(0.058)	(0.077)	(0.084)	(0.069)
β_M	0.337	0.446	0.471	0.242	0.337	0.388
	(0.095)	(0.090)	(0.135)	(0.064)	(0.081)	(0.138)
β_J	-0.613	0.157	-0.15	-11.968	-3.222	-10.221
	(0.447)	(0.326)	(0.181)	(6.144)	(4.361)	(5.025)
$R^2_{HAR-RV-J}$	0.46	0.57	0.49	0.56	0.69	0.57
R^2_{HAR-RV}	0.21	0.23	0.26	0.27	0.31	0.29

Table 6
Daily, weekly, and monthly volatility forecasting HAR-RV-CJ regression

$$RV_{t,t+k} = \beta_0 + \beta_{CD}C_t + \beta_{CW}C_{t-4,t} + \beta_{CM}C_{t-21,t} + \beta_{JD}J_t + \beta_{JW}J_{t-4,t} + \beta_{JM}J_{t-21,t} + \varepsilon_{t,t+k}$$
$$RV^{1/2}_{t,t+k} = \beta_0 + \beta_{CD}C^{1/2}_t + \beta_{CW}C^{1/2}_{t-4,t} + \beta_{CM}C^{1/2}_{t-21,t} + \beta_{JD}J^{1/2}_t + \beta_{JW}J^{1/2}_{t-4,t} + \beta_{JM}J^{1/2}_{t-21,t} + \varepsilon_{t,t+k}$$

The table reports the OLS estimates for daily ($k = 1$), overlapping weekly (k=5) and monthly (k=22) HAR-RV-CJ volatility forecast regressions. The realized volatility and jumps are constructed from five-minute returns from January 2004 to October 2007. The weekly and monthly measures are the scaled sums of the corresponding daily measures. The construction of significant daily jump and continuous sample path variability measures are described in the text. The standard errors reported in parenthesis are based on Newey-West/Bartlett correction allowing for serial correlation of up to order 5 (k=1), 10 (k=5), and 44 (k=22), respectively.

