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Intraday Dynamics of Volatility and Duration: Evidence from the Chinese Stock Market

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Abstract

We propose a new joint model of intraday returns and durations to study the dynamics of several Chinese stocks. We include IBM from the U.S. market for comparison purposes. Flexible innovation distributions are used for durations and returns, and the total variance of returns is decomposed into different volatility components associated with different transaction horizons. Our new model strongly dominates existing specifications in the literature. The conditional hazard functions are non-monotonic and there is strong evidence for different volatility components. Although diurnal patterns, volatility components, and market microstructure implications are similar across the markets, there are interesting differences. Durations for lightly traded Chinese stocks tend to carry more information than heavily traded stocks. Chinese investors usually have longer investment horizons, which may be explained by the specific trading rules in China.

Key words: market microstructure, transaction horizon, high-frequency data, ACD, GARCH
JEL: C22, C11, G10

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1   Introduction

As China moves toward its potential output and commands an increasing share of world output, trade and commerce, it is important to study the properties of its domestic asset market. Despite the importance that China has on the world stage, there is little to no research on the time-series properties of intraday Chinese stock returns.[1] The purpose of this paper is to begin to fill that gap. We propose a new joint model of intraday returns and duration to study the dynamics of several Chinese stocks. Besides using flexible innovation distributions the conditional variance is made of multiple components based on transaction time which contributes to large improvements in density forecasts compared to existing models. We include IBM from the U.S. market for comparison purposes and highlight the similarities and differences.

The final frontier in the time-series analysis of asset returns is intraday transactions. This is the highest frequency that data is available and the structure of this data generating process determines all lower frequency dynamics. Lower frequency returns are derived from the high frequency process. Hence the time series features of this process are critical to understanding the characteristics of daily, and weekly returns. Compared with the traditional low frequency analysis, high frequency data have an immense number of observations, a pronounced seasonal structure and random time between trades.

Research on the duration process, or time between trades, is large and began with the seminar paper of Engle and Russell (1998) which proposes the univariate Autoregressive Conditional Duration (ACD) model. Many extensions have been considered, such as Bauwens and Giot (2000), Lunde (1999), Grammig and Maurer (2000), Zhang, Russell and Tsay (2001), Ghysels, Gourieroux and Jasiak (2004) and Bauwens and Veredas (2004).

Among all the characteristics associated with high-frequency transaction records, the trading time and the price are the most important. The bivariate dynamics of returns and duration are taken up in Engle (2000). The joint model of return and duration allows for density forecasts in the duration to the next trade and the associated return distribution. A joint model is necessary to provide a clear picture of the dynamics of the volatility process. Durations have an important effect on the volatility of the returns, see for example, Dufour and Engle (2000), Grammig and Wellner (2002), and Ait-Sahalia and Mykland (2003). A joint model can help discriminate market microstructure theories. Specifically, the waiting time between events plays a key role in understanding the process of private and public information in financial markets.

Besides Engle (2000), bivariate models of returns and duration include Engle and Sun (2005), and Ghysels and Jasiak (1998). They use a GARCH-type model for the volatility and an ACD model for the duration. In this paper, we propose a new joint model to describe the dynamics of the high-frequency data. Specifically, we model the volatility dynamics by a component approach, where the volatility components are associated with different transaction horizons.[2] The components are essentially a *realized volatility* measure calculated

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[1]There is unrelated work by Shao et al. (2009) who consider a Realized Range Model for VaR, and Tian and Guo (2007) who compare interday and intraday volatility. Lee et al. (2008) and Chong and Su (2006) investigate the differences in asset classes due to ownership restrictions. Finally, Cai et al. (2006) study which trades move prices.

[2]The idea is also related to the realized volatility literature such as Andersen, Bollerslev, Diebold and

according to trading time and not calendar time.[3] The use of volatility components is motivated by the Heterogeneous Market Hypothesis (HMH) of Muller et al. (1997). The HMH recognizes the existence of heterogeneity in markets. Different types of traders trade for different purposes, and thus decide to execute their transactions in different market situations. They create different volatilities.

In the daily time horizon, Corsi (2009) proposes the Heterogeneous Autoregressive (HAR) model based on the HMH. The HAR model is popular in modeling daily realized volatility.[4] Other research which decomposes daily volatility includes Calvet and Fisher (2008), Engle and Lee (1999), and Maheu (2005). These papers deal with fixed-interval volatility and ignore the information from the duration process.

Besides the component model for the conditional variance, return innovations follow a t-distribution and duration innovations follow a Burr distribution. We demonstrate that the proposed new joint model provides a dramatic improvement over the existing models. It provides better in-sample performance and displays improved out-of-sample forecasting power.

The new model is estimated for three stocks from the Chinese market. We also include IBM from the U.S. market to provide a comparison with and to gauge the differences. Chinese stocks are segmented into two groups according to investor entrance permission. The first, share-A stock, is dominated by the Chinese Yuan, and open only to domestic investors. The second is share-B stock, dominated by U.S. dollar and open to both domestic and foreign investors. In addition, we are also interested in the different performance of stocks with different market capitalization in the Chinese market. We randomly choose one stock from each of the groups: the Share-A large stock group, the Share-A small stock group, and the Share-B group.

We optimally select the number of volatility components according to model fit. They include the squared instantaneous return from the last transaction and the average of those ranging from several minutes up to one hour. Information beyond one hour has no effect on intraday volatility for any of the stocks considered. Contemporaneous durations have important effects on the volatility process. The longer the duration, the lower is the conditional variance.[5]

We find a number of common properties that Chinese markets share with developed ones. Like the U.S. market, trade durations and the conditional variance of returns display strong serial dependence. Diurnal patterns of durations and the volatility are similar. There are more transactions and larger price changes at the beginning of a day and prior to the close of the market, while less transactions and more stable prices around lunch time.[6] The added flexibility of the Burr distribution results in an inverted "U" shape for the conditional hazard

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Labys (2001), Andersen, Bollerslev, Diebold and Ebens (2001) and Barndorff-Nielsen and Shephard (2002a, 2002b) since we compute realized volatility over various transaction horizons.

[3]For a recent review of volatility including realized volatility see Andersen et. al. (2009).

[4]Recent literature using HAR models includes Andersen, Bollerslev and Diebold (2007), Andersen, Bollerslev, and Huang (2006), Bollerslev, Kretschmer, Pigorsch and Tauchen (2009), Corsi, Kretschmer, Mittnik, and Pigorsch (2005), Forsberg and Ghysels (2007), and Maheu and McCurdy (2010).

[5]The results support the Easley and O'Hara (1992) formulation in which the long waiting time means no information.

[6]The Chinese market closes for a 90 minute lunch period.

functions. This is inconsistent with the exponential distribution.

However, we find some interesting differences. The autocorrelation function of returns and our model estimates indicate a lower degree of dependence in volatility measures compared to IBM. Durations for lightly traded Chinese stocks tend to carry more information than heavily traded Chinese stocks and IBM. In the Chinese market, the trading frequency is much lower than for IBM. Long-term volatility components have a larger effect than the short-term components. One explanation is the existence of longer investment horizon in China. This may be related to particular institutional trading rules in China and the overall shorter market open time per day.

The remainder of this paper is structured as follows. Section 2 discusses our new model along with existing benchmark specifications. Estimation issues are presented in Section 3. Section 4 reviews the institutional features of the Chinese market and the data. Section 5 presents empirical results. The last section summarizes.

