FINANCIAL MARKET VOLATILITY AND JUMPS

by

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Dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy
in the Department of Economics
in the Graduate School of
Duke University

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ABSTRACT

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Abstract

This dissertation consists of three related chapters that study financial market volatility, jumps and the economic factors behind them. Each of the chapters analyzes a different aspect of this problem.

The first chapter examines tests for jumps based on recent asymptotic results. Monte Carlo evidence suggests that the daily ratio z-statistic has appropriate size, good power, and good jump detection capabilities revealed by the confusion matrix comprised of jump classification probabilities. Theoretical and Monte Carlo analysis indicate that microstructure noise biases the tests against detecting jumps, and that a simple lagging strategy corrects the bias. Empirical work documents evidence for jumps that account for seven percent of stock market price variance.

Building on realized variance and bi-power variation measures constructed from high-frequency financial prices, the second chapter proposes a simple reduced form framework for modelling and forecasting daily return volatility. The chapter first decomposes the total daily return variance into three components, and proposes different models for the different variance components: an approximate long-memory HAR-GARCH model for the daytime continuous variance, an ACH model for the jump occurrence hazard rate, a log-linear structure for the conditional jump size, and an augmented GARCH model for the overnight variance. Then the chapter combines the different models to generate an overall forecasting framework, which improves the volatility forecasts for the daily, weekly and monthly horizons.

The third chapter studies the economic factors that generate financial market volatility and jumps. It extends the recent literature by separating market responses into continuous variance and discontinuous jumps, and differentiating the market's disagreement and uncertainty. The chapter finds that there are more large jumps on news days than on no-news days, with the fixed-income market being more responsive than the equity market, and non-farm payroll employment being the most influential news. Surprises in forecasts impact volatility and jumps in the fixed-income market more than the equity market, while disagreement and uncertainty influence both markets with different effects on volatility and jumps.

Keywords: Stochastic Volatility, Jump, Realized Variance, Bipower Variation, Macroeconomic News Announcements, Economic Derivatives.

JEL classification: C1, C2, C5, C51, C52, F3, F4, G1, G14

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Chapter 1

The Relative Contribution of Jumps to Total Price Variance

This chapter examines tests for jumps based on recent asymptotic results using Monte Carlo evidence, and applies the tests to high-frequency data on S&P 500 Index cash and futures.

1.1 Introduction

Observers of financial markets have long noted that financial movements exhibit unusual behavior relative to what would be expected from the Gaussian distribution. There are too many small changes (inliers) and too many large changes (outliers). Clark (1973) is perhaps the first to formally investigate this behavior using econometric methods. He provides an explanation based on an embryonic form of the now-familiar stochastic volatility model, as made formal in Taylor (1982, 1986), and studied extensively in the vast literature that follows (see Shephard (2005)). We now know that stochastic volatility can account for much of the dynamics of short-term financial price movements.

Modelling financial price changes in a way that implies the price series is the realization of a continuous time diffusive process plays a central role in modern financial economics. The assumption of local continuous Gaussianity, among other things, simplifies the hedging calculations that underlie modern derivatives pricing. Furthermore, as is well known, the superposition of multiple diffusive stochastic volatility processes can potentially accommodate the unusual dynamics mentioned just above; some examples are Chernov, Gallant, Ghysels, and Tauchen (1999) and Alizadeh, Brandt, and Diebold (2002), among others.

Although the diffusive models are of great analytical convenience, there remains the open issue of whether such models are empirically consistent with the extreme violent movements sometimes seen in financial price series. It is natural to ask whether jump diffusions, with discontinuous sample paths, provide a more appropriate empirical model for financial price series. Jump diffusions have a long and rich history in financial economics dating back at least to Merton (1976).

Jump diffusion models present two practical problems, which some might view as nearly insurmountable while others might view as more minor nuisances. First, jump models are difficult to estimate, at least by simulation-based methods. The discontinuous sample paths create discontinuities in the econometric objective function, which have to be accommodated by rounding out the corners as in Andersen, Benzoni, and Lund (2002) and Chernov, Gallant, Ghysels, and Tauchen (2003). Still, the nonlinear optimization remains difficult. It could well be the case that approximate likelihood methods based on Duffie, Pan, and Singleton (2000) or Aït-Sahalia (2004) entail a better-behaved econometric objective function, but that empirical work remains, to our knowledge, undone. Second, jumps introduce additional parameters into the derivatives pricing problem such as the price of jump risk and the price of intensity risk if the intensity is state dependent. These risk parameters are hard to interpret, not estimable in the time series alone, and difficult to pin down in the cross section. A case in point is Andersen, Benzoni, and Lund (2002), who estimate jump models and explore the implications of many of the possible branches for candidate values of these risk parameters. Thus, it seems reasonable to attempt to preserve the simpler structure of purely diffusive models and thereby retain their convenience.

Chernov et al. (2003) provide empirical evidence that there are alternative, mildly nonlinear, purely diffusive models that provide, at the daily level, dynamics comparable to those of jump diffusions. However, they are unable to reach any firm conclusion on the empirical validity of one class of models over the other, and it is self evident that higher frequency data are needed to provide more conclusive evidence on the empirical importance of jumps.

Barndorff-Nielsen and Shephard (2004b, 2006) develop a very powerful toolkit for detecting the presence of jumps in higher frequency financial time series. An appealing feature of their approach is that it does not require a fully observed state variable as in Aït-Sahalia (2002). Their basic idea is to compare two measures of variance, one of which includes the contribution of jumps, if any, to the total variance, while the second is robust to the jump contribution. A test of the statistical significance of the difference, suitably adjusted to improve asymptotic approximation, provides evidence on the presence of jumps. They implement the test on a high frequency data set of exchange rates, as do Andersen, Bollerslev, and Diebold (2006) on a broader set of assets; both papers adduce evidence that seemingly points to the presence of jumps on particular days of their data sets.

This chapter evaluates the properties of these newly developed jump detection tests. For the Monte Carlo DGP we mainly use the single-factor log linear stochastic volatility model with jumps, which is the workhorse of applied econometrics on financial data. We supplement the analysis with consideration of the two-factor model of Chernov et al. (2003), a purely diffusive serious competitor to a jump diffusion. We examine size, power, and, in order to assess the tests' ability to identify correctly trading days on which a jump has occurred, we examine the confusion matrix, whose elements are the probabilities of correct and incorrect classification. We also consider tests designed to address the question of whether an entire data set is one generated from either a pure diffusion or jump diffusion model; to our knowledge, the full-sample type tests have not been previously considered or analyzed.

Jump detection tests are constructed from very high frequency financial price data, which are potentially seriously contaminated by market microstructure noise. We examine theoretically the robustness of a generic jump test to microstructure noise of the sort commonly considered in the literature, and we consider the appropriateness of a correction strategy due to Andersen, Bollerslev, and Diebold (2006). The theory delivers sharp predictions, which are assessed by further Monte Carlo analysis.

Our empirical work focuses on five-minute returns on the S&P Index, cash 1997–2002, and futures 1982–2002, with the objective of identifying the empirical importance of jumps as a source of price variance.

The remainder of this chapter is organized as follows. Section 1.2 sets up the notation and introduces the realized variance measures used for forming the jump test statistics. Section 1.3 reviews the joint asymptotic distribution of the realized measures, and Section 1.4 summarizes the various jump detection tests. Section 1.5 reports on extensive Monte Carlo experiments that examine the behavior of the test statistics. Section 1.6 applies the tests to the S&P 500 Index cash and futures data. Section 1.7 introduces market microstructure noise, and it examines both analytically and by Monte Carlo the effects of the noise on the jump tests. This chapter also examines an adjustment for the noise and reports the outcome of applying the adjusted tests to the S&P 500 futures data. Finally, Section 1.8 contains the concluding remarks.

1.2 Setup

We consider a scalar log-price $p(t)$ evolving in continuous time as

$$dp(t) = \mu(t)dt + \sigma(t)dw(t) + d\mathcal{L}_J(t), \tag{1.1}$$

where $\mu(t)$ and $\sigma(t)$ are the drift and instantaneous volatility, $w(t)$ is standardized Brownian motion, $\mathcal{L}_J$ is a pure jump Lévy process with increments $\mathcal{L}_J(t) - \mathcal{L}_J(s) =$

$\sum_{s\le\tau\le t}\kappa(\tau)$, and $\kappa(\tau)$ is the jump size. We adopt this notation from Basawa and Brockwell (1982). In this chapter, we focus on a special class of the Lévy process called the Compound Poisson Process (CPP). It has constant jump intensity λ, and the jump size $\kappa(t)$ is independent identically distributed. Throughout, time is measured in daily units, and for integer t we define the within-day geometric returns

$$r_{t,j} = p(t-1+j/M) - p(t-1+(j-1)/M), \quad j = 1, 2, \ldots, M,$$

where M is the sampling frequency.

Barndorff-Nielsen and Shephard (2004b) study general measures of realized within-day price variance, and two natural measures emerge from their work. The first is the now-familiar **Realized Variance**

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2,$$

and the other is the realized **Bipower Variation**

$$BV_t = \mu_1^{-2}(\frac{M}{M-1})\sum_{j=2}^{M}|r_{t,j-1}||r_{t,j}| = \frac{\pi}{2}(\frac{M}{M-1})\sum_{j=2}^{M}|r_{t,j-1}||r_{t,j}|,$$

where

$$\mu_a = \mathrm{E}(|Z|^a), \quad Z \sim N(0,1),\, a > 0.$$

We use a slightly different notation that absorbs μ_1^{-2} into the definition of the Bipower Variation and thereby makes it directly comparable to the Realized Variance.

As noted in Andersen, Bollerslev, and Diebold (2005), the Realized Variance satisfies

$$\lim_{M\to\infty} RV_t = \int_{t-1}^{t}\sigma^2(s)ds + \sum_{j=1}^{N_t}\kappa_{t,j}^2,$$

where N_t is the number of jumps within day t and $\kappa_{t,j}$ is the jump size. Thus the RV_t is a consistent estimator of the integrated variance $\int_{t-1}^{t} \sigma^2(s)ds$ plus the jump contribution. On the other hand, the results of Barndorff-Nielsen and Shephard (2004b), along with extensions in Barndorff-Nielsen, Graversen, Jacod, Podolskij, and Shephard (2005) and Barndorff-Nielsen, Graversen, Jacod, and Shephard (2005) imply that under reasonable assumptions about the dynamics (1.1)

$$\lim_{M\to\infty} BV_t = \int_{t-1}^{t} \sigma^2(s)ds.$$

Thus, BV_t provides a consistent estimator of the integrated variance unaffected by jumps. Evidently, the difference $RV_t - BV_t$ is a consistent estimator of the pure jump contribution and, as emphasized by Barndorff-Nielsen and Shephard (2004b, 2006), can form the basis of a test for jumps. Andersen, Bollerslev, and Diebold (2006) use these results to generate evidence suggesting that there are too many large within-day movements in equity, fixed income, and foreign exchange prices to be consistent with the standard continuous time stochastic volatility model with Markov volatility dynamics.

We also consider the **Relative Jump** measure

$$RJ_t = \frac{RV_t - BV_t}{RV_t}, \tag{1.2}$$

which is an indicator of the contribution (if any) of jumps to the total within-day variance of the process. An equivalent statistic, $-RJ_t$, called the ratio statistic, is proposed and studied by Barndorff-Nielsen and Shephard (2006). We have a slight preference for the term Relative Jump since $100 \cdot RJ$ is a direct measure of the percentage contribution of jumps, if any, to total price variance.

Given a sample of T days, we denote the total realized variance as

$$RV_{1:T} = \sum_{t=1}^{T} RV_t,$$

and the total bipower variation as

$$BV_{1:T} = \sum_{t=1}^{T} BV_t.$$

The corresponding relative jump measure is

$$RJ_{1:T} = \frac{RV_{1:T} - BV_{1:T}}{RV_{1:T}}.$$

1.3 Asymptotic Distributions

Under the assumption of no jump and some other regularity conditions, Barndorff-Nielsen and Shephard (2006) first give the joint asymptotic distribution of RV_t and BV_t, conditional on the volatility path, as $M \to \infty$

$$M^{\frac{1}{2}} \left[\int_{t-1}^{t} \sigma^4(s)ds \right]^{-\frac{1}{2}} \left(\begin{array}{c} RV_t - \int_{t-1}^{t} \sigma^2(s)ds \\ BV_t - \int_{t-1}^{t} \sigma^2(s)ds \end{array} \right) \xrightarrow{\mathcal{D}} N(0, \left[\begin{array}{cc} v_{qq} & v_{qb} \\ v_{qb} & v_{bb} \end{array} \right]),$$

where

$$\left[\begin{array}{cc} v_{qq} & v_{qb} \\ v_{qb} & v_{bb} \end{array} \right] = \left[\begin{array}{cc} \mu_4 - \mu_2^2 & 2(\mu_3\mu_1^{-1} - \mu_2) \\ 2(\mu_3\mu_1^{-1} - \mu_2) & (\mu_1^{-4} - 1) + 2(\mu_1^{-2} - 1) \end{array} \right],$$

and using $\mu_1 = \sqrt{\frac{2}{\pi}}$, $\mu_2 = 1$, $\mu_3 = 2\sqrt{\frac{2}{\pi}}$, $\mu_4 = 3$,

$$\begin{array}{rcl} v_{qq} & = & 2, \\ v_{qb} & = & 2, \\ v_{bb} & = & (\frac{\pi}{2})^2 + \pi - 3. \end{array}$$

The fact that asymptotically $v_{qb} = v_{qq}$ is no coincidence and reflects a situation exactly analogous to that of the Hausman (1978) test. Asymptotically, the situation is one with Gaussian errors, and RV_t is the most efficient estimate of the integrated variance $\int_{t-1}^{t} \sigma^2(s)ds$. The bipower variation is a less efficient estimator under the maintained assumption of no jumps, though it is also more robust. Thus, following the logic of the Hausman test:

PROPOSITION 1. Under the maintained assumptions of no jumps, then asymptotically $RV_t - BV_t$ is independent of RV_t conditional on the volatility path, and thus RJ_t in (1.2) is asymptotically the ratio of two conditionally independent random variables.

The proof is obvious by inspection. The above asymptotic distribution theory can be generalized considerably as in Barndorff-Nielsen, Graversen, Jacod, Podolskij, and Shephard (2005) and Barndorff-Nielsen, Graversen, Jacod, and Shephard (2005); see Barndorff-Nielsen and Shephard (2005b) for a survey.

The relative jump measure RJ_t has a natural notion of scale. If one is satisfied with this sense of scale, then there is no need to estimate the integrated quarticity $\int_{t-1}^{t} \sigma^4(s)ds$ as required for a standard deviation notion of scale.

To determine the scale of $RV_t - BV_t$ in units of conditional standard deviation, one needs to estimate the integrated quarticity $\int_{t-1}^{t} \sigma^4(s)ds$. Andersen, Bollerslev, and Diebold (2006) suggest using the jump-robust realized **Tri-Power Quarticity** statistic, which is a special case of the multipower variations studied in Barndorff-Nielsen and Shephard (2004b)

$$TP_t = M\mu_{4/3}^{-3}(\frac{M}{M-2})\sum_{j=3}^{M} |r_{t,j-2}|^{4/3}|r_{t,j-1}|^{4/3}|r_{t,j}|^{4/3}, \tag{1.3}$$

and they note that

$$TP_t \to \int_{t-1}^{t} \sigma^4(s)ds$$

even in the presence of jumps. There is a scale normalizing constant M in front of the summation because each absolute return is of order $\sqrt{\triangle t}$, so the product is of order $(\triangle t)^2$, and the summation $\triangle t$. M is $\frac{1}{\triangle t}$, which cancels out the summation order, and the whole expression approaches a well defined limit. As mentioned before, the value normalizing term is now $\mu_{4/3}^{-3}$ since each absolute return is raised to power 4/3 and there are three such terms in one product. Notice that the power of each absolute return should be strictly less than two for the statistics to be robust to jumps. If it is equal to two, the statistics will behave just like RV, picking up both the jump and the continuous-time parts, and, if it is greater than two, the whole expression will blow up to infinity, because of the interaction between the scale normalizing constant and the jump component. Another estimator, based on Barndorff-Nielsen and Shephard (2004b), is the realized **Quad-Power Quarticity**

$$QP_t = M\mu_1^{-4}(\frac{M}{M-3})\sum_{j=4}^{M} |r_{t,j-3}||r_{t,j-2}||r_{t,j-1}||r_{t,j}|. \tag{1.4}$$

Given a sample of T days, the corresponding full-sample measures for TP and QP are:

$$TP_{1:T} = \sum_{t=1}^{T} TP_t,$$

$$QP_{1:T} = \sum_{t=1}^{T} QP_t.$$

1.4 Some Jump Test Statistics

1.4.1 Daily Statistics

One strategy is to use the above theoretical results to compute a measure of extreme movements on a day-by-day basis and then inspect for days where the price movements appear abnormally large, which would be indicative of at least one jump that day. Based on Barndorff-Nielsen and Shephard (2006) theoretical results, Andersen, Bollerslev, and Diebold (2006) use the time series

$$z_{TP,t} = \frac{RV_t - BV_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}TP_t}} \tag{1.5}$$

to test for daily jumps. For each t, $z_{TP,t} \xrightarrow{\mathcal{D}} N(0,1)$ as $M \to \infty$, on the assumption of no jumps. Thus the sequence $\{z_{TP,t}\}_{t=1}^{T}$ provides evidence on the daily occurrence of jumps in the price process. Another closely related measure is

$$z_{QP,t} = \frac{RV_t - BV_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}QP_t}},$$

which uses the realized quad-power quarticity (1.4) in place of the realized tri-power quarticity (1.3) in the computation of the conditional scale of $RV_t - BV_t$.

Following Andersen, Bollerslev, Diebold, and Labys (2001, 2003), and Barndorff-Nielsen and Shephard (2005a), one might expect to be able to improve finite sample performance by basing the test statistics on the logarithm of the variation measures. In the case of (1.5), the statistic is

$$z_{TP,l,t} = \frac{\log(RV_t) - \log(BV_t)}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{TP_t}{BV_t^2}}}, \tag{1.6}$$

which is also used in Andersen, Bollerslev, and Diebold (2006). Another modification based on Barndorff-Nielsen and Shephard (2005a) entails the maximum adjustment

$$z_{TP,lm,t} = \frac{\log(RV_t) - \log(BV_t)}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(1, \frac{TP_t}{BV_t^2})}}. \tag{1.7}$$

Analogous to the logarithmic adjustment to $z_{TP,t}$, we also have the statistic

$$z_{QP,l,t} = \frac{\log(RV_t) - \log(BV_t)}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{QP_t}{BV_t^2}}},$$

and with the additional maximum adjustment, as used in Barndorff-Nielsen and Shephard (2004b), is

$$z_{QP,lm,t} = \frac{\log(RV_t) - \log(BV_t)}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(1, \frac{QP_t}{BV_t^2})}}.$$

We also recall the measure of the relative jump (equivalent to negative of the ratio statistic):

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

and the statistics based on it are

$$z_{TP,r,t} = \frac{RJ_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{TP_t}{BV_t^2}}}, \tag{1.8}$$

$$z_{QP,r,t} = \frac{RJ_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{QP_t}{BV_t^2}}},$$

$$z_{TP,rm,t} = \frac{RJ_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(1, \frac{TP_t}{BV_t^2})}}, \tag{1.9}$$

$$z_{QP,rm,t} = \frac{RJ_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(1, \frac{QP_t}{BV_t^2})}}.$$

The QP-versions of these statistics are equivalent to the ratio jump statistics of Barndorff-Nielsen and Shephard (2006). By visual inspection, one can see that the denominators of the log tests and the ratio tests are the same. In other words, the numerators of the second and third pairs of the jump statistics have identical asymptotic distributions conditional on the volatility path. The intuition is that the first order Taylor expansions of the numerators of the log and the ratio test statistics around the asymptotic mean of RV_t and BV_t, i.e., the integrated variance $\int_{t-1}^{t} \sigma^2(s)ds$, are the same, thus the delta method generates the same asymptotic distribution.

In Section 1.5 below we examine, among other things, the quality of the asymptotic normal approximation to each of these statistics under the null hypothesis of no jumps.

1.4.2 Full Sample Statistics

We also consider the finite sample properties of the test statistics for jumps in a given sample. In this case, the test statistics are computed over the entire sample instead of on a day-by-day basis.

A natural asymptotically normal test statistic, following Andersen, Bollerslev, and Diebold (2006), is

$$z_{TP,1:T} = \frac{RV_{1:T} - BV_{1:T}}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}TP_{1:T}}}. \tag{1.10}$$

Another, based on the results of Barndorff-Nielsen and Shephard (2004b), is

$$z_{QP,1:T} = \frac{RV_{1:T} - BV_{1:T}}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}QP_{1:T}}}. \tag{1.11}$$

The log versions of these statistics are

$$z_{TP,l,1:T} = \frac{\log(RV_{1:T}) - \log(BV_{1:T})}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{TP_{1:T}}{BV_{1:T}^2}}}, \tag{1.12}$$

$$z_{QP,l,1:T} = \frac{\log(RV_{1:T}) - \log(BV_{1:T})}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{QP_{1:T}}{BV_{1:T}^2}}}. \tag{1.13}$$

With the additional maximum adjustment, the statistics become

$$z_{TP,lm,1:T} = \frac{\log(RV_{1:T}) - \log(BV_{1:T})}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(\frac{1}{T}, \frac{TP_{1:T}}{BV_{1:T}^2})}}, \tag{1.14}$$

$$z_{QP,lm,1:T} = \frac{\log(RV_{1:T}) - \log(BV_{1:T})}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(\frac{1}{T}, \frac{QP_{1:T}}{BV_{1:T}^2})}}. \tag{1.15}$$

There are similar full-sample statistics based on $RJ_{1:T}$ using $TP_{1:T}$ and $QP_{1:T}$ as well:

$$z_{TP,r,1:T} = \frac{RJ_{1:T}}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{TP_{1:T}}{BV_{1:T}^2}}}, \tag{1.16}$$

$$z_{QP,r,1:T} = \frac{RJ_{1:T}}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\frac{QP_{1:T}}{BV_{1:T}^2}}}, \tag{1.17}$$

$$z_{TP,rm,1:T} = \frac{RJ_{1:T}}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(\frac{1}{T}, \frac{TP_{1:T}}{BV_{1:T}^2})}}, \tag{1.18}$$

$$z_{QP,rm,1:T} = \frac{RJ_{1:T}}{\sqrt{(v_{bb} - v_{qq})\frac{1}{M}\max(\frac{1}{T}, \frac{QP_{1:T}}{BV_{1:T}^2})}}. \tag{1.19}$$

A simple t-test on the **Relative Jump** measure is

$$t_{RJ,classic} = \frac{\frac{1}{T}\sum_{t=1}^{T} RJ_t}{\sqrt{v_{classic}}}, \tag{1.20}$$

where $v_{classic}$ is the classical estimate of the variance of the mean computed under the assumption of no serial dependence. One can also form

$$t_{RJ,GMM} = \frac{\frac{1}{T}\sum_{t=1}^{T} RJ_t}{\sqrt{v_{HAC}}}, \tag{1.21}$$

where v_{HAC} is a HAC estimator of the variance of the mean. A bootstrap version is

$$t_{RJ,boot} = \frac{\frac{1}{T}\sum_{t=1}^{T} RJ_t}{\sqrt{v_{boot}}}, \tag{1.22}$$

where v_{boot} is a bootstrap estimate of the variance of the mean. Finally, by bootstrapping $t_{RJ,classic}$ one can get a bootstrap confidence interval (t_{low}, t_{up}) for the t-statistic and form a test that way. We have not computed these more complicated t statistics because the evidence and theory suggest that the RJ_t are essentially serially uncorrelated, if the jump part follows the CPP process. Interested readers are referred to Gonçalves and Meddahi (2005) for an in-depth study of the test statistics based on the bootstrap variance of the realized variance measures.

1.5 Monte Carlo Analysis

1.5.1 Setup

We analyze the behavior of the various tests above under two classes of models for the log price process p_t. The first is a stochastic volatility jump diffusion model of the form

SV1FJ

$$\begin{aligned} dp(t) &= \mu\, dt + \exp\left[\beta_0 + \beta_1 v(t)\right] dw_p(t) + d\mathcal{L}_J(t) \\ dv(t) &= \alpha_v v(t)\, dt + dw_v(t) \end{aligned} \tag{1.23}$$

where the w's are standard Brownian motions, $\text{Corr}(dw_p, dw_v) = \rho$ is the leverage correlation, $v(t)$ is a stochastic volatility factor, $\mathcal{L}_J(t)$ is a Compound Poisson Process with constant jump intensity λ and random jump size distributed as $N(0, \sigma^2_{jmp})$. The model **SV1FJ** has one stochastic volatility factor and a jump; it has been widely studied. Barndorff-Nielsen and Shephard (2004b) term this a stochastic volatility model with rare jumps. A special case without a jump term is

SV1F

$$\begin{aligned} dp(t) &= \mu\, dt + \exp\left[\beta_0 + \beta_1 v(t)\right] dw_p(t) \\ dv(t) &= \alpha_v v(t)\, dt + dw_v(t) \end{aligned}$$

We also follow Chernov et al. (2003) and consider a two factor stochastic volatility model

SV2F

$$\begin{aligned} dp(t) &= \mu\, dt + \text{s-exp}\left[\beta_0 + \beta_1 v_1(t) + \beta_2 v_2(t)\right] dw_p(t) \\ dv_1(t) &= \alpha_{v1} v_1(t)\, dt + dw_{v1}(t) \\ dv_2(t) &= \alpha_{v2} v_2(t)\, dt + [1 + \beta_{v2} v_2(t)] dw_{v2}(t) \end{aligned} \tag{1.24}$$

where $v_1(t)$ and $v_2(t)$ are stochastic volatility factors. The process $v_1(t)$ is a standard Gaussian process while $v_2(t)$ exhibits a feedback term in the diffusion function. The feedback is found to be important in Chernov, Gallant, Ghysels, and Tauchen (2003). The function s-exp means the usual exponential function with a polynomial function splined in at very high values of its argument to ensure that the system (1.24) with $\beta_{v2} \neq 0$ satisfies the growth conditions for a solution to exist and for the Euler scheme to work. The s-exp function is considered more fully below. The leverage correlations are $\text{Corr}(dw_p, dw_{v1}) = \rho_1$ and $\text{Corr}(dw_p, dw_{v2}) = \rho_2$.

The **SV2F** model has continuous sample paths but it can generate quite rugged appearance price series via the volatility feedback and the exponential function, which is splined only at relatively high values of its argument. One of our objectives is to examine whether the various jump test statistics will falsely signal jumps under a process with continuous sample paths.

Table 1.1 shows the parameter settings used in the simulations for the **SV1FJ** model, with, of course, **SV1F** representing the null hypothesis. The parameter values are based on the empirical results reported in Andersen, Benzoni, and Lund (2002), Andersen, Bollerslev, and Diebold (2006), and Chernov et al. (2003). The three values of the volatility mean reversion parameter α_v represent very slow mean reversion, with a half life of two years (2×252 trading days), medium mean reversion, with a half life just over one week, and very strong mean reversion with a half life of 0.50 days. The very slow and very strong values for the mean reversion parameter are based on Chernov et al. (2003) while the medium value is based on Andersen, Benzoni, and Lund (2002). There are four values for the jump intensity (λ). The smallest jump intensity is estimated by Andersen, Benzoni, and Lund (2002) for the daily S&P 500 Cash Index, while the other three come from Andersen, Bollerslev, and Diebold (2006) for the high-frequency data on the DM/$ spot, S&P 500 Index futures, and U.S. T-Bond futures markets. The parameter σ_{jmp} varies over a range that includes Andersen, Benzoni, and Lund (2002) estimate of about 1.50 percent. The value of the leverage parameter is from Andersen, Benzoni, and Lund (2002), though our experiments suggest that the findings are not very sensitive to this parameter. The scaling parameters, i.e., the β's, are selected on the basis of the studies and some experiments guided by plots of simulated data. For computational reasons, the above-mentioned empirical studies use different normalizations, different timing conventions, and they simulated arithmetic, not geometric returns, so it is difficult to match up the values exactly to those previously estimated.

The simulation details are as follows: the basic unit of time is one day throughout. Simulations of the diffusion parts of the **SV1FJ** and **SV2F** models are generated using the basic Euler scheme with an increment of 1 second per tick on the Euler clock. We first simulate the log price level, then compute the 1-minute, 3-minute, 5-minute and 30-minute geometric returns by taking the difference of the corresponding log price levels, with the objective to see how sampling frequency affects the properties of the test statistics. In order to make results comparable across sampling intervals, it is important to simulate a **single** Brownian motion at a very fine time interval, use the Euler scheme to solve for a simulation from the nonlinear model, and then sample that series at coarser intervals. The jump component is simulated by drawing the jump times from the exponential distribution and the jump size from $\mathrm{N}(0, \sigma^2_{jmp})$.

The simulation of the **SV2F** model requires some special attention to satisfy the growth conditions (KP1992, p. 128) of Ito's theorem. Following Chernov et al. (2003) we spline smoothly to the far right-hand side of the exponential function the growth function itself, so the model satisfies the regularity conditions by construction. The knot point for the spline is a value of the argument of the exponential that implies a 100 percent annualized volatility, which is unlikely to occur in the normal U.S. financial markets. Inspection of very long simulations revealed the spline has no essential effect, except for attenuating the influences of a very few really large values of the argument.

Figure 1.1 and Figure 1.2 show the simulated realizations of length 10,000 days (about 40 years) at the daily frequency from the **SV1F** and **SV1FJ** models, with medium mean reversion, $\sigma_{jmp} = 1.50$, and $\lambda = 0.014$ in the latter case. The daily returns seen in the second panel appear reasonable for a financial time series. Likewise, Figure 1.3 shows a simulation at the daily frequency from the **SV2F** model which looks very similar to the plots of daily returns found in the financial econometrics literature.

1.5.2 Monte Carlo Findings

1.5.2.1 Daily Statistics

We first consider the characteristics of the daily statistics computed over a long simulated realizations, $\{z_{TP,t}\}_{t=1}^{N}$ and $\{z_{QP,t}\}_{t=1}^{N}$, of length N=45,000.

1.5.2.1.1 Size

Figure 1.4 shows QQ plots of the raw, log-max, and ratio-max adjusted versions of $z_{TP,t}$ defined in (1.5), (1.7), (1.9) above. Since the log and ratio adjusted versions are similar, they are not shown here. The data generation process is the null case in Table 1.1, $\sigma_{jmp} = 0.00$, with medium mean reversion ($\alpha_v = -0.100$) and 5-minute returns. Since large values of the z statistics discredit the null hypothesis of no jumps, we are only interested in the right-hand tail. As is clear from the figures, the raw statistic has a size distortion towards over rejecting in the range 2.00 to 3.00, about 0.99 to 0.999 significance level, which is the usual range considered for these daily z test statistics. However, the log transformation and the statistic based on RJ correct the size distortions, except perhaps in the extreme right-hand tail. Although the boundary in the maximum adjustment is hit a lot, the QQ plots do not appear to change much when we add the maximum adjustment. A similar situation shows up when we study the full sample statistics. Apparently, the deviations from the boundary are not serious, thus they do not affect the value of the z statistics significantly.