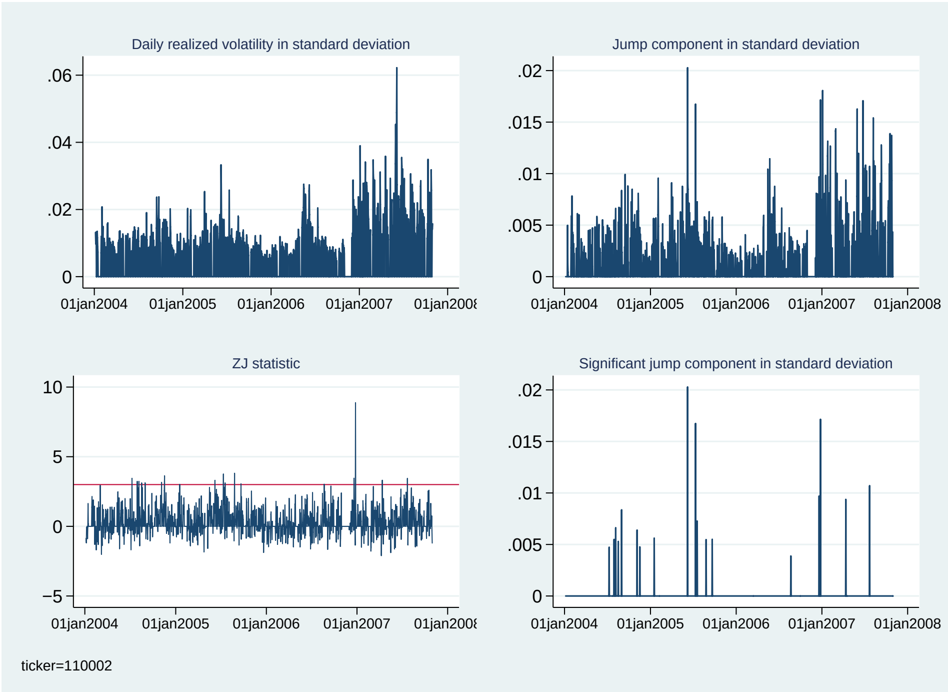
	$RV_{t,t+k}$			$RV^{1/2}_{t,t+k}$		
	k=1	k=5	k=22	k=1	k=5	k=22
Panel A: Shanghai Stock Exchange A Share Index						
β_{CD}	0.528	0.476	0.176	0.522	0.518	0.238
	(0.110)	(0.067)	(0.018)	(0.065)	(0.049)	(0.030)
β_{CW}	-0.028	-0.102	0.078	0.075	0.009	0.180
	(0.076)	(0.078)	(0.063)	(0.071)	(0.083)	(0.085)
β_{CM}	0.382	0.484	0.428	0.294	0.383	0.346
	(0.107)	(0.091)	(0.120)	(0.072)	(0.086)	(0.144)
β_{JD}	0.268	0.495	0.242	0.086	0.259	0.117
	(0.290)	(0.309)	(0.342)	(0.126)	(0.142)	(0.144)
β_{JW}	0.373	0.364	0.083	0.077	0.063	-0.038
	(1.053)	(0.887)	(1.027)	(0.167)	(0.167)	(0.231)
β_{JM}	0.894	1.366	2.64	0.042	0.074	0.246
	(1.697)	(2.261)	(2.732)	(0.153)	(0.200)	(0.267)
$R^2_{HAR-RV-CJ}$	0.44	0.62	0.52	0.55	0.71	0.59
$R^2_{HAR-RV-J}$	0.44	0.58	0.51	0.56	0.69	0.58
R^2_{HAR}	0.29	0.29	0.35	0.33	0.36	0.35
Panel B: Shanghai Stock Exchange B Share Index						
β_{CD}	0.285	0.367	0.183	0.417	0.502	0.266
	(0.079)	(0.047)	(0.038)	(0.048)	(0.024)	(0.035)
β_{CW}	0.103	0.163	0.127	0.311	0.254	0.237
	(0.213)	(0.158)	(0.085)	(0.097)	(0.093)	(0.058)
β_{CM}	0.034	-0.019	-0.09	0.041	0.03	-0.05
	(0.115)	(0.123)	(0.092)	(0.077)	(0.085)	(0.122)
β_{JD}	1.833	2.436	2.851	0.407	0.533	0.602
	(0.377)	(0.397)	(0.550)	(0.113)	(0.135)	(0.179)
β_{JW}	-1.651	-0.669	3.750	-0.054	-0.06	0.455
	(2.905)	(1.699)	(0.657)	(0.257)	(0.219)	(0.127)
β_{JM}	27.642	19.254	15.343	0.732	0.811	1.221
	(10.881)	(9.132)	(7.574)	(0.354)	(0.363)	(0.716)
$R^2_{HAR-RV-CJ}$	0.45	0.73	0.53	0.57	0.75	0.52
$R^2_{HAR-RV-J}$	0.48	0.68	0.41	0.58	0.71	0.45
R^2_{HAR}	0.42	0.31	0.22	0.42	0.36	0.23

to be continued.

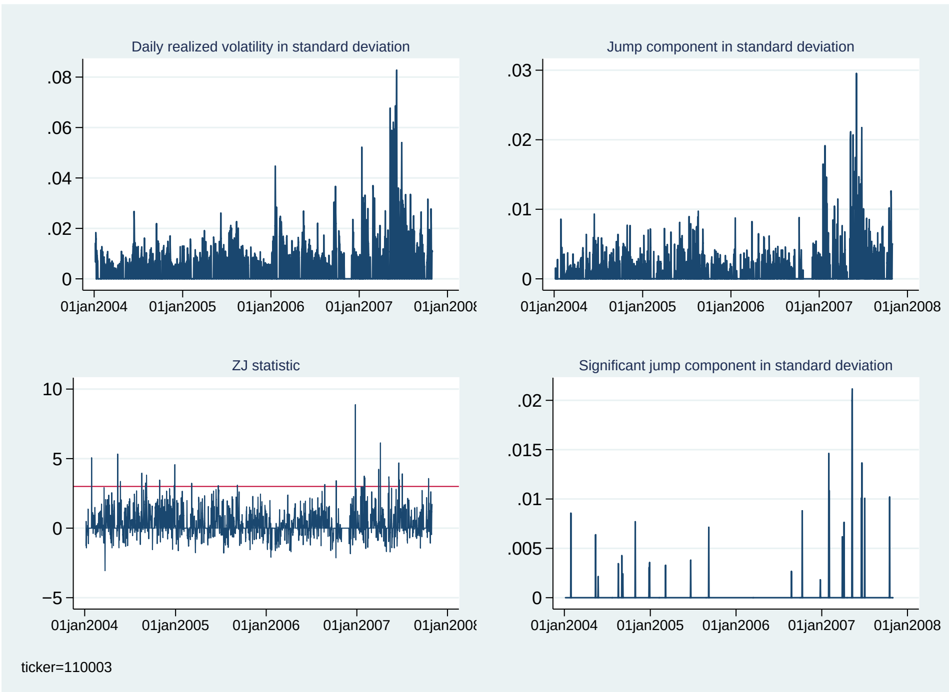
Table 6, continued.