2   Models

The high-frequency transaction data contain two types of observations. One is the time of the transaction. The other is a vector of the quantities, called the marks, observed at the time of the transaction. The marks include price, volume, and spread in addition to other characteristics. In our model, the time information is summarized by duration x_i between adjacent trades. Specifically, denoting t_i as the time associated with the transaction i, the duration is then defined as the time between two transactions, i.e., $x_i = t_i - t_{i-1}$. The return is the difference of log prices, $\widetilde{r}_i = p_i - p_{i-1}$. Engle (2000) argues that the natural measure of volatility is the variance per unit of time. Since the variances are connected to the squared returns, we construct our model based on the return per square root of time, which is defined as $r_i = \widetilde{r}_i / \sqrt{x_i}$. Therefore, the data we are dealing with are a sequence of joint observations of the duration and return denoted by $\{(x_i, r_i), i = 1, \ldots, T\}$, where T is the total number of observations.[7]

2.1   ACD Models for Duration

We assume the duration process follows the ACD(1,1) model proposed by Engle and Russell (1998)

$$x_i = \psi_i z_i \text{ with } \psi_i = \omega_a + \alpha_a x_{i-1} + \beta_a \psi_{i-1} \tag{1}$$

where ψ_i is the expectation of the duration conditional on the last period's information, and the duration innovation z_i follows independent identical distribution $f_z(\cdot)$ with a non-negative support. The standard ACD model assumes that $f_z(\cdot)$ is an exponential distribution, which is called an EACD model.

In an EACD model, the conditional hazard function $h(t) = \psi_i^{-1}$ is constant. Bauwens and Veredas (2004), Lunde (1999), Hamilton and Jorda (2002) and Zhang et al. (2001) question whether imposing this restriction on the hazard function is appropriate, and propose specifications that offer greater flexibility. Bauwens, Giot, Grammig and Veredas (2004)

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[7]In this paper, we are dealing with returns per square root of time except when specified.

compare most of the popular duration models, and suggest the ACD specification with a more flexible innovation distribution, such as a Burr or a Generalized Gamma distribution.

2.2 Burr ACD (BACD) Model

Grammig and Maurer (2000) use the Burr distribution, denoted as $\text{Burr}(\mu, \kappa, \varpi^2)$ to provide a more flexible innovation distribution, z_i. Coupled with the time-series dynamics of x_i in (1) we have the BACD model. It allows for different forms of the hazard function with different parameter values. Under the restriction $\mu = 1$, the duration innovation z_i is

$$z_i = x_i / f(\psi_i) \tag{2}$$

where

$$f(\psi_i) = \psi_i \frac{(\varpi^2)^{\left(1 + \frac{1}{\kappa}\right)} \cdot \Gamma\left(\frac{1}{\varpi^2} + 1\right)}{\Gamma\left(1 + \frac{1}{\kappa}\right) \cdot \Gamma\left(\frac{1}{\varpi^2} - \frac{1}{\kappa}\right)} \tag{3}$$

with $0 < \varpi^2 < \kappa$. The density for z_i is a Burr distribution and can be written as

$$g(z_i) = \frac{\kappa z_i^{\kappa-1}}{\left(1 + \varpi^2 z_i^\kappa\right)^{(1/\varpi^2)+1}}, \quad z_i \geq 0. \tag{4}$$

The conditional hazard function is

$$h(x_i) = \frac{f(\psi_i)^{-\kappa} \cdot \kappa \cdot x_i^{\kappa-1}}{1 + \varpi^2 \cdot f(\psi_i)^{-\kappa} \cdot x_i^\kappa} \tag{5}$$

which is non-monotonic with respect to duration for $\kappa \geq 1$ and $\varpi^2 > 0$.

The BACD reduces to a Weibull ACD model when $\varpi^2 \to 0$. The standard EACD model is also a special case if both $\varpi^2 \to 0$ and $\kappa = 1$.

2.3 Benchmark GARCH-BACD Model

Engle (2000) uses a GARCH-ACD model for the joint process of returns and duration. Duration follows an ACD model and the conditional variance has a GARCH-type structure. There is usually a pronounced market microstructure effect for high frequency data. For example, an i.i.d. noise process that is uncorrelated with the latent price would induce an MA(1) structure in the observed returns. In a more general case of dependent noise an ARMA(1,1) process is usually adopted for the observed return process.[8] Using Engle's model as a starting point we consider

$$r_i = \rho r_{i-1} + u_i + \phi u_{i-1} \tag{6}$$

where the innovation u_i is

$$u_i = \sqrt{q_i} \zeta_i \text{ with } \zeta_i \overset{iid}{\sim} t_\nu(0,1), \tag{7}$$

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[8]Refer to Campbell, Lo and Mackinlay (1997) for a review.

and q_i is the variance of the return conditional on past volatility and current duration information. In contrast to Engle who assumes normal innovations[9], $t_\nu(0,1)$ denotes a Student-t distribution with mean 0, scale parameter 1, and degree of freedom ν to account for the fat tails in high-frequency returns.

Engle (2000) suggests several versions of the GARCH model to describe the dynamics of the conditional variance. The most successful one with current duration information is

$$q_i = \omega_g + \alpha_g u_{i-1}^2 + \beta_g q_{i-1} + \gamma_1 x_i^{-1} + \gamma_2 \frac{x_i}{\psi_i} + \gamma_3 \psi_i^{-1} + \gamma_4 \xi_i. \tag{8}$$

Here, three parts affect the conditional variance q_i. The first part is a GARCH(1,1)-type effect including the previous squared innovation u_{i-1}^2 and the last conditional variance q_{i-1}. The second part captures the interaction between the volatility and the duration. It includes the reciprocal duration x_i^{-1}, the reciprocal of expected duration ψ_i^{-1}, and the duration surprise x_i/ψ_i. The third part is the long-run volatility variable ξ_i, which captures the long-term persistence of the conditional variance. It is computed by exponentially smoothing squared returns r^2 with a preset parameter 0.995, as in $\xi_i = .005r_{i-1}^2 + .995\xi_{i-1}$.

This generalized GARCH-BACD model is our benchmark specification in our empirical work.

2.4 HAR-BACD Model

In addition to including the more flexible Burr distribution for durations and the Student-t for returns, our main contribution from a modelling perspective is to improve the conditional variance specification.

We apply a component approach to high-frequency volatility. The basic idea is motivated from the Heterogeneous Market Hypothesis (HMH) of Muller et al. (1997), which recognizes the presence of heterogeneity in traders.[10] Market participants have different time horizons, and therefore perceive, react to, and cause different types of volatility. For example, market makers and intraday speculators have very short time horizons and focus on the tick-by-tick data; while, on the other end, the central banks and some pension funds may only be concerned with the long-term performance of the markets. In a heterogeneous market, different types of traders trade for different purposes and thus decide to execute their transactions in different market situations, hence they create different volatilities. Motivated by HMH, Corsi (2009) proposes the Heterogeneous Autoregressive (HAR) model for the daily volatility. He shows that although the HAR-type model is not a true long-memory model, it does provide a good approximation to the dynamics of long memory which is a stylized fact of high frequency data.[11]

We apply this idea in the high-frequency framework, and decompose the conditional volatility into components which are associated with different transaction horizons in business

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[9]He uses this in quasi-maximum likelihood estimation.

[10]A close and related idea is advocated by Andersen and Bollerslev (1998) where they show different fractions of return volatility are associated with different information flows.

[11]For evidence of strong temporal dependence in high frequency data, see for example Engle and Russell (2009).

time. Specifically, the M-component HAR-BACD model includes (1), (2), (6) and (7) along with the following conditional variance,

$$q_i = \beta_0 + \sum_{m=1}^{M} \beta_m RV_{i-1,h_m} + \gamma_1 x_i^{-1} + \gamma_2 \frac{x_i}{\psi_i} + \gamma_3 \psi_i^{-1}. \tag{9}$$

M is the total number of the components, and RV_{i-1,h_m} is the m-th realized volatility component defined as

$$RV_{i-1,h_m} = \frac{u_{i-1}^2 + \cdots + u_{i-h_m}^2}{h_m} \tag{10}$$

where h_m is the number of ticks (transactions) associated with each component. Therefore, components are associated with transaction times and not calendar time as in Corsi (2009). Oomen (2006) shows that transaction time sampling leads to more efficient estimates of volatility.