As seen from Figures 1.5, the raw statistic $z_{QP,t}$ has the same size problem and the effects of the log, ratio and max adjustments are the same as with $z_{TP,t}$. It appears that the choice between TP_t and QP_t does not matter in any important way for the estimation of $\int_{t-1}^{t} \sigma^4(s)ds$. Interestingly, Figures 1.6 indicates that the relative jump statistic, RJ_t, is very well approximated by a Gaussian distribution.

With the exception of the $z_{TP,rm,t}$ statistic, the sampling frequency has a significant impact on the size. As the sampling frequency decreases, i.e., the sampling interval increases, the actual sizes of all statistics except $z_{TP,rm,t}$ increase above the Monte Carlo confidence band, which can be seen in Figure 1.7 for the medium mean reversion case. The behavior of the size for the slow mean reversion and the fast cases are the same, so they are not shown here.

Figure 1.8 shows a simulation of length 1400 days of the five versions of $z_{TP,t}$ statistics under the null of no jumps and $\alpha_v = -0.100$. We choose 1400 because that is very close to the sample size for the Cash Index in the empirical application below. The size problem is apparent in the top panel as is the correction due to the log adjustment and ratio adjustment. Note that $z_{TP,rm,t}$ in the bottom panel appears to have the best size property among the five statistics.

1.5.2.1.2 Jump Detection

For evidence on the ability of the tests to detect jumps under the SV1FJ setting, Figure 1.9 shows a simulation of the versions of $z_{TP,t}$ under the same conditions as in Figure 1.8 except with $\sigma_{jmp} = 1.50$ and $\lambda = 0.014$. As is clear, the statistics do a very good job of picking out the jumps.

To see how the parameter settings affect the detection ability of the test statistics, we report the confusion matrix under different parameter settings. The matrix consists of four cells: the upper left cell is the proportion of the statistic smaller than the 99% standard Gaussian critical value among days without jumps, the upper right cell is the proportion greater than the 99% critical value among the no-jump days; the lower left cell is the proportion smaller than the 99% critical value among the days that jumps occur on, and the lower right one is the proportion greater than the 99% critical value among the jump days. The diagonal elements of this matrix represent the ability of the test statistic to tell correctly whether or not there is a jump(s) in a particular day, and the off-diagonal represent the proportion of days when the statistic signals the wrong answer. The row sums of this matrix equal unity. Under the asymptotic theory presented in the previous sections, we expect the (1,1) element of this matrix to be close to 99%, as the sampling interval goes to zero; however, the (2,2) element of this matrix needs not approach unity, as explained in Subsection 4.2.1.3. below.

Table 1.3 contains the confusion matrices for the three test statistics, $z_{TP,t}$, $z_{TP,lm,t}$ and $z_{TP,rm,t}$ over different jump intensities and sampling frequencies under medium mean reversion ($\alpha_v = -0.100$) and jump size 1.50. The mean reversion does not significantly impact the daily statistics, and the jump size positively affects the rejection frequency in the expected manner, so we do not report variations in these two parameters here. By comparing the first rows of the matrices for the three test statistics, we can see that $z_{TP,t}$ tends to signal more false jumps when there is no jump in a particular day, and the problem becomes more severe with longer sampling intervals. On the other hand, $z_{TP,rm,t}$ is more robust with a false rejection rate close to the nominal size of 1 percent. By examining the second rows of the matrices, we see that as the sampling interval increases from 1 minute to 30 minutes, the test statistics signal fewer instances of jumps when jumps occur because of the time averaging effect. An increase in jump intensity, λ, has a positive effect on the detection rate. The reason is that the statistics detect jumps through the proportion of the total price variation attributable to jumps. When λ increases, the expected number of jumps per day increases. This increases the expected accumulated jump contribution per day, making it more likely that the statistics detect the jumps.

1.5.2.1.3 Power

The above jump detection results are most likely to be important for daily application purposes, but from the statistical view point, we are also interested in the power of the tests. Table 1.4 reports the power of the three test statistics, $z_{TP,t}$, $z_{TP,lm,t}$ and $z_{TP,rm,t}$, over different jump intensities and jump sizes under medium mean reversion using 5-minute simulated returns. Jump intensity and jump size have positive effects on power. These results are intuitive. Table 1.5 shows the power property of $z_{TP,rm,t}$ over different jump intensities, jump sizes and sampling frequencies. Just like the effect on the jump detection rate, the sampling frequency impacts power positively. So combining the results in size, jump detection rate and power, we can see that, in the absence of market microstructure noise, for lower sampling frequency the statistics not only neglect true jumps when there are jumps (lower jump detection rate and lower power), but also signal more false jumps when there is no jump (larger size). So high-frequency data is necessary for jump detection when we use this types of statistics.

In addition to the effects of different parameters on the test statistics, an important phenomenon is apparent in these two tables. The test is inconsistent; that is, its power will not approach one as the sample size goes to infinity. The reason is that, for any finite jump intensity, the underlying jump-diffusion process does not have jump(s) every day. The time interval between two jumps is exponentially distributed, and the probability of having no jump for a day is $e^{-\lambda}$, which is not zero for any $\lambda < \infty$. Even when λ is as high as 2 (unlikely to occur in the empirical data), such a probability is still 0.135. Since the test statistics signal jumps for only a very small portion of the no-jump days, their power, defined to be the proportion of signalled jump days over the whole sample, will not approach one.

1.5.2.1.4 The SV2F Model

The above results show that the test statistics have excellent size property under the SV1F(J) model. By way of contrast, however, Figure 1.10 shows a simulation of the $z_{TP,t}$ statistics under the **SV2F** model described above. The underlying model does not contain jumps, though the simulation indicates detection of spurious jumps. The figure suggests the test statistics have incorrect size. Table 1.6 for 5-minute returns further illustrates this point. The 95% confidence band for the nominal size of 5% over 45,000 simulation days is [0.04799, 0.05201], that for the size of 1% is [0.00908, 0.01092], that for the size of 0.5% is [0.00435, 0.00565], and that for the size of 0.1% is [0.00071, 0.00129]. However, all the empirical sizes are outside these confidence bands, although the size of the $z_{TP,rm,t}$ is least affected. The finding of over rejection is in contrast to that of Barndorff-Nielsen and Shephard (2006), who utilize the superposition of two square-root (CIR) volatility processes. It suggests that the curvature of the volatility functions influences the properties of the test statistics somewhat, although the size distortions in Table 1.6 are not very large from a practical point of view.

1.5.2.2 Monte Carlo Assessment of Full Sample Statistics

We now consider the test of the null hypothesis that a given data set has been generated from a DGP without jumps versus the alternative of one with jumps. This question is different from the one just considered, where the issue was whether or not a jump occurred on a particular day. Tests of this null hypothesis are based on the full sample, rather than being computed day-by-day. The candidate test statistics are displayed in Equations (1.10)–(1.22) above.

Perhaps the most interesting tests are those based on $z_{TP,1:T}$ and $z_{QP,1:T}$ and their transforms as defined in equations (1.10)–(1.19). Table 1.9 shows the rejection frequencies under the one factor **SV1FJ** and two-factor **SV2F** models, for 1000 repetitions of a time series with 1400 days. The tests appear to have excellent size and power properties under the **SV1FJ** model with the strong and medium mean reversions, while, as might be expected, the power of each test under the slow mean reversion is somewhat lower, because the diffusive part of the model accounts for a relatively larger share of the variance. However, the tests seem to have incorrect size under the **SV2F** model for this sample size.

The finding that, under the **SV2F** model, the full-sample statistics incorrectly reject the null of no jump more often than the daily statistics is notable, but needs to be interpreted properly. The realized Bipower Variation and Realized Variance, though consistent, are not unbiased for the integrated variance. That is, for any finite sampling frequency M, it can be the case that, if the expectations exist,

$$\mathrm{E}\left(RV_t - BV_t\right) \doteq \mathcal{B}(M) \neq 0, \tag{1.25}$$

although one expects $\mathcal{B}(M)$ to be rather small. However, relative to the daily statistics, the full sample statistics increase the time span without shrinking the sampling interval, so in effect the small bias gets inflated to $T \cdot \mathcal{B}(M)$ and the z statistics can become very large. Therefore, the larger the sample size, the more apparent the difference between $RV_{1:T}$ and $BV_{1:T}$, and hence the greater the rejection frequency of the full sample z statistics.

There are other strategies for forming full sample test statistics. For example, one can add the sum of squared daily z statistics and treat it as a Chi-squared random variable. Another is to compute over the simulated sample of length T the proportion of days on which the individual z-statistics are statistically significant at some given level α, and then form the usual pivotal statistic based on the Gaussian approximation to the Binomial. We experimented with these strategies, and always found the same conclusions as just described above. When replicated over many samples of length T, the tests can incorrectly over-reject the null of no jumps, because a tiny daily bias gets inflated by the factor T.

Full sample tests can potentially become consistent tests for jumps with proper size, if a way can be found to eliminate the bias. There are possible strategies to knock it out based on the behavior of $T \cdot \mathcal{B}(M)$ for different M, but they all appear to us to entail additional assumptions and models that would be inconsistent with the nonparametric character of the jump detection strategies. So, for now, the daily statistics are perhaps more reliable than the full sample statistics, at least in terms of their size, though the full sample statistics offer some tantalizing longer term possibilities for development of consistent tests. For the related asymptotic results as both T and M go to infinity, see Corradi and Distaso (2004) in the framework of testing the specification of stochastic volatility models.

1.6 Empirical Application

The data set consists of five-minute observations on the S&P Index; the cash data is from April 21, 1997 to October 22, 2002 and the futures data is from April 21, 1982 (the beginning of the S&P futures contract) to December 9, 2002. We eliminated a few days where trading was thin and the market was open for a shortened session. Figure 1.11 shows plots of the daily price level and the daily geometric returns of the Cash Index and the Index futures. For the within-day computations, we used five-minute data after applying a standard adjustment for the deterministic pattern of volatility over the trading day.

To investigate jumps, we first consider Figures 1.12 and 1.13, which shows in each panel a time series plot of the five versions (1.5), (1.6), (1.7), (1.8), and (1.9) of the $z_{TP,t}$ statistic computed over this data set, along with the upper 0.99 percent and 0.999 percent critical values of the standard Gaussian distribution. From the Monte Carlo evidence generated in Section 1.5, the second to the last panels provide the more reliable evidence on days on which large jump(s) occurred conditional on the **SV1FJ** model (1.23). Evidently, the statistics indicate far more jumps than would be expected under a purely diffusive model satisfying the rather mild regularity conditions of Barndorff-Nielsen and Shephard (2006). Similarly, there appear to be many more jumps than could possibly be generated as false jumps under the continuous **SV2F** model, which casts doubt on the validity of that model in describing the very high frequency character of stock prices.

We now consider the relative contribution of jumps to total price variance. Table 1.8 shows that the proportion of days that the daily z statistics identify as having jump(s) is larger for the Cash Index than those for the Index futures in the corresponding periods or in the full sample. Moreover, Table 1.9 shows that about 4.4% to 4.6% of the total realized variance comes from the jump component in the Index futures, and, somewhat surprisingly, smaller than the value (7.328%) in the Cash Index. A similar relationship holds for the full sample statistics ($RJ_{1:T}$) as well. On the other hand, $RV_{1:T}$ and $BV_{1:T}$ for the Index futures are larger than those for the Cash Index, for both the shorter (1997–2002) and the longer samples (1982–2002).

Taken together, the results reported in Figures 1.12 and 1.13 along with those in Tables 1.8 and 1.9 indicate that jumps are a statistically important component of aggregate stock price movements. This evidence is generated using statistical techniques validated in the Monte Carlo work of Section 1.5, which makes the case for jumps all that more compelling. The jumps appear to contribute about 4.4 to 7.3 percent to the total variance of daily stock price movements.

1.7 Market Microstructure Noise

Our empirical evidence on the jumps in the financial price process is consistent with the findings in Andersen, Bollerslev, and Diebold (2006). Eraker, Johannes, and

Polson (2003) also find similar proportions of return variance due to jumps in S&P 500 and Nasdaq 100 index returns using their jumps in volatility and returns models. These sets of findings suggest more instances of jumps and higher jump contribution to total return variance than most of the existing literature in this aspect does. However, since we are using high-frequency data, the observed return series can be contaminated by market microstructure noise. That raises the issue of whether the jumps detected by the above statistics are true jumps or spurious ones induced by the market microstructure noise. To address this question, we conduct the following analysis of the effects of the market microstructure noise on jump detection.

1.7.1 The Noise Structure

We now assume the observed log price at time t_j is

$$p(t_j) = p^*(t_j) + u_{t,j} \tag{1.26}$$

where $p^*(t)$ is the true continuous-time log price assumed to satisfy the conditions given in Section 1.2 above, and $u_{t,j}$ is the microstructure noise. We follow Aït-Sahalia, Mykland, and Zhang (2005); Zhang, Mykland, and Aït-Sahalia (2005), and Bandi and Russell (2006), among others, and assume that the $u_{t,j}$'s are i.i.d.; for tractability, we additionally assume the $u_{t,j}$'s are $\mathrm{N}(0, \sigma_{mn}^2)$. We discuss further below the (important) deviations from this setup. For detailed studies on the realized volatility measures under non-i.i.d. market microstructure noise, see the above literature as well as Bandi and Russell (2005), and Hansen and Lunde (2004, 2006); a comprehensive survey is Barndorff-Nielsen and Shephard (2005b).

Under these assumptions, the observed return is

$$r_{t,j} = r_{t,j}^* + \epsilon_{t,j} \tag{1.27}$$

where $r_{t,j}^*$ is the true geometric return based on $p^*(t_j)$ and $\epsilon_{t,j}$ is an MA(1) process with $\text{Var}(\epsilon_{t,j}) = 2\sigma^2_{mn}$, and $\text{Cov}(\epsilon_{t,j}, \epsilon_{t,j-1}) = -\sigma^2_{mn}$. As above, we assume equally spaced sampling, where $\delta = t_j - t_{j-1}$ denotes the sampling interval and is equal to $\frac{1}{M}$. Let σ^2_d denote the unconditional daily variance of the true returns, so, as noted by Aït-Sahalia, Mykland, and Zhang (2005),

$$\pi_{mn}(\delta) = \frac{2\sigma^2_{mn}}{\sigma^2_d \delta + 2\sigma^2_{mn}} \tag{1.28}$$

is the proportion of the variance of the return over the interval $[t_j - \delta, t_j]$ attributable to the microstructure noise.

1.7.2 Staggered Returns

Recall from Section 1.2 the definition of the **Bipower Variation**

$$BV_t = \mu_1^{-2}(\frac{M}{M-1})\sum_{j=2}^{M} |r_{t,j-1}||r_{t,j}|.$$

The effect of the microstructure noise introduced in Subsection 1.7.1 above is to induce correlation in the two adjacent returns, $r_{t,j-1}$ and $r_{t,j}$, appearing in this summation. Andersen, Bollerslev, and Diebold (2006) suggest breaking the correlation by using staggered returns as in $|r_{t,j-2}||r_{t,j}|$, or more generally as in $|r_{t,j-(1+i)}||r_{t,j}|$, where the nonnegative integer i denotes the offset. The asymptotics of various bipower measures using staggered returns are studied in depth by Barndorff-Nielsen and Shephard (2004a). Here we consider the generalized bipower measure based on staggered returns

$$BV_{i,t} = \mu_1^{-2}\left(\frac{M}{M-1-i}\right)\sum_{j=2+i}^{M} |r_{t,j-(1+i)}||r_{t,j}|, \quad i \geq 0. \tag{1.29}$$

The above reduces to the **Bipower Variation** defined in Section 1.2 if $i = 0$. Likewise, we consider the generalized tri-power quarticity measure

$$TP_{i,t} = M\mu_{4/3}^{-3}\left(\frac{M}{M-2(1+i)}\right)\sum_{j=1+2(1+i)}^{M}|r_{t,j-2(1+i)}|^{4/3}|r_{t,j-(1+i)}|^{4/3}|r_{t,j}|^{4/3}, \quad i \geq 0, \tag{1.30}$$

and the quad-power quarticity measure

$$QP_{i,t} = M\mu_{1}^{-4}\left(\frac{M}{M-3(1+i)}\right)\sum_{j=1+3(1+i)}^{M}|r_{t,j-3(1+i)}||r_{t,j-2(1+i)}||r_{t,j-(1+i)}||r_{t,j}|, \quad i \geq 0. \tag{1.31}$$

With $BV_{i,t}$, $TP_{i,t}$, $QP_{i,t}$ used in place of BV_t, TP_t, QP_t, the asymptotic theory of Section 1.3 for the various z-test statistics of Section 1.4 is exactly the same for each fixed i as $M \to \infty$.

1.7.3 Some Analytics

To analyze the relationship between the Realized Variance and the Bipower Variation in the presence of microstructure noise, we retain the simple standard Gaussian i.i.d. structure of Subsection 1.7.1 above; later we discuss the implications of deviations from this setup. With these assumptions for the noise, assuming no leverage, working conditional on the volatility process, and with the t subscript suppressed, we can write the j^{th} within-day return as

$$r_j \stackrel{\mathcal{D}}{=} (\sigma_j^2\delta + \sigma_{mn}^2)^{\frac{1}{2}}\, Z_j \tag{1.32}$$

where the Z_j's are standard Gaussian random variables and σ_j^2 is the integrated variance averaged over the sampling interval of width δ. The correlations of the Z_j's are

$$\rho_{j,k} \equiv \mathrm{Corr}(Z_j, Z_{j-k}) = \begin{cases} \frac{-\sigma_{mn}^2}{\sqrt{(\sigma_j^2\delta+\sigma_{mn}^2)(\sigma_{j-k}^2\delta+\sigma_{mn}^2)}} & |k| = 1, \\ 0 & |k| \geq 1 \end{cases} \tag{1.33}$$

All of the jump-test z-statistics displayed in Section 1.4 have the common structure of a studentized measure of discrepancy

$$z = \frac{\mathcal{D}\left(RV, BV\right)}{\sqrt{\text{Avar}\left[\mathcal{D}\left(RV, BV\right)\right]}} \tag{1.34}$$

where the numerator of the z statistic, $\mathcal{D}(\cdot,\cdot)$, is a measure of the discrepancy between the realized variance RV and the bipower variation BV, and the denominator is the square root of the asymptotic variance of the discrepancy under the Barndorff-Nielsen and Shephard theory. The asymptotic variance of $\mathcal{D}(\cdot,\cdot)$ depends upon the integrated quarticity which is estimated by either the realized tri-power quarticity or the realized quad-power quarticity.

To gain insight into the behavior of the z-statistic (1.34), we consider the conditional expectations, given the volatility process, of the numerator and the realized tri-power quarticity term for the denominator in (1.34) for the basic case where the discrepancy $\mathcal{D}(\cdot,\cdot)$ is simply the difference, as in (1.5) above. For simplicity, we ignore the small sample adjustment $M/(M-1)$ along with end effects due to lagging, and we presume the same number of terms $M = 1/\delta$ in the summations.

The relevant conditional expectation for the numerator is thus

$$\text{E}_\sigma\left(\sum_1^M r_j^2\right) - \text{E}_\sigma\left(\frac{\pi}{2}\sum_1^M |r_{j-(1+i)}||r_j|\right) \tag{1.35}$$

where, as before, $i \geq 0$ is the offset, and E_σ denotes the expectation computed conditional on the trajectory of volatility. From (1.32) we have that (1.35) is

$$\begin{aligned} &\textstyle\sum_1^M (\sigma_j^2\delta + \sigma_{mn}^2)^{\frac{1}{2}}\left[(\sigma_j^2\delta + \sigma_{mn}^2)^{\frac{1}{2}} - (\sigma_{j-(1+i)}^2\delta + \sigma_{mn}^2)^{\frac{1}{2}}\right] \quad + \\ &\textstyle\sum_1^M (\sigma_j^2\delta + \sigma_{mn}^2)^{\frac{1}{2}}(\sigma_{j-(1+i)}^2\delta + \sigma_{mn}^2)^{\frac{1}{2}}\left[\frac{2}{\pi} - g(\rho_{j,1+i})\right]\frac{\pi}{2}, \end{aligned} \tag{1.36}$$

where

$$g(\rho) = \text{E}\left(|(1-\rho^2)^{\frac{1}{2}}Z_a + \rho Z_b||Z_b|\right), \quad Z_a, Z_b \text{ independent N}(0,1), \tag{1.37}$$

is the expected value of the product of the absolute values of two correlated standard Guassian random variables. The function $g(\rho)$ is symmetric about zero with $g(0) = 2/\pi$, $g(1) = 1$, and it is easily numerically evaluated. For an explicit expression for $g(\rho)$ and its properties, see Barndorff-Nielsen and Shephard (2004a) Theorem 3 and Remark 5. Application of the mean value theorem to the square-root function $(\cdot)^{\frac{1}{2}}$ appearing in the first square bracket in (1.36) gives

$$\mathrm{E}_\sigma\left(\sum_1^M r_j^2\right) - \mathrm{E}_\sigma\left(\tfrac{\pi}{2}\sum_1^M |r_{j-(1+i)}||r_j|\right) =$$
$$\sum_1^M \tfrac{1}{2}\left[\tfrac{\sigma_j^2\delta+\sigma_{mn}^2}{\sigma_j^2\delta+\sigma_{mn}^2+\phi_j(\sigma_j^2-\sigma_{j-(1+i)}^2)\delta}\right]^{\frac{1}{2}}\left(\sigma_j^2-\sigma_{j-(1+i)}^2\right)\delta+$$
$$\sum_1^M(\sigma_j^2\delta+\sigma_{mn}^2)^{\frac{1}{2}}(\sigma_{j-(1+i)}^2\delta+\sigma_{mn}^2)^{\frac{1}{2}}\left[\tfrac{2}{\pi}-g(\rho_{j,1+i})\right]\tfrac{\pi}{2}$$

where $|\phi_j| < 1$. Hence the conditional expectation of the numerator of the z-statistic (1.34) is the sum of two terms

$$\mathrm{E}_\sigma\left(\sum_1^M r_j^2\right) - \mathrm{E}_\sigma\left(\frac{\pi}{2}\sum_1^M |r_{j-(1+i)}||r_j|\right) = A_1 + A_2 \tag{1.38}$$

where

$$A_1 = \frac{1}{M}\sum_1^M \frac{1}{2}\left[\frac{\sigma_j^2\delta+\sigma_{mn}^2}{\sigma_j^2\delta+\sigma_{mn}^2+\phi_j(\sigma_j^2-\sigma_{j-(1+i)}^2)\delta}\right]^{\frac{1}{2}}\left(\sigma_j^2-\sigma_{j-(1+i)}^2\right), \tag{1.39}$$

$$A_2 = \sum_1^M(\sigma_j^2\delta+\sigma_{mn}^2)^{\frac{1}{2}}(\sigma_{j-(1+i)}^2\delta+\sigma_{mn}^2)^{\frac{1}{2}}\left[\frac{2}{\pi}-g(\rho_{j,1+i})\right]\frac{\pi}{2}, \tag{1.40}$$

and recall $\delta = \frac{1}{M}$. For any fixed $i \geq 0$, the first term A_1 converges to zero as δ goes to 0, so it is robust with respect to the microstructure noise. As for the second term, if returns are not staggered so $i = 0$, it does not converge to 0, and the numerator is biased in the negative direction against finding jumps. In contrast, if returns are staggered, $i > 0$, then because of the i.i.d. assumption $\rho_{j,1+i} = 0$ and the term A_2 vanishes, leaving only the term A_1. It is important to keep in mind that the Gaussian assumption determines the characteristics of the function $g(\rho)$ in (1.37), and so that assumption plays a key role in our results regarding the behavior of the term A_2.

We now consider the denominator of (1.34), and we examine the case where the realized tri-power quarticity is used to estimate the asymptotic variance in (1.34). The relevant conditional expectation is

$$\mu_{4/3}^{-3}\ \mathrm{E}_\sigma\left(\sum_{j=1}^{M} |r_{j-2(1+i)}|^{4/3}|r_{j-(1+i)}|^{4/3}|r_j|^{4/3}\right). \tag{1.41}$$

Using the representation (1.32), the above becomes

$$\sum_{j=1}^{M}(\sigma_{j-2(1+i)}^2\delta + \sigma_{mn}^2)^{2/3}(\sigma_{j-(1+i)}^2\delta + \sigma_{mn}^2)^{2/3}(\sigma_j^2\delta + \sigma_{mn}^2)^{2/3}\mu_{4/3}^{-3}h(\rho_{j-(1+i),1+i}, \rho_{j,1+i}) \tag{1.42}$$

where $\rho_{j,k}$ is defined in (1.33) above, and the function h is given by

$$h(\rho_a, \rho_b) = \mathrm{E}\left(|(1 - \frac{\rho_a^2}{1-\rho_b^2})^{\frac{1}{2}}\, Z_a + \frac{\rho_a}{\sqrt{1-\rho_b^2}}\, Z_b|^{4/3} \cdot |(1-\rho_b^2)\frac{1}{2}\, Z_b + \rho_b Z_c|^{4/3} \cdot |Z_c|^{4/3}\right)$$

The function h is equivalently written as

$$h(\rho_a, \rho_b) = \mathrm{E}(|Y_a|^{4/3}|Y_b|^{4/3}|Y_c|^{4/3})$$

where Y_a, Y_b, Y_c are three standard Gaussian random variables with pairwise correlations $\mathrm{Corr}(Y_a, Y_b) = \rho_a$, $\mathrm{Corr}(Y_b, Y_c) = \rho_b$, $\mathrm{Corr}(Y_a, Y_c) = 0$. The function is easily numerically evaluated.

The expression (1.42) indicates that the effect of the microstructure noise is to inflate the realized tri-power quarticity for two reasons, although the inflation can be substantially mitigated by staggering returns. First, the noise variance σ_{mn}^2 inflates terms like $(\sigma_j^2\delta + \sigma_{mn}^2)^{\frac{1}{2}}$. Second, if there is no staggering, then adjacent returns are negatively correlated, so their magnitudes are positively correlated in (1.41), and therefore

$$\mu_{4/3}^{-3} h(\rho_{j-1,1}, \rho_{j,1}) > 1. \tag{1.43}$$

Table 1.10 shows the value of the factor $\mu_{4/3}^{-3}h$ for different values of the correlations, and it suggests the inflation of the realized tri-power quarticity can be substantial, as high as 25 to 39 percent. On the other hand, if the returns are staggered via $i \geq 1$, then the inflation due to the correlation of adjacent returns is absent.

The upshot of our analytical analysis is that without staggering, our results suggest the jump test statistics to be biased downwards, i.e., in favor of finding fewer jumps in the presence of market microstructure noise. The reason is that the numerator of the test statistic is negatively biased. At the same time, the noise inflates the estimate of the integrated quarticity used to form the estimate of scale in the denominator of (1.34). The two effects together bias the z_{TP} statistic against rejection. We expect the same logic to work for the other forms of the z statistics.

If returns are staggered, $i \geq 1$, in forming the requisite power measures (1.29)–(1.31) above, then the term A_2 is knocked out of the numerator, and $\mu_{4/3}^{-3}h = 1$. In this case, the asymptotic approximation of the Barndorff-Nielsen and Shephard theory is expected to be more accurate. Nonetheless, one must keep in mind the presumption of i.i.d. Gaussian microstructure noise. If the microstructure noise is non-Gaussian, then the decomposition (1.39)–(1.40) is unavailable, although the results are still suggestive; we defer non-Gaussian noise to future work. If the microstructure noise is Gaussian, but serially correlated such as an MA(k) process, then one can reasonably expect an appropriately long lag i for the staggering to work, but again we defer formal verification to later work.

Clearly, our separate analysis of the conditional expectations of the numerator and denominator of the z jump statistic can only provide some guidance of what to expect for the z-statistic in the presence of microstructure noise. A formal theoretical analysis of the z-statistic itself would entail complicated higher order approximations, so we turn to a Monte Carlo assessment instead.

1.7.4 Monte Carlo Assessment of the Effects of Microstructure Noise

We need to run the simulations over a plausibly wide range of values for the standard deviation σ_{mn} of the microstructure noise that appears in equation (1.26). To calibrate σ_{mn}, we use equation (1.28) with a presumed return volatility of one percent per day, so that

$$\pi_{mn}(5/390) = \frac{2\sigma_{mn}^2}{1 \cdot (5/390) + 2\sigma_{mn}^2} \tag{1.44}$$

is the proportion of the variance of the five-minute return attributable to microstructure noise for a market open 6.50 hours per day. We consider values of $\pi_{mn}(5/390)$ ranging from 0.00 to 0.50 in the increment of 0.10, which thereby determines the grid of values for σ_{mn} and also values of $\pi_{mn}(\delta)$ for all other sampling frequencies as well; see Table 1.11. The upper value of $\pi_{mn}(5/390) = 0.50$ implies that 50 percent of the variance of the five minute return is accounted for by the noise, which appears to be more than adequately high enough for an index cash or an index future like those usually found in most empirical work, such as Madhavan, Richardson, and Roomans (1997), Hasbrouck (1993), Conrad, Kaul, and Nimalendran (1991), and Conrad, Kaul, and Nimalendran (1991), among others.

The following subsections summarize the Monte Carlo findings with the market microstructure noise.

1.7.4.1 Size

Table 1.12 shows the size of the three z_{tp} statistics under different noise sizes (σ_{mn}) and sampling intervals, with i =0, 1, and 2. It is clear from this table that without staggering, the z statistics' rejection frequency is seriously downward biased at the 1-minute level, but not at the 30-minute level, since the market microstructure noise impact decreases as the sampling interval increases. Moreover, the larger the noise size, the more serious the under-rejection is, as explained in the above Section 1.7.3.

Staggering in BV_t and TP_t, one the other hand, restores the nominal size, and makes the rejection rate robust to the noise proportion. Extra lagging ($i = 2$) retains the robustness feature, but leads to a little over-rejection. Thus, to achieve the correct empirical size of the statistics, we can only stagger the returns up to the level that breaks the serial dependence of the observed returns induced by the market microstructure noise. Any extra lagging might introduce the finite-sample bias due to the longer interval covered in each return product term, making the asymptotic approximation worse off.

1.7.4.2 Power and Jump Detection

Tables 1.13 summarizes the power of the three z_{TP} statistics, and Table 1.14 shows the jump detection rate of the $z_{TP,rm,t}$ statistic, under different noise sizes and sampling intervals, with i =0, 1, and 2. Without staggering, noise size reduces the power and the jump detection rate of the statistics, due to the noise contribution of the total price variance, which has different characteristics from those of the jump part. Staggering helps to improve the jump detection rate at the high frequency levels (1-minute and 3-minute returns).

We did the same experiment for the constant volatility setup as the benchmark case. It turns out that the above features hold true under the constant volatility setup, showing the robustness of the results.

1.7.5 Empirical Data Revisited

The Monte Carlo evidence points toward the conclusion that in Section 1.6 above the jumps detected in the S&P data are bona fide jumps, instead of the market microstructure noise. We re-conduct the same calculation, using staggered returns from $i = 0$ up to $i = 2$. Here we only use the S&P 500 Index futures, because the Cash Index is made up of 500 underlying stocks without a sensible notion of the market microstructure noise. For comparability, we use the same subperiods as those in Section 1.6 above.