	$RV_{t,t+k}$			$RV_{t,t+k}^{1/2}$		
	k=1	k=5	k=22	k=1	k=5	k=22
Panel C: Shanghai Stock Exchange Government Bond Index						
β_{CD}	0.315	0.317	0.145	0.321	0.421	0.216
	(0.107)	(0.034)	(0.031)	(0.070)	(0.031)	(0.034)
β_{CW}	0.152	0.264	0.253	0.166	0.164	0.219
	(0.112)	(0.125)	(0.079)	(0.069)	(0.097)	(0.090)
β_{CM}	0.228	0.087	-0.108	0.204	0.158	-0.055
	(0.136)	(0.087)	(0.079)	(0.081)	(0.086)	(0.085)
β_{JD}	0.02	0.222	0.089	0.049	0.224	0.104
	(0.062)	(0.033)	(0.024)	(0.038)	(0.027)	(0.024)
β_{JW}	0.154	0.067	-0.078	0.074	0.049	-0.031
	(0.189)	(0.111)	(0.135)	(0.079)	(0.082)	(0.094)
β_{JM}	0.366	0.422	0.730	0.190	0.226	0.378
	(0.353)	(0.253)	(0.403)	(0.095)	(0.121)	(0.206)
$R^2_{HAR-RV-CJ}$	0.12	0.4	0.25	0.2	0.45	0.28
$R^2_{HAR-RV-J}$	0.11	0.38	0.19	0.19	0.42	0.22
R^2_{HAR-RV}	0.14	0.2	0.13	0.13	0.15	0.11
Panel D: Shanghai Stock Exchange 50 Index						
β_{CD}	0.568	0.502	0.176	0.538	0.548	0.249
	(0.127)	(0.075)	(0.015)	(0.076)	(0.053)	(0.026)
β_{CW}	-0.022	-0.103	0.04	0.104	0.021	0.129
	(0.087)	(0.085)	(0.058)	(0.077)	(0.084)	(0.071)
β_{CM}	0.332	0.453	0.476	0.247	0.342	0.395
	(0.095)	(0.091)	(0.133)	(0.064)	(0.079)	(0.138)
β_{JD}	-0.319	0.368	-0.334	-0.141	0.048	-0.041
	(0.159)	(0.312)	(0.320)	(0.083)	(0.099)	(0.105)
β_{JW}	0.711	0.585	-2.481	0.019	0.011	-0.083
	(1.306)	(1.417)	(1.881)	(0.192)	(0.247)	(0.287)
β_{JM}	1.898	3.461	7.489	0.191	0.27	0.278
	(3.527)	(4.537)	(6.577)	(0.218)	(0.281)	(0.600)
$R^2_{HAR-RV-CJ}$	0.45	0.61	0.5	0.56	0.72	0.57
$R^2_{HAR-RV-J}$	0.46	0.57	0.49	0.56	0.69	0.57
R^2_{HAR-RV}	0.21	0.23	0.26	0.27	0.31	0.29