We will discuss how to choose M and h_m later. When $h_m > 1$, RV_{i-1,h_m} is the realized volatility constructed from squared return innovations during the time period from transaction $i - h_m$ to transaction $i - 1$. When trading is light (heavy) the calendar time over which RV_{i-1,h_m} is computed will be large (small) and in general will vary throughout the day.

Compared with the conditional volatility equation (8) the HAR-BACD decomposes the total volatility into different volatility components RV_{i-1,h_m} for $m = 1, \ldots, M$. According to HMH, each component corresponds to a group of market participants with a transaction horizon h_m. Short-run components are captured by small h_m, and medium to long-run components are captured by larger h_m. Of course the components are relative to the trading activity in the market. By summing up all the M terms, the dynamics of the total volatility process is just the aggregate of the different market volatility components. Since we have included volatility components with a variety of transaction time horizons, the HAR-BACD model takes into account any long-run volatility component naturally, thus we exclude the term ξ_i found in the GARCH model (8). The remaining interaction terms between the duration and volatility are the same.

3 Econometric Issues

3.1 The Likelihood

The information set up to observations s is $I_s = \{(x_i, r_i), i = 1, \ldots, s\}$. Given the model parameter θ, denote the sample data $Y_T = \{y_i\}_{i=1}^T = \{(x_i, r_i)\}_{i=1}^T$, then the likelihood of the T observations is

$$p(Y_T|\theta) = \prod_{i=1}^{T} f(r_i, x_i|I_{i-1}, \theta). \tag{11}$$

The conditional distribution of each observation (r_i, x_i) can be written as

$$f(r_i, x_i|I_{i-1}, \theta) = f(x_i|I_{i-1}, \theta) f(r_i|I_{i-1}, x_i, \theta) \tag{12}$$

where $f\left(x_i|I_{i-1}, \theta\right)$ is the marginal density of the duration and $f\left(r_i|x_i, I_{i-1}, \theta\right)$ is the density of the return conditional on current duration. The marginal density of duration is calculated from (1) as

$$f\left(x_i|I_{i-1}, \theta\right) = \left(\frac{1}{\psi_i}\right) f_z\left(\frac{x_i}{\psi_i} \mid I_{i-1}, \theta\right), \tag{13}$$

where $f_z\left(\cdot\right)$ is the Burr density function for duration innovation z_i. The density of the return conditional on current duration can be calculated from equation (6) as

$$\begin{aligned} f\left(r_i|I_{i-1}, x_i, \theta\right) &= f_u\left(u_i|I_{i-1}, x_i, \theta\right) \\ &= f_u\left(r_i - \rho r_{i-1} - \phi u_{i-1}|I_{i-1}, x_i, \theta\right) \end{aligned} \tag{14}$$

where $f_u\left(\cdot\right)$ refers to the probability density function for u_i which is a Student-t with variance q_i and degree of freedom ν.

3.2   Bayesian Estimation

We estimate the models in the Bayesian framework. According to Bayes rule, the posterior distribution $p\left(\theta|I_T\right)$ is proportional to the product of the likelihood and the prior density, $p\left(\theta|I_T\right) \propto p\left(Y_T|\theta\right) p\left(\theta\right).$ Since neither the posterior nor the conditional posterior distributions have a known distribution, we cannot use the Gibbs sampling algorithm. Instead, we adopt the random walk Metropolis-Hastings (M-H) algorithm to simulate from the posterior. Good introductions to MCMC methods for Bayesian estimation can be found in Koop (2003) and Geweke (2005).

We iterate over the following steps to jointly sample all parameters at once.

1. Given the current value of the parameter vector θ, propose a new parameter vector according to

$$\theta' = \theta + V, \ V \sim N(0, \tau\Sigma). \tag{15}$$

2. Accept θ' with probability

$$\eta = \min\left\{p(\theta'|Y_T)/p(\theta|Y_T), 1\right\}. \tag{16}$$

Otherwise retain θ as the current draw from the chain.

τ is a tuning constant set to achieve an acceptance frequency between 0.3-0.5. Σ is the sample covariance matrix estimate calculated from an initial first run using a single-move version of the above algorithm. The single-move samples from each conditional posterior density $p(\theta_j|\theta_{-j}, Y_T)$ until each component of the parameter vector is updated.

After dropping an initial set of burn-in draws from step 1–2 we collect the remaining N draws, $\{\theta^{(j)}\}_{j=1}^N$ which are then used in posterior inference. For instance, the posterior mean of θ can be consistently ($N \rightarrow \infty$) estimated as

$$\widehat{\theta} = \frac{1}{N}\sum_{j=1}^N \theta^{(j)}. \tag{17}$$

3.3 Model Comparison

The Bayesian approach allows for the comparison and the ranking of nested and non-nested models by Bayes factor or posterior odds. The Bayes factor for model M_0 versus M_1 is defined as $BF \equiv p(Y_T|M_0)/p(Y_T|M_1)$, which is the ratio of marginal likelihoods and summarizes the evidence for model M_0 against M_1. The marginal likelihood (ML) for model M_j, $j = 0, 1$ is defined as

$$p(Y_T|M_j) = \int p(Y_T|\theta, M_j)p(\theta|M_j)d\theta, \tag{18}$$

where $p(Y_T|\theta, M_j)$ is the likelihood and $p(\theta|M_j)$ the prior for model M_j. This is a measure of the success the model has in accounting for the data after the parameter uncertainty has been integrated out. Model comparison by Bayes factors penalizes highly parametrized models that do not deliver improved predictive content. For a discussion on the advantages of Bayes factors for model comparison see Koop and Potter (1999).

For the marginal likelihood we use the method of Gelfand and Dey (1994) adapted by Geweke (2005) (Section 8.2.4). This estimate is based on

$$\frac{1}{N}\sum_{i=1}^{N}\frac{g(\theta^{(i)})}{p(Y_T|\theta^{(i)}, M_j)p(\theta^{(i)}|M_j)} \rightarrow p(Y_T|M_j)^{-1} \quad \text{as} \quad N \rightarrow \infty, \tag{19}$$

where $g(\theta^{(i)})$ is a truncated multivariate Normal. $\theta^{(i)}$ is a MCMC draw from the posterior. Note that the prior, likelihood and $g(\theta)$ must contain all integrating constants. Finally, to avoid underflow/overflow we use logarithms in this calculation.

3.4 Out-of-Sample Density Forecasts

The comparison of out-of-sample forecasting power is also very straightforward in Bayesian framework. As argued in Geweke and Whiteman (2006), the predictive likelihood (PL) evaluates the out-of-sample prediction of a model, making it the central quantity of interest for model comparison. Specifically, the predictive likelihood (Geweke (1995, 2005)) is defined for data $y_s, ..., y_t$, $s < t$ and model M_j as

$$p(y_s, ..., y_t|I_{s-1}, M_j) = \int p(y_s, ..., y_t|\theta, I_{s-1}, M_j)p(\theta|I_{s-1}, M_j)d\theta \tag{20}$$

and it is the predictive density evaluated at the realized outcome $y_s, ..., y_t$. The integration is performed with respect to the posterior distribution based on the information set I_{s-1}. Specially, if $s = 1$, this is the marginal likelihood we defined above. Since

$$p(y_s, ..., y_t|I_{s-1}, M_j) = p(y_1, ..., y_t|M_j)/p(y_1, ..., y_s|M_j), \tag{21}$$

the log(PL) for the out-of-sample data can be calculated by taking the difference between the log(ML) for the full sample and the Log(ML) for the in-sample data.

4 Institutional Features and Data

According to World Federation of Exchanges[12], at the end of August 2009, the New York Stock Exchange had a market value of 10,842 billion dollars with total share turnover of 12,158 billion. The London Stock Exchange had a market value 2,560 billion and turnover of 2,321 billion. The two stock exchanges in China, the Shanghai Stock Exchange and Shenzhen Stock Exchange had a total market value of 2,739 billion and turnover of 5,017 billion. The Chinese markets are comparable with developed markets.