The empirical evidence, especially over the entire sample period April 21, 1982 – December 9, 2002, is generally consistent with the above analytical and Monte Carlo findings. Staggering suggests a slightly more important role for jumps both in terms of the number of jump days and the jump contribution in the total price variance, as exhibited in Tables 1.15 and 1.16.

1.8 Conclusion

The Monte Carlo evidence suggests that, under the arguably realistic scenarios considered here, the recently developed z-tests for jumps perform impressively and are not easily fooled. Computed on a daily basis in ratio form, with a maximum adjustment in the estimate of scale, the size and power properties are excellent, and the test statistics appear to do an outstanding job of identifying the days on which jump(s) occur. Under modelling assumptions that include Gaussian microstructure noise, the effect of market microstructure noise is to bias the tests against finding jumps. That bias can be corrected by using Andersen, Bollerslev, and Diebold (2006) technique of staggering returns sufficiently to diminish the effects of the local serial correlation induced by microstructure noise. Although any Monte Carlo study is necessarily limited, and the theoretical work is constrained by the assumptions, it nonetheless seems reasonable to make valid nonparametric claims for the reliability of the tests. That claim could be further buttressed (or possibly discredited) by additional research using more complicated data generating processes such as those with regime shifts or jumps in volatility. A good starting point for the latter would be the pure jump nonnegative OU processes introduced in Barndorff-Nielsen and Shephard (2001), with generalizations reviewed and simulation schemes presented in Todorov and Tauchen (2006). Another avenue to strengthen the nonparametric claim would be to check whether the jump tests can uncover possible serial correlation in jumps as suggested by evidence in Andersen, Bollerslev, and Huang (2007).

The Monte Carlo work also suggests that the new test statistics, while powerful, are not consistent tests. We believe that only by computing the statistics over a full sample, instead of day-by-day, can a consistent test be developed. However, our Monte Carlo work identifies a serious pitfall in this effort. Successful development requires a nonparametric way of knocking out a small sample bias that otherwise gets greatly magnified when summed over many days. We defer this task to future work.

The empirical work indicates strong evidence for jumps, where jumps account for about 4.5 to 7.0 percent of the total daily variance of the S&P Index, cash or futures. Interestingly, that evidence is obtained with a test likely biased away from finding jumps, and redoing the tests with the adjustment for microstructure noise raises the test statistics somewhat. The case for jumps thus appears compelling. The presence of jumps perforce precludes the prevalent assumption of local continuity and suggests that financial econometricians will need to enrich considerably the class of parametric models used to model very high frequency price series. The recent book by Cont and Tankov (2004) provides a powerful toolkit for creating more elaborate models. Although parametric modelling of very high frequency time series with jumps presents an intriguing statistical challenge, there is the serious issue of how economically important is the relatively small average contribution of 4.5 to 7.0 percent of total daily price variance. That question can only be addressed by examining the portfolio optimization behavior of an economic agent facing price series generated by the enhanced statistical models just discussed.

1.9 Tables

Table 1.1: Experimental Design for SV1FJ Models

μ	0.030
β_0	0.000
β_1	0.125
α_v	{ -0.137e-2, -0.100, -1.386 }
ρ	-0.620
λ	{0.014, 0.058 , 0.082 , 0.118 }
	{0.50, 1.00 , 1.50 , 2.00 }
σ_{jmp}	{0.00 ... 2.50 by 0.50 }
ntick	60
nstep	390

Table 1.2: Experimental Design for SV2F Model

μ	0.030
β_0	-1.200
β_1	0.040
β_2	1.500
α_{v1}	-0.137e-2
α_{v2}	-1.386
β_{v2}	0.250
$\rho_{p,v1}$	-0.300
$\rho_{p,v2}$	-0.300

Table 1.3: Confusion Matrices

Interval			$\lambda = 0.014$		$\lambda = 0.118$		$\lambda = 1.000$		$\lambda = 2.000$	
			(NJ)	(J)	(NJ)	(J)	(NJ)	(J)	(NJ)	(J)
1-minute	$z_{TP,t}$	(NJ)	0.980	0.020	0.981	0.019	0.989	0.011	0.995	0.005
		(J)	0.205	0.795	0.178	0.822	0.132	0.868	0.080	0.920
	$z_{TP,lm,t}$	(NJ)	0.986	0.014	0.986	0.014	0.993	0.007	0.996	0.004
		(J)	0.208	0.792	0.184	0.816	0.136	0.864	0.084	0.916
	$z_{TP,rm,t}$	(NJ)	0.988	0.012	0.989	0.011	0.994	0.006	0.997	0.003
		(J)	0.214	0.786	0.187	0.813	0.139	0.861	0.086	0.914
3-minute	$z_{TP,t}$	(NJ)	0.968	0.032	0.969	0.031	0.982	0.018	0.992	0.008
		(J)	0.273	0.727	0.261	0.739	0.198	0.802	0.125	0.875
	$z_{TP,lm,t}$	(NJ)	0.981	0.019	0.982	0.018	0.989	0.011	0.996	0.004
		(J)	0.286	0.714	0.274	0.726	0.208	0.792	0.132	0.868
	$z_{TP,rm,t}$	(NJ)	0.988	0.012	0.988	0.012	0.993	0.007	0.997	0.003
		(J)	0.292	0.708	0.285	0.715	0.219	0.781	0.141	0.859
5-minute	$z_{TP,t}$	(NJ)	0.960	0.040	0.963	0.037	0.980	0.020	0.991	0.009
		(J)	0.302	0.698	0.314	0.686	0.239	0.761	0.160	0.840
	$z_{TP,lm,t}$	(NJ)	0.977	0.023	0.978	0.022	0.988	0.012	0.994	0.006
		(J)	0.347	0.653	0.337	0.663	0.257	0.743	0.175	0.825
	$z_{TP,rm,t}$	(NJ)	0.986	0.014	0.987	0.013	0.993	0.007	0.997	0.003
		(J)	0.360	0.640	0.358	0.642	0.274	0.726	0.191	0.809
30-minute	$z_{TP,t}$	(NJ)	0.894	0.106	0.899	0.101	0.943	0.057	0.974	0.026
		(J)	0.558	0.442	0.543	0.457	0.489	0.511	0.432	0.568
	$z_{TP,lm,t}$	(NJ)	0.954	0.047	0.957	0.043	0.975	0.025	0.988	0.012
		(J)	0.620	0.380	0.641	0.359	0.590	0.410	0.540	0.460
	$z_{TP,rm,t}$	(NJ)	0.986	0.014	0.987	0.013	0.992	0.008	0.996	0.004
		(J)	0.744	0.257	0.749	0.251	0.706	0.294	0.671	0.329

Fixed parameters: level of significance = 0.01, $\sigma_{jmp} = 1.50$, $\alpha_v = -0.10$. The columns represent the jump days signaled by the statistics and the rows are the actual days on which jumps occur in the simulation.

Table 1.4: Power for Different Jump Statistics

	λ	σ_{jmp}: 0.5	1.0	1.5	2.0	2.5
$z_{TP,t}$	0.500	0.14718	0.25651	0.30640	0.33291	0.34789
	1.000	0.24060	0.42038	0.49578	0.53458	0.55727
	1.500	0.31969	0.54704	0.63264	0.67322	0.69687
	2.000	0.39227	0.64382	0.73042	0.77042	0.79278
$z_{TP,lm,t}$	0.500	0.12260	0.23538	0.28713	0.31613	0.33236
	1.000	0.21082	0.39747	0.47767	0.51931	0.54389
	1.500	0.28569	0.52367	0.61540	0.65993	0.68567
	2.000	0.35569	0.62182	0.71567	0.75967	0.78309
$z_{TP,rm,t}$	0.500	0.10493	0.21949	0.27309	0.30480	0.32216
	1.000	0.18669	0.37782	0.46264	0.50660	0.53282
	1.500	0.25767	0.50193	0.59967	0.64758	0.67436
	2.000	0.32433	0.59936	0.70044	0.74709	0.77291

Fixed parameters: level of significance=0.010, $\alpha_v = -0.100$, and 5-minute returns.

Table 1.5: Power of $z_{TP,rm,t}$ for Different Sampling Frequencies

	λ	σ_{jmp}: 0.5	1.0	1.5	2.0	2.5
1-minute	0.500	0.20420	0.29744	0.33033	0.34693	0.35651
	1.000	0.36213	0.50140	0.54920	0.57158	0.58462
	1.500	0.48840	0.64236	0.69351	0.71711	0.72993
	2.000	0.58822	0.74833	0.79222	0.81340	0.82502
3-minute	0.500	0.13633	0.24873	0.29624	0.32167	0.33607
	1.000	0.24687	0.42813	0.49971	0.53400	0.55520
	1.500	0.33969	0.56329	0.64049	0.67773	0.69902
	2.000	0.42362	0.66578	0.74324	0.77909	0.79756
5-minute	0.500	0.10493	0.21949	0.27309	0.30480	0.32216
	1.000	0.18669	0.37782	0.46264	0.50660	0.53282
	1.500	0.25767	0.50193	0.59967	0.64758	0.67436
	2.000	0.32433	0.59936	0.70044	0.74709	0.77291
30-minute	0.500	0.02500	0.06642	0.11384	0.15609	0.18787
	1.000	0.03451	0.10747	0.19082	0.25720	0.30787
	1.500	0.04102	0.13958	0.24260	0.32618	0.38818
	2.000	0.04893	0.16556	0.28342	0.37276	0.43624

Fixed parameters: level of significance = 0.010, $\alpha_v = -0.100$.

Table 1.6: SV2F Model Results, Daily

	size(5%)	size(1%)	size(0.5%)	size(0.1%)
$z_{TP,t}$	0.13589	0.07616	0.06209	0.04056
$z_{TP,l,t}$	0.12024	0.05931	0.04544	0.02664
$z_{TP,lm,t}$	0.11709	0.05642	0.04284	0.02436
$z_{TP,r,t}$	0.10171	0.04167	0.03016	0.01471
$z_{TP,rm,t}$	0.09829	0.03867	0.02747	0.01276

Fixed parameters: 5-minute returns; see Table 1.2 for the others.

Table 1.7: Rejection Frequencies, Full Sample

	z_{TP}		$z_{TP,lm}$		$z_{TP,rm}$		z_{QP}		$z_{QP,lm}$		$z_{QP,rm}$	
σ_{jmp}	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05
SV1FJ: $\alpha_v = -1.3860$, Fast Mean Reversion												
0.00	0.015	0.056	0.015	0.055	0.015	0.055	0.015	0.057	0.015	0.057	0.015	0.056
0.50	0.106	0.306	0.106	0.306	0.105	0.303	0.106	0.307	0.106	0.307	0.105	0.303
1.00	0.885	0.948	0.882	0.947	0.882	0.947	0.885	0.948	0.883	0.947	0.883	0.947
1.50	0.994	0.995	0.994	0.995	0.994	0.995	0.994	0.995	0.994	0.995	0.994	0.995
2.00	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2.50	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
SV1FJ: $\alpha_v = -0.100$, Medium Mean Reversion												
0.00	0.009	0.059	0.008	0.059	0.008	0.058	0.009	0.059	0.008	0.059	0.008	0.058
0.50	0.067	0.209	0.064	0.209	0.064	0.206	0.068	0.212	0.066	0.210	0.064	0.206
1.00	0.743	0.878	0.740	0.878	0.739	0.878	0.743	0.878	0.742	0.878	0.739	0.878
1.50	0.983	0.990	0.983	0.990	0.983	0.990	0.983	0.990	0.983	0.990	0.983	0.990
2.00	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
2.50	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
SV1FJ: $\alpha_v = -0.137e-02$, Slow Mean Reversion												
0.00	0.004	0.032	0.003	0.031	0.003	0.031	0.003	0.033	0.003	0.032	0.003	0.032
0.50	0.081	0.137	0.079	0.136	0.079	0.134	0.080	0.139	0.080	0.138	0.079	0.134
1.00	0.229	0.288	0.228	0.288	0.228	0.286	0.228	0.288	0.228	0.288	0.228	0.287
1.50	0.295	0.355	0.293	0.354	0.292	0.352	0.295	0.353	0.294	0.352	0.291	0.351
2.00	0.361	0.426	0.361	0.425	0.357	0.424	0.361	0.427	0.357	0.425	0.357	0.424
2.50	0.430	0.478	0.429	0.478	0.427	0.477	0.433	0.481	0.430	0.479	0.426	0.478

SV2F: Two Factor Continuous Model

	z_{TP}		$z_{TP,lm}$		$z_{TP,rm}$		z_{QP}		$z_{QP,lm}$		$z_{QP,rm}$	
Interval	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05
30-min	0.495	0.670	0.475	0.658	0.452	0.639	0.548	0.716	0.534	0.696	0.519	0.681
5-min	0.084	0.200	0.079	0.195	0.074	0.188	0.089	0.206	0.084	0.204	0.079	0.198
3-min	0.036	0.129	0.035	0.127	0.035	0.124	0.039	0.132	0.038	0.128	0.038	0.127
1-min	0.045	0.124	0.044	0.123	0.044	0.119	0.045	0.125	0.044	0.124	0.043	0.122

Fixed parameters: 5-minute returns and $\lambda = 0.014$ for **SV1FJ** model.

Table 1.8: Proportion of Identified Jumps Days

level of significance	0.500	0.950	0.990	0.995	0.999
	S&P 500 Cash Index (04/21/1997 – 10/22/2002)				
$z_{TP,t}$	0.74215	0.28488	0.18335	0.14609	0.10299
$z_{TP,l,t}$	0.74215	0.26150	0.14536	0.12199	0.07159
$z_{TP,lm,t}$	0.74215	0.24543	0.12929	0.09715	0.05698
$z_{TP,r,t}$	0.74215	0.23886	0.11907	0.08839	0.04383
$z_{TP,rm,t}$	0.74215	0.22060	0.09204	0.06866	0.03214
	S&P 500 Index Futures (04/21/1997 – 10/22/2002)				
$z_{TP,t}$	0.66108	0.20918	0.11152	0.09402	0.05175
$z_{TP,l,t}$	0.66108	0.18440	0.09329	0.06851	0.03717
$z_{TP,lm,t}$	0.66108	0.17566	0.07726	0.05831	0.03061
$z_{TP,r,t}$	0.66108	0.16618	0.06778	0.04227	0.02041
$z_{TP,rm,t}$	0.66108	0.14942	0.05758	0.03499	0.01603
	S&P 500 Index Futures (04/21/1982 – 12/09/2002)				
$z_{TP,t}$	0.64886	0.20960	0.11705	0.09583	0.05997
$z_{TP,l,t}$	0.64886	0.18801	0.09526	0.07231	0.04319
$z_{TP,lm,t}$	0.64886	0.17875	0.08427	0.06479	0.03779
$z_{TP,r,t}$	0.64886	0.16815	0.07038	0.05110	0.02680
$z_{TP,rm,t}$	0.64886	0.15523	0.06190	0.04223	0.02140

Table 1.9: Summary of RV, BV and RJ

Statistics	RV	BV	$RV - BV$	RJ
	S&P 500 Cash Index (04/21/1997 – 10/22/2002)			
Sample Mean	1.26702	1.18084	0.08618	0.07328
Std of Mean	0.04086	0.03746	0.00340	0.00294
Full-Sample Statistics	1734.55618	1616.57673	117.97945	0.06802
	S&P 500 Index Futures (04/21/1997 – 10/22/2002)			
Sample Mean	2.10718	2.01193	0.09525	0.04445
Std. of Mean	0.06690	0.06266	0.00424	0.00279
Full-Sample Statistics	2891.05330	2760.37224	130.68106	0.04520
	S&P 500 Index Futures (04/21/1982 – 12/09/2002)			
Sample Mean	1.63393	1.46074	0.17319	0.04562
Std. of Mean	0.21083	0.12375	0.08708	0.00152
Full-Sample Statistics	8473.55466	7575.38272	898.17194	0.10600

Table 1.10: Values of $\mu_{4/3}^{-3} h(\rho_a, \rho_b)$

ρ_a \ ρ_b	-0.50	-0.40	-0.30	-0.20	-0.10	0.00
-0.50	1.39	1.32	1.27	1.23	1.21	1.21
-0.40	1.32	1.25	1.19	1.15	1.13	1.13
-0.30	1.27	1.19	1.13	1.08	1.07	1.06
-0.20	1.23	1.15	1.08	1.04	1.02	1.02
-0.10	1.21	1.13	1.07	1.02	1.01	1.00
0.00	1.21	1.13	1.06	1.02	1.00	1.00

This table is computed by numerical integration using Gauss-Hermite Quadrature.

Table 1.11: Proportions of Noise Contribution under Different Sampling Intervals in Monte Carlo

Interval	π_{mn}					
1 minute	0.000	0.357	0.556	0.682	0.769	0.833
3 minute	0.000	0.156	0.294	0.417	0.526	0.625
5 minute	0.000	0.100	0.200	0.300	0.400	0.500
30 minute	0.000	0.018	0.040	0.067	0.100	0.143
σ_{mn}:	0.000	0.027	0.040	0.052	0.065	0.080

Table 1.12: Size of Different Jump Statistics under Market Microstructure Noise

Interval	σ_{mn}:	0.000	0.027	0.040	0.052	0.065	0.080
			(i = 0)				
1-minute	$z_{TP,t}$	0.020	0.007	0.002	0.001	0.000	0.000
	$z_{TP,lm,t}$	0.014	0.005	0.002	0.000	0.000	0.000
	$z_{TP,rm,t}$	0.012	0.004	0.001	0.000	0.000	0.000
3-minute	$z_{TP,t}$	0.032	0.027	0.020	0.014	0.009	0.005
	$z_{TP,lm,t}$	0.019	0.017	0.013	0.008	0.005	0.003
	$z_{TP,rm,t}$	0.012	0.011	0.008	0.005	0.003	0.002
5-minute	$z_{TP,t}$	0.041	0.038	0.034	0.029	0.022	0.017
	$z_{TP,lm,t}$	0.023	0.022	0.019	0.015	0.012	0.009
	$z_{TP,rm,t}$	0.014	0.014	0.011	0.009	0.007	0.005
30-minute	$z_{TP,t}$	0.107	0.107	0.107	0.107	0.107	0.107
	$z_{TP,lm,t}$	0.047	0.047	0.047	0.046	0.046	0.046
	$z_{TP,rm,t}$	0.014	0.015	0.015	0.015	0.014	0.014
			(i = 1)				
1-minute	$z_{TP,t}$	0.021	0.020	0.021	0.021	0.022	0.022
	$z_{TP,lm,t}$	0.015	0.015	0.015	0.015	0.015	0.015
	$z_{TP,rm,t}$	0.012	0.012	0.011	0.012	0.012	0.012
3-minute	$z_{TP,t}$	0.031	0.034	0.033	0.032	0.032	0.032
	$z_{TP,lm,t}$	0.020	0.020	0.021	0.020	0.019	0.019
	$z_{TP,rm,t}$	0.014	0.014	0.014	0.013	0.013	0.013
5-minute	$z_{TP,t}$	0.042	0.041	0.041	0.042	0.041	0.041
	$z_{TP,lm,t}$	0.024	0.023	0.024	0.024	0.024	0.022
	$z_{TP,rm,t}$	0.014	0.014	0.015	0.014	0.014	0.014
30-minute	$z_{TP,t}$	0.129	0.128	0.128	0.127	0.127	0.126
	$z_{TP,lm,t}$	0.058	0.057	0.058	0.059	0.058	0.057
	$z_{TP,rm,t}$	0.021	0.020	0.020	0.020	0.020	0.020
			(i = 2)				
1-minute	$z_{TP,t}$	0.022	0.021	0.021	0.022	0.023	0.023
	$z_{TP,lm,t}$	0.016	0.015	0.015	0.016	0.016	0.017
	$z_{TP,rm,t}$	0.013	0.011	0.011	0.012	0.013	0.013
3-minute	$z_{TP,t}$	0.034	0.035	0.034	0.035	0.035	0.035
	$z_{TP,lm,t}$	0.022	0.021	0.021	0.022	0.021	0.022
	$z_{TP,rm,t}$	0.015	0.014	0.014	0.015	0.015	0.015
5-minute	$z_{TP,t}$	0.044	0.042	0.043	0.043	0.043	0.042
	$z_{TP,lm,t}$	0.025	0.024	0.024	0.024	0.024	0.024
	$z_{TP,rm,t}$	0.016	0.014	0.014	0.015	0.015	0.015
30-minute	$z_{TP,t}$	0.144	0.145	0.145	0.146	0.146	0.145
	$z_{TP,lm,t}$	0.070	0.069	0.069	0.068	0.068	0.068
	$z_{TP,rm,t}$	0.025	0.026	0.026	0.025	0.025	0.026

Fixed parameters: level of significance = 0.010, $\alpha_v = -0.100$.

Table 1.13: Rejection Frequencies of Different Jump Statistics under Market Microstructure Noise

Interval	σ_{mn}:	0.000	0.027	0.040	0.052	0.065	0.080
			(i = 0)				
1-minute	$z_{TP,t}$	0.032	0.018	0.012	0.010	0.008	0.007
	$z_{TP,lm,t}$	0.026	0.016	0.011	0.009	0.008	0.007
	$z_{TP,rm,t}$	0.023	0.015	0.011	0.009	0.008	0.006
3-minute	$z_{TP,t}$	0.042	0.036	0.030	0.023	0.017	0.013
	$z_{TP,lm,t}$	0.029	0.027	0.022	0.017	0.013	0.010
	$z_{TP,rm,t}$	0.022	0.021	0.018	0.014	0.011	0.009
5-minute	$z_{TP,t}$	0.050	0.048	0.043	0.037	0.030	0.025
	$z_{TP,lm,t}$	0.033	0.032	0.028	0.024	0.020	0.017
	$z_{TP,rm,t}$	0.023	0.023	0.020	0.018	0.015	0.013
30-minute	$z_{TP,t}$	0.112	0.113	0.113	0.112	0.112	0.111
	$z_{TP,lm,t}$	0.052	0.052	0.052	0.051	0.050	0.050
	$z_{TP,rm,t}$	0.018	0.019	0.019	0.018	0.018	0.018
			(i = 1)				
1-minute	$z_{TP,t}$	0.032	0.031	0.031	0.031	0.031	0.030
	$z_{TP,lm,t}$	0.026	0.026	0.025	0.025	0.025	0.024
	$z_{TP,rm,t}$	0.023	0.022	0.022	0.021	0.021	0.020
3-minute	$z_{TP,t}$	0.042	0.044	0.043	0.042	0.041	0.040
	$z_{TP,lm,t}$	0.030	0.031	0.030	0.029	0.028	0.027
	$z_{TP,rm,t}$	0.024	0.024	0.024	0.023	0.022	0.021
5-minute	$z_{TP,t}$	0.052	0.051	0.051	0.051	0.049	0.049
	$z_{TP,lm,t}$	0.033	0.033	0.033	0.033	0.032	0.030
	$z_{TP,rm,t}$	0.024	0.023	0.024	0.022	0.022	0.021
30-minute	$z_{TP,t}$	0.134	0.133	0.133	0.132	0.132	0.131
	$z_{TP,lm,t}$	0.063	0.062	0.063	0.063	0.062	0.061
	$z_{TP,rm,t}$	0.024	0.024	0.024	0.024	0.023	0.023
			(i = 2)				
1-minute	$z_{TP,t}$	0.034	0.032	0.031	0.031	0.032	0.032
	$z_{TP,lm,t}$	0.027	0.026	0.025	0.025	0.025	0.025
	$z_{TP,rm,t}$	0.024	0.022	0.021	0.021	0.022	0.022
3-minute	$z_{TP,t}$	0.044	0.045	0.043	0.044	0.044	0.044
	$z_{TP,lm,t}$	0.032	0.031	0.031	0.031	0.030	0.030
	$z_{TP,rm,t}$	0.025	0.024	0.024	0.024	0.024	0.023
5-minute	$z_{TP,t}$	0.053	0.051	0.052	0.051	0.051	0.050
	$z_{TP,lm,t}$	0.035	0.033	0.033	0.032	0.032	0.032
	$z_{TP,rm,t}$	0.025	0.023	0.023	0.023	0.023	0.023
30-minute	$z_{TP,t}$	0.150	0.151	0.150	0.151	0.151	0.150
	$z_{TP,lm,t}$	0.074	0.074	0.073	0.073	0.072	0.073
	$z_{TP,rm,t}$	0.029	0.029	0.029	0.029	0.028	0.029

Fixed parameters: level of significance = 0.010, $\alpha_v = -0.100$, $\sigma_{jmp} = 1.50$, $\lambda = 0.014$.

Table 1.14: Confusion Matrices, Large Rare Jumps and Market Microstructure Noise ($z_{TP,rm,t}$)

Interval		$\sigma_{mn} = 0.000$		$\sigma_{mn} = 0.027$		$\sigma_{mn} = 0.052$		$\sigma_{mn} = 0.080$	
				(i = 0)					
		(NJ)	(J)	(NJ)	(J)	(NJ)	(J)	(NJ)	(J)
1-minute	(NJ)	0.988	0.012	0.996	0.004	1.000	0.000	1.000	0.000
	(J)	0.214	0.786	0.260	0.740	0.393	0.607	0.558	0.442
3-minute	(NJ)	0.988	0.012	0.989	0.011	0.995	0.005	0.998	0.002
	(J)	0.292	0.708	0.308	0.692	0.377	0.623	0.461	0.539
5-minute	(NJ)	0.986	0.014	0.986	0.014	0.991	0.009	0.995	0.005
	(J)	0.360	0.640	0.354	0.646	0.396	0.604	0.503	0.497
30-minute	(NJ)	0.986	0.014	0.985	0.015	0.985	0.015	0.986	0.014
	(J)	0.744	0.257	0.724	0.276	0.734	0.266	0.740	0.260
				(i = 1)					
1-minute	(NJ)	0.988	0.012	0.989	0.011	0.988	0.012	0.988	0.012
	(J)	0.224	0.776	0.253	0.747	0.321	0.679	0.432	0.568
3-minute	(NJ)	0.986	0.014	0.986	0.014	0.987	0.013	0.988	0.012
	(J)	0.286	0.714	0.305	0.695	0.341	0.659	0.416	0.584
5-minute	(NJ)	0.986	0.014	0.986	0.014	0.986	0.014	0.986	0.014
	(J)	0.344	0.656	0.370	0.630	0.422	0.578	0.481	0.519
30-minute	(NJ)	0.980	0.020	0.980	0.020	0.980	0.020	0.981	0.019
	(J)	0.708	0.292	0.721	0.279	0.718	0.282	0.750	0.250
				(i = 2)					
1-minute	(NJ)	0.988	0.012	0.989	0.011	0.988	0.012	0.987	0.013
	(J)	0.221	0.779	0.266	0.734	0.331	0.669	0.409	0.591
3-minute	(NJ)	0.985	0.015	0.986	0.014	0.985	0.015	0.985	0.015
	(J)	0.286	0.714	0.325	0.675	0.383	0.617	0.442	0.558
5-minute	(NJ)	0.984	0.016	0.986	0.014	0.985	0.015	0.985	0.015
	(J)	0.360	0.640	0.390	0.610	0.435	0.565	0.490	0.510
30-minute	(NJ)	0.975	0.025	0.974	0.026	0.975	0.025	0.974	0.026
	(J)	0.737	0.263	0.730	0.270	0.737	0.263	0.750	0.250

Fixed parameters: level of significance = 0.010, $\alpha_v = -0.100$, $\sigma_{jmp} = 1.50$, $\lambda = 0.014$.