Figure 1. Daily realized volatility and jump components



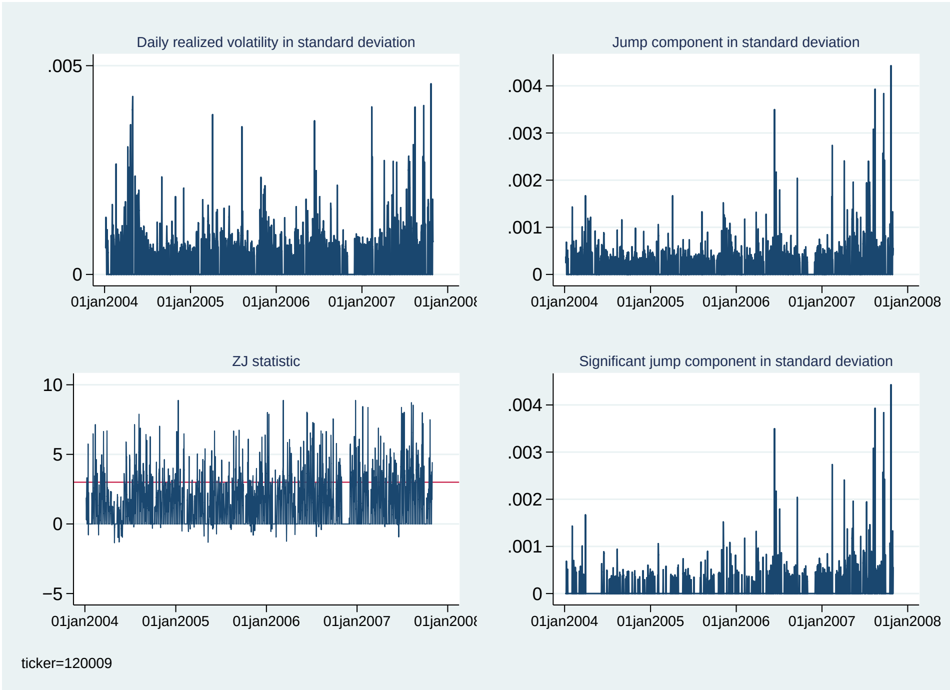
(a) SSE A Share Index



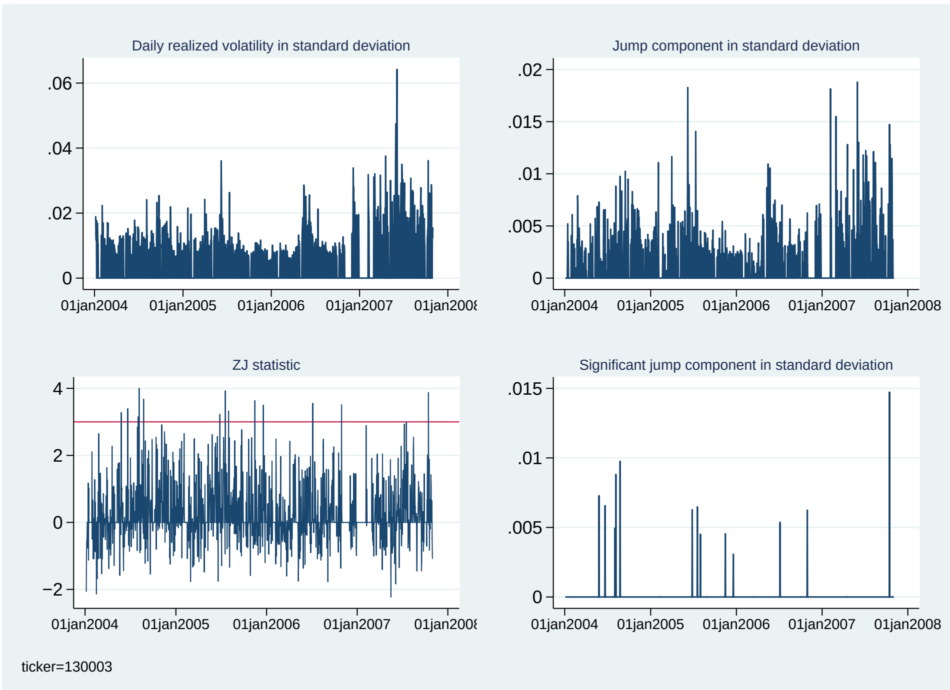
(b) SSE B Share Index

The top left figure in each panel graphs daily realized volatility in standard deviation from, or $RV^{1/2}$. The top right figure of each panel shows the jump component defined in (8), $\tilde{J}^{1/2}$. The bottom left figure of each panel shows the ZJ_t statistic with the 0.99 significance level indicated by the horizontal line. The bottom right figure of each panel graphs the the significant jumps corresponding to $\alpha = 0.99$, or $J_{t,\alpha}^{1/2}$. See the text for details.