There are some unique features of the Chinese stock market. First, there is a "T+1" rule, which means that if an investor buys a stock today, it cannot be sold until tomorrow. Second, short sales are forbidden. Third, there is a limit move rule, where the daily price change of an individual stock cannot exceed 10%. These rules discourage short-term transactions since a lot of intraday trading opportunities (day traders) are curtailed. As a consequence, the investment horizon tends to be longer, and the trading intensity can be expected to be lower in Chinese markets.

There are two separate stock markets in China: Share A and Share B markets. The Share A market is open only to domestic investors, while Share B market is open to both domestic and foreign investors.

We select three stocks from the Chinese stock markets and one stock from the U.S. market. Specifically, we classify Chinese stocks into 3 groups, and randomly choose one stock from each group: 1) The China Petroleum and Chemical Corporation (Sinopec) from the Share-A large market capitalization group; 2) Xinfu Pharmaceutical Co. Ltd (XFPC) from the Share-A small market capitalization group; 3) China Wanke Co. Ltd B share (WKB) from the Share-B group.[13] In the U.S. market, we select IBM data which is heavily traded.

All Chinese stock market data are provided by the China Finance Online Company. We include all the normal trading days from March 1, 2006 to May 31, 2006. There are 60 valid days.[14] The Chinese stock market opens 4 hours a day, which is from 9:30am to 11:30am, and 1:00pm to 3:00pm. We use the observations within this period. Since records in high frequency data usually contain many errors or redundant information, we filter them first. Specifically, we start by deleting the error records. Then, if more than 1 transaction happens at the same time, we take it as a single transaction and record the transaction price as the volume weighted average price. As our main concern is the volatility dynamics, those records with no price changes are discarded.

Table 1 displays the reduction in data due to filtering. The error records are usually less than 1%. Transactions with the same time stamp are around 5% of the total observations. However, there are a lot of transactions with no price change, ranging from 48.47% (XFPC),

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[12]http://www.world-exchanges.org/statistics/

[13]Sinopec (Code: 600028) is one of the major petroleum companies in China. It is a component of the local major stock indexes. XFPC (Code: 002019) is a manufacturer and supplier of Vitamin B5, which was established in November 1994 and listed in Shenzhen Stock Exchange as a high-tech enterprise in July 2004. China Wanke Company Limited (Code: 200002) is the largest residential real estate developer in China. Its stocks are traded in both Share-A market and Share-B market. Here we choose its B Shares.

[14]There are 61 normal trading days in this period. Because of the shareholder meeting, each stock trading is closed for 1 day: the Sinopec on May 24, XFPC on May 22 and WKB on May 30.

50.45% (WKB) to 55% (Sinopec) of the total observations. The average number of the valid observations per day is 513 for Sinopec, 227 for XFPC and 167 for WKB. As the maximum lag length that we consider in the conditional variance is 1 month, we reserve the first approximate 1 month of data as startup values. We then divide the remaining observations into the in-sample period and the out-of-sample period, with the out-of-sample data extending roughly 3 weeks. These details are listed in the bottom panel of Table 1.

The IBM transaction data are obtained from the Trade and Quotes (TAQ) database. We choose the same sample period as in Chinese stock market, which is from March 1, 2006 to May 31, 2006 (64 days). Keeping only those records within normal trading hours (9:30 am to 4:00 pm), we filter the data in a similar way.[15] The filter result is reported in the last column of Table 1. Compared with the Chinese market data, IBM trading intensity is much heavier. It has very high percentage of observations (30.63%) happening at the same time. There are around 500 transactions each hour, compared to the most active Chinese stock, Sinopec, which has around 125 observations each hour. The statistics of the duration, the absolute return and the return for all the four stocks are summarized in Table 2. Average duration is much larger for the Chinese stocks.

The autocorrelation function of returns and absolute returns for Sinopec and IBM are presented in Figure 1.[16] In those diagrams, the two dotted horizontal lines are the Bartlett standard error bands. Most of the autocorrelation function for the returns are within the confidence bands except for the first lag. In contrast, most autocorrelations of the absolute returns exceed the bounds even at 500 lags for Sinopec and 3000 for IBM. The standard GARCH functional form will have problems capturing this, while our HAR-BACD model is designed to deal with this.

4.1 Diurnal Adjustments

Intraday data typically contain a very strong diurnal pattern. The diurnal adjustments for the durations and the returns follow Engle and Russell (1998). We regress the durations on the time of day using a cubic spline specification, and then we take the ratios of the durations and their fitted values to obtain *diurnally adjusted* durations. The internal knots are set on each hour. Since the transaction frequency drops quickly at the end of the day, we add an extra knot in the last half hour (knots at 10:00, 11:00, 11:30 (1:00), 2:00 and 2:30 for Chinese stocks, and at 10:00, 11:00, 12:00, 1:00, 2:00, 3:00 and 3:30 for IBM). Recall that the Chinese markets close from 11:30 to 1:00pm. For observed returns $\widetilde{r}_i$, we first divide them by the square root of actual durations as $r_i = \widetilde{r}_i / \sqrt{x_i}$, and then regress the absolute values of r_i on the time of day in the same way as durations. *Diurnally adjusted* returns are obtained by taking the ratios of r_i and their corresponding fitted values.

The daily spline estimates for duration and the absolute return are displayed in Figure 2.[17]

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[15]In U.S. market, the error-removing step is to keep only the records with correction indicator = 0 or 1, and sale condition is blank or "E". According to TAQ files, correction indicator =0 or 1 signal those trades as good trades where 0 means "Regular trade that was not corrected, changed, or signified as cancel or error", and 1 means "trade which was later corrected". The blank sell condition means a trade made without any stated conditions. "E" stands for "the high-speed electronic connection for immediate automatic execution".

[16]The autocorrelation functions for XFPC and WKB are not reported but display a similar pattern.

[17]For Chinese stocks, we only report Sinopec here. The other two stocks are very similar.

The top panel is for Sinopec data and bottom Panel for IBM. Both series have very similar daily patterns. The daily spline for durations has an inverse "U" shape. Durations are very short after the open and prior to the close of the market, indicating more transactions during these periods. The durations are much longer around the lunch time in the U.S. market. In Chinese market the transaction durations are still very long before and after the lunch break. The diurnal pattern for the absolute returns is also quite similar among stocks. We can see a peak at the open, flat during most of the day until it increases again before the close. These daily patterns are consistent with daily information flow. Investors adjust their positions intensively at the beginning of the day to incorporate new information from the overnight period. However, for the Chinese data, there is a small peak around mid-day because price volatility jumps as the market is re-opened after the lunch closure.

5   Empirical Results

For all posterior simulations we use a burn-in sample of $10,000$. The number of draws for the first single-move sampler is $10,000$ and for the joint block sampling step is $40,000$. These latter draws are used for all posterior inference in this paper. We investigate running the chain from different starting values and compute convergence diagnostics such as Geweke (1992). The results show that our posterior draws mix well and the chain converges quickly.

The priors for the following parameters are independent normal $N(0,100)$: ρ and ϕ in the ARMA equation, ω_g, α_g, β_g, β_0, all β_m and γ_i, $i = 1, 2, 3$, in the conditional variance equation. To guarantee the non-negativity of the duration, we set priors for the ACD parameters: ω_a, α_a and β_a to be truncated $N(0,100)$ with positive supports. The stationary condition $\alpha_a + \beta_a < 1$ is imposed. All priors are very uninformative. When the degree of freedom ν is larger than 30, the t-distribution is close to the normal, therefore we select gamma prior $\nu \sim Gamma(8, 0.5)$, that favors fat-tails with the restriction $\nu > 2$ to ensure the variance exists. This puts most weight on the region $(2, 40)$. The priors for the Burr distribution parameters κ and ϖ^2 are set to be truncated $N(0,100)$ with positive supports and the restriction $\kappa > \varpi^2$.

5.1   Which Components are Important?

The conditional variance of returns in (9) requires the selection of the number of components and the number of transactions that enter into a component.[18] In principle we could include M and h_m in our main estimation procedure, however, due to the large number of observations this would increase the computation costs substantially. Therefore, we select optimal values of these parameters based on a first step of estimation using Bayes factors.