Table 1.15: Proportion of Days Identified as Jumps by the Daily Statistics

level of significance	0.500	0.950	0.990	0.995	0.999
			S&P 500 Index Futures		
			(04/21/1982 – 04/18/1997)		
			(i = 0)		
$z_{TP,t}$	0.64384	0.20941	0.11925	0.09651	0.06293
$z_{TP,lm,t}$	0.64384	0.17980	0.08699	0.06716	0.04019
$z_{TP,rm,t}$	0.64384	0.15732	0.06346	0.04469	0.02327
			(i = 1)		
$z_{TP,t}$	0.68112	0.25754	0.15415	0.12850	0.08726
$z_{TP,lm,t}$	0.68112	0.22263	0.11687	0.09228	0.05500
$z_{TP,rm,t}$	0.68112	0.19751	0.08858	0.06319	0.03411
			(i = 2)		
$z_{TP,t}$	0.71549	0.29799	0.18879	0.16288	0.11528
$z_{TP,lm,t}$	0.71549	0.25939	0.14728	0.11819	0.07377
$z_{TP,rm,t}$	0.71549	0.23559	0.11396	0.08726	0.04707
			(04/21/1997 – 10/22/2002)		
			(i = 0)		
$z_{TP,t}$	0.66108	0.20918	0.11152	0.09402	0.05175
$z_{TP,lm,t}$	0.66108	0.17566	0.07726	0.05831	0.03061
$z_{TP,rm,t}$	0.66108	0.14942	0.05758	0.03499	0.01603
			(i = 1)		
$z_{TP,t}$	0.62026	0.20408	0.11953	0.09184	0.06195
$z_{TP,lm,t}$	0.62026	0.17055	0.08163	0.06341	0.03134
$z_{TP,rm,t}$	0.62026	0.15452	0.05977	0.03790	0.02332
			(i = 2)		
$z_{TP,t}$	0.60714	0.19096	0.11006	0.09111	0.06706
$z_{TP,lm,t}$	0.60714	0.16327	0.08309	0.06924	0.04519
$z_{TP,rm,t}$	0.60714	0.14213	0.06560	0.05248	0.02551
			(04/21/1982 – 12/09/2002)		
			(i = 0)		
$z_{TP,t}$	0.64886	0.20960	0.11705	0.09583	0.05997
$z_{TP,lm,t}$	0.64886	0.17875	0.08427	0.06479	0.03779
$z_{TP,rm,t}$	0.64886	0.15523	0.06190	0.04223	0.02140
			(i = 1)		
$z_{TP,t}$	0.66506	0.24277	0.14462	0.11859	0.08060
$z_{TP,lm,t}$	0.66506	0.20845	0.10740	0.08465	0.04859
$z_{TP,rm,t}$	0.66506	0.18569	0.08099	0.05650	0.03105
			(i = 2)		
$z_{TP,t}$	0.68608	0.26938	0.16776	0.14366	0.10220
$z_{TP,lm,t}$	0.68608	0.23351	0.13016	0.10490	0.06595
$z_{TP,rm,t}$	0.68608	0.21037	0.10085	0.07790	0.04126

Table 1.16: Summary of RV, BV and RJ

Statistics	RV	BV	$RV - BV$	RJ
		S&P 500 Index Futures		
		(04/21/1982 – 04/18/1997)		
		(i = 0)		
Sample Mean	1.45438	1.25291	0.20146	0.04601
Std of Mean	0.28803	0.16804	0.12000	0.00182
Full-Sample Statistics	5500.46066	4738.52390	761.93676	0.13852
		(i = 1)		
Sample Mean	1.45438	1.26816	0.18622	0.06017
Std of Mean	0.28803	0.20411	0.08393	0.00189
Full-Sample Statistics	5500.46066	4796.18426	704.27640	0.12804
		(i = 2)		
Sample Mean	1.45438	1.24790	0.20647	0.07269
Std of Mean	0.28803	0.19699	0.09105	0.00198
Full-Sample Statistics	5500.46066	4719.57255	780.88811	0.14197
		(04/21/1997 – 10/22/2002)		
		(i = 0)		
Sample Mean	2.10718	2.01193	0.09525	0.04445
Std of Mean	0.06690	0.06266	0.00424	0.00279
Full-Sample Statistics	2891.05330	2760.37224	130.68106	0.04520
		(i = 1)		
Sample Mean	2.10718	2.01341	0.09378	0.04095
Std of Mean	0.06690	0.06133	0.00557	0.00302
Full-Sample Statistics	2891.05330	2762.39293	128.66038	0.04450
		(i = 2)		
Sample Mean	2.10718	2.02129	0.08589	0.03556
Std of Mean	0.06690	0.06211	0.00479	0.00311
Full-Sample Statistics	2891.05330	2773.21121	117.84209	0.04076
		(04/21/1982 – 12/09/2002)		
		(i = 0)		
Sample Mean	1.63393	1.46074	0.17319	0.04562
Std of Mean	0.21083	0.12375	0.08708	0.00152
Full-Sample Statistics	8473.55466	7575.38272	898.17194	0.10600
		(i = 1)		
Sample Mean	1.63393	1.47225	0.16168	0.05500
Std of Mean	0.21083	0.14980	0.06103	0.00160
Full-Sample Statistics	8473.55466	7635.08331	838.47135	0.09895
		(i = 2)		
Sample Mean	1.63393	1.45973	0.17420	0.06266
Std of Mean	0.21083	0.14467	0.06616	0.00168
Full-Sample Statistics	8473.55466	7570.17627	903.37839	0.10661

1.10 Figures

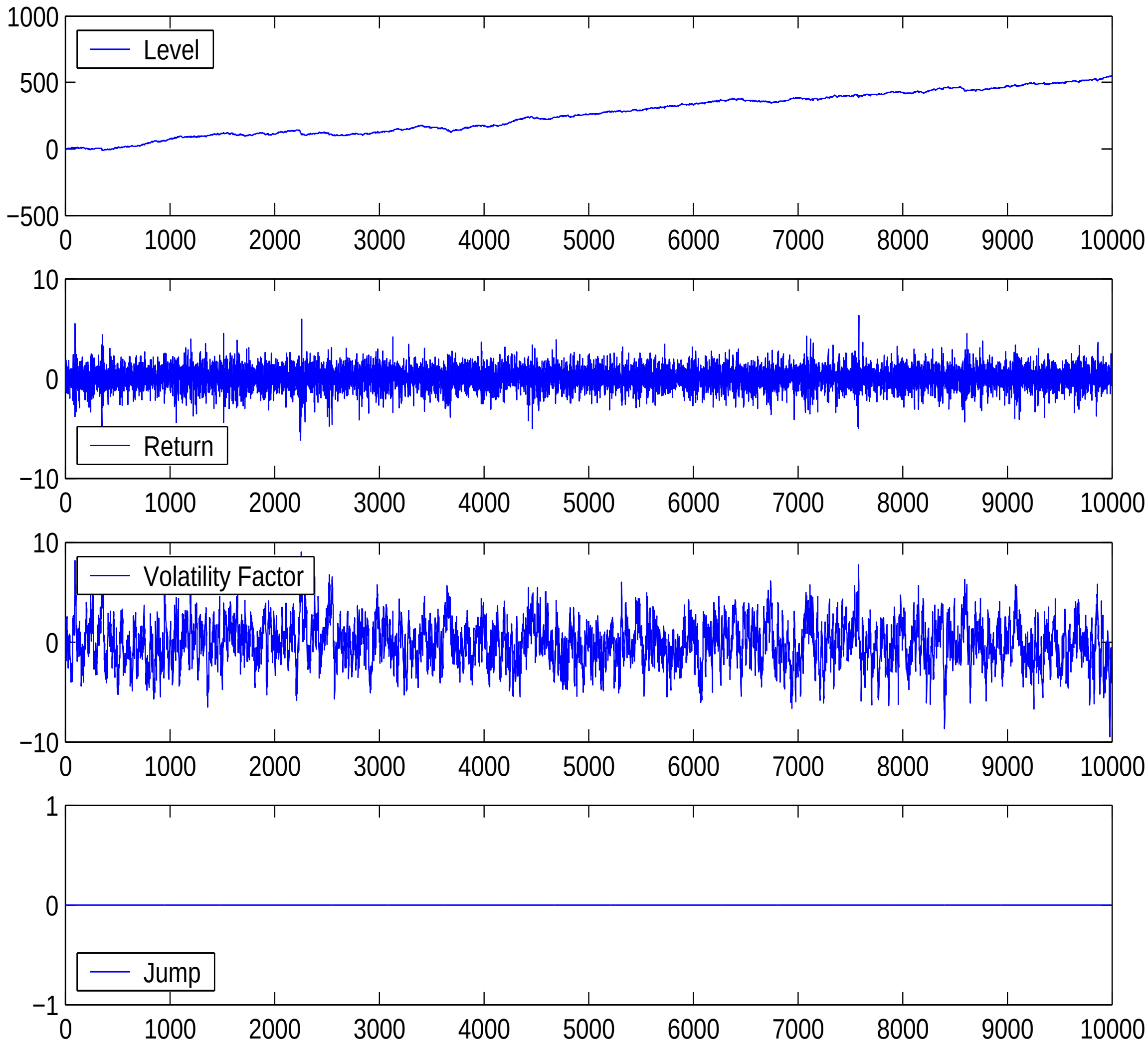

Figure 1.1: Simulated Realization from the SV1F Model, Daily Frequency, 10,000 Days, Using 5-minute Returns under Medium Mean Reversion ($\alpha_v = -0.100$)

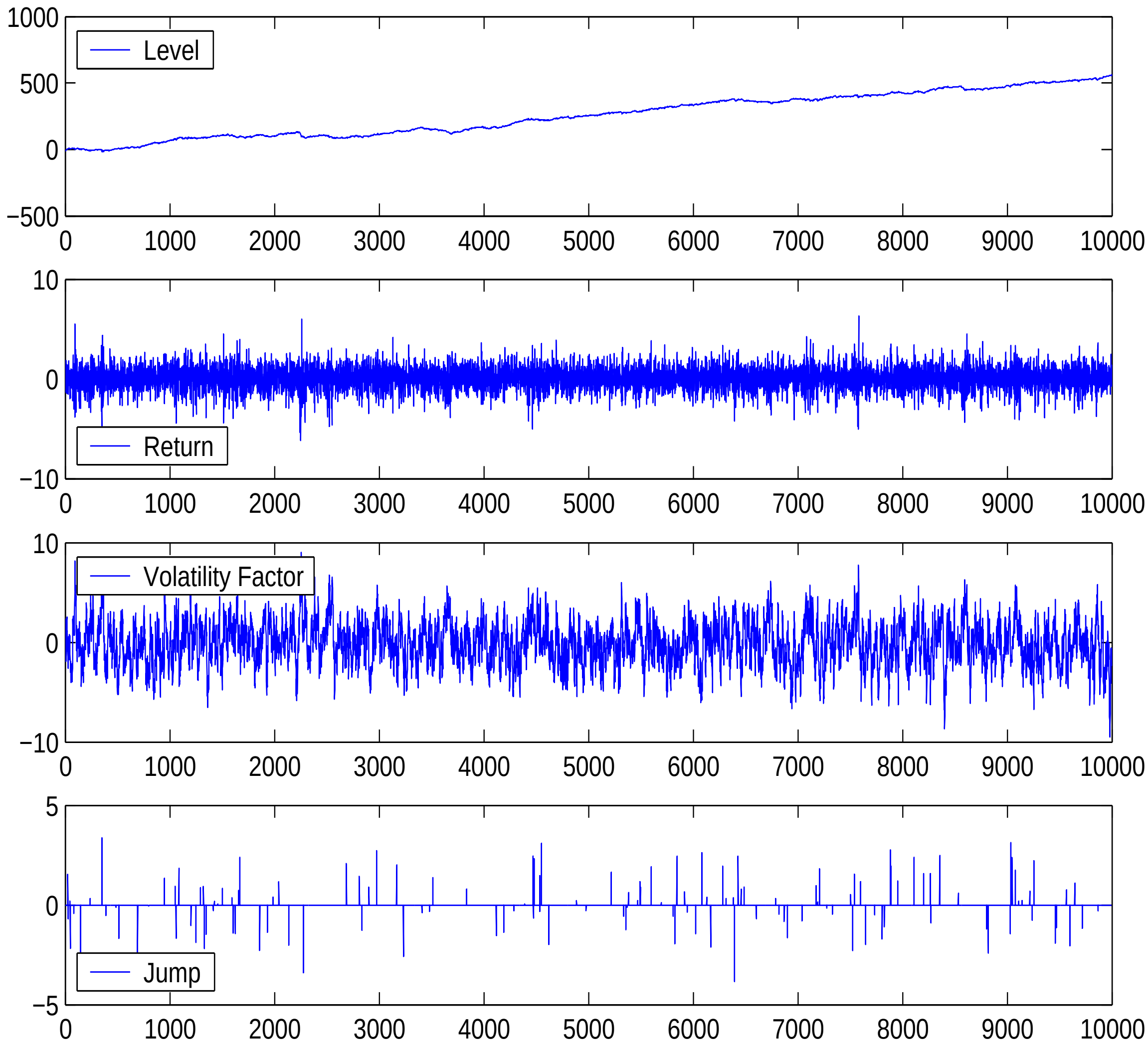

Figure 1.2: Simulated Realization from the SV1FJ Model, Daily Frequency, 10,000 Days, Using 5-minute Returns under Medium Mean Reversion ($\alpha_v = -0.100$), $\sigma_{jmp} = 1.50$, and $\lambda = 0.014$

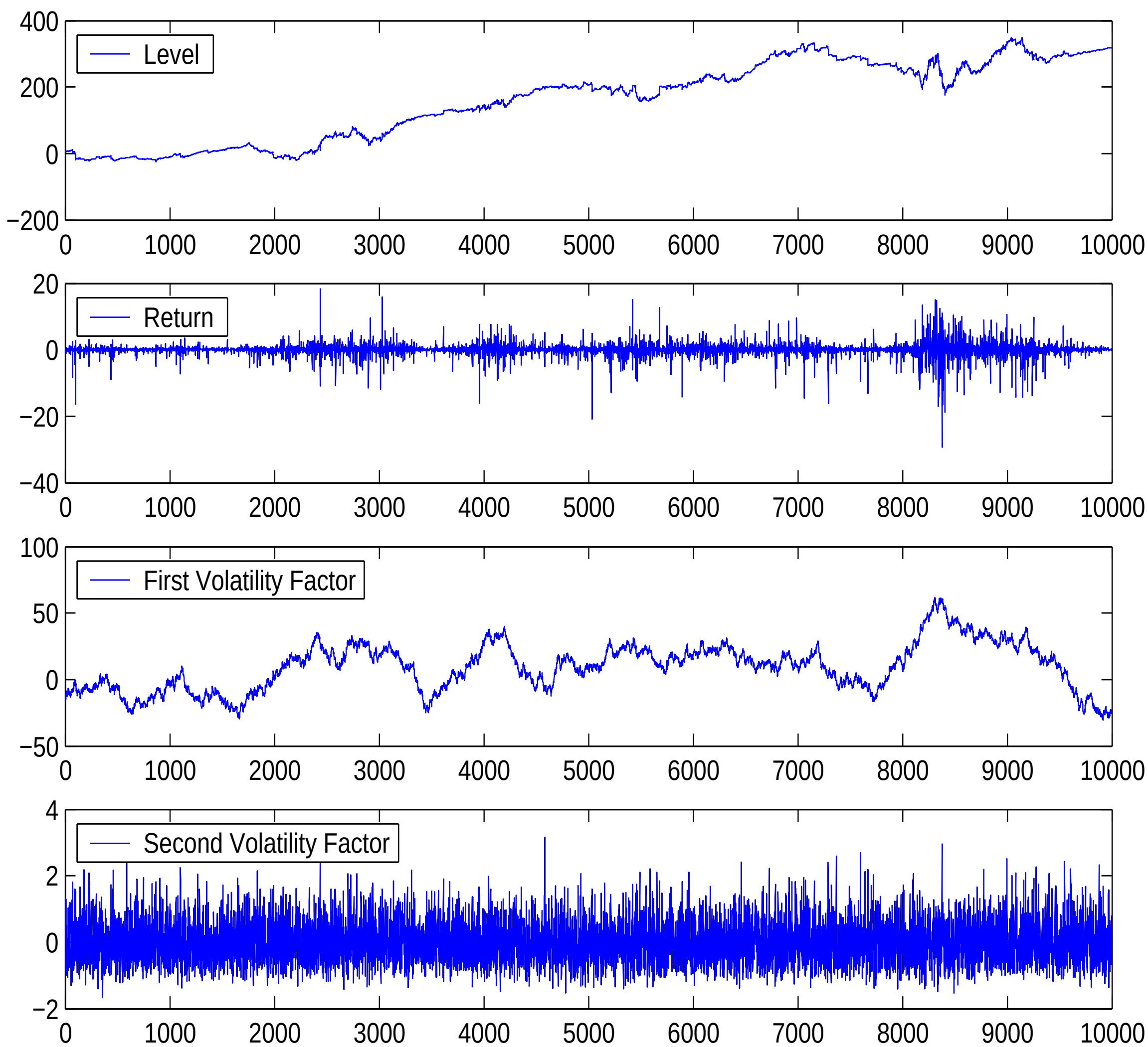

Figure 1.3: Simulated Realization from the SV2F Model, Daily Frequency, 10,000 Days, Using 5-minute Returns

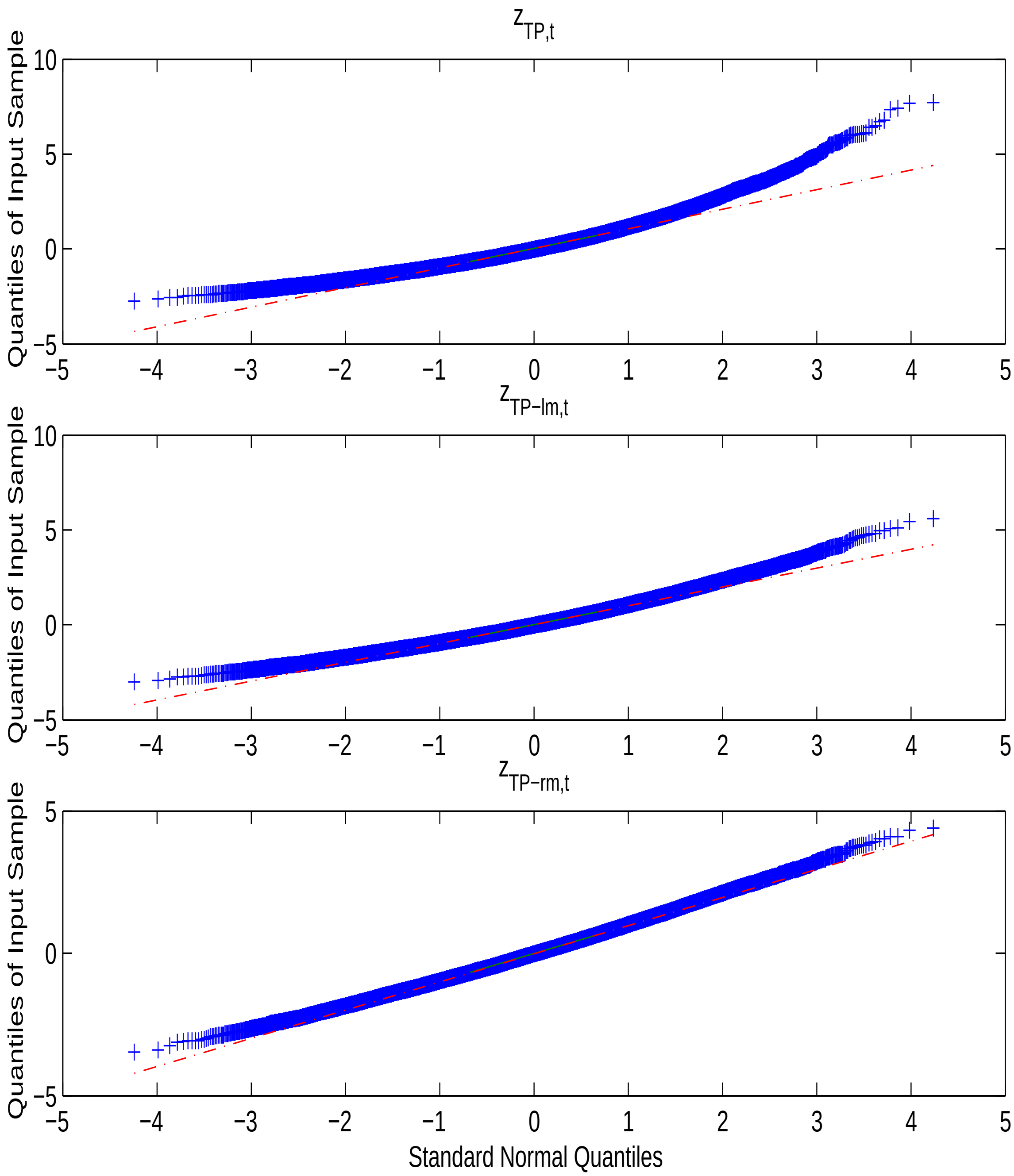

Figure 1.4: QQ Plots, z_{TP} Daily Statistics, 45,000 Days, Using 5-minute Returns under Medium Mean Reversion ($\alpha_v = -0.100$)

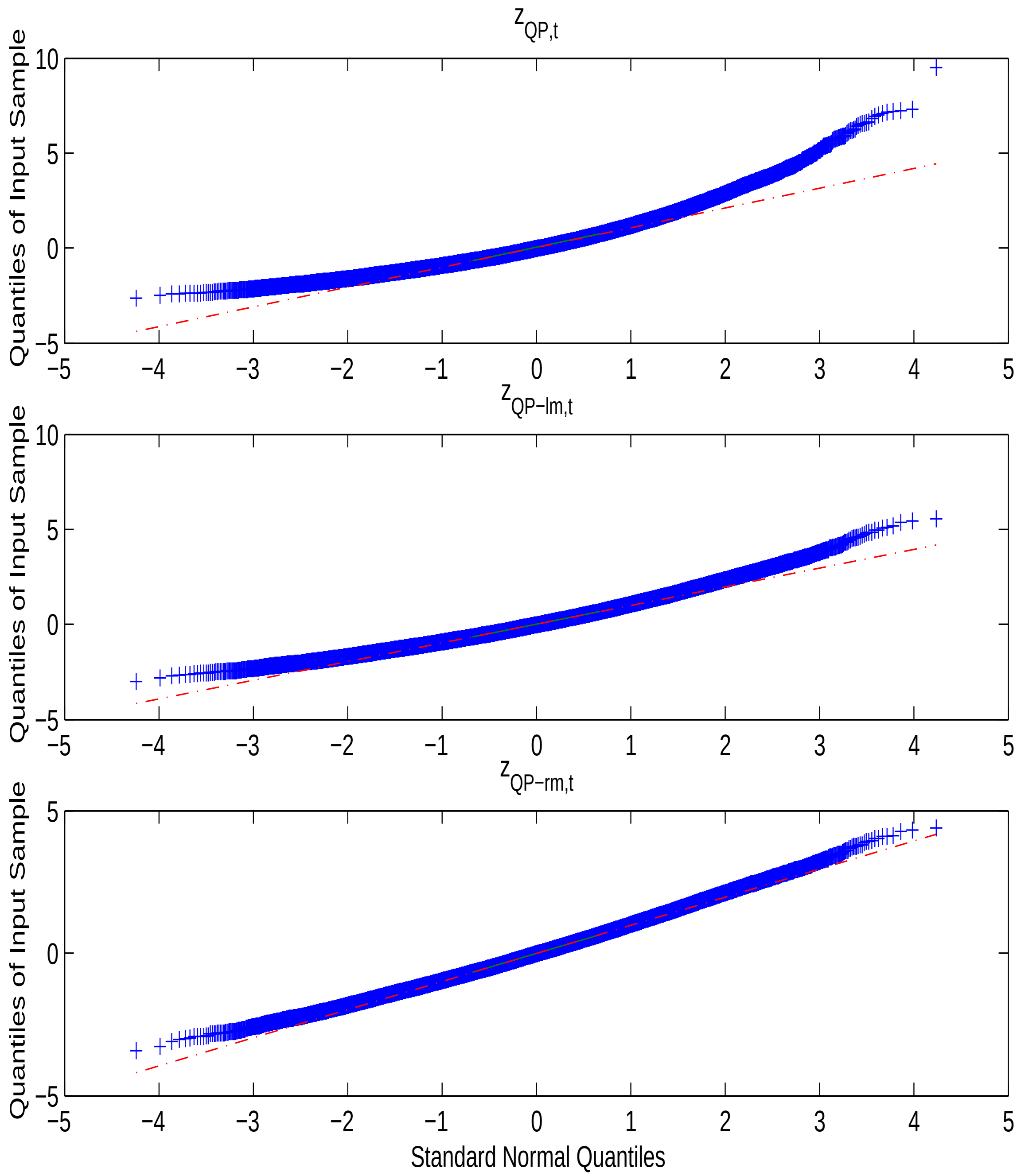

Figure 1.5: QQ Plots, z_{QP} Daily Statistics, 45,000 Days, Using 5-minute Returns under Medium Mean Reversion ($\alpha_v = -0.100$)

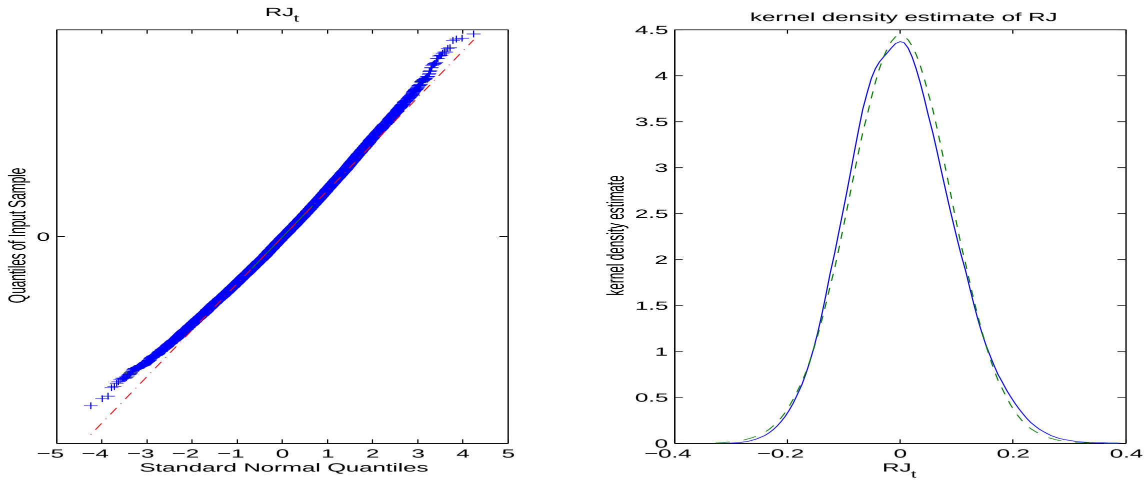

Figure 1.6: QQ Plot and Kernel Density Plot for RJ_t Daily Statistic, 45,000 Days, Using 5-minute Returns under Medium Mean Reversion ($\alpha_v = -0.100$)

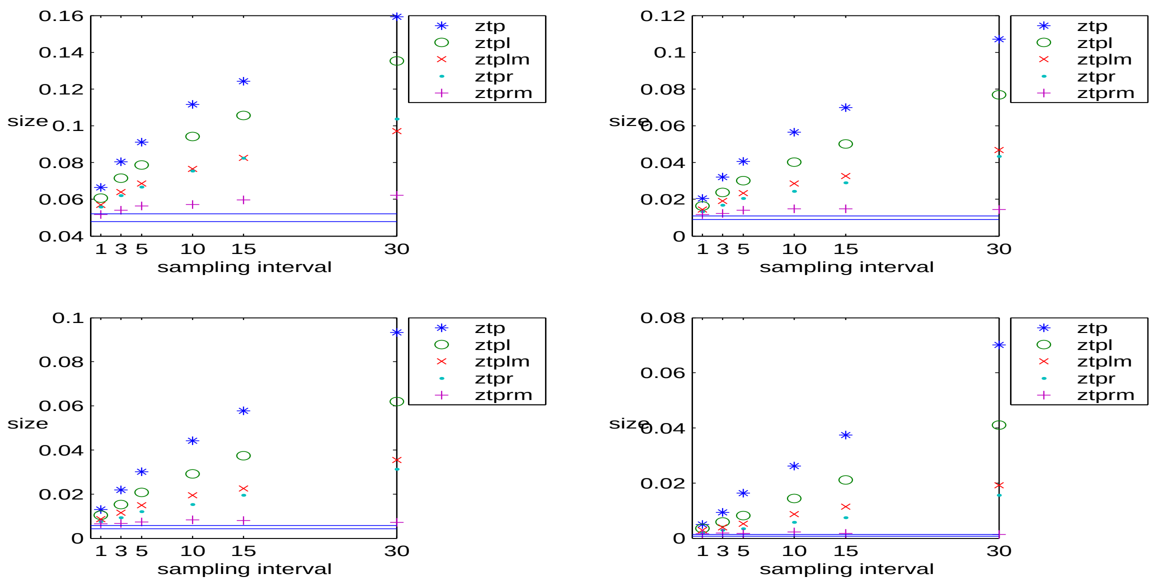

Figure 1.7: Size of the Jump Statistics over Different Sampling Intervals under the Medium Mean Reversion (α_v=-0.100)

The nominal size is 0.05 for the upper left subplot, 0.005 for the lower left subplot, 0.01 for the upper right subplot, and 0.001 for the lower right subplot. The two horizontal lines are the 95% Monte Carlo confidence bands corresponding to the nominal size. The sample size is 45,000 days and the return horizon is 5 minutes.

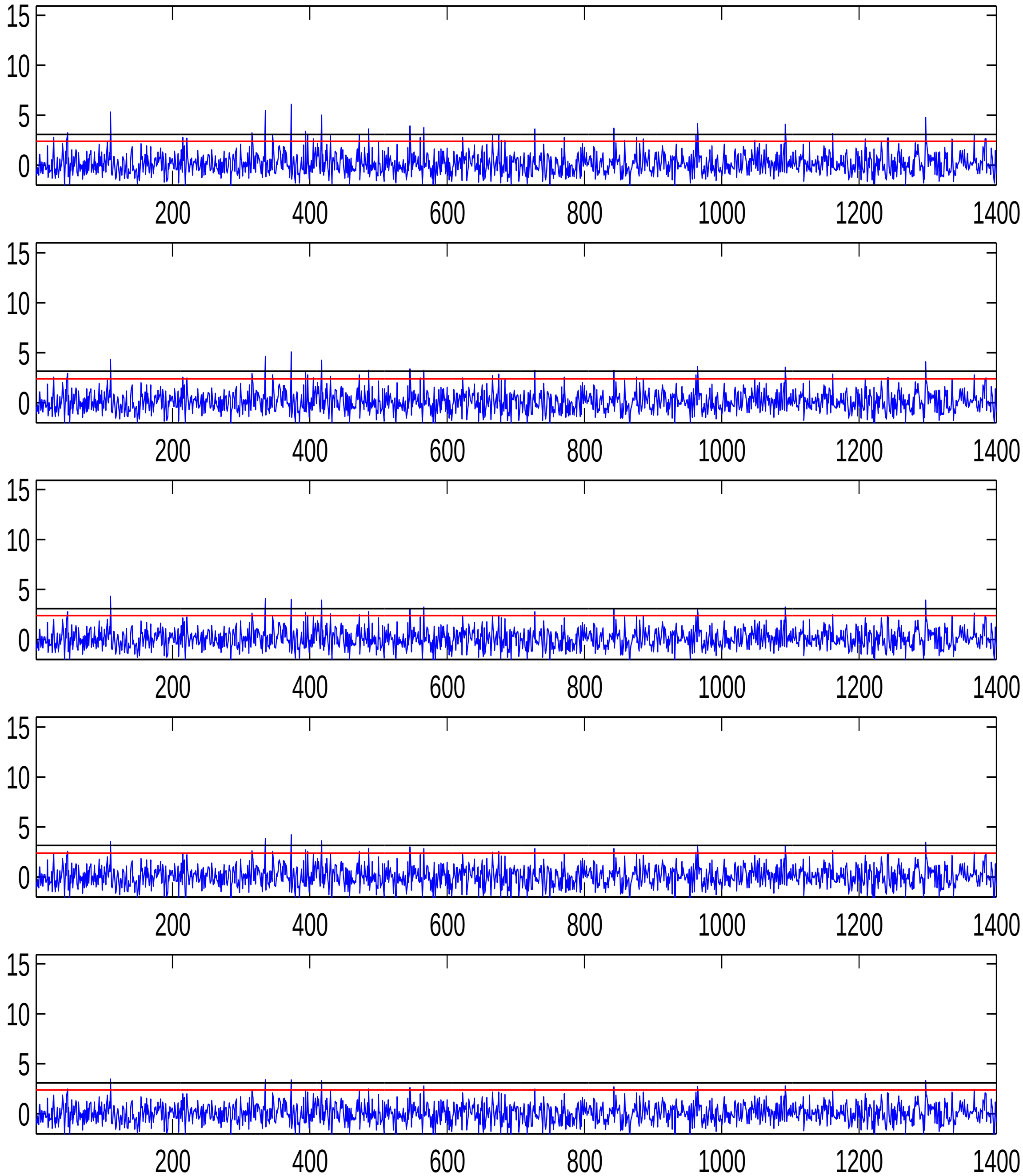

Figure 1.8: Simulated Time Series of $z_{TP,t}$'s under the SV1F Model
The five panels show simulations of the basic statistic, the log version, the max-log version, the ratio version and the max-ratio version for $\sigma_{jmp} = 0$ under medium mean reversion. The horizontal lines are the upper 0.99 and 0.999 critical points of the standard Gaussian distribution. The sample size is 1400 days and the return horizon is 5 minutes.