Figure 1 continued.



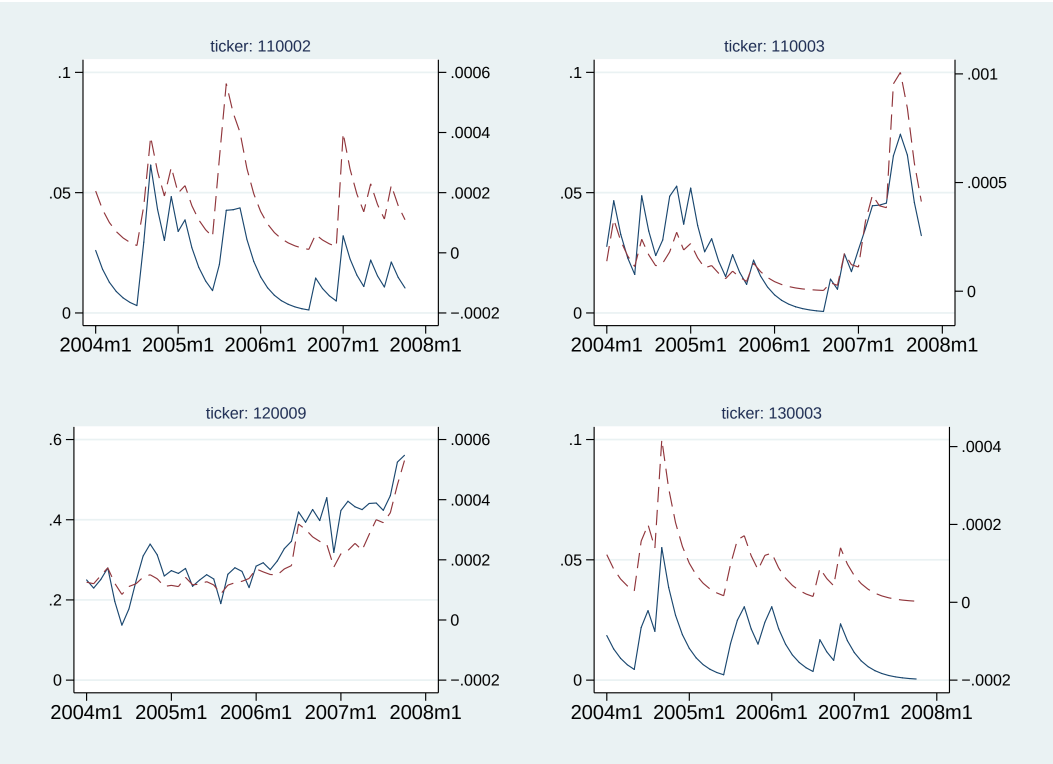
(c) SSE Government Bond Index



(d) SSE 50 Index

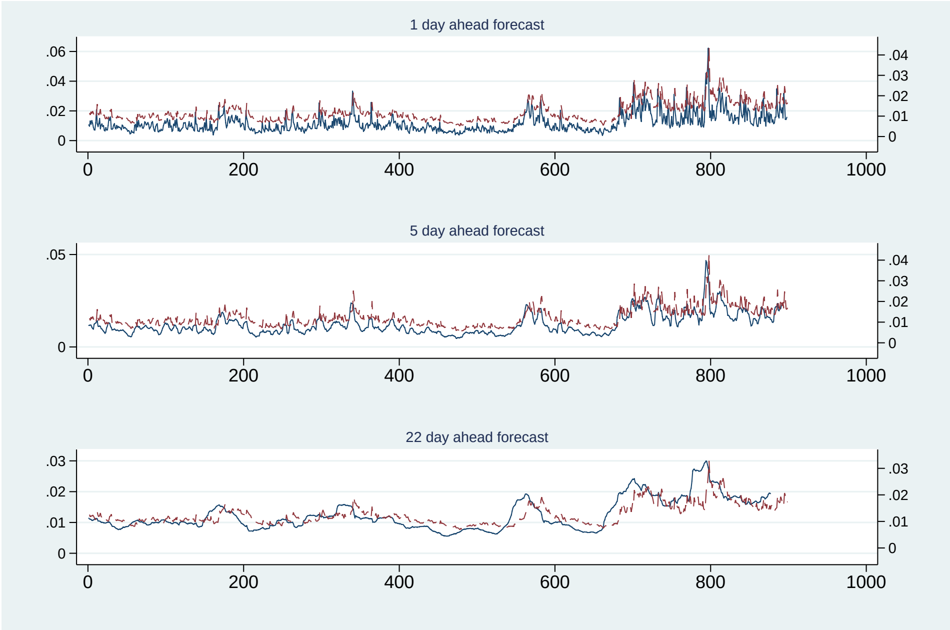
The top left figure in each panel graphs daily realized volatility in standard deviation from, or $RV^{1/2}$. The top right figure of each panel shows the jump component defined in (8), $\tilde{J}^{1/2}$. The bottom left figure of each panel shows the ZJ_t statistic with the 0.99 significance level indicated by the horizontal line. The bottom right figure of each panel graphs the the significant jumps corresponding to $\alpha = 0.99$, or $J_{t,\alpha}^{1/2}$. See the text for details.