Although the components are associated with transaction time an approximate correspondence with calendar time can nevertheless be established for each stock depending on

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[18]According to the HMH, there are different market components, but there is no specific rule on how to determine either the optimal number of the components M or the time horizon associated with each component. For example, Muller et al. (1997) study the half-hourly time series in ϑ-time, which is transformed data in a time scale in where no intraday seasonalities exist. They select $M = 7$ market components in ϑ-time. Corsi (2009) uses 3 components, daily, weekly and monthly volatility to forecast daily realized volatility.

the trading intensity. The candidate volatility components are listed in Table 3. We classify all the volatility components into 5 groups according to their approximate time horizons: instantaneous components (with the time horizon $H < 1$ minute), short-term components (1 minute $\leq H \leq 10$ minutes), medium-term components (10 minutes $< H \leq 1$ hour), long-term components (1 hour$\leq H \leq 1$ day), and very-long term components ($H > 1$ day). The number of ticks we use to construct each component is also listed. For example, for Sinopec stock, the average duration for 1 tick is around 30 seconds, so 30 seconds is its volatility component for the minimum time horizon.

We use the coarser set of ticks in Table 3 to construct the volatility components from. Our method begins with a model with no components (M=0). We set this model as a benchmark and record its marginal likelihood (ML). We add the first component and compute the ML. The ML from new models are directly comparable by Bayes factors as discussed in Section 3.3. If the component improves the ML (log-Bayes Factor is greater than 0) we have an improvement in the specification. However, if the ML from the benchmark is larger (log-Bayes Factor is less than 0), the method stops, assuming the benchmark ML is larger for the next two specifications with $M + 1$ and $M + 2$ components. Otherwise, we choose the new model with the larger ML and set it as the new benchmark. The evaluation process is repeated until no remaining component terms can improve the ML. This is done separately for each stock. The selected terms in the optimal model are fixed and used throughout the remainder of the paper.

The chosen volatility components are listed in Table 3 with $**$. The Chinese stocks display a similar structure. The volatility dynamics are best described by four components. Among them, the volatility of the previous trade is the most important, as all the components associated with the previous tick are selected. Short-term components are also important, as 2, 3 and 10 ticks are selected. Middle-term components have some presence. At least one component is from this group. All the long-term and very-long term components are found to be of no importance. The coefficients on terms which have time horizons more than 1 hour are very close to 0, and including them in the conditional variance equation does not improve the ML. This suggests that when considering the intraday volatility behaviour, the information beyond 1 hour has little to no effect on current price change.

The best IBM model has five components consisting of 1,5,9, 85 and 500 ticks which are associated with 7 seconds, 30 seconds, 1 minute, 10 minutes and 1 hour. Similar to the Chinese stocks, the short-term and middle-term components are most important, with long-term components negligible. However, as the IBM stock has a higher trading frequency there are two instantaneous (less than 1 minute) components that affect volatility dynamics.

5.2   Model Comparison

Table 4 reports the model comparison for the specifications GARCH-BACD, HAR-EACD and HAR-BACD. The HAR-EACD model combines the new conditional variance with the less flexible exponential distribution for durations. Panel A of the table reports marginal likelihood values and associated Bayes factors using the in-sample data listed in Table 1.[19]

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[19]We have also compared models with a normal distribution for return innovations and found it to be dominated by the Student-t distribution used in this paper.

Panel B presents the results for the out-of-sample predictive likelihoods and predictive Bayes factors for the data observations listed in the bottom of Table 1.

Looking at the first log-Bayes factors we see a huge improvement on model fit in moving from the exponential distribution to the Burr distribution for duration innovations. This is true for all stocks. The second log-Bayes factor compares the GARCH functional form with the new variance specification. Here again the evidence is very strong in favor of the component model for the conditional variance. For instance, the log evidence for the HAR-BACD is 80 for Sinopec, 48 for XFPC, 77 for WKB and 198 for IBM data.

The log-predictive likelihood results are based on a smaller sample of data but they continue to rank the models in exactly the same way. The main different between the marginal likelihood and the predictive likelihood is that the latter minimizes any impact of the prior distributions. Since the cumulative log-predictive likelihood measures the quality of out-of-sample density forecasts with parameter uncertainty integrated out, the HAR-BACD provides the best forecast performance.

By both measures, over different portions of the data sample, the new HAR-BACD model completely dominates the other parametrizations.

5.3   Parameter Estimates

The estimation results for the best joint model of durations and returns are presented in Table 5. As discussed in Section 5.1, the conditional volatility equation of the HAR-BACD model consists of 4 volatility components for Chinese stocks, and 5 components for IBM. We report the posterior means of the coefficients and their associated standard deviations. The cells with stars have 0.95 posterior density intervals that exclude 0.

Panel A of this table reports the coefficients for the return equation. All stocks have a strong and negative AR coefficient ρ, which is consistent with the presence of market microstructure dynamics. The degree of freedom parameter in the t-distribution ν is estimated around 7 for all stocks except for Sinopec. The smaller ν, the more fat-tailed is the return distribution relative to a normal. The relatively large value of ν for Sinopec is consistent with the small level of kurtosis for its returns in Table 2.

Panel B lists the parameter estimates for the duration process. All the coefficients are significant. The coefficient β_a is large and around 0.9, while the effect of the last duration α_a is around 0.05. All the estimated parameters of the Burr distribution have $\kappa > 1$ and $\varpi^2 > 0$. This shows that the Burr distribution is much more appropriate for duration innovations than the exponential distribution which restricts the hazard function to be constant. The implied conditional hazard functions for all the stock durations are unimodal with an inverse "U" shape. The conditional hazard functions are displayed in Figure 3.

Panel C describes the effects of the duration on the conditional variance. All the coefficients are different from 0, indicating that contemporaneous duration terms are very important. The signs of the coefficients are the same across all the stocks, suggesting common interactions between trading times and price movements. Specifically, the coefficient for the inverse of the duration $1/x_i$ is positive, which means a longer contemporaneous duration is associated with a lower volatility. This is supportive for Easley and O'Hara (1992) in which long durations are interpreted as having no information so that volatility decreases. The coefficients for the duration surprise x_i/ψ_i are all positive. When the actual duration is

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more than expected, the transaction tends to be associated with a larger price change. The coefficients for the lightly traded stocks (XFPC and WKB) are much larger than those of the heavily traded stocks (Sinopec and IBM). For the heavily traded stocks, more investors may be noise traders[20] and they may trade for reasons other than the new information, e.g., because of liquidity or hedging considerations. As a consequence, if there is no news, transactions based on information tend to halt but the noise traders will continue trading. Short durations and duration surprises, which have information content, tend to change the return volatility by a smaller amount for heavily traded stocks.

The estimated coefficients for the conditional variance are listed in the last panel. All the volatility components are positive and the majority of them have 0.95 density intervals that exclude 0. However, the volatility components with different time horizons have different effects on current volatility. Recent volatility, as measured by u_{i-h}^2, has a larger impact on the conditional variance. The derivative of the conditional variance q_i with respect to u_{i-h}^2 is displayed in Figure 4 for each of the stocks. h denotes the lagged transactions. In transaction time the Chinese stocks show a slower decay in the effect of past return innovations as compared to IBM.

The differences in volatility dynamics suggest investors in the Chinese stock market focus on longer-term information and more investors behave this way than in the U.S.. There are several explanations for why investors have longer horizons in China. There is the "T+1" rule, no short sales and the "limit move" that was discussed in Section 4. These institutional rules largely discourage short-term transactions. As a consequence, the investment horizon tends to be longer, and the trading intensity is less in China.