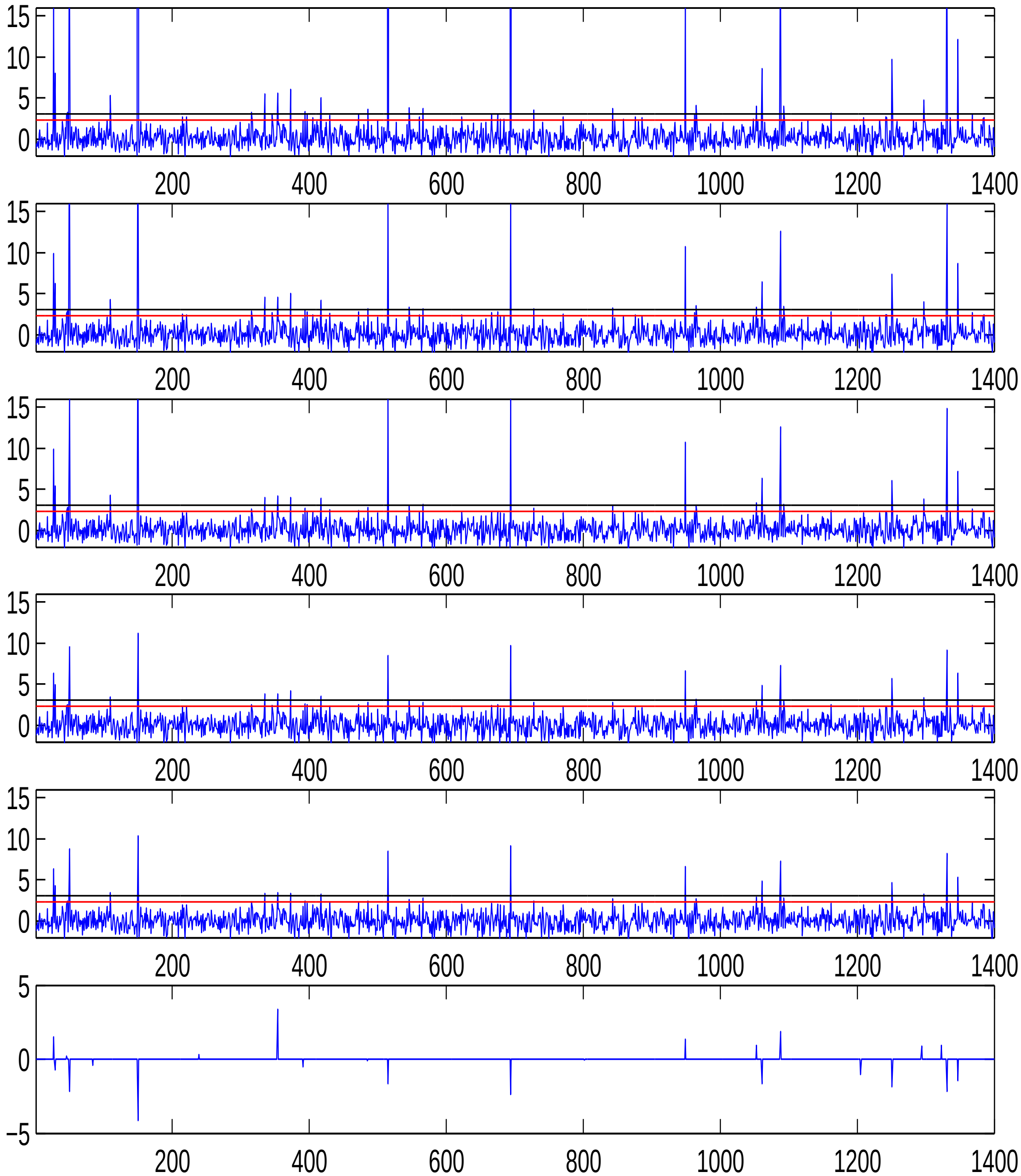

Figure 1.9: Simulated Time Series of $z_{TP,t}$'s under the SV1FJ Model
The five panels show simulations of the basic statistic, the log version, the max-log version, the ratio version and the max-ratio version for $\sigma_{jmp} = 0$ and $\lambda = 0.014$ under medium mean reversion. The horizontal lines are the upper 0.99 and 0.999 critical points of the standard Gaussian distribution. The bottom panel shows the jumps in the simulated realization. The sample size is 1400 days and the return horizon is 5 minutes.

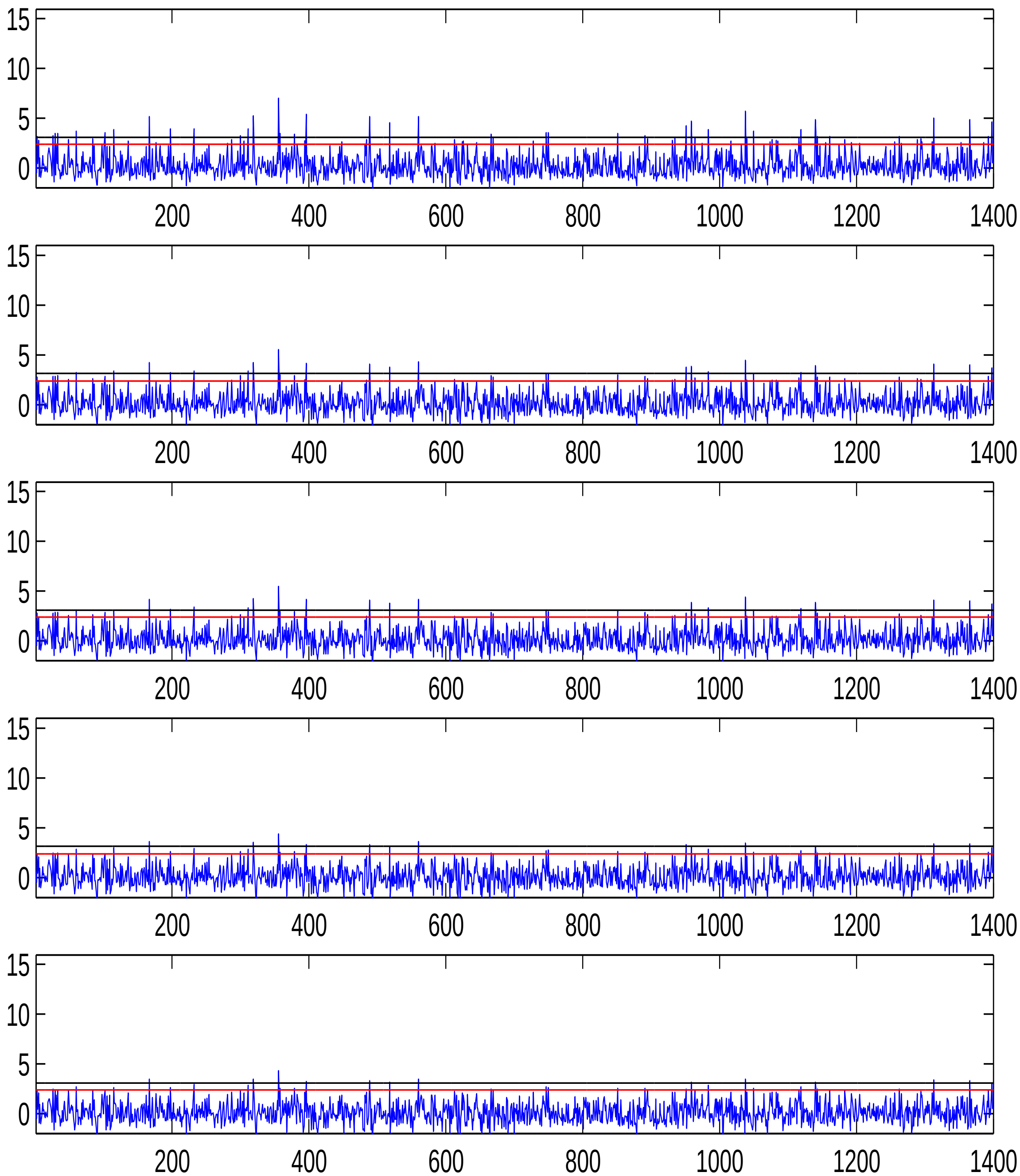

Figure 1.10: Simulated Time Series of $z_{TP,t}$'s under the SV2F Model
The five panels show simulations of the basic statistic, the log version, the max-log version, the ratio version and the max-ratio version. The horizontal lines are the upper 0.99 and 0.999 critical points of the standard Gaussian distribution. The sample size is 1400 days and the return horizon is 5 minutes.

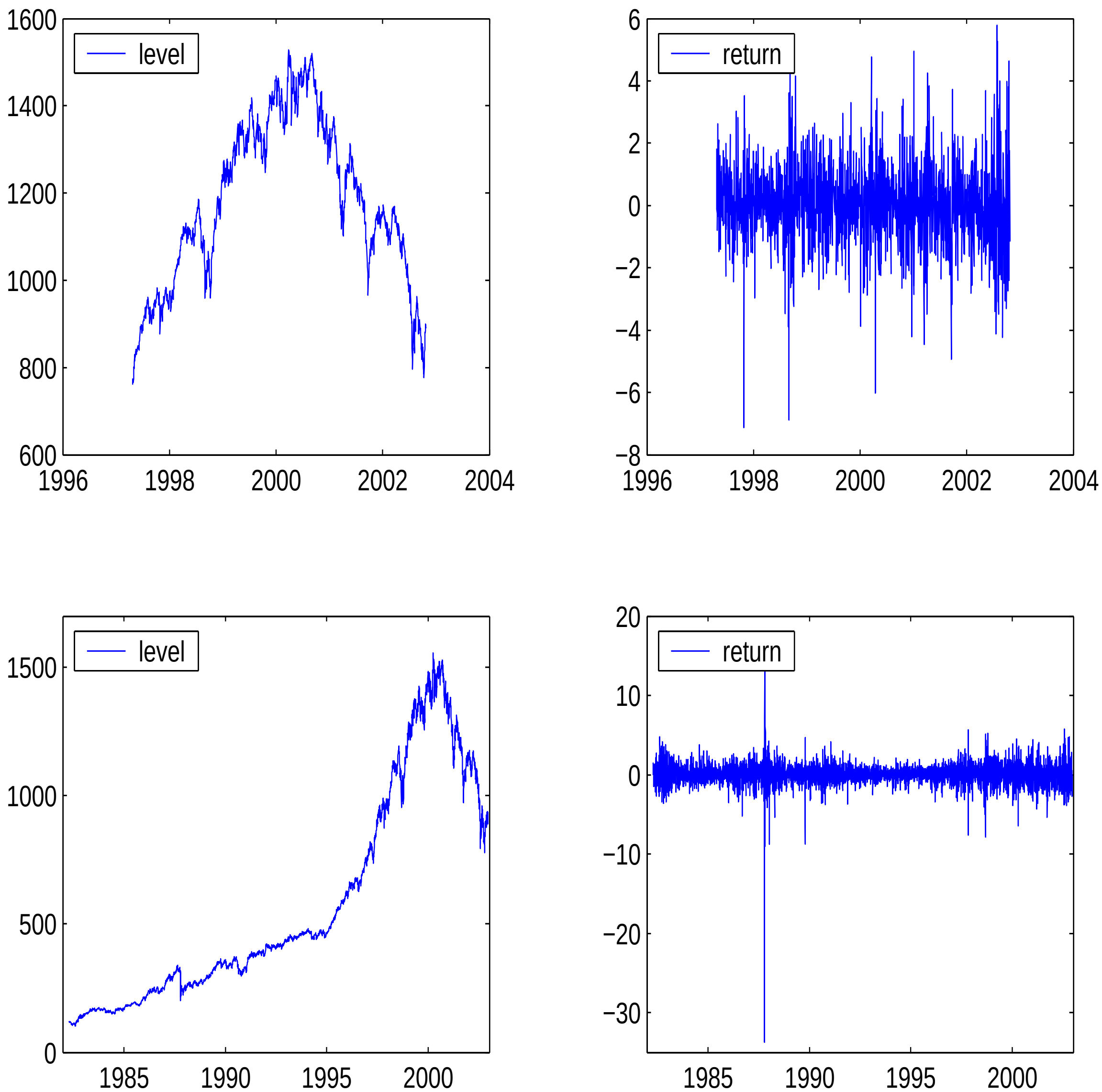

Figure 1.11: Daily Price and Return
The top two panels show the daily closing price and the daily geometric return of the S&P Cash Index, April 21, 1997–October 22, 2002. The bottom two panels show the daily closing price and the daily geometric return of the S&P Index futures, April 21, 1982–December 9, 2002.

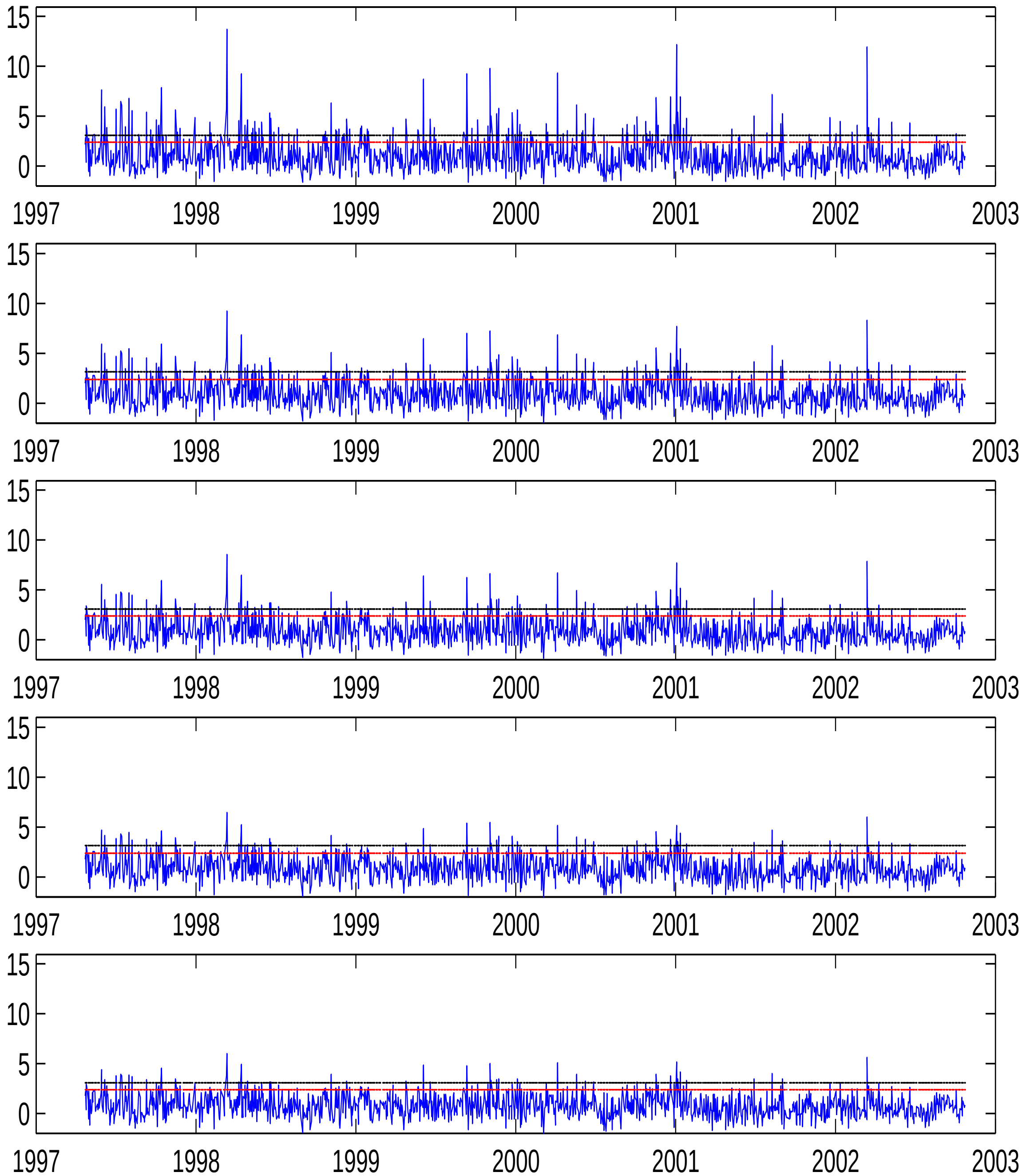

Figure 1.12: Daily z Statistics on S&P Cash Index
The five panels show observed values of the five daily jump statistics $z_{TP,t}$, $z_{TP,l,t}$, $z_{TP,lm,t}$, $z_{TP,r,t}$ and $z_{TP,rm,t}$, computed using the five-minute returns on the S&P Cash Index, April 21, 1997–October 22, 2002. The horizontal lines are the upper 0.99 and 0.999 critical values of the standard Gaussian distribution.

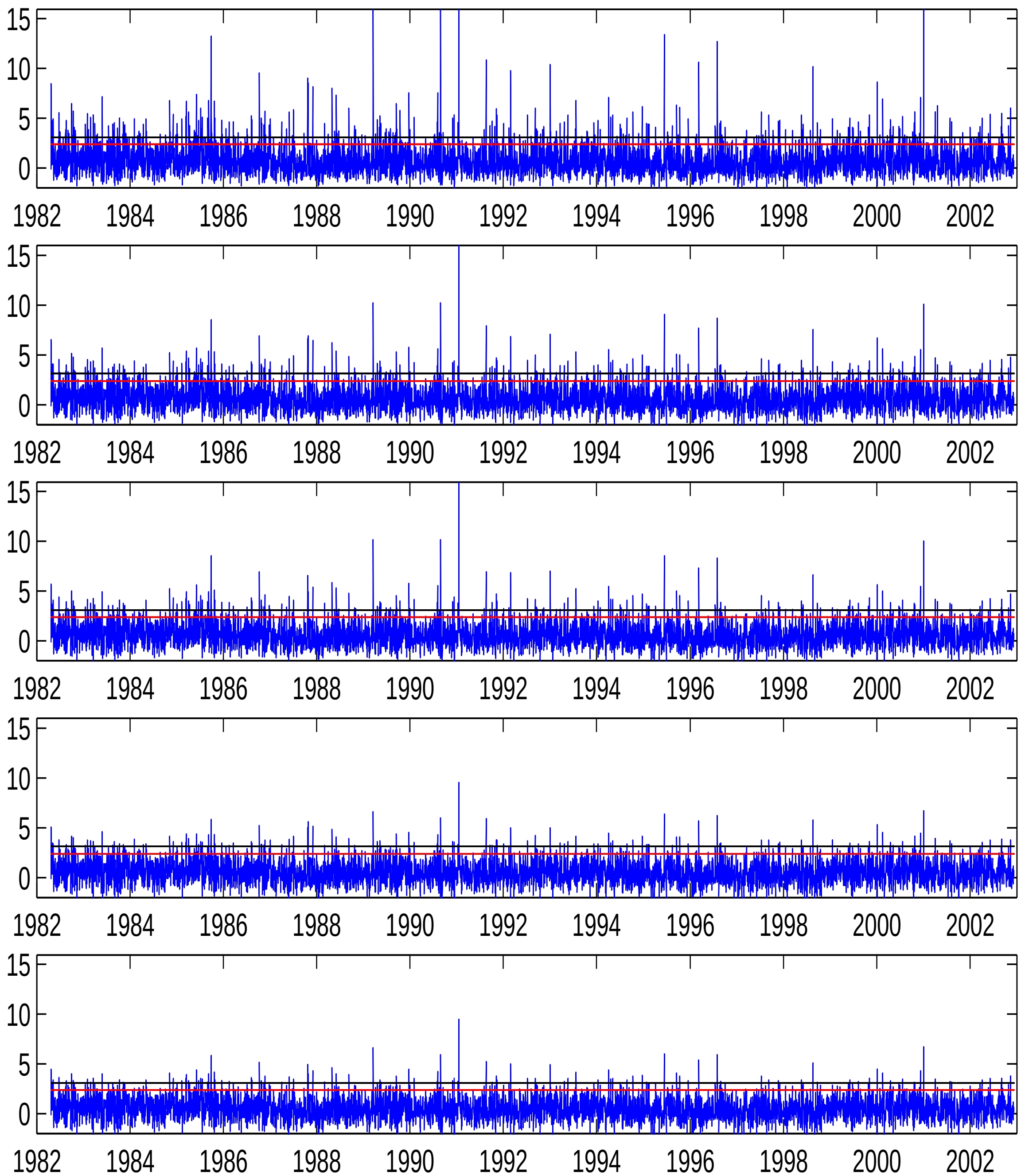

Figure 1.13: Daily z Statistics on S&P Index Futures
The five panels are the time series plots of the observed values of the daily statistics $z_{TP,t}$, $z_{TP,l,t}$, $z_{TP,lm,t}$, $z_{TP,r,t}$ and $z_{TP,rm,t}$, computed using the five-minute returns on the S&P Index futures, April 21, 1982–December 9, 2002. The horizontal lines are the upper 0.99 and 0.999 critical values of the standard Gaussian distribution.

Chapter 2

A Reduced Form Framework for Modelling Volatility of Speculative Prices based on Realized Variation Measures

This chapter proposes a simple reduced form framework for effectively incorporating intraday data into modelling and forecasting daily return volatility, by decomposing the total daily return variability into the continuous sample path variance and the discontinuous jumps over the trading day as well as the overnight return.

2.1 Introduction

A burgeoning literature concerned with modelling and forecasting the dynamic dependencies in financial market volatility has emerged over the past two decades. Up until fairly recently, most of the empirical results in the literature were based on the use of daily, or coarser frequency data, coupled with formulations within the GARCH or stochastic volatility class of models; for a recent survey see Andersen, Bollerslev, Christoffersen, and Diebold (2006). Meanwhile, somewhat of a paradigm shift has started to occur in which high-frequency data is now incorporated into longer-run volatility modelling and forecasting problems through the use of simple reduced-form time series models for non-parametric daily realized volatility measures based on the summation of intraday squared returns; see, e.g., Andersen, Bollerslev, Diebold, and Labys (2003) and the supportive theoretical results in Andersen, Bollerslev, and Meddahi (2004).[1] Further, decomposing the total daily return variability into its

[1]Closely related empirical findings have been reported in Anderson and Vahid (2007), Areal and Taylor (2002), Corsi (2004), Deo, Hurvich, and Lu (2006), Koopman, Jungbacker, and Hol (2005),

continuous and discontinuous components based on the bi-power variation measures developed by Barndorff-Nielsen and Shephard (2004b, 2006), the empirical results in Andersen, Bollerslev, and Diebold (2006) suggest that most of the predictable variation in the volatility stems from the strong own dynamic dependencies in the continuous price path variability, while the predictability of the (squared) jumps is typically minor. The present chapter takes this analysis one step further by developing, estimating and implementing separate reduced-form time series forecasting models for each of the different components that make up the total daily price variation.

Following the analysis in Andersen, Bollerslev, and Diebold (2006), we begin by decomposing the total return variability over the trading day into its continuous sample path variation and the variation due to jumps based on the bi-power variation measure developed by Barndorff-Nielsen and Shephard (2004b, 2006). Our empirical results with a fifteen year sample of high-frequency intraday S&P 500 and T-Bond futures returns confirm earlier findings that the dynamic dependencies in the daily continuous sample path variability is well described by an approximate long-memory Heterogenous AR (HAR) model, as originally proposed by Corsi (2004). Meanwhile, careful analysis of the non-parametrically identified jumps reveals some new and interesting dynamic dependencies vis-a-vis the results reported in the existing literature. In particular, while the time series of statistically significant squared jumps appear to be approximately serially uncorrelated, the times between jumps and the sizes of the jumps are both autocorrelated.[2] We successfully model these dependencies by the combination of an Autoregressive Conditional Hazard (ACH) model, as developed

Martens, van Dijk, and de Pooter (2002), yan Eddie Pong, Shackleton, Taylor, and Xu (2004), and Thomakos and Wang (2003), among others.

[2]The occurrences of jumps in the T-Bond market also appear to be related to the releases of macroeconomic news announcements, as documented in, e.g., Andersen, Bollerslev, Diebold, and Vega (2005) and Johannes (2004).

by Hamilton and Òscar Jordà (2002), for the time-varying jump intensities, coupled with a log-linear model with GARCH errors for the size of the jumps.[3]

The two separate model structures described above effectively account for the variability over the active part of the trading day when the market is formally open. However, the opening price typically differs from the closing price from the previous day, and the corresponding overnight return often accounts for a non-trivial fraction of the total daily return. The most common approach for dealing with this issue when modelling and forecasting realized volatilities is to scale the intraday measures and/or model forecasts by a constant to make them unconditionally unbiased for the total daily variation; see, e.g., Martens (2002), Fleming, Kirby, and Ostdiek (2003), Koopman, Jungbacker, and Hol (2005). An alternative approach based on minimizing the mean square error for the realized variance over the whole day has also been advocated by Hansen and Lunde (2005). Instead, we treat the overnight returns as a time series of regularly occurring jumps. We model these by a discrete-time GARCH model in which the conditional variance explicitly depends on the continuous sample path variation over the immediately preceding active part of the trading day.

We also show how the three separate models discussed above may be combined in the construction of recursive forecasts for the total daily and longer horizon return volatility.[4] Comparing both in- and out-of-sample daily, weekly and monthly forecasts to those from other discrete-time volatility models, including a standard GARCH(1,1) model and the HAR-RV model, our results suggest that the more detailed modelling

[3] The idea of modelling the jump process in terms of the occurrence and the size of the jumps has a natural precedent in the bin model for tick-by-tick transaction prices proposed by Rydberg and Shephard (2003).

[4] The separate model estimates and accompanying forecasts reported here ignore any contemporaneous dependencies among the innovations to the continuous sample path variability and jump equations. Incorporating this into a fully efficient multivariate system estimation is severely complicated by the fact that the time series of significant jumps are effectively censored and the corresponding equations only estimated based on a subset of the sample.

approach developed here can in fact result in important forecast improvements.

This chapter is most directly related to Bollerslev, Kretschmer, Pigorsch, and Tauchen (2005), who estimate a discrete-time model for the joint dynamics of daily S&P 500 returns, realized variance and bi-power variation. However, in contrast to the present chapter, the former paper makes no attempt at separately identifying or modelling the dynamics of the jump and the overnight return components. Closely related results have also been reported in independent work by Lanne (2006). This chapter is also related to the concurrent work of Tauchen and Zhou (2006), who document time-varying jump intensities based on the same realized variation measures and test statistics used here. Discrete-time GARCH models incorporating Poisson jump processes with time-varying jump intensities based solely on daily data have also previously been estimated by Chan and Maheu (2002), and Maheu and McCurdy (2004), while earlier work by Neely (1999) highlights the potential benefits from removing jumps when forecasting volatility using GARCH type models.

At a somewhat broader level our results also speak to the vast finance literature based on continuous-time methods and corresponding parametric models. In particular, the compound Poisson model of Merton (1976) and the many subsequent studies that rely on time-invariant jump-diffusions, are all at odds with the empirical findings reported here. On the other hand, the more recent studies by Andersen, Benzoni, and Lund (2002), Chernov, Gallant, Ghysels, and Tauchen (2003), Eraker, Johannes, and Polson (2003) that explicitly allow for time-varying jump intensities all report difficulties in precisely estimating the process from daily data. Meanwhile, consistent with the empirical results for the high-frequency realized variation measures reported here, Bates (2000), Pan (2002), Carr and Wun (2003) and Eraker (2004) all point to the existence of time-varying jump intensities when incorporating additional information from options data.

The rest of this chapter is organized as follows. Section 2.2 sets up the notation and reviews the jump detection statistic used in revealing the latent jump processes. Section 2.3 reports the initial empirical evidence for the distinct dynamic characteristics of the different components that make up the total daily return variation. Section 2.4 models the continuous sample path variance, while Section 2.5 and 2.6 develop our models for the discrete jump contribution and the overnight return dynamics, respectively. Section 2.7 discusses the construction of forecasts and compares the results to those from other procedures. Section 2.8 concludes.

2.2 Jump Detection Test Statistics

2.2.1 General Setup and Notation

We assume that the scalar logarithmic asset price within the active part of the trading day follows a standard jump-diffusion process

$$dp(\tau) = \mu(\tau)d\tau + \sigma(\tau-)dw(\tau) + \kappa(\tau)dq(\tau), \tag{2.1}$$

where $\tau \in \mathbb{R}^+$, and the time scale is normalized so that the unit interval corresponds to a trading day; $\mu(\tau)$ denotes the drift term with a continuous and locally finite variation sample path; $\sigma(\tau) > 0$ is the spot volatility process, assumed to be càdlàg; $w(\tau)$ is a standard Brownian motion; $\kappa(\tau)dq(\tau)$ refers to the pure jump part, where $dq(\tau) = 1$ if there is a jump at time τ and 0 otherwise, where the jumps occur with potentially time-varying jump intensity $\lambda(\tau)$, and size $\kappa(\tau)$. We denote the corresponding discrete-time within-day geometric returns by

$$r_{t,j} = p(t-1+j/M) - p(t-1+(j-1)/M), \quad j = 1, 2, \ldots, M, \tag{2.2}$$

where $t \in \mathbb{N}^+$, and M refers the number of (equally spaced) return observations over the trading day.

The continuous-time diffusion process above only applies for the active part of the trading day. However, the opening price on one day typically differs from the closing price recorded on the previous day. In fact, as discussed further below, it is natural to think of the overnight returns as random jumps occurring at the deterministic times $t = 1, 2, \ldots$. As such, the total return for day t equals

$$r_t \; = \; r_{t,n} \; + \; \sum_{j=1}^{M} r_{t,j} \; = \; r_{t,n} \; + \; r_{t,d}, \tag{2.3}$$

where $r_{t,n}$ denotes the overnight logarithmic price change from day $t-1$ to day t, and we follow the convention of measuring the daily returns as close-to-close.

2.2.2 Realized Variation Measures

The volatility over the active part of the trading day t is measured by the quadratic variation

$$QV_t = \int_{t-1}^{t} \sigma^2(s) ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2. \tag{2.4}$$

The first integrated variance term represents the contribution from the continuous price path, while N_t gives the number of jumps over day t, and $\sum_{j=1}^{N_t} \kappa_{t,j}^2$ accounts for the corresponding contribution to the variance from the within-day jumps.

The quadratic variation process and its separate components are, of course, not directly observable. Instead, we resort to recently popularized model-free non-parametric consistent measures, including the now familiar realized variance

$$RV_t(M) = \sum_{j=1}^{M} r_{t,j}^2. \tag{2.5}$$

As noted in Andersen and Bollerslev (1998), Comte and Renault (1998), Andersen, Bollerslev, Diebold, and Labys (2001, 2003), and Barndorff-Nielsen and Shephard

(2002a,b), among others, $RV_t(M)$ converges uniformly in probability to QV_t as the sampling frequency goes to infinity

$$RV_t(M) \xrightarrow[M\to\infty]{P} \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2, \tag{2.6}$$

or equivalently, the length of the return interval goes to zero.

Meanwhile, a host of practical market microstructure complications prevents us from sampling too frequently while maintaining the fundamental semimartingale assumption underlying equation (1). Ways in which to best deal with these complications and the practical choice of M have been the subject of intensive recent research efforts; see, e.g., Aït-Sahalia, Mykland, and Zhang (2005), Bandi and Russell (2005), Barndorff-Nielsen, Hansen, Lunde, and Shephard (2006), and Hansen and Lunde (2006). In the analysis reported on below, we simply follow most of the existing empirical literature in the use of a fixed five-minute sampling frequency, corresponding to M equal to 80 and 79 for each of the two markets that we study.