Figure 2. Smoothed Jump Intensity and Jump Size

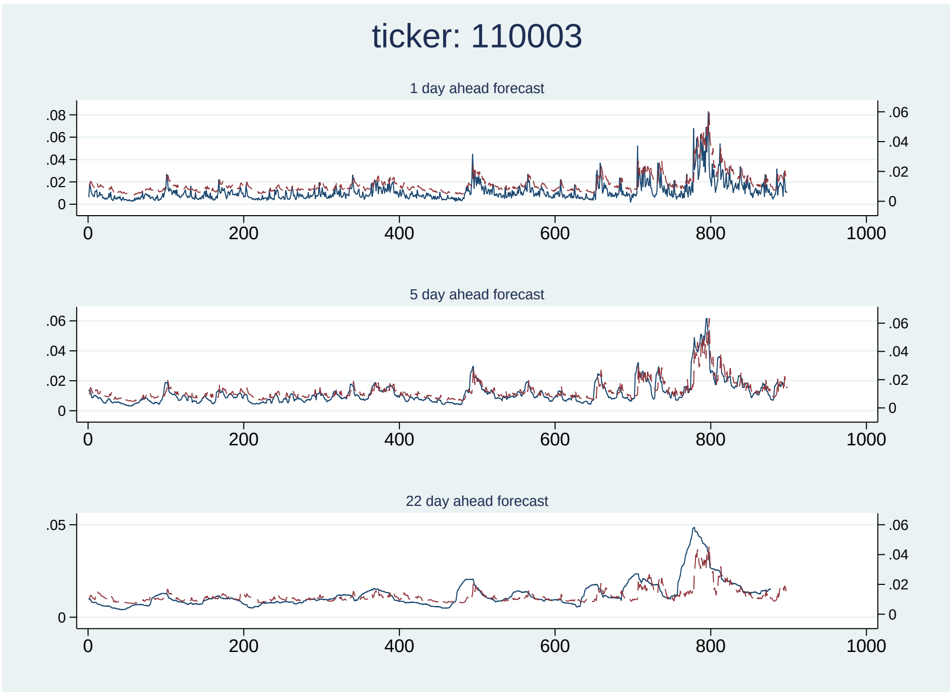


The figure graphs the exponentially smoothed average monthly jump intensity (solid line to the left scale) and sizes (dash line to thr right scale) for the significant jumps based on $\alpha = 0.99$. The jump sizes are expressed in standard deviation form or $J_{t,0.99}^{1/2}$. The top left panel is for Shanghai Stock Exchange A Share Index; the top right panel is for Shanghai Stock Exchange B Share Index; the bottom left panel is for Shanghai Stock Exchange Government Bond Index; and the bottom right panel is for Shanghai Exchange 50 Index.