6   Summary

In this paper, we study the intraday dynamics of three stocks from the Chinese stock market and include IBM from the U.S. stock market for comparison. We propose a new joint model of volatility of returns and the duration between trades. Specifically, we apply a component approach to the conditional variance and construct a HAR-type model of volatility at the highest available frequency. Components are based on transaction time and not calendar time. Applying our model to the Sinopec, XFPC, WKB and IBM tick-by-tick data, we find a dramatic improvement over the traditional GARCH-ACD model. The total volatility is decomposed into 4 components for Chinese stocks and 5 volatility components for IBM. The common components are the stock volatility from the last transaction and the average volatility from several minutes up to one hour. Information past 1 hour does not help in the modeling or the forecasting of the high frequency data.

The stocks have similar diurnal patterns and the same market microstructure implications across the markets. Compared to IBM the Chinese stocks display much lower trading activity. For lightly traded stocks, duration carries more information content and is a more important determinant of volatility dynamics. The long-term volatility components have a larger effect than the short-term components. We attribute this to a longer investment horizon in China,

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[20]According to Dow and Gorton (1997), professional traders and money managers are the main noise trader. And they usually allocate more assets in those heavily traded stocks because those markets have higher liquidity and market capitalization.

which may be the consequence of specific trading rules.

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Table 1: Data Filtering

	Sinopec	XFPC	WKB	IBM
Trading days	61	61	61	64
Excluding Special Close Day	May-24	May-22	May-30	
Total valid days	60	60	60	64
Total Obs.	79,229	29,925	22530	578,925
	(100%)	(100%)	(100%)	(100%)
After Irregulars Removed	79,162	29,805	22410	576,765
	(99.92%)	(99.60%)	(99.47%)	(99.63%)
Integrating 0 Duration Records	74,321	28128	21399	399,453
	(93.81%)	(94.00%)	(94.98%)	(69.00%)
Excluding 0 Return Records	30,752	13,624	10032	209,474
	(38.81%)	(45.53%)	(44.53%)	(36.18%)
Average Obs. per day	513	227	167	3273
Range of the # of the daily obs.	214-771	53-569	37-387	2413-5005
Startup Values	11,000	5,500	3,500	65,000
In-Sample Data	11,752	4,124	3,532	94,474
Out-of-Sample Data	8,000	4,000	3,000	50,000

This table reports the filtering process for transactions data from the 4 stocks: China Petroleum and Chemical Corporation (Sinopec), Xinfu Pharmaceutical Co. Ltd (XFPC), China Wanke Co. Ltd (WKB) and IBM in normal trading days from March 1, 2006 to June 31, 2006. The Chinese stock data is from 9:30am-11:30am and 1:00pm-3:00pm and IBM data is between 9:30am and 4:00pm. The first two panels report the process to obtain the valid observations. The final panel reports how we divide total sample into in-sample and out-of-sample data.

Table 2: Summary statistics

	Mean	Stdev	Max	Min	Skewness	Kurtosis
A: Duration						
Sinopec	11.4863	7.0605	140	1	2.6650	20.1182
XFPC	29.7477	33.9704	553	1	4.1848	28.0509
WKB	41.5603	54.1286	1196	1	5.6875	60.9800
IBM	3.9106	4.5759	80	1	3.5318	20.1310
B: Return						
Sinopec	2.3298e-6	6.9684e-4	8.3931e-3	-7.6823e-3	0.0277	2.4968
XFPC	-1.0115e-6	6.5013e-4	8.0002e-3	-7.6471e-3	-0.1758	13.5275
WKB	2.3832e-6	7.4911e-4	1.5976e-2	-9.4131e-3	0.5479	30.4000
IBM	-1.1873e-6	-0.6887e-6	4.0114e-3	-6.8887e-3	-0.5826	71.0670
C: Absolute Return						
Sinopec	6.0592e-4	3.4415e-4	8.3931e-3	3.9252e-17	3.4980	36.5590
XFPC	4.5805e-4	4.6315e-4	8.0002e-3	2.4672e-17	4.5157	37.3537
WKB	5.0303e-4	5.5508e-4	1.5976e-2	1.32697e-17	5.5426	82.1145
IBM	1.0148e-4	1.0862e-4	6.8887e-3	2.5640e-16	7.6877	222.1023

This table reports the statistics for the 4 stocks in normal trading days from March 1, 2006 to June 31, 2006. The Chinese stock data is from 9:30am-11:30am and 1:00pm-3:00pm and IBM data is between 9:30am and 4:00pm.

Table 3: Candidate Volatility Components

	Approximate Time	Number of ticks			
		Sinopec	XFPC	WKB	IBM
Instantaneous Components	7 seconds				1**
(H<1 minute)	30 seconds	1**			5**
Short-Term Components	1 minute	2**	1**		9**
(1 minute≤ H <10minutes)	2 minutes	4	2**	1**	15
	5 minutes	10**	4	3**	40
Middle-Term Components	10 minutes	20	8**	6**	85**
(10 minutes≤ H ≤1 hour)	15 minutes	30	13	9	125
	30 minutes	60	25**	20**	250
	1 hour	125**	50	40	500**
Long-Term Components	1.5 hours	180	75	60	750
(1 hour< H ≤1 day)	0.5 day	250	125	80	1750
	1 day	500	250	160	3200
Very-Long Components	1 week	2500	1250	800	16000
(1 day<H)	1 month	11000	5500	3500	65000

This table reports the candidate volatility components (the possible HAR terms) that we consider. Their approximate calendar times H are reported. The "numbers of ticks" column reports the exact number of transactions that are used to construct the component in the conditional variance. Those cells with two stars are the optimally chosen components in the conditional variance.

Table 4: Comparison of the Models

	Sinopec	XFPC	WKB	IBM
A		Log(ML)		
GARCH-BACD	-22571	-15265	-13962	-223693
HAR-EACD	-26249	-15862	-14298	-235521
HAR-BACD	-22491	-15217	-13885	-223495
Log-Bayes Factors				
HAR-BACD vs HAR-EACD	3758	645	413	12026
HAR-BACD vs GARCH-BACD	80	48	77	198
B		Log(PL)		
GARCH-ACD	-15013	-14452	-11335	-120401
HAR-EACD	-17670	-15216	-11617	-128716
HAR-ACD	-14969	-14381	-11287	-120280
Log-Predictive Bayes Factors				
HAR-BACD vs HAR-EACD	2701	835	330	8436
HAR-BACD vs GARCH-BACD	44	71	48	121

Panel A reports the log-marginal likelihoods (log(ML)) for the models and the log-Bayes factors. Panel B reports the cumulative log-predictive likelihoods (log(PL)) and log-predictive Bayes factors. The model are the GARCH-BACD, the HAR-EACD which has exponential duration innovations and the HAR-BACD model. The sample periods for panels A and B are reported in Table 1.