In order to separately measure the jump part, we rely on the realized bipower variation measure developed by Barndorff-Nielsen and Shephard (2004b, 2006),

$$RBV_{1,t} = \mu_1^{-2} \left(\frac{M}{M-2} \right) \sum_{j=3}^{M} |r_{t,j-2}||r_{t,j}|, \tag{2.7}$$

where $\mu_a = E(|Z|^a)$ for $Z \sim N(0,1)$. The bipower variation measure defined above involves an additional stagger relative to the measure originally considered in Barndorff-Nielsen and Shephard (2004b), which helps render it robust to certain types of market microstructure noise; see Huang and Tauchen (2005) for some initial analytical investigations and simulation-based evidence along these lines. Under the assumption that the logarithmic price process is a continuous-time stochastic volatility semimartingale plus a finite-activity jump process, $RBV_{1,t}(M)$ converges in probability to the integrated variance. Consequently, the difference between the realized variance and the realized bipower variation consistently estimates the part of the quadratic variation due to jumps

$$RV_t(M) - RBV_{1,t}(M) \xrightarrow[\mathrm{M}\to\infty]{\mathrm{P}} \sum_{j=1}^{N_t} \kappa_{t,j}^2. \tag{2.8}$$

Moreover, under the same regularity conditions, the test statistic

$$Z_t = \frac{\frac{RV_t - RBV_{1,t}}{RV_t}}{\sqrt{((\frac{\pi}{2})^2 + \pi - 5)\frac{1}{M}\max(1, \frac{RTQ_t}{RBV_{1,t}^2})}}. \tag{2.9}$$

where

$$RTQ_{1,t} = M\mu_{4/3}^{-3}\left(\frac{M}{M-6}\right)\sum_{j=}^{M} |r_{t,j-4}|^{4/3}|r_{t,j-2}|^{4/3}|r_{t,j}|^{4/3}, \tag{2.10}$$

is asymptotically standard normally distributed under the null hypothesis of no within-day jumps.[5]

Based on the above jump detection test statistic, the realized measure of the jump contribution to the quadratic variation of the logarithmic price process is then measured by

$$J_t(M) = I(Z_t > \Phi_\alpha) \cdot (RV_t(M) - RBV_{i,t}(M)), \tag{2.11}$$

where $I(\cdot)$ denotes the indicator function and Φ_α refers to the appropriate critical value from the standard normal distribution. Accordingly, our realized measure for the integrated variance is defined by

$$C_t(M) = I(Z_t \leq \Phi_\alpha) \cdot RV_t(M) + I(Z_t > \Phi_\alpha) \cdot RBV_{i,t}(M). \tag{2.12}$$

This definition automatically ensures that the non-parametric measures for the jump and continuous components add up to $RV_t(M)$. This same decomposition of the

[5] Huang and Tauchen (2005) report extensive simulation evidence showing that this particular jump detection test statistic exhibits excellent size and power properties for a one-factor logarithmic stochastic volatility model augmented with compound Poisson jumps.

within day variance has also previously been explored by Andersen, Bollerslev, and Diebold (2006), among others. Of course, the actual implementation requires a choice of α. In the results reported on below, we use a critical value of $\alpha = 0.99$, but very similar results (available in Section 2.11) were obtained for other values of α.[6] For notational simplicity, we will refer to these empirical measures as RV_t, C_t and J_t in the sequel.

2.3 Data and Summary Statistics

2.3.1 Data

Our data consist of five-minute prices for the S&P 500 futures (SP) and 30-year U.S. treasury bond futures (US) contracts. The raw transaction prices for both contracts were obtained from Price-Data. The sample period for both assets begins on January 2, 1990, and ends on February 4, 2005. The intraday five-minute prices for the SP contracts span the time interval from 9:35 to 16:15 (EST), resulting in $M = 80$ non-overlapping return observations per day. The five-minute prices for the US contracts cover the period from 8:25 to 15:00 (EST), for a total of $M = 79$ intraday returns. Our use of a five-minute sampling frequency parallels many previous studies in the literature, and as discussed further in Andersen, Bollerslev, Diebold, and Vega (2005), for the two contracts analyzed here strikes a reasonable balance between the desire for as finely sampled observations as possible on the one hand, and robustness to contaminating market microstructure influences on the other.[7]

[6] In the actual implementation we also imposed a hard lower bound of 0.001 on the daily $C_t(M)$.

[7] For further details concerning the previous-tick method used in the construction of the five-minute returns and the specific contract rollover scheme, see Wasserfallen and Zimmermann (1985) and Dacorogna, Gençay, Müller, Pictet, and Olsen (2001), and Andersen, Bollerslev, Diebold, and Vega (2005) and Fleming, Kirby, and Ostdiek (2003), respectively. For SP around 98% of the prices occur within one minute of each five-minute mark, while for US the proportion is around 86%.

2.3.2 Summary Statistics

To get an idea about the properties of the different components that make up the total daily return variance for each of the two markets, we plot in Figures 2.1 and 2.2 the daily return r_t, our measure for the continuous sample path variation C_t, the sum of the within day squared jumps J_t, and the overnight squared returns $r_{t,n}^2$. The figures clearly indicate rather distinct dynamic dependencies in each of the different components, with the jump time series appearing noticeably more erratic and less predictable than the other series.

To better understand these dependencies, we further decompose the J_t series into two separate processes: one describing the occurrence of jumps, and the other the size of the squared jump(s) within the day when at least one jump occurs. We denote these two processes by I_t and S_t, respectively. More precisely, $Pr(J_t = 0|\mathcal{F}_{t-1}) = Pr(I_t = 0|\mathcal{F}_{t-1})$, while $Pr(0 < J_t \leq j|\mathcal{F}_{t-1}) = Pr(I_t = 1|\mathcal{F}_{t-1}) \cdot Pr(S_t \leq j|\mathcal{F}_{t-1}, I_t = 1)$. The resulting summary statistics reported in Tables 2.1 and 2.2 do indeed reveal some significant dynamic dependencies in the I_t and S_t series that are largely masked in the corresponding J_t series. Of course, the Ljung-Box Q-statistics reported in the tables only capture own linear dependencies. As discussed further in Section 2.5, there are also strong non-linear dynamic dependencies embedded in the series for both markets. The reduced form models for each of the different components discussed next are explicitly designed to account for these features.

2.4 Continuous Sample Path Variation

We start by detailing our model for the strongly serially correlated continuous sample path variation process, C_t. The HAR-RV model first proposed by Corsi (2004), and further developed by Andersen, Bollerslev, and Diebold (2006), provides a particularly convenient framework for modelling these dependencies.[8] The specific HAR-C model adopted here takes the form,

$$\begin{aligned} log(C_{t+1}) &= \beta_0 + \beta_{CD}log(C_t) + \beta_{CW}log(C_{t-5,t}) + \beta_{CM}log(C_{t-22,t}) \\ &\quad + \beta_{JD}log(J_t + 1) + \beta_{JW}log(J_{t-5,t} + 1) + \beta_{JM}log(J_{t-22,t} + 1) + \epsilon_{t+1,C}, \end{aligned} \tag{2.13}$$

where $C_{t-h,t} \equiv h^{-1}[C_{t-h+1} + C_{t-h+2} + ... + C_t]$ and $J_{t-h,t} \equiv h^{-1}[J_{t-h+1} + J_{t-h+2} + ... + J_t]$. The logarithmic transform obviously prevents the implied continuous variation defined by exponentiating C_{t+1} from becoming negative.[9]

The left columns in Table 2.3 report the resulting OLS parameter estimates, together with robust standard errors in parentheses and p-values in square brackets. The estimation results confirm the strong own dynamic dependencies in C_t. Consistent with the results reported in Andersen, Bollerslev, and Diebold (2006) the coefficient estimates associated with the lagged squared jumps for SP are generally insignificant, albeit all negative, while there is some evidence of significant anti-persistent effects of the squared jumps for US. Meanwhile, the Ljung-Box Q-statistics for the squared and absolute residuals (available in Section 2.11) reveal clear evidence for significant conditional heteroskedasticity.

Hence, we augment the basic HAR-C model above with a GARCH error structure for the time-varying volatility-of-volatility.[10] Further, to allow for the possibility of fat-tails, we estimate the model under the assumption of conditionally t-

[8]Following Müller, Dacorogna, Davé, Olsen, Pictet, and von Weizsäcker (1997), the HAR type specification is sometimes given a structural interpretation as arising from the interaction of agents with different investment horizons. We merely view the HAR-C model as providing a convenient, or "poor-man's", approximation to long-memory.

[9]Moreover, the unconditional distributions of realized logarithmic volatilities often appear approximately normal; see, e.g., Andersen, Bollerslev, Diebold, and Labys (2001), Andersen, Bollerslev, Diebold, and Ebens (2001), and Barndorff-Nielsen and Shephard (2005b), among others.

[10]The presence of time-varying volatility-of-volatility is consistent with most of the continuous-time stochastic volatility models used in the asset pricing finance literature. For instance, in the square-root affine, or Heston, diffusion model, the conditional variance of the future instantaneous variance is an affine function of the current instantaneous variance and the current instantaneous variance squared; see, e.g., Bollerslev and Zhou (2002).

distribution errors as in Bollerslev (1987). After some experimentation, we found that a GARCH(2,1) model provided a good fit for both markets,

$$\begin{aligned} \epsilon_{t+1,C} &= \sigma_{t+1,C} \cdot \sqrt{\tfrac{v-2}{v}} \cdot z_{t+1,C}, \quad z_{t+1,C} \sim t(\nu) \\ \sigma^2_{t+1,C} &= \omega_C + \alpha_{1,C}\epsilon^2_{t,C} + \alpha_{2,C}\epsilon^2_{t-1,C} + \beta_{1,C}\sigma^2_{t,C}. \end{aligned} \tag{2.14}$$

The estimates from this augmented model are reported in the right columns of Table 2.3. The conditional mean parameters are generally close to the previously reported OLS estimates.[11] The coefficient estimates associated with the past squared jumps again suggest that, everything else equal, large jumps tend to lower the future continuous sample path volatility, and particularly so for US.[12] The residual diagnostics (reported in Section 2.11) also confirm that the estimated GARCH(2,1) models adequately account for the conditional heteroskedasticity.

2.5 Jump Variation

Our model for the trading-time jump variation consists of two parts: a model for the occurrence of jumps coupled with a model for the squared jump sizes.[13] We begin by a discussion of our model for jump occurrences.

[11]Since the model is formulated in terms of $log(C_{t+1})$, the form of the conditional heteroskedasticity plays a direct role in determining the expected value of C_{t+1}. Specifically, under the simplifying assumption of conditional normality, or $\nu = \infty$, $E[C_{t+1}|\mathcal{F}_t] = exp\{E[log(C_{t+1})|\mathcal{F}_t] + 1/2Var[log(C_{t+1})|\mathcal{F}_t]\}$. We will return to a discussion of the numerical procedure that we actually use in the calculation of the expectations from the more general model in the forecasting section below.

[12]Although some of the estimated coefficients are not significantly different from zero at the usual five percent level, we purposely maintain the same HAR-C GARCH(2,1) specification for both markets. Also note, that even though the ARCH(2) coefficients are estimated to be negative for both markets, the implied coefficients in the infinite ARCH representations are all positive, so that the models are indeed well-defined.

[13]The model-free approach used here only identifies days with at least one significant jump and in turn the sum of the within day squared jump(s). Further refinements along the lines of Andersen, Bollerslev, Frederiksen, and Nielsen (2006) for actually estimating each of the individual significant jumps could be used in the formulation of even richer reduced form models.

2.5.1 The ACH Model

Let $\{t_0, t_1, ..., t_n, ...\}$ denote the random arrival times, or days, associated with significant jumps. The Autoregressive Conditional Duration (ACD) model proposed by Engle and Russell (1998), is ideally suited for modelling dynamic dependencies in the jump-durations $d_i = t_i - t_{i-1}$, or the number of days between two adjacent significant jumps. However, the ACD model only updates the conditional expected durations on event, or jump, days. From a forecasting perspective, it is desirable to continuously incorporate new information as it becomes available. The autoregressive conditional hazard (ACH) model of Hamilton and Òscar Jordà (2002) was explicitly designed with this objective in mind.

In order to more formally define the ACH model, let $N(t)$ denote the counting process representing the number of jump days that have occurred up until time t. Also, define the hazard rate

$$h_t = Pr[N(t) \neq N(t-1)|\mathcal{F}_{t-1}]. \tag{2.15}$$

The relationship between the hazard rate and the expected duration, say $\psi_N(t-1)$, if no new information occurs between jump days, is then given by,

$$\psi_{N(t-1)} = \sum_{j=1}^{\infty} j(1-h_t)^{j-1}h_t = \frac{1}{h_t}. \tag{2.16}$$

The ACH model directly parameterizes the hazard rate, h_t, allowing it to depend on any relevant time $t-1$ information.

To illustrate, consider the simple ACH(1,1) model without any information updating between jump days,

$$\begin{aligned} h_t &= \tfrac{1}{\psi_{N(t)-1}}, \\ \psi_{N(t)} &= \omega + \alpha_1 d_{N(t)-1} + \beta_1 \psi_{N(t)-1}. \end{aligned} \tag{2.17}$$

Under appropriate distributional assumptions this ACH(1,1) model is asymptotically equivalent to the ACD(1,1) model, which parameterizes the conditional durations as $\psi_i = \omega + \alpha_1 d_{i-1} + \beta_1 \psi_{i-1}$; see Hamilton and Òscar Jordà (2002) for further details. The parameter estimates from this ACH(1,1) model are reported in the first part of Table 2.4. The estimates confirm the existence of strong persistence in the hazard rates, or equivalently the durations, in both markets. The Ljung-Box Q-statistics for any remaining own dynamic dependencies in the standardized durations implied by the model (reported in Section 2.11), $d_i/\hat{\psi}_i$, are generally also insignificant.

The second set of estimates reported in Table 2.4 augments the basic ACH(1,1) model by four weekday dummies for Monday, Tuesday, Wednesday and Thursday. We explicitly exclude the Friday dummy to avoid singularity, so that the estimated coefficients represent the effects relative to Friday. In addition, we include the logarithm of the number of days to the next nearest news announcements of the Employment Report (representing the real side of the economy) and the Consumer Price Index (representing the nominal side of the economy).[14] Specifically,

$$
\begin{aligned}
h_t &= \frac{1}{\alpha_1 d_{N(t)-1} + \beta_1 \psi_{N(t)-1} + \delta' z_{t-1}}, \\
\delta' z_{t-1} &= \delta_0 + \delta_M D_M + \delta_T D_T + \delta_W D_W + \delta_{Th} D_{Th} \\
&\quad + \delta_{ES} log(n_{ES} + 1) + \delta_{CPI} log(n_{CPI} + 1).
\end{aligned} \tag{2.18}
$$

Consistent with the extant news announcement literature, the results suggest a statistically significant decreasing hazard for the occurrence of jumps in the US market as a function of the number of days until the release of one of the two announcements. Also, the corresponding coefficients for SP are both positive, albeit insignificant. The Monday through Thursday weekday dummies are all positive, but they do not indicate any statistically significant day-of-the-week effects in the jump occurrences.

[14] The results in Andersen, Bollerslev, Diebold, and Vega (2005) suggest that these are the two most important macroeconomic news announcements.

Nonetheless, in order to highlight the added flexibility afforded by the augmented ACH model, we maintain this as our preferred specification for both markets.[15]

To better illustrate the workings of the two different ACH specifications, Figures 2.3 and 2.4 plot the resulting implied conditional hazard rates, $\hat{h}_t$. Comparing the two figures, the impact of the day-to-day updating for the latter set of plots is immediately evident. Still, the two sets of figures reveal the same general patterns in the estimated hazard rates, with jumps appearing more than twice as likely for US compared to SP over most of the sample. Again, we believe that this is partly due to the much bigger impact of macroeconomic news announcements for the fixed-income market. There is also a pronounced tendency for even fewer jumps in the equity market during the middle part of the sample, almost akin to a level shift in the estimated hazard rates. It is not clear what drives this change.

2.5.2 The HAR-J Model

Most continuous-time parametric jump diffusion models assume that the size of the jumps is *i.i.d.* distributed through time. By directly observing the squared jumps, or more precisely the realized measure of the sum of within-the-day squared jumps, the present framework affords us much greater flexibility in terms of modelling the jump sizes.

Following the same basic idea underlying the HAR-C model, we parameterize the conditional jump sizes as a function of the past continuous sample path variations.[16]

[15] We also experimented with augmenting the ACH model by C_t and J_t, but the estimated hazard rates did not appear plausible, so we decided not to include any of these variables in our final model specification.

[16] We also tried including various lags of $log(S_t)$, as well as the raw and expected durations. All of these other variables turned out to be insignificant.

In particular,

$$log(S_{t(i)}) = \beta_0 + \beta_{CD} log(C_{t(i)-1}) + \beta_{CW} log(C_{t(i)-5,t(i)}) + \beta_{CM} log(C_{t(i)-22,t(i)}) + \epsilon_{t(i)}, \tag{2.19}$$

where $t(i)$ maps the jump counter i into the corresponding trading day t, so that the lagged variation measures on the right-hand-side are always measured in calendar time relative to the time of the jump. The estimation results from this model are reported in the left columns in Table 2.5. As seen from the table, the one month lagged continuous volatility generally has the most explanatory power. Also, the sizes of the jumps for US are much more persistent than those for SP. Meanwhile, the Ljung-Box Q-statistics for the squared and absolute residuals (reported in Section 2.11) again clearly indicate the existence of conditional heteroskedasticity in the residuals from the model for both markets.

We therefore augment the basic HAR-J model above with a GARCH(1,1)-t error structure,

$$\begin{aligned} \epsilon_{t(i)} &= \sigma_{t(i)} \cdot \sqrt{\tfrac{v-2}{v}} \cdot z_{t(i)}, \quad z_{t(i)} \sim t(\nu), \\ \sigma^2_{t(i)} &= \omega + \alpha_1 \epsilon^2_{t(i-1)} + \beta_1 \sigma^2_{t(i-1)}. \end{aligned} \tag{2.20}$$

The estimates from this preferred model are reported in the right columns in Table 2.5. The results confirm the existence of significant GARCH effects. Otherwise, the estimated dependencies in the conditional mean are directly in line with those for the homoskedastic model.

2.6 Overnight Return Variance

The realized variation measures and corresponding reduced form models developed above pertain to the return variation observed during the regular trading hours when the exchanges are open. However, as previously noted, the opening price on one day typically differs from the closing price on the previous day. Since most investors hold their portfolios over longer inter-daily horizons, the corresponding overnight return variability will directly affect the risks of their positions. In particular, the proportion of the total daily variation due to the over-night returns, as measured by the sample means of $r_{t,n}^2/(RV_t + r_{t,n}^2)$, equals 0.160 and 0.165 for the SP and US markets, respectively.

Two common ways of dealing with this non-trivial overnight variation have emerged in the realized volatility literature. The first approach simply scales up the daytime realized variation measures to provide an unbiased estimate for the variation over the whole-day. This is the method used in, e.g., Martens (2002), Fleming, Kirby, and Ostdiek (2003), Koopman, Jungbacker, and Hol (2005). Alternatively, the overnight squared returns may be added to the within-day realized variation so that it covers the whole day. This approach, along with its pros and cons, is discussed further in Hansen and Lunde (2005), who also propose an improved estimator by optimally weighting, in a minimum mean-square-error sense, the daytime realized volatility and the squared overnight return. Both of these approaches implicitly assumes that the overnight squared returns may somehow be viewed as part of the same process that generates the within day realized volatility. Here we take a different approach and directly model the overnight returns, or jumps, by a separate discrete time model.[17]

2.6.1 The GARCH-t Model

The summary statistics previously reported and discussed in Section 2.3.2, not surprisingly, indicate the presence of serial correlation in the squared overnight returns. This naturally suggests a GARCH type approach for capturing these dependencies. Since the overnight returns are separated by the returns during the regular trading

[17] The studies by Chan, Chan, and Karolyi (1991) and Martens (2002), which estimate individual discrete-time models for the trading-time and overnight returns, provide an earlier precedent.

hours, we include the immediately preceding daytime realized volatility as an additional explanatory variable in the conditional variance equation. Moreover, since the continuous and discrete sample-path variation over the day may affect the subsequent overnight return differently, we split up the realized volatility into C_t and J_t. Furthermore, to allow for the possibility that positive and negative daytime shocks may have different effects, we condition the estimated coefficients for C_t and J_t on the sign of the daytime return, $r_{t,d}$. The resulting specification for the overnight returns takes the form,

$$\begin{aligned} r_{t+1,n} &= \mu + \epsilon_{t+1,n} \\ \epsilon_{t+1,n} &= \sigma_{t+1,n} \cdot \sqrt{\tfrac{v-2}{v}} \cdot z_{t+1,n}, \quad z_{t+1,n} \sim t(v) \\ \sigma^2_{t+1,n} &= \omega_n + \alpha_{1,n}\epsilon^2_{t,n} + \beta_{1,n}\sigma^2_{t,n} + \beta_{CP}C_t^P + \beta_{CN}C_t^N + \beta_{JP}J_t^P + \beta_{JN}J_t^N, \end{aligned} \tag{2.21}$$

where $C_t^P = C_t \cdot (r_{t,d} \geq 0)$, $C_t^N = C_t \cdot (r_{t,d} < 0)$, and similarly for J_t^P and J_t^N.

The left columns in Table 2.6 report the estimation results. As expected, the estimates for α_1 and β_1 are both highly statistically significant and broadly in line with the typical daily GARCH(1,1) model estimates, although their sums are slightly less than what is generally found with daily returns. Of course, some of this "lack" in persistence is made up by significant positive dependence on the within day realized continuous sample path variation, C_t^P and C_t^N. Interestingly, the jump components, J_t^P and J_t^N, are generally not significant. Furthermore, the Wald test for the hypothesis of no volatility asymmetry, or $\beta_{CP} = \beta_{CN}$, equals 0.267 and 1.647 for each of the two markets respectively, with corresponding asymptotic p-values of 0.606 and 0.199.[18]

The right columns in Table 2.6 report the estimation results from the more parsimonious GARCH(1,1)-t model obtained by eliminating the jump components and

[18] On estimating the same GARCH models under the assumption of conditionally normal errors, the asymmetry appears significant for SP, indirectly suggesting that the effect is associated with the tails of the distribution.

combining the positive and negative continuous variation components,

$$\sigma^2_{t+1,n} = \omega_n + \alpha_{1,n}\epsilon^2_{t,n} + \beta_{1,n}\sigma^2_{t,n} + \beta_C C_t. \quad (2.22)$$

The estimated parameters are directly in line with those from the earlier more general specification, and the corresponding values for the maximized log likelihood functions are also close to those for the unrestricted models. We consequently maintain this simpler model as our preferred specification for the overnight return variation.

2.7 Forecasting

One of the many potentially useful applications of the reduced form modelling framework developed above relates to volatility forecasting. In particular, consider the question of calculating one-day-ahead return volatility forecasts, or $Var(r_{t+1}|\mathcal{F}_t)$. The standard GARCH based approach directly parameterizes this conditional expectation as a function of its own past value(s) and the lagged squared return(s). This, of course, does not include any high-frequency information. On the other hand, the now popular HAR-RV model parameterizes the conditional variance as a distributed lag of the past realized variation measures. While this does incorporate high-frequency information into the resulting forecasts, the traditional HAR-RV model does not distinguish between the continuous sample path variation and the discontinuous jump part. However, as discussed at length above, the dynamic dependencies in these two components are very different. Moreover, the standard approaches of scaling the realized volatilities or treating the overnight return as another intraday return in order to get an unbiased measure for the full day variance both ignore the distinct dynamic dependencies in the overnight returns.

In contrast, the framework proposed here explicitly decomposes the conditional variance into three separate components,[19]

$$Var(r_{t+1}|\mathcal{F}_t) = E(C_{t+1}|\mathcal{F}_t) + E(J_{t+1}|\mathcal{F}_t) + Var(r_{t+1,n}|\mathcal{F}_t). \qquad (2.23)$$

The last term on the right-hand-side comes directly from the GARCH-t model discussed in the previous section. As for the second term, our results suggest that the occurrences of jumps and the sizes of the jumps are independent. Thus,

$$\begin{aligned}
E[J_{t+1}|\mathcal{F}_t] &= \int_0^\infty j dP(0 < J_{t+1} \leq j|\mathcal{F}_t) \\
&= \int_0^\infty j dP(S_{t+1} \leq j|\mathcal{F}_t, I_{t+1} = 1) \cdot P(I_{t+1} = 1|\mathcal{F}_t) \\
&= [\int_0^\infty j f(S_{t+1} \leq j|\mathcal{F}_t, I_{t+1} = 1) dj] \cdot P(I_{t+1} = 1|\mathcal{F}_t) \\
&= E(S_{t+1}|\mathcal{F}_t, I_{t+1} = 1) \cdot h_{t+1}.
\end{aligned}$$

Forecast for the hazard rate, h_t, follows directly from the estimated ACH models. Since the models for S_{t+1} and C_{t+1} are formulated in logarithmic terms, the two conditional expectations $E(S_{t+1}|\mathcal{F}_t, I_{t+1} = 1)$ and $E(C_{t+1}|\mathcal{F}_t)$ will both involve a Jensen's inequality type correction. However, numerical evaluations of these expectations are easily accomplished by means of simulations. Similarly, even though the highly nonlinear dynamic dependencies among the different model components render closed-form expressions for the multi-step ahead conditional expectations, $Var(r_{t+h}|\mathcal{F}_t)$ for $h > 1$, infeasible, these are relatively easy to compute by means of recursive simulations.[20]

[19] The validity of this decomposition for the conditional expectations implicitly assumes that the aforementioned convergence in probability of the realized variation measures implies convergence in mean. The assumption of a bounded return process, or a weaker uniform integrability condition, is sufficient to ensure that this holds; see, e.g., the discussion in Andersen, Bollerslev, Diebold, and Labys (2003).

[20] In the results reported on below we rely on a total of 10,000 replications in calculating the expectations. To minimize the impact of large influential outliers and stabilize the algorithm, we also trim any simulated values more than twice the largest in-sample observation. Further details are available upon request.

To assess the accuracy of the HAR-CJN model forecasts, we compare the predictions to the actual realized variation measures; i.e., for the one-day horizon forecasts $RV_{t+1} + r^2_{t+1,n}$. In addition to the one-day forecasts, we also calculate one-week and one-month forecasts defined by the average of the forecasts from 1 to 5, and 1 to 22 days ahead, respectively. As a benchmark comparison, we consider the forecasts from a simple GARCH(1,1) model estimated on the daily returns, and an HAR-RV model properly scaled by the contribution from the overnight return so that the forecasts are unconditionally unbiased.[21] The first subsection below discuss the results for the full sample period, labeled in-sample, while the subsequent section reports on the results from a true out-of-sample forecast comparison.

2.7.1 In-Sample Forecasts

To begin, Table 2.7 reports the standard Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for the forecasts from each of the three different models based on the data over the full sample period.[22] As is clear from the table, these in-sample summary statistics clearly favor the more complicated HAR-CJN model for SP. Meanwhile, the in-sample RMSE and MAE for US are not as clear-cut.

In order to further analyze relative performance of the HAR-CJN model, we also estimate a series of Mincer-Zarnowitz style regressions. In particular, for the one-day-ahead forecasts,

$$(RV_{t+1} + r^2_{t+1,n}) = b_0 + b_1 V_{t,GARCH} + b_2 V_{t,HAR-RV} + b_3 V_{t,HAR-CJN} + \epsilon_{t+1} \qquad (2.24)$$

[21] An alternative to these popular forecasting models and the HAR-CJN model developed here suggested by one of the referees would be to project $RV_{t+1} + r^2_{t+1,n}$ on all of the variables in the time t information set, including information about the jumps and the overnight returns. While this procedure might perform well in a pure forecasting sense, it would obviously be completely void of any detailed information about the individual components that make up the total daily variation.

[22] Patton (2006) has recently cautioned against the use of the MAE criteria with a noisy volatility proxy. The realized volatility measures that we use here effectively mitigate these concerns.

where $V_{t,\mathcal{M}}$ refers to the time t one-day-ahead forecast from model $\mathcal{M}$. In addition to the one-day-ahead forecasts, we run the same regressions for the 5- and 22-steps ahead forecasts, appropriately correcting the standard errors of the parameter estimates for the serial correlation in the residuals induced by the overlap in the data. Following the discussion in, e.g., Anderson and Vahid (2007), these regressions are naturally interpreted as volatility forecast encompassing regressions, in the sense that a coefficient significantly different from zero implies that the information in that particular model forecast is not encompassed in the forecasts by the two other models. As a further robustness check, we also report the results from the simple Mincer-Zarnowitz regressions, in which the ex-post variation measures are regressed on a constant and one of the three individual model forecasts in isolation.

The results from these joint and individual Mincer-Zarnowitz regressions are all reported in Table 2.8. In the joint regressions for SP the forecasts from the HAR-CJN model invariably receives a weight indistinguishably different from unity in a statistical sense, while the estimated coefficients for the other two model forecasts are close to zero and insignificant, indicating that the HAR-CJN forecasts encompass the forecasts from other two models. The individual SP regressions reported in the bottom part of the table further corroborate these findings. In particular, the R^2's from the HAR-CJN models are always the highest,[23] with the estimated intercept and slope coefficients very close to zero and unity, respectively. The corresponding in-sample results for US generally also favor the HAR-CJN model, although the differences among the three model forecasts are not as large.

[23]As discussed in Andersen, Bollerslev, and Meddahi (2004, 2005), the reported R^2's understate the true degree of predictability due to the measurement errors in the realized volatility proxies. This does not, however, impede any cross model comparisons.

2.7.2 Out-of-Sample Forecasts

Even though the loss functions used in evaluating the forecasts discussed in the previous section formally differ from the likelihood functions used in estimating the models, the in-sample comparisons may seem to tilted toward making the more complicated HAR-CJN model perform well. Hence, in order to more closely mimic a real-world forecast situation, we also report on the results obtained by re-estimating all of the models with data up until the end of 1999, retaining the last five years of the sample from January 2, 2000 to February 4, 2005 for out-of-sample forecast comparisons.[24] Due to the relatively time consuming calculations involved in the estimation of the non-linear models, we did not re-estimate the models on a rolling basis over the out-of-sample period, instead simply freezing all of the parameters at their estimates based on the full 1990-1999 in-sample period.

The out-of-sample results essentially affirm the earlier in-sample findings. The RMSE's and MAE's for SP reported in Table 2.9 again achieve their lowest values across all horizons for the HAR-CJN models. The out-of-sample values for US are also the lowest for the HAR-CJN model, although the numerical differences are not particularly large. Interestingly, however, limiting the out-of-sample forecast comparisons for US to the last two years of the sample, which tend to exhibit both larger and more frequent jumps, results in sharper differences among the RMSE and MAE criteria. As such, this indirectly suggests that the benefits from a forecasting perspective from separately modelling the two volatility components are to some extend period specific.