Figure 3. Daily, weekly, and monthly realized volatility and HAR-RV-CJ forecasts



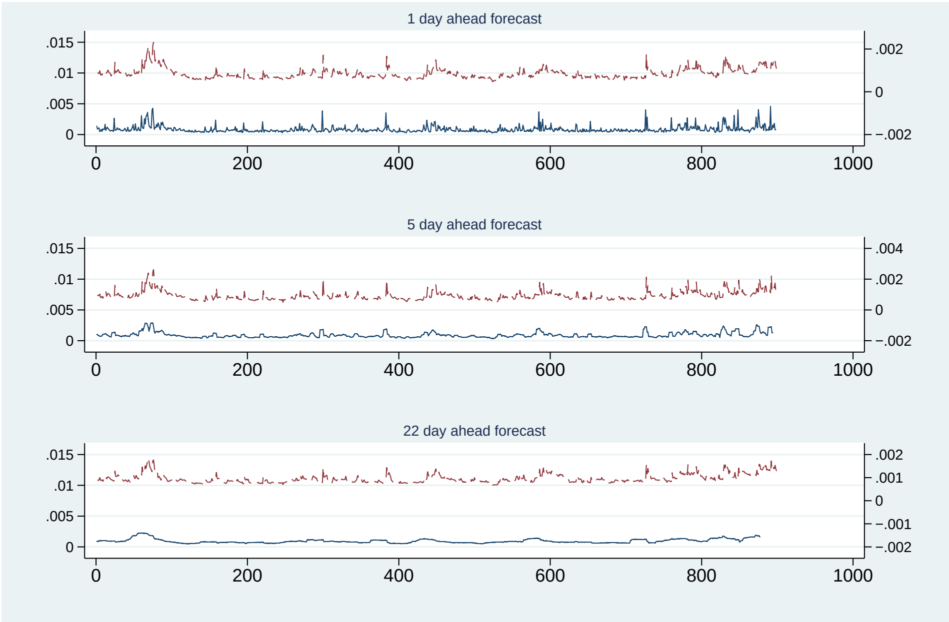
(a) SSE A Share Index



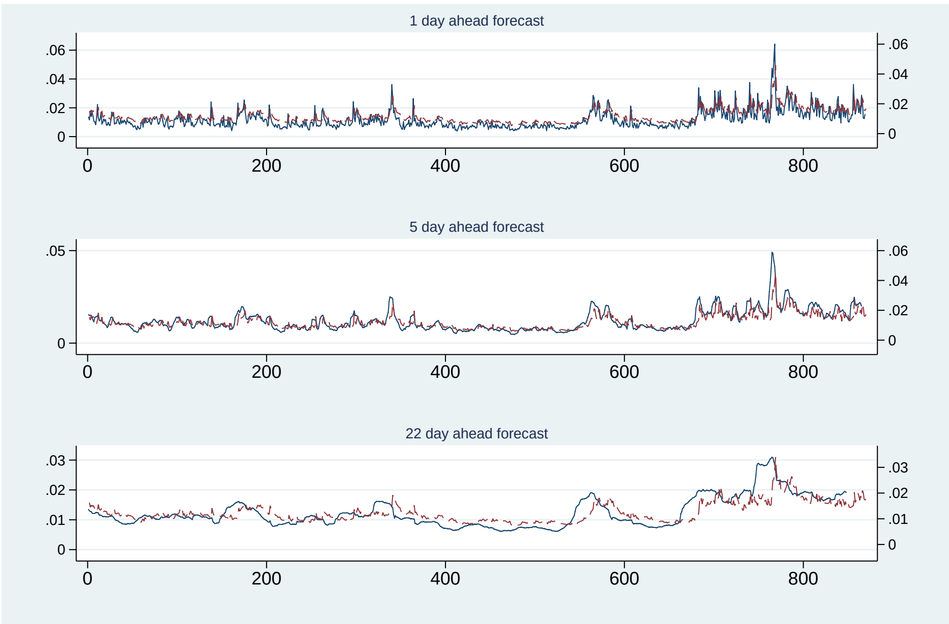
(b) SSE B Share Index

The top, middle, and bottom panels show daily ($k = 1$), weekly ($k = 5$), and monthly ($k = 22$) realized volatility, $RV_{t,t+k}^{1/2}$ (solid line to the left scale), and the corresponding forecasts (dash line to the right scale) from the nonlinear HAR-RV-CJ model in standard deviation form in equation (23). See the text for details.

Figure 3 continued.



(c) SSE Government Bond Index



(d) SSE 50 Index

The top, middle, and bottom panels show daily ($k = 1$), weekly ($k = 5$), and monthly ($k = 22$) realized volatility, $RV_{t,t+k}^{1/2}$ (solid line to the left scale), and the corresponding forecasts (dash line to the right scale) from the nonlinear HAR-RV-CJ model in standard deviation form in equation (23). See the text for details.