Table 5: Estimation Results

	Sinopec		XFPC		WKB		IBM	
	Mean	Stdev	**Mean**	Stdev	**Mean**	Stdev	**Mean**	Stdev
A: Return Equation								
ρ	**-0.5361***	(0.0138)	**-0.3856***	(0.0272)	**-0.3270***	(0.0311)	**-0.2102***	(0.0114)
ϕ	**0.0503***	(0.0167)	**0.1257***	(0.0299)	**0.0371**	(0.0339)	**-0.0068***	(0.0118)
ν	**19.2073***	(2.8659)	**7.9890***	(0.5137)	**6.3176***	(0.4070)	**7.0947***	(0.1210)
B: ACD Equation								
ω_a	**0.0058***	(0.0016)	**0.0218***	(0.0032)	**0.0309***	(0.0050)	**0.2687***	(0.0328)
α_a	**0.0154***	(0.0021)	**0.0627***	(0.0055)	**0.0722***	(0.0068)	**0.0849***	(0.0086)
β_a	**0.9784***	(0.0033)	**0.9094***	(0.0084)	**0.8959***	(0.0108)	**0.9142***	(0.0087)
κ	**2.4986***	(0.0309)	**2.4287***	(0.0445)	**2.1209***	(0.0444)	**4.6750***	(0.0431)
ϖ^2	**0.3548***	(0.0203)	**0.8579***	(0.0423)	**0.9141***	(0.0501)	**4.3615***	(0.0408)
C: Duration Effects								
γ_1	**0.6816***	(0.0308)	**12.7942***	(0.7362)	**12.9265***	(0.7010)	**0.6647***	(0.0072)
γ_2	**0.0976***	(0.0220)	**1.7614***	(0.4748)	**1.0539***	(0.2758)	**0.0146***	(0.0030)
γ_3	**-0.4137***	(0.1105)	**-6.9552***	(1.0640)	**-5.0458***	(0.8600)	**-0.8554***	(0.0931)
D: Volatility Components								
β_0	**-0.1074**	(0.1084)	**-1.5764**	(1.4786)	**-2.3281***	(0.9074)	**-0.0364***	(0.0220)
β_{I1}	**0.0183**	(0.0124)					**0.0913***	(0.0042)
β_{I2}							**0.0566***	(0.0061)
β_{S1}	**0.0679***	(0.0184)	**0.1198***	(0.0240)	**0.1370***	(0.0265)	**0.0352***	(0.0061)
β_{S2}	**0.1611***	(0.0236)	**0.1231***	(0.0300)	**0.2105***	(0.0344)	**0.0572***	(0.0068)
β_{M1}	**0.1727***	(0.0378)	**0.1594***	(0.0270)	**0.0601**	(0.0385)	**0.0661***	(0.0078)
β_{M2}			**0.1181***	(0.0216)	**0.0986***	(0.0305)		

This table reports the posterior means and the standard deviations of the coefficients for all the stocks using HAR-BACD model. The cells with $*$ have 0.95 density intervals (not reported) that exclude 0. The model is

$$\text{Return: } r_i = \rho r_{t-i} + u_i + \phi u_{i-1} \text{ with } u_i = \sqrt{q_i}\zeta_i, \ \ \zeta_i \overset{iid}{\sim} t_\nu(0,1),$$

$$\text{Duration: } x_i = \psi_i z_i, \ \ z_i \sim Burr(1, \kappa, \varpi^2), \text{ with } \psi_i = \omega_a + \alpha_a x_{i-1} + \beta_a \psi_{i-1}$$