Several procedures to formally test for the statistical significance of the observed differences in the RMSE and MAE criteria and the superior predictive ability of the underlying forecasting models have recently been proposed in the literature. As

[24]We also experimented with other out-of-sample periods, resulting in the same basic conclusions. Further details concerning these additional robustness checks are reported in Section 2.11.

a simple guide we here rely on the easy-to-calculate Diebold and Mariano (1995) test involving a pairwise comparison of the forecasts from each of the two traditional models to the forecasts from the HAR-CJN model.[25] The test is based on the heteroskedasticity and autocorrelation consistent t-statistic for the sample mean of $L_{t,HAR-CJN} - L_{t,\mathcal{M}}$, where $L_{t,\mathcal{M}}$ denotes the time t squared or absolute loss from the particular model $\mathcal{M}$. Many of the corresponding p-values reported in parentheses in Table 2.9 do indeed indicate statistically significant superior out-of-sample performance of the HAR-CJN model.

The out-of-sample Mincer-Zarnowitz regressions adjusted for the in-sample parameter estimation error uncertainty following West and McCracken (1998) reported in Table 2.10 generally also favor the HAR-CJN model. Although the high degree of co-linearity among the three forecasts render most of the estimated coefficients for the joint encompassing regressions rather imprecise, the individual regressions all achieve their highest R^2's for the HAR-CJN model. Moreover, the estimated intercept and slope coefficients for the individual HAR-CJN regressions are all close to zero and unity, respectively.

To further appreciate these results and the basic features of the different models, Figures 2.5 and 2.6 plot the one-day ahead out-of-sample forecasts. The overall level of the forecasts obviously matches fairly closely across the three models for both of the markets. Consistent with the results from the Mincer-Zarnowitz regressions, it also appears more difficult to discern any sharp differences in the three US forecasts. Nonetheless, the HAR-CJN based forecasts do seem to adapt more quickly to changes in the volatility than do the GARCH and, to a lesser degree, the HAR-RV based forecasts. Not surprisingly, on comparing the forecasts to the actual realiza-

[25] Although the Diebold and Mariano (1995) test does not explicitly account for the effect of estimation uncertainty, the out-of-sample version of the test coincides with the generally valid test for equal unconditional predictive ability recently developed by Giacomini and White (2006).

tion in Figures 2.1 and 2.2, all of the models miss the very largest observations which inherently must represent genuine large volatility innovations.

2.8 Conclusion

We use two fifteen-year samples of high-frequency intraday data for the S&P 500 and T- Bond futures markets along with the model-free bi-power variation measures and corresponding jump statistics of Barndorff-Nielsen and Shephard (2004b, 2006) to non-parametrically identify and measure the daily continuous sample path variation and squared jumps. Directly in line with earlier studies we find that the volatility associated with the continuous price movements within the day is a highly persistent process for both markets. Counter to a number of previous studies, however, we detect important dynamic dependencies in both the times between significant jumps and the sizes of the jumps. Further, the time series of overnight returns, or price jumps, associated with the change in the closing price from one day to the opening price of the next exhibits strong volatility clustering. To satisfactorily account for these dependencies, we formulate and estimate a combination of several reduced form time series models. In addition, we compare and contrast the forecasting performance of the estimated models for each of the three non-parametrically identified volatility components to other commonly used volatility forecasting models.

Looking ahead, our estimation results for the ACH model indicate that the occurrence of jumps in the T-Bond market is directly related to certain macroeconomic news releases. In this regard, it would be interesting to more systematically investigate the economic determinants behind the apparent discontinuities. What is it that causes financial markets to jump? The reduced form modelling setup developed here provides a particular convenient framework for further exploring this important question.

In the model diagnostics and forecast comparisons presented in the chapter, we have primarily focused on mean square error type criteria. However, separately modelling the intraday jumps and the overnight returns are likely to prove especially beneficial for better understanding the tails of the return distributions. It would be interesting to more directly analyze this issue, and the model's ability to capture the more extreme tail behavior and corresponding expected shortfalls, as would be of interest in many practical risk management situations.

As previously noted, the specification and estimation of empirically realistic continuous-time jump diffusion models have been the subject of extensive recent research efforts. In this regard, the relatively simple reduced form model structures for each of the different variation measures developed here could also be used as auxiliary models in an indirect inference setting to more effectively estimate and discriminate among some of these competing continuous-time specifications, naturally extending the earlier realized variation based inferential procedures of Barndorff-Nielsen and Shephard (2002a) and Bollerslev and Zhou (2002).

In a related context, the recent studies by Santa-Clara and Yan (2003) and Todorov (2006) suggest that the premia required by investors in options markets to compensate for jump and continuous volatility risks differ. By easily allowing for different risk premia associated with the future risks originating from the continuous sample path price process and the harder-to-hedge intraday jump and overnight components, it is possible that our relatively simple-to-implement reduced form forecasting model may be used in the calculation of more accurate derivatives prices.

We leave further work along these lines for future research.

2.9 Tables

Table 2.1: Descriptive Statistics for SP

	C_t	J_t	I_t	S_t	$r^2_{t,n}$
Mean	0.856	0.042	0.086	0.491	0.261
Std. Dev.	1.098	0.610	0.281	2.025	0.865
Skewness	5.274	34.77	2.947	10.37	16.44
Kurtosis	47.20	1390	9.683	123.8	483.3
Min	0.004	0.000	0.000	0.006	0.000
Max	14.33	27.59	1.000	27.59	31.38
Obs.	3801	3801	3801	328	3800

Ljung-Box Q-statistics

Lags	C_t		J_t		I_t		S_t		$r^2_{t,n}$	
5	6109	(0.000)	2.773	(0.735)	7.361	(0.195)	3.606	(0.607)	577.3	(0.000)
10	10039	(0.000)	24.69	(0.006)	15.50	(0.115)	6.190	(0.799)	727.3	(0.000)
15	12629	(0.000)	24.79	(0.053)	32.95	(0.005)	6.884	(0.961)	861.2	(0.000)
20	15050	(0.000)	26.75	(0.143)	37.47	(0.010)	7.077	(0.996)	962.9	(0.000)

Table 2.2: Descriptive Statistics for US

	C_t	J_t	I_t	S_t	$r^2_{t,n}$
Mean	0.253	0.037	0.255	0.143	0.066
Std. Dev.	0.205	0.158	0.436	0.286	0.160
Skewness	3.312	13.72	1.123	7.798	13.46
Kurtosis	23.99	281.5	2.261	88.71	340.9
Min	0.001	0.000	0.000	0.009	0.000
Max	2.742	4.519	1.000	4.519	5.271
Obs.	3781	3781	3781	965	3780

Ljung-Box Q-statistics

Lags	C_t		J_t		I_t		S_t		$r^2_{t,n}$	
5	1492	(0.000)	5.511	(0.357)	38.11	(0.000)	4.648	(0.460)	72.6	(0.000)
10	2444	(0.000)	7.946	(0.634)	58.27	(0.000)	38.15	(0.000)	128.8	(0.000)
15	3192	(0.000)	10.42	(0.793)	93.10	(0.000)	44.12	(0.000)	152.2	(0.000)
20	3939	(0.000)	158.2	(0.000)	142.5	(0.000)	63.82	(0.000)	182.8	(0.000)

Table 2.3: HAR-C Model Estimates

	Homoscedastic		GARCH(2,1)	
	SP	US	SP	US
β_0	-0.085 (0.011)[0.000]	-0.166 (0.052)[0.001]	-0.097 (0.010)[0.000]	-0.249 (0.038)[0.000]
β_{CD}	0.349 (0.024)[0.000]	0.144 (0.043)[0.001]	0.331 (0.020)[0.000]	0.109 (0.020)[0.000]
β_{CW}	0.338 (0.034)[0.000]	0.315 (0.062)[0.000]	0.369 (0.030)[0.000]	0.327 (0.036)[0.000]
β_{CM}	0.262 (0.029)[0.000]	0.501 (0.061)[0.000]	0.252 (0.025)[0.000]	0.444 (0.039)[0.000]
β_{JD}	-0.109 (0.071)[0.126]	-0.342 (0.135)[0.012]	-0.087 (0.078)[0.267]	-0.278 (0.116)[0.017]
β_{JW}	-0.118 (0.077)[0.124]	0.099 (0.224)[0.657]	-0.081 (0.100)[0.418]	0.281 (0.221)[0.205]
β_{JM}	-0.122 (0.088)[0.165]	-0.820 (0.402)[0.041]	-0.175 (0.099)[0.079]	-1.460 (0.329)[0.000]
ω	–	–	0.049 (0.015)[0.001]	0.015 (0.003)[0.000]
α_1	–	–	0.111 (0.027)[0.000]	0.129 (0.026)[0.000]
α_2	–	–	-0.024 (0.032)[0.457]	-0.090 (0.026)[0.000]
β_1	–	–	0.720 (0.076)[0.000]	0.921 (0.015)[0.000]
ν	–	–	7.696 (0.740)[0.000]	7.370 (0.822)[0.000]
LogL	-2805.434	-3890.313	-2671.580	-3341.914
Obs.	3779	3759	3779	3759

Table 2.4: ACH Model Estimates

	ACH(1,1)		Augmented ACH	
	SP	US	SP	US
ω	0.227(0.241)[0.346]	0.212(0.084)[0.012]	–	–
α_1	0.038(0.021)[0.061]	0.088(0.020)[0.000]	0.056(0.029)[0.053]	0.088(0.019)[0.000]
β_1	0.942(0.036)[0.000]	0.858(0.035)[0.000]	0.900(0.059)[0.000]	0.859(0.033)[0.000]
δ_0	–	–	0.654(2.771)[0.813]	-0.282(0.423)[0.505]
δ_M	–	–	0.320(1.695)[0.850]	0.412(0.298)[0.166]
δ_T	–	–	1.117(1.731)[0.519]	0.387(0.271)[0.154]
δ_W	–	–	2.979(1.962)[0.129]	0.681(0.299)[0.023]
δ_{Th}	–	–	1.144(1.666)[0.492]	0.325(0.266)[0.222]
δ_{ES}	–	–	0.629(0.575)[0.274]	0.199(0.094)[0.034]
δ_{CPI}	–	–	0.757(0.629)[0.229]	0.396(0.089)[0.000]
LogL	-1107.797	-2111.457	-1106.136	-2098.906
Obs.	3792	3778	3792	3778

Table 2.5: HAR-J Model Estimates

	Homoscedastic		GARCH(1,1)	
	SP	US	SP	US
β_0	-1.093 (0.072)[0.000]	-1.479 (0.113)[0.000]	-1.299 (0.122)[0.000]	-1.535 (0.114)[0.000]
β_{CD}	0.281 (0.114)[0.014]	-0.057 (0.053)[0.280]	0.172 (0.122)[0.158]	-0.085 (0.051)[0.095]
β_{CW}	0.460 (0.185)[0.013]	0.269 (0.112)[0.017]	0.440 (0.172)[0.011]	0.338 (0.099)[0.001]
β_{CM}	0.345 (0.150)[0.022]	0.489 (0.111)[0.000]	0.343 (0.147)[0.020]	0.474 (0.103)[0.000]
ω	–	–	0.068 (0.110)[0.540]	0.013 (0.007)[0.046]
α_1	–	–	0.039 (0.042)[0.355]	0.035 (0.010)[0.000]
β_1	–	–	0.866 (0.009)[0.000]	0.950 (0.010)[0.000]
ν	–	–	3.265 (0.659)[0.000]	6.430 (1.608)[0.000]
LogL	-387.854	-1281.353	-353.162	-1250.054
Obs.	327	960	327	960

Table 2.6: Overnight GARCH Model Estimates

	Unrestricted		Restricted	
	SP	US	SP	US
μ	0.015(0.005)[0.004]	0.006(0.004)[0.121]	0.015(0.005)[0.003]	0.006(0.004)[0.105]
ω_n	-0.001(0.001)[0.233]	0.002(0.001)[0.014]	-0.001(0.001)[0.199]	0.002(0.001)[0.020]
$\alpha_{1,n}$	0.041(0.012)[0.001]	0.045(0.011)[0.000]	0.044(0.012)[0.000]	0.046(0.010)[0.000]
$\beta_{1,n}$	0.817(0.024)[0.000]	0.852(0.027)[0.000]	0.806(0.025)[0.000]	0.854(0.027)[0.000]
β_{CP}	0.040(0.009)[0.000]	0.014(0.006)[0.013]	–	–
β_{CN}	0.045(0.007)[0.000]	0.023(0.006)[0.000]	–	–
β_{JP}	-0.031(0.012)[0.010]	-0.000(0.011)[0.964]	–	–
β_{JN}	0.023(0.022)[0.305]	0.005(0.009)[0.574]	–	–
β_C	–	–	0.045(0.007)[0.000]	0.019(0.005)[0.000]
ν	5.004(0.434)[0.000]	7.906(0.747)[0.000]	4.944(0.422)[0.000]	7.847(0.730)[0.000]
LogL	-1863.415	-8.696	-1865.451	-10.300
Obs.	3799	3779	3799	3779

Table 2.7: In-Sample Forecast Statistics

		RMSE			MAE		
	Horizon	1	5	22	1	5	22
SP	GARCH	1.519	0.995	0.869	0.626	0.506	0.504
	HAR-RV	1.477	0.943	0.827	0.556	0.453	0.466
	HAR-CJN	1.412	0.855	0.748	0.542	0.417	0.420
US	GARCH	0.325	0.170	0.119	0.176	0.112	0.087
	HAR-RV	0.325	0.169	0.118	0.175	0.112	0.086
	HAR-CJN	0.322	0.167	0.120	0.176	0.114	0.086

Table 2.8: In-Sample Mincer-Zarnowitz Regressions

	Joint Regressions					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	-0.030(0.045)	0.025(0.055)	0.140(0.083)	-0.004(0.020)	-0.015(0.024)	-0.012(0.033)
GARCH	-0.096(0.106)	-0.136(0.106)	-0.022(0.150)	0.524(0.110)	0.459(0.109)	0.358(0.128)
HAR-RV	-0.103(0.071)	-0.189(0.123)	-0.410(0.226)	-0.302(0.148)	0.003(0.187)	0.097(0.156)
HAR-CJN	1.264(0.142)	1.353(0.161)	1.363(0.216)	0.774(0.097)	0.565(0.120)	0.539(0.132)
R^2	0.399	0.601	0.564	0.123	0.310	0.408
	Individual Regressions					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	0.044(0.046)	0.127(0.061)	0.257(0.073)	-0.023(0.019)	-0.009(0.025)	0.022(0.036)
GARCH	0.939(0.050)	0.868(0.068)	0.750(0.062)	1.093(0.059)	1.053(0.077)	0.963(0.109)
R^2	0.301	0.460	0.450	0.098	0.259	0.324
Intercept	-0.066(0.081)	-0.098(0.083)	-0.083(0.104)	-0.007(0.021)	-0.018(0.027)	-0.031(0.037)
HAR-RV	1.150(0.089)	1.180(0.095)	1.169(0.111)	1.043(0.062)	1.076(0.080)	1.113(0.111)
R^2	0.346	0.523	0.473	0.095	0.265	0.345
Const.	-0.061(0.050)	-0.022(0.056)	0.046(0.066)	0.038(0.016)	0.044(0.019)	0.042(0.030)
HAR-CJN	1.091(0.058)	1.068(0.065)	1.024(0.072)	0.870(0.045)	0.838(0.052)	0.805(0.080)
R^2	0.397	0.579	0.558	0.117	0.291	0.385

Table 2.9: Out-of-Sample Forecast Statistics

			RMSE			MAE	
	Horizon	1	5	22	1	5	22
SP	GARCH	1.929 (0.001)	1.269 (0.004)	1.130 (0.069)	0.836 (0.000)	0.669 (0.000)	0.694 (0.019)
	HAR-RV	1.868 (0.002)	1.234 (0.004)	1.147 (0.009)	0.717 (0.224)	0.600 (0.002)	0.642 (0.005)
	HAR-CJN	1.793	1.127	1.055	0.705	0.557	0.586
US	GARCH	0.375 (0.044)	0.199 (0.107)	0.150 (0.133)	0.193 (0.305)	0.130 (0.191)	0.105 (0.436)
	HAR-RV	0.375 (0.000)	0.198 (0.010)	0.151 (0.041)	0.192 (0.251)	0.130 (0.041)	0.108 (0.135)
	HAR-CJN	0.368	0.188	0.132	0.190	0.124	0.098

Table 2.10: Out-of-Sample Mincer-Zarnowitz Regressions

	Joint Regressions					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	0.008(0.117)	0.114(0.170)	0.394(0.250)	-0.029(0.062)	-0.039(0.072)	-0.050(0.100)
GARCH	-0.194(0.270)	-0.187(0.262)	-0.097(0.294)	0.852(0.301)	0.762(0.279)	0.516(0.329)
HAR-RV	-0.238(0.594)	-0.813(0.779)	-2.428(1.545)	-0.709(0.379)	-0.361(0.404)	-0.061(0.446)
HAR-CJN	1.515(0.542)	2.019(0.716)	3.333(1.321)	1.018(0.247)	0.797(0.265)	0.795(0.402)
R^2	0.375	0.568	0.518	0.124	0.321	0.413

	Individual Regressions					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	0.077(0.124)	0.201(0.187)	0.487(0.259)	-0.049(0.060)	-0.034(0.079)	0.016(0.102)
GARCH	0.989(0.099)	0.915(0.154)	0.746(0.119)	1.282(0.166)	1.250(0.224)	1.137(0.288)
R^2	0.260	0.404	0.348	0.094	0.262	0.310
Const.	-0.128(0.150)	-0.043(0.202)	0.182(0.296)	0.025(0.070)	0.002(0.085)	-0.033(0.107)
HAR-RV	1.325(0.144)	1.300(0.200)	1.217(0.194)	1.062(0.183)	1.139(0.234)	1.286(0.304)
R^2	0.346	0.506	0.402	0.084	0.250	0.333
Const.	-0.078(0.144)	-0.008(0.168)	0.170(0.232)	0.048(0.084)	0.048(0.064)	0.012(0.098)
HAR-CJN	1.154(0.124)	1.157(0.156)	1.137(0.150)	0.944(0.138)	0.948(0.162)	1.058(0.257)
R^2	0.371	0.554	0.466	0.109	0.287	0.383

2.10 Figures

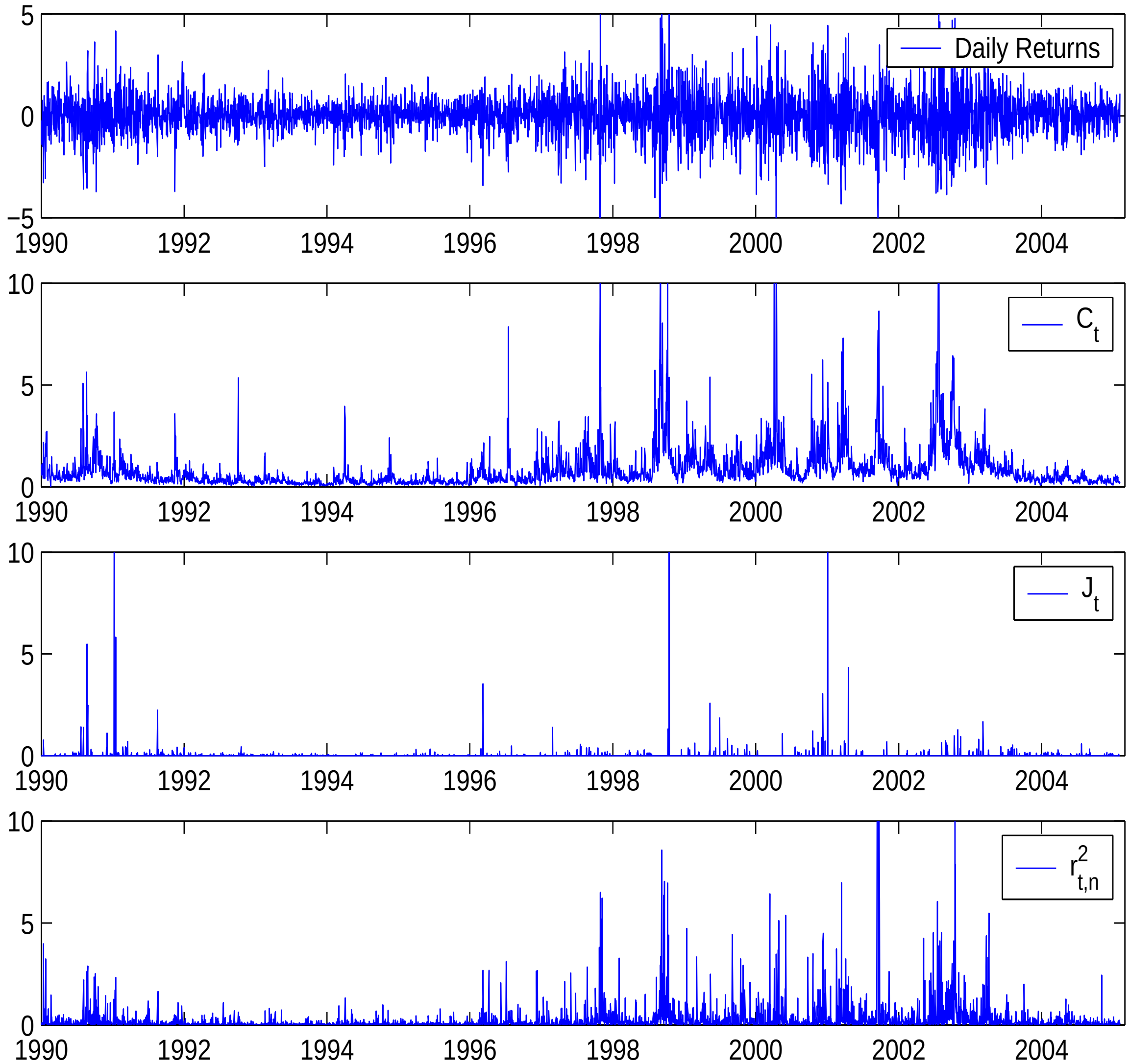

Figure 2.1: Daily Returns and Variation Components for SP

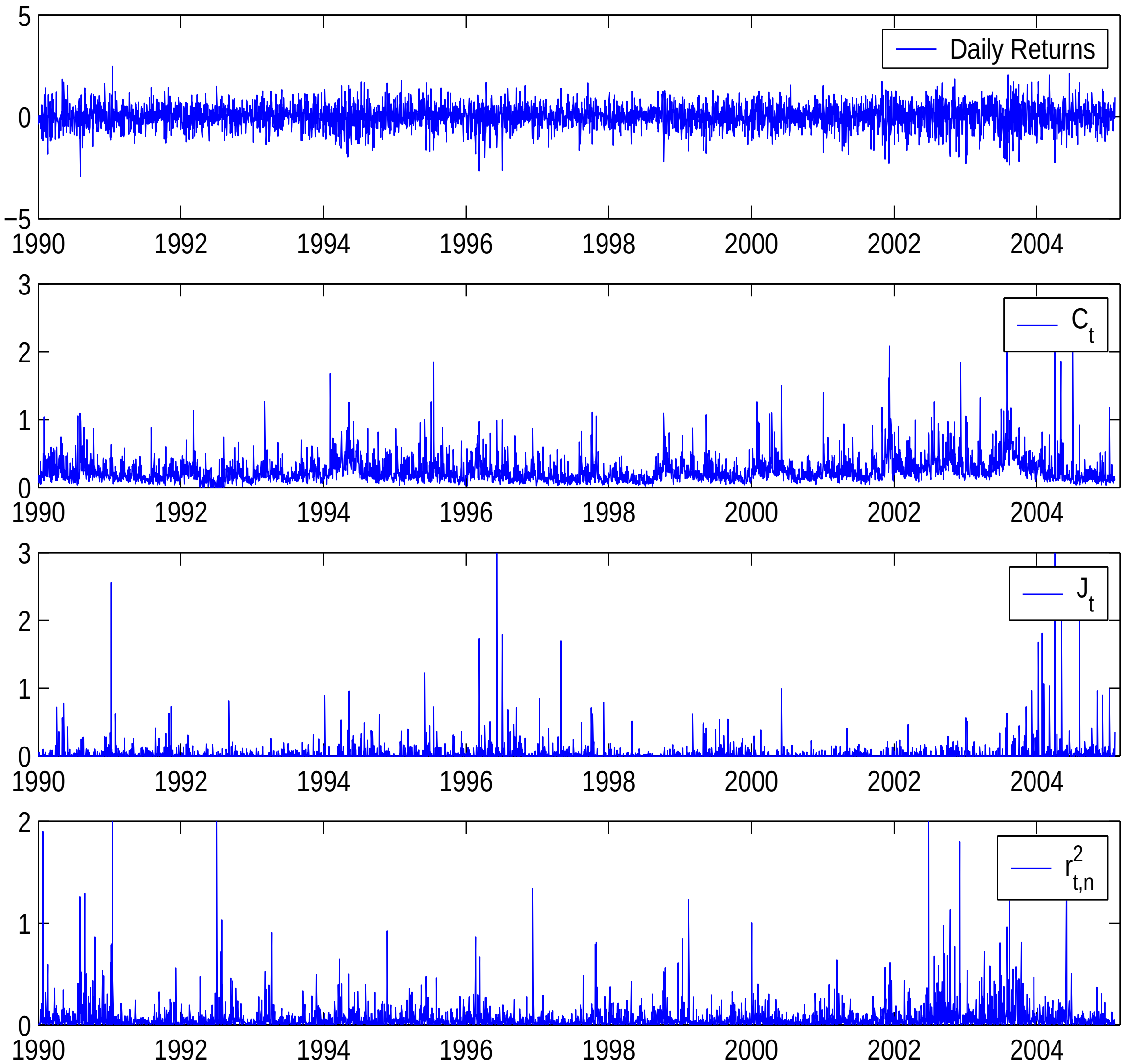

Figure 2.2: Daily Returns and Variation Components for US

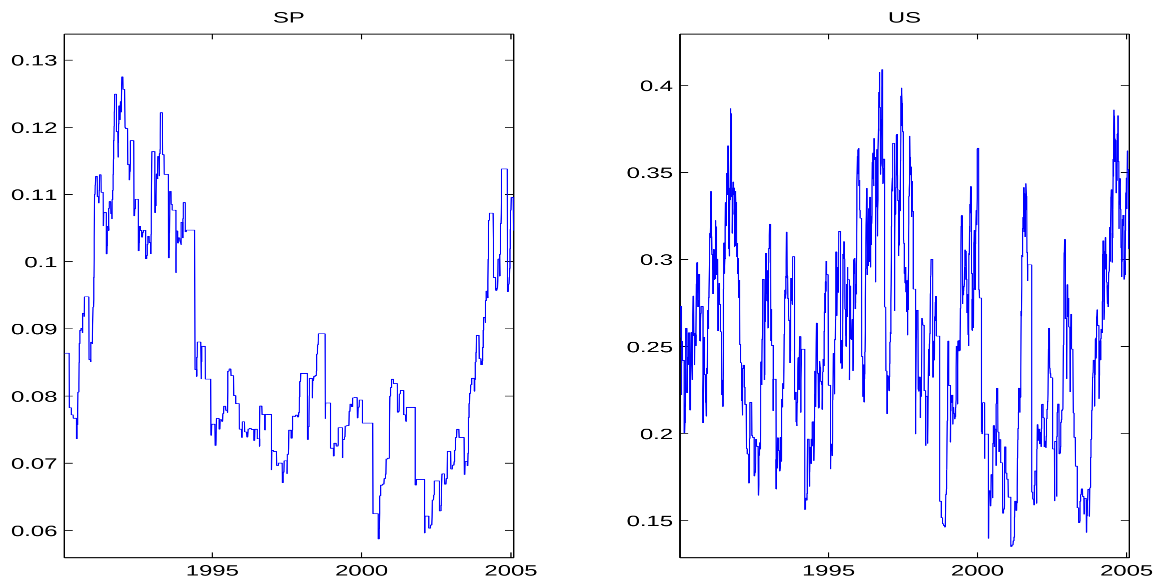

Figure 2.3: Conditional Hazard Rates from ACH(1,1) Model

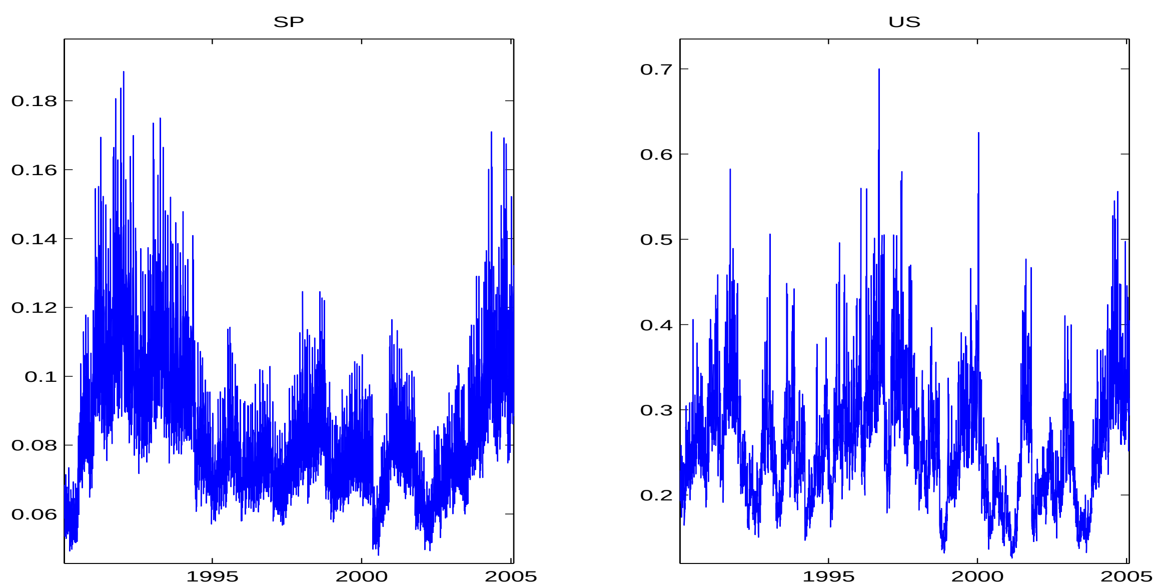

Figure 2.4: Conditional Hazard Rates from Augmented ACH Model

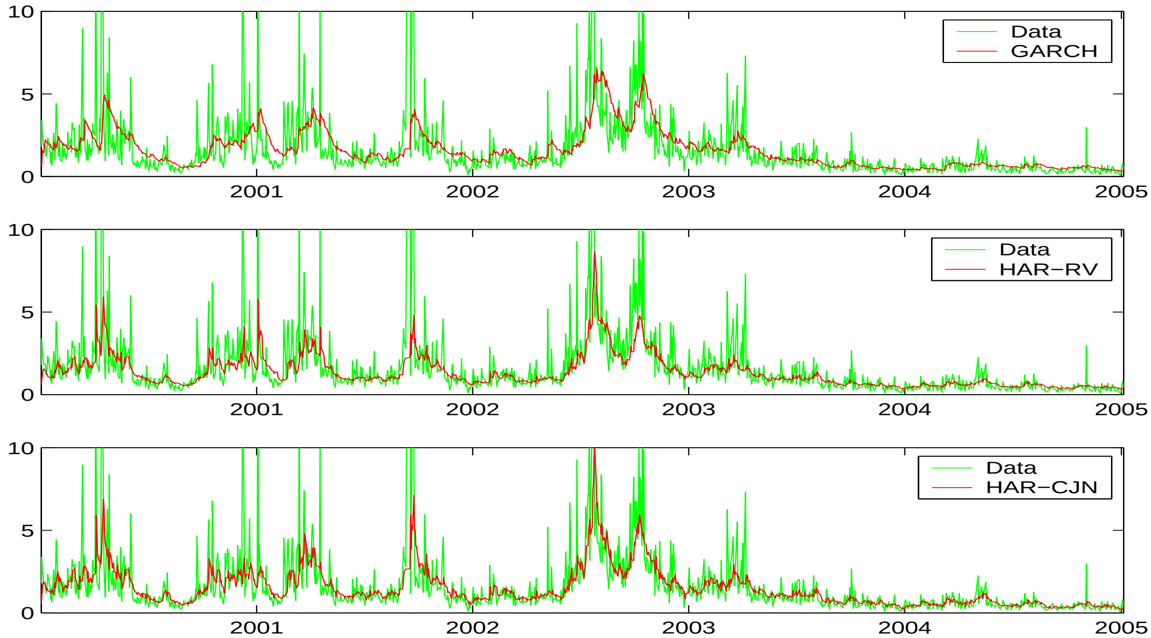

Figure 2.5: One-Day-Ahead Out-of-Sample Forecasts for SP

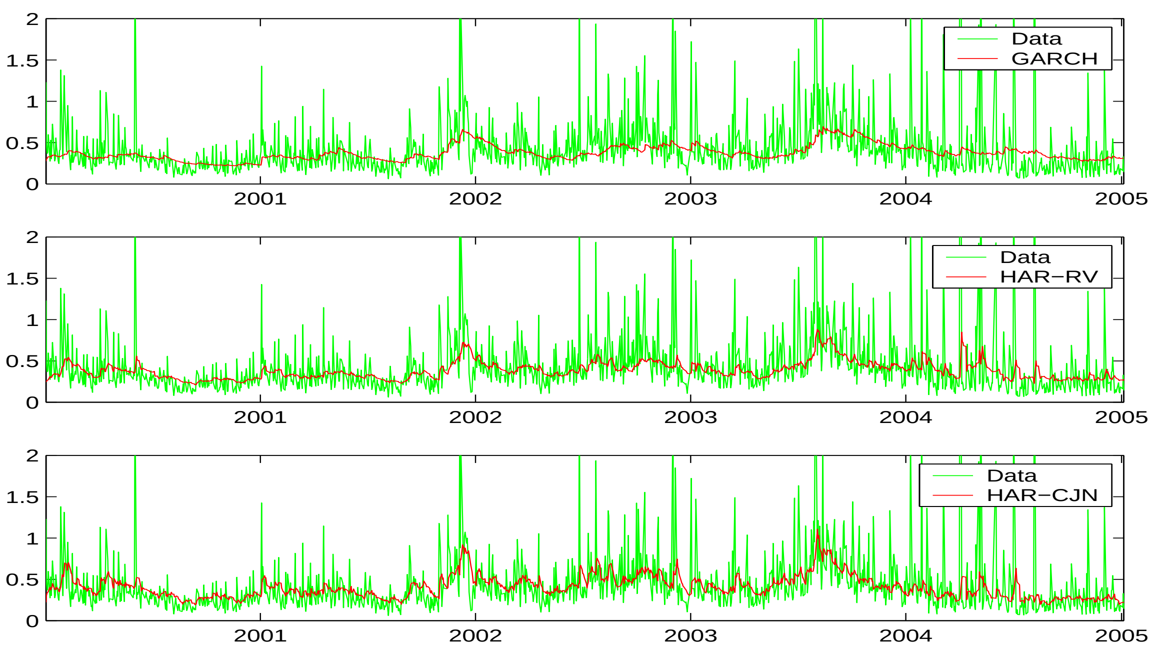

Figure 2.6: One-Day-Ahead Out-of-Sample Forecasts for US

2.11 Supplemental Tables and Figures

Table 2.11: Descriptive Statistics for SP (α=0.95)