$$\text{Conditional Variance: } q_i = \beta_h + \sum_{m=1}^{M} \beta_m RV_{i-1,h_m} + \gamma_1 x_i^{-1} + \gamma_2 \frac{x_i}{\psi_i} + \gamma_3 \psi_i^{-1}$$
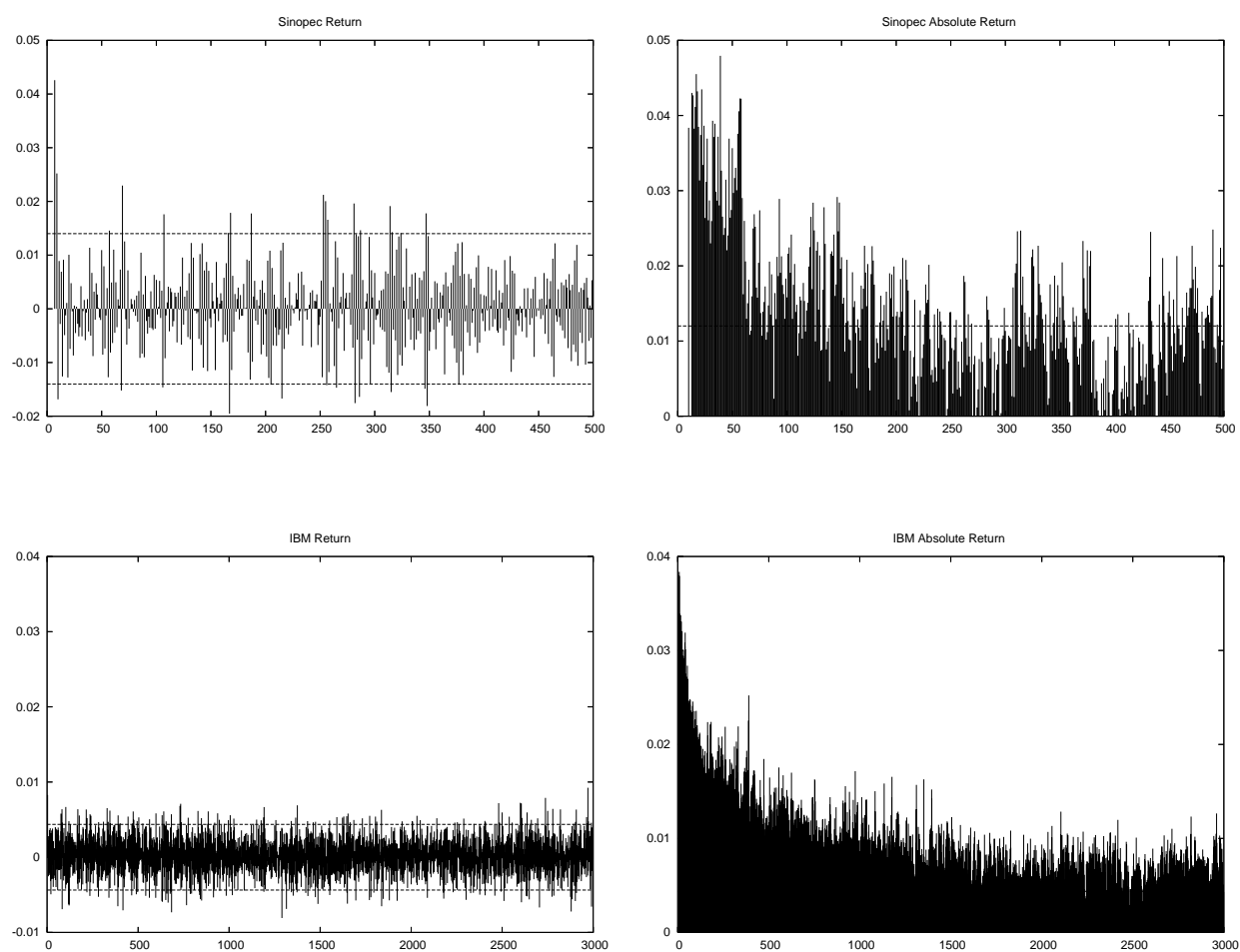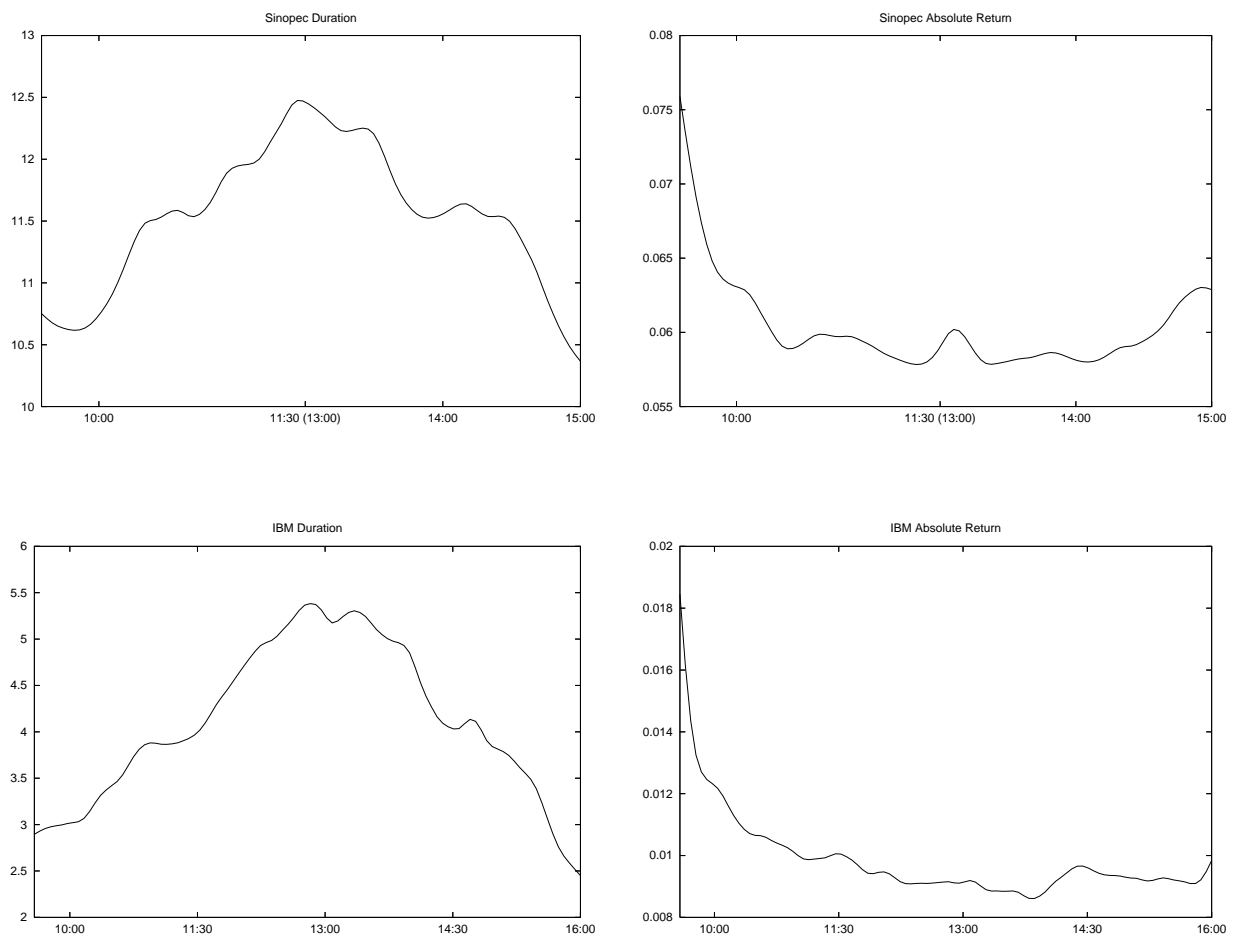
Figure 1: Autocorrelation Functions
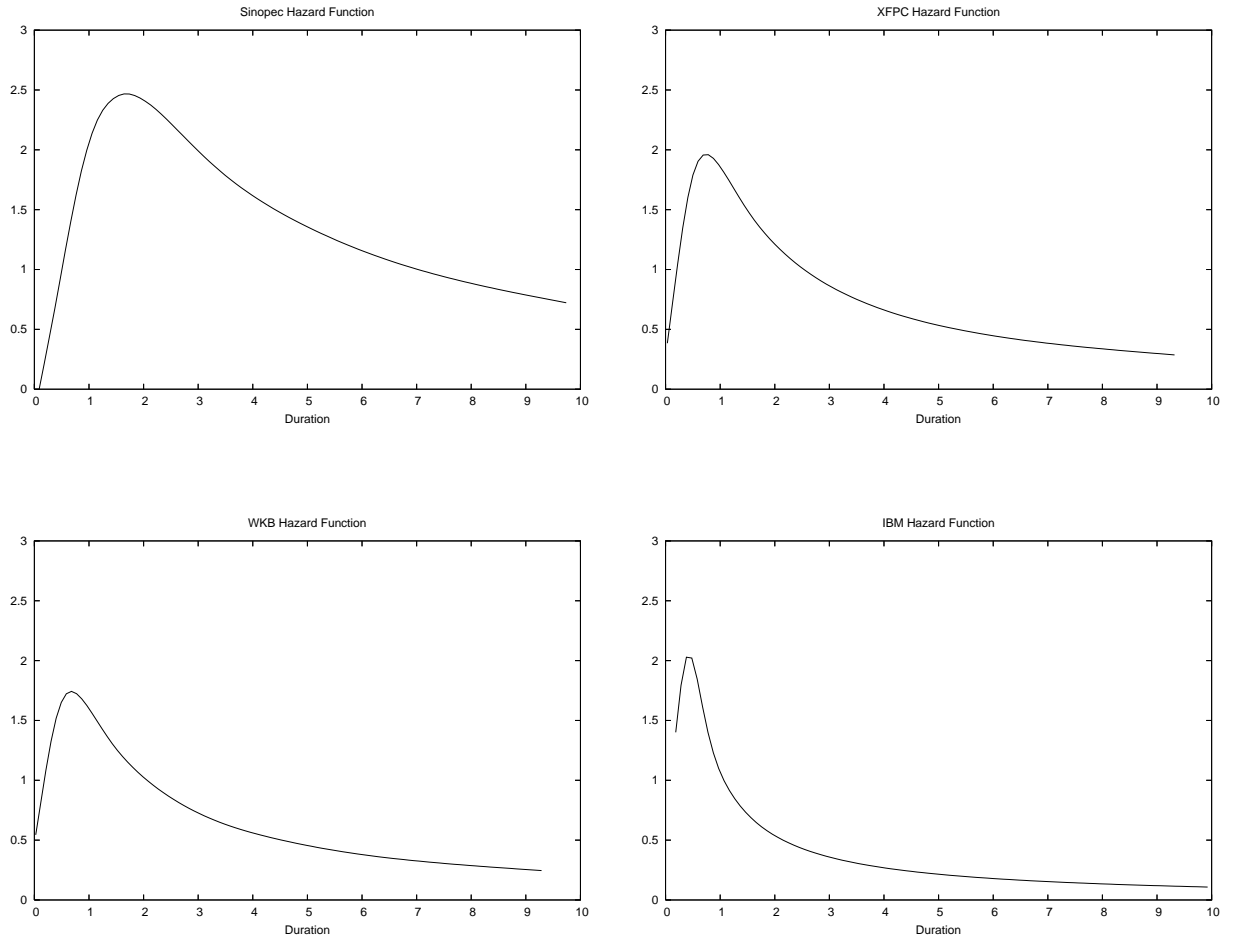
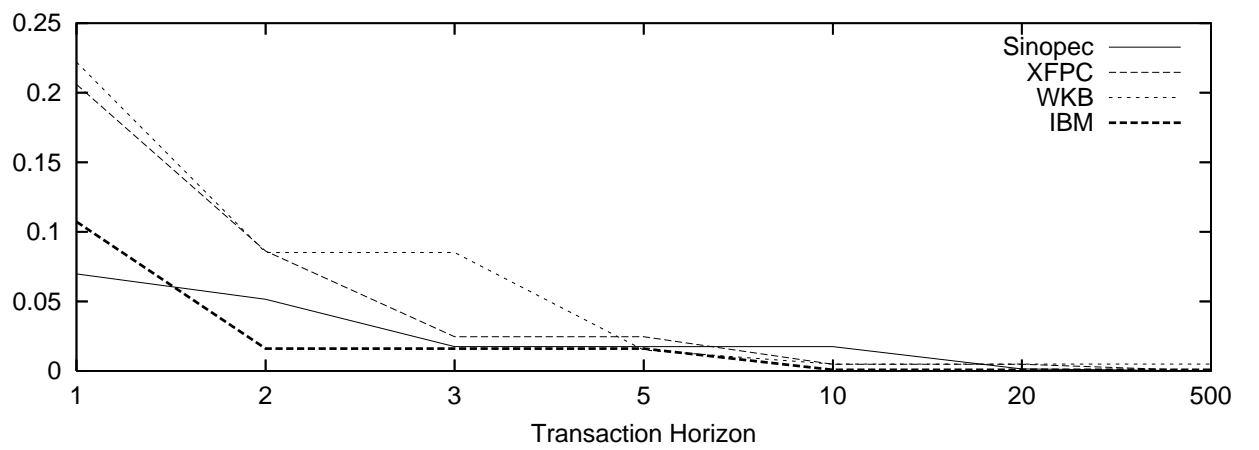Figure 2: Diurnal Patterns

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Figure 3: Hazard Functions

Figure 4: Impact of a Volatility Shock on the Conditional Variance