	Sample Moments				
	C_t	J_t	I_t	S_t	$r^2_{t,n}$
Mean	0.842	0.056	0.184	0.305	0.261
Std. Dev.	1.091	0.612	0.387	1.401	0.865
Skewness	5.334	34.320	1.632	15.042	16.439
Kurtosis	48.195	1366.711	3.663	260.283	483.337
Min	0.004	0.000	0.000	0.006	0.000
Max	14.331	27.594	1.000	27.594	31.378
Obs.	3801	3801	3801	699	3800

Ljung-Box Q-statistics										
Lags	C_t		J_t		I_t		S_t		$r^2_{t,n}$	
5	6070.279	(0.000)	2.989	(0.702)	15.343	(0.009)	8.599	(0.126)	577.275	(0.000)
10	9979.074	(0.000)	26.822	(0.003)	24.492	(0.006)	10.012	(0.439)	727.276	(0.000)
15	12530.228	(0.000)	26.874	(0.030)	33.951	(0.003)	10.075	(0.815)	861.244	(0.000)
20	14926.402	(0.000)	28.775	(0.092)	41.826	(0.003)	14.018	(0.830)	962.853	(0.000)

Table 2.12: Descriptive Statistics for US (α=0.95)

	Sample Moments				
	C_t	J_t	I_t	S_t	$r^2_{t,n}$
Mean	0.245	0.045	0.414	0.109	0.066
Std. Dev.	0.197	0.160	0.493	0.234	0.160
Skewness	3.094	13.277	0.350	9.388	13.461
Kurtosis	21.307	266.574	1.122	129.375	340.858
Min	0.001	0.000	0.000	0.004	0.000
Max	2.742	4.519	1.000	4.519	5.271
Obs.	3781	3781	3781	1565	3780

Ljung-Box Q-statistics										
Lags	C_t		J_t		I_t		S_t		$r^2_{t,n}$	
5	1667.578	(0.000)	4.995	(0.416)	44.545	(0.000)	2.784	(0.733)	72.562	(0.000)
10	2749.527	(0.000)	6.754	(0.748)	70.276	(0.000)	14.616	(0.147)	128.797	(0.000)
15	3594.191	(0.000)	8.976	(0.879)	102.738	(0.000)	69.335	(0.000)	152.246	(0.000)
20	4442.701	(0.000)	144.129	(0.000)	138.979	(0.000)	83.529	(0.000)	182.789	(0.000)

Table 2.13: HAR-C Model Estimates ($\alpha = 0.99$)

	homoscedastic		GARCH(2,1)-normal	
	SP	US	SP	US
β_0	-0.085 (0.011) [0.000]	-0.166 (0.052) [0.001]	-0.078 (0.011) [0.000]	-0.240 (0.035) [0.000]
β_{CD}	0.349 (0.024) [0.000]	0.144 (0.043) [0.001]	0.336 (0.024) [0.000]	0.109 (0.021) [0.000]
β_{CW}	0.338 (0.034) [0.000]	0.315 (0.062) [0.000]	0.368 (0.039) [0.000]	0.338 (0.038) [0.000]
β_{CM}	0.262 (0.029) [0.000]	0.501 (0.061) [0.000]	0.250 (0.027) [0.000]	0.435 (0.040) [0.000]
β_{JD}	-0.109 (0.071) [0.126]	-0.342 (0.135) [0.012]	-0.091 (0.066) [0.167]	-0.246 (0.118) [0.037]
β_{JW}	-0.118 (0.077) [0.124]	0.099 (0.224) [0.657]	-0.104 (0.074) [0.160]	0.182 (0.207) [0.379]
β_{JM}	-0.122 (0.088) [0.165]	-0.820 (0.402) [0.041]	-0.144 (0.079) [0.070]	-1.200 (0.384) [0.002]
ω	–	–	0.008 (0.006) [0.185]	0.008 (0.003) [0.003]
α_1	–	–	0.099 (0.023) [0.000]	0.116 (0.025) [0.000]
α_2	–	–	-0.074 (0.026) [0.004]	-0.079 (0.025) [0.002]
β_1	–	–	0.944 (0.035) [0.000]	0.940 (0.017) [0.000]
LogL	-2805.434	-3890.313	-2745.237	-3401.131
Obs.	3779	3759	71	49

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	17.412	0.004	42.387	0.000	14.785	0.011	18.736	0.002
10	30.617	0.001	92.919	0.000	27.754	0.002	44.805	0.000
15	33.507	0.004	137.710	0.000	30.450	0.010	55.712	0.000
20	35.309	0.019	167.890	0.000	32.274	0.040	81.042	0.000

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	42.414	0.000	1076.400	0.000	2.812	0.729	11.946	0.036
10	45.703	0.000	2473.200	0.000	4.276	0.934	36.157	0.000
15	47.007	0.000	3435.400	0.000	5.688	0.985	40.239	0.000
20	50.635	0.000	3933.900	0.000	8.602	0.987	48.481	0.000

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	97.276	0.000	621.390	0.000	9.878	0.079	12.040	0.034
10	106.910	0.000	1224.300	0.000	11.066	0.352	20.494	0.025
15	115.920	0.000	1702.800	0.000	13.136	0.592	24.215	0.062
20	136.490	0.000	2025.400	0.000	18.119	0.580	36.068	0.015

Table 2.14: HAR-C Model Estimates ($\alpha = 0.95$)

	homoscedastic		GARCH(2,1)-normal	
	SP	US	SP	US
β_0	-0.082 (0.012) [0.000]	-0.125 (0.053) [0.019]	-0.076 (0.012) [0.000]	-0.206 (0.037) [0.000]
β_{CD}	0.351 (0.024) [0.000]	0.151 (0.043) [0.000]	0.339 (0.024) [0.000]	0.112 (0.022) [0.000]
β_{CW}	0.338 (0.034) [0.000]	0.322 (0.063) [0.000]	0.367 (0.038) [0.000]	0.340 (0.039) [0.000]
β_{CM}	0.262 (0.029) [0.000]	0.501 (0.061) [0.000]	0.250 (0.027) [0.000]	0.444 (0.041) [0.000]
β_{JD}	-0.078 (0.071) [0.274]	-0.440 (0.135) [0.001]	-0.065 (0.064) [0.311]	-0.307 (0.118) [0.009]
β_{JW}	-0.105 (0.079) [0.183]	0.011 (0.232) [0.961]	-0.096 (0.077) [0.210]	0.081 (0.213) [0.704]
β_{JM}	-0.133 (0.091) [0.142]	-0.906 (0.396) [0.022]	-0.145 (0.081) [0.074]	-1.221 (0.388) [0.002]
ω	–	–	0.008 (0.006) [0.184]	0.008 (0.003) [0.003]
α_1	–	–	0.100 (0.024) [0.000]	0.112 (0.025) [0.000]
α_2	–	–	-0.074 (0.027) [0.005]	-0.074 (0.025) [0.003]
β_1	–	–	0.943 (0.035) [0.000]	0.939 (0.018) [0.000]
LogL	-2818.208	-3866.503	-2757.209	-3397.965
Obs.	3779	3759	62	59

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	18.297	0.003	38.259	0.000	15.188	0.010	19.594	0.001
10	31.495	0.000	84.375	0.000	28.180	0.002	46.375	0.000
15	34.985	0.002	122.280	0.000	31.407	0.008	57.360	0.000
20	37.111	0.011	151.300	0.000	33.740	0.028	85.405	0.000

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	44.242	0.000	1063.900	0.000	2.925	0.712	15.662	0.008
10	48.244	0.000	2445.300	0.000	5.213	0.876	41.548	0.000
15	49.684	0.000	3407.300	0.000	6.114	0.978	46.588	0.000
20	54.076	0.000	3898.900	0.000	9.259	0.980	55.825	0.000

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	99.103	0.000	591.910	0.000	10.609	0.060	12.179	0.032
10	112.250	0.000	1179.200	0.000	11.510	0.319	22.190	0.014
15	122.920	0.000	1636.400	0.000	12.975	0.604	25.087	0.049
20	145.680	0.000	1947.800	0.000	18.989	0.523	37.311	0.011

Table 2.15: HAR-C Model Estimates ($\alpha = 0.99$)

	homoscedastic		GARCH(2,1)-t	
	SP	US	SP	US
β_0	-0.085 (0.011) [0.000]	-0.166 (0.052) [0.001]	-0.097 (0.010) [0.000]	-0.249 (0.048) [0.000]
β_{CD}	0.349 (0.024) [0.000]	0.144 (0.043) [0.001]	0.331 (0.020) [0.000]	0.109 (0.023) [0.000]
β_{CW}	0.338 (0.034) [0.000]	0.315 (0.062) [0.000]	0.369 (0.030) [0.000]	0.327 (0.040) [0.000]
β_{CM}	0.262 (0.029) [0.000]	0.501 (0.061) [0.000]	0.252 (0.025) [0.000]	0.444 (0.050) [0.000]
β_{JD}	-0.109 (0.071) [0.126]	-0.342 (0.135) [0.012]	-0.087 (0.078) [0.267]	-0.278 (0.116) [0.017]
β_{JW}	-0.118 (0.077) [0.124]	0.099 (0.224) [0.657]	-0.081 (0.100) [0.418]	0.281 (0.296) [0.343]
β_{JM}	-0.122 (0.088) [0.165]	-0.820 (0.402) [0.041]	-0.175 (0.099) [0.079]	-1.460 (0.468) [0.002]
ω	–	–	0.049 (0.015) [0.001]	0.015 (0.007) [0.039]
α_1	–	–	0.111 (0.027) [0.000]	0.129 (0.037) [0.000]
α_2	–	–	-0.024 (0.032) [0.457]	-0.090 (0.031) [0.004]
β_1	–	–	0.720 (0.076) [0.000]	0.921 (0.017) [0.000]
ν	–	–	7.696 (0.740) [0.000]	7.370 (10.514) [0.483]
LogL	-2805.434	-3890.313	-2671.580	-3341.914
Obs.	3779	3759	3778	3758

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	17.412	0.004	42.387	0.000	14.098	0.015	20.305	0.001
10	30.617	0.001	92.919	0.000	30.494	0.001	45.697	0.000
15	33.507	0.004	137.710	0.000	32.980	0.005	56.577	0.000
20	35.309	0.019	167.890	0.000	34.566	0.023	81.436	0.000

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	42.414	0.000	1076.400	0.000	1.030	0.960	11.413	0.044
10	45.703	0.000	2473.200	0.000	8.736	0.557	43.898	0.000
15	47.007	0.000	3435.400	0.000	9.701	0.838	50.614	0.000
20	50.635	0.000	3933.900	0.000	12.339	0.904	58.919	0.000

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	97.276	0.000	621.390	0.000	2.859	0.722	11.179	0.048
10	106.910	0.000	1224.300	0.000	5.082	0.886	19.982	0.029
15	115.920	0.000	1702.800	0.000	8.377	0.908	24.617	0.055
20	136.490	0.000	2025.400	0.000	17.315	0.632	37.321	0.011

Table 2.16: HAR-C Model Estimates ($\alpha = 0.95$)

	homoscedastic		GARCH(2,1)-t	
	SP	US	SP	US
β_0	-0.088 (0.011) [0.000]	-0.179 (0.051) [0.001]	-0.100 (0.010) [0.000]	-0.274 (0.036) [0.000]
β_{CD}	0.346 (0.024) [0.000]	0.148 (0.043) [0.001]	0.333 (0.020) [0.000]	0.115 (0.020) [0.000]
β_{CW}	0.338 (0.034) [0.000]	0.306 (0.062) [0.000]	0.367 (0.030) [0.000]	0.311 (0.035) [0.000]
β_{CM}	0.263 (0.029) [0.000]	0.499 (0.061) [0.000]	0.249 (0.025) [0.000]	0.442 (0.038) [0.000]
β_{JD}	-0.116 (0.082) [0.157]	-0.355 (0.134) [0.008]	-0.101 (0.095) [0.288]	-0.332 (0.116) [0.004]
β_{JW}	-0.109 (0.089) [0.221]	0.101 (0.218) [0.643]	-0.079 (0.116) [0.494]	0.285 (0.214) [0.182]
β_{JM}	-0.146 (0.089) [0.099]	-0.793 (0.400) [0.047]	-0.187 (0.101) [0.065]	-1.424 (0.329) [0.000]
ω	–	–	0.054 (0.014) [0.000]	0.015 (0.004) [0.000]
α_1	–	–	0.132 (0.027) [0.000]	0.127 (0.026) [0.000]
α_2	–	–	-0.029 (0.032) [0.368]	-0.090 (0.026) [0.001]
β_1	–	–	0.686 (0.072) [0.000]	0.921 (0.016) [0.000]
ν	–	–	7.817 (3.714) [0.035]	6.889 (0.756) [0.000]
LogL	-2793.551	-3853.315	-2655.608	-3293.807
Obs.	3779	3759	3778	3758

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	18.024	0.003	36.578	0.000	14.104	0.015	24.350	0.000
10	33.125	0.000	85.823	0.000	32.070	0.000	48.256	0.000
15	35.972	0.002	128.400	0.000	34.445	0.003	58.478	0.000
20	38.232	0.008	153.930	0.000	36.454	0.014	82.624	0.000

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	47.442	0.000	994.560	0.000	1.396	0.925	11.011	0.051
10	50.416	0.000	2354.200	0.000	8.301	0.599	49.826	0.000
15	51.432	0.000	3250.300	0.000	9.633	0.842	58.882	0.000
20	54.041	0.000	3719.200	0.000	11.603	0.929	65.797	0.000

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	110.990	0.000	609.070	0.000	4.301	0.507	11.327	0.045
10	120.200	0.000	1195.100	0.000	6.651	0.758	21.914	0.016
15	126.810	0.000	1650.000	0.000	10.669	0.776	26.432	0.034
20	147.870	0.000	1967.400	0.000	20.633	0.419	33.572	0.029

Table 2.17: ACH Model Estimates ($\alpha = 0.99$)

	Simple ACH		Augmented ACH	
	SP	US	SP	US
ω	0.227(0.241)[0.346]	0.212(0.084)[0.012]	–	–
α_1	0.038(0.021)[0.061]	0.088(0.020)[0.000]	0.056(0.029)[0.053]	0.088(0.019)[0.000]
β_1	0.942(0.036)[0.000]	0.858(0.035)[0.000]	0.900(0.059)[0.000]	0.859(0.033)[0.000]
δ_0	–	–	0.654(2.771)[0.813]	-0.282(0.423)[0.505]
δ_M	–	–	0.320(1.695)[0.850]	0.412(0.298)[0.166]
δ_T	–	–	1.117(1.731)[0.519]	0.387(0.271)[0.154]
δ_W	–	–	2.979(1.962)[0.129]	0.681(0.299)[0.023]
δ_{Th}	–	–	1.144(1.666)[0.492]	0.325(0.266)[0.222]
δ_{ES}	–	–	0.629(0.575)[0.274]	0.199(0.094)[0.034]
δ_{CPI}	–	–	0.757(0.629)[0.229]	0.396(0.089)[0.000]
LogL	-1107.797	-2111.457	-1106.136	-2098.906
Obs.	3792	3778	3792	3778

Ljung-Box Q-statistics for d_i

	Simple ACH				Augmented ACH			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	7.870	0.164	65.924	0.000	7.870	0.164	65.924	0.000
10	18.595	0.046	109.279	0.000	18.595	0.046	109.279	0.000
15	20.609	0.150	124.201	0.000	20.609	0.150	124.201	0.000
20	26.485	0.150	129.073	0.000	26.485	0.150	129.073	0.000

Ljung-Box Q-statistics for d_i/ψ_i

	Simple ACH				Augmented ACH			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	2.309	0.805	1.389	0.925	4.701	0.453	2.965	0.705
10	8.829	0.548	6.089	0.808	11.087	0.351	7.854	0.643
15	11.568	0.711	7.062	0.956	13.484	0.565	11.109	0.745
20	13.797	0.841	10.375	0.961	18.763	0.537	17.555	0.617

Table 2.18: ACH Model Estimates ($\alpha = 0.95$)

	Simple ACH		Augmented ACH	
	SP	US	SP	US
ω	0.050(0.053)[0.343]	0.081(0.033)[0.014]	–	–
α_1	0.021(0.010)[0.035]	0.054(0.012)[0.000]	0.029(0.013)[0.023]	0.055(0.012)[0.000]
β_1	0.969(0.017)[0.000]	0.913(0.022)[0.000]	0.955(0.023)[0.000]	0.910(0.023)[0.000]
δ_0	–	–	1.444(1.096)[0.187]	0.332(0.253)[0.189]
δ_M	–	–	0.405(0.541)[0.454]	-0.070(0.128)[0.586]
δ_T	–	–	0.498(0.537)[0.354]	0.167(0.136)[0.219]
δ_W	–	–	0.969(0.577)[0.093]	0.209(0.138)[0.130]
δ_{Th}	–	–	0.560(0.534)[0.295]	0.125(0.132)[0.341]
δ_{ES}	–	–	0.065(0.190)[0.731]	0.070(0.046)[0.133]
δ_{CPI}	–	–	-0.059(0.207)[0.777]	0.150(0.044)[0.001]
LogL	-1803.616	-2526.102	-1802.796	-2517.133
Obs.	3800	3778	3800	3778

Ljung-Box Q-statistics for d_i

	Simple ACH				Augmented ACH			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	8.998	0.109	44.953	0.000	8.998	0.109	44.953	0.000
10	13.674	0.188	80.577	0.000	13.674	0.188	80.577	0.000
15	22.880	0.087	128.223	0.000	22.880	0.087	128.223	0.000
20	33.824	0.027	145.524	0.000	33.824	0.027	145.524	0.000

Ljung-Box Q-statistics for d_i/ψ_i

	Simple ACH				Augmented ACH			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	2.284	0.809	1.917	0.861	2.171	0.825	4.081	0.538
10	3.678	0.961	6.540	0.768	4.751	0.907	10.795	0.374
15	6.635	0.967	12.016	0.678	7.372	0.947	13.738	0.545
20	14.864	0.784	12.768	0.887	15.560	0.744	15.651	0.738

Table 2.19: HAR-J Model Estimates ($\alpha = 0.99$)

	homoscedastic		GARCH(1,1)-normal	
	SP	US	SP	US
β_0	-1.093 (0.072) [0.000]	-1.479 (0.113) [0.000]	-1.087 (0.084) [0.000]	-1.523 (0.102) [0.000]
β_{CD}	0.281 (0.114) [0.014]	-0.057 (0.053) [0.280]	0.316 (0.120) [0.009]	-0.061 (0.053) [0.246]
β_{CW}	0.460 (0.185) [0.013]	0.269 (0.112) [0.017]	0.357 (0.182) [0.051]	0.305 (0.110) [0.006]
β_{CM}	0.345 (0.150) [0.022]	0.489 (0.111) [0.000]	0.422 (0.131) [0.001]	0.436 (0.109) [0.000]
ω	–	–	0.019 (0.016) [0.258]	0.011 (0.010) [0.268]
α_1	–	–	0.063 (0.040) [0.119]	0.029 (0.013) [0.025]
β_1	–	–	0.909 (0.051) [0.000]	0.959 (0.021) [0.000]
LogL	-387.854	-1281.353	-380.467	-1268.633
Obs.	327	960	327	960

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	5.657	0.341	7.490	0.187	3.235	0.664	8.622	0.125
10	12.955	0.226	16.660	0.082	9.855	0.453	19.749	0.032
15	20.501	0.154	21.330	0.127	14.775	0.468	25.008	0.050
20	22.450	0.317	38.126	0.009	15.447	0.750	41.770	0.003

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	18.459	0.002	2.531	0.772	4.137	0.530	5.936	0.313
10	19.425	0.035	26.481	0.003	6.014	0.814	14.631	0.146
15	22.779	0.089	28.960	0.016	9.769	0.834	17.896	0.268
20	22.930	0.292	50.077	0.000	11.404	0.935	26.674	0.145

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	12.585	0.028	6.527	0.258	4.487	0.482	7.162	0.209
10	13.420	0.201	33.553	0.000	5.816	0.830	18.477	0.047
15	20.466	0.155	36.332	0.002	9.536	0.848	21.654	0.117
20	22.236	0.328	57.822	0.000	15.084	0.772	30.195	0.067

Table 2.20: HAR-J Model Estimates ($\alpha = 0.95$)

	homoscedastic		GARCH(1,1)-normal	
	SP	US	SP	US
β_0	-1.469 (0.042) [0.000]	-1.769 (0.084) [0.000]	-1.475 (0.044) [0.000]	-1.780 (0.077) [0.000]
β_{CD}	0.241 (0.080) [0.003]	-0.040 (0.037) [0.277]	0.225 (0.075) [0.003]	-0.048 (0.037) [0.193]
β_{CW}	0.481 (0.120) [0.000]	0.217 (0.084) [0.010]	0.549 (0.129) [0.000]	0.265 (0.083) [0.001]
β_{CM}	0.232 (0.094) [0.014]	0.492 (0.086) [0.000]	0.179 (0.103) [0.084]	0.449 (0.082) [0.000]
ω	–	–	0.100 (0.068) [0.143]	0.006 (0.005) [0.224]
α_1	–	–	0.107 (0.071) [0.132]	0.022 (0.008) [0.006]
β_1	–	–	0.711 (0.165) [0.000]	0.971 (0.012) [0.000]
LogL	-766.601	-2024.805	-754.370	-2000.509
Obs.	695	1558	695	1558

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	4.705	0.453	4.179	0.524	3.087	0.687	4.168	0.525
10	12.676	0.242	11.097	0.350	9.270	0.507	12.915	0.228
15	13.884	0.534	19.618	0.187	10.112	0.813	21.626	0.118
20	18.265	0.570	28.458	0.099	14.005	0.830	29.239	0.083

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	21.302	0.001	0.520	0.991	2.361	0.797	4.582	0.469
10	25.932	0.004	18.167	0.052	6.892	0.736	9.435	0.491
15	28.248	0.020	41.045	0.000	11.049	0.749	11.700	0.702
20	32.436	0.039	52.481	0.000	14.992	0.777	16.357	0.694

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value	Q stat.	*P*-Value
5	13.942	0.016	5.069	0.408	3.424	0.635	6.139	0.293
10	19.953	0.030	37.931	0.000	8.186	0.611	13.720	0.186
15	24.577	0.056	46.577	0.000	16.246	0.366	15.093	0.445
20	30.914	0.056	62.317	0.000	24.846	0.207	19.509	0.489

Table 2.21: HAR-J Model Estimates ($\alpha = 0.99$)

	homoscedastic		GARCH(1,1)-t	
	SP	US	SP	US
β_0	-1.093 (0.072) [0.000]	-1.479 (0.113) [0.000]	-1.299 (0.122) [0.000]	-1.535 (0.114) [0.000]
β_{CD}	0.281 (0.114) [0.014]	-0.057 (0.053) [0.280]	0.172 (0.122) [0.158]	-0.085 (0.051) [0.095]
β_{CW}	0.460 (0.185) [0.013]	0.269 (0.112) [0.017]	0.440 (0.172) [0.011]	0.338 (0.099) [0.001]
β_{CM}	0.345 (0.150) [0.022]	0.489 (0.111) [0.000]	0.343 (0.147) [0.020]	0.475 (0.103) [0.000]
ω	–	–	0.068 (0.110) [0.540]	0.013 (0.007) [0.046]
α_1	–	–	0.039 (0.042) [0.355]	0.035 (0.010) [0.000]
β_1	–	–	0.866 (0.009) [0.000]	0.950 (0.000) [0.000]
ν	–	–	3.265 (3.875) [0.400]	6.430 (1.609) [0.000]
LogL	-387.854	-1281.353	-353.162	-1250.054
Obs.	327	960	327	960

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	5.657	0.341	7.490	0.187	4.052	0.542	7.187	0.207
10	12.955	0.226	16.660	0.082	11.576	0.314	16.172	0.095
15	20.501	0.154	21.330	0.127	19.391	0.197	19.856	0.178
20	22.450	0.317	38.126	0.009	21.744	0.355	34.581	0.022

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	18.459	0.002	2.531	0.772	5.438	0.365	6.523	0.259
10	19.425	0.035	26.481	0.003	7.430	0.684	13.063	0.220
15	22.779	0.089	28.960	0.016	10.895	0.760	16.972	0.321
20	22.930	0.292	50.077	0.000	11.472	0.933	27.315	0.127

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	12.585	0.028	6.527	0.258	5.840	0.322	9.011	0.109
10	13.420	0.201	33.553	0.000	7.960	0.633	17.855	0.057
15	20.466	0.155	36.332	0.002	12.195	0.664	21.372	0.125
20	22.236	0.328	57.822	0.000	18.247	0.571	33.505	0.030

Table 2.22: HAR-J Model Estimates ($\alpha = 0.95$)

	homoscedastic		GARCH(1,1)-t	
	SP	US	SP	US
β_0	-1.469 (0.042) [0.000]	-1.769 (0.084) [0.000]	-1.586 (0.034) [0.000]	-1.797 (0.085) [0.000]
β_{CD}	0.241 (0.080) [0.003]	-0.040 (0.037) [0.277]	0.202 (0.071) [0.005]	-0.050 (0.036) [0.167]
β_{CW}	0.481 (0.120) [0.000]	0.217 (0.084) [0.010]	0.491 (0.098) [0.000]	0.279 (0.074) [0.000]
β_{CM}	0.232 (0.094) [0.014]	0.492 (0.086) [0.000]	0.201 (0.082) [0.014]	0.484 (0.078) [0.000]
ω	–	–	0.135 (0.045) [0.003]	0.008 (0.003) [0.014]
α_1	–	–	0.061 (0.034) [0.073]	0.023 (0.005) [0.000]
β_1	–	–	0.693 (0.035) [0.000]	0.967 (0.000) [0.000]
ν	–	–	3.849 (1.164) [0.001]	5.220 (0.956) [0.000]
LogL	-766.601	-2024.805	-703.372	-1957.210
Obs.	695	1558	695	1558

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	4.705	0.453	4.179	0.524	4.380	0.496	4.193	0.522
10	12.676	0.242	11.097	0.350	12.265	0.268	11.984	0.286
15	13.884	0.534	19.618	0.187	13.538	0.561	19.653	0.186
20	18.265	0.570	28.458	0.099	17.198	0.640	26.337	0.155

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	21.302	0.001	0.520	0.991	5.102	0.404	5.226	0.389
10	25.932	0.004	18.167	0.052	9.951	0.445	8.879	0.544
15	28.248	0.020	41.045	0.000	13.310	0.578	10.811	0.766
20	32.436	0.039	52.481	0.000	17.969	0.589	15.470	0.749

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	13.942	0.016	5.069	0.408	2.612	0.760	5.998	0.306
10	19.953	0.030	37.931	0.000	9.076	0.525	11.126	0.348
15	24.577	0.056	46.577	0.000	16.875	0.326	11.806	0.694
20	30.914	0.056	62.317	0.000	26.817	0.140	16.018	0.716

Table 2.23: Overnight GARCH-normal Model Estimates ($\alpha = 0.99$)

	Unrestricted		Restricted	
	SP	US	SP	US
μ	0.006 (0.006) [0.305]	0.004 (0.004) [0.292]	0.007 (0.006) [0.202]	0.004 (0.004) [0.270]
ω_n	-0.001 (0.001) [0.144]	0.002 (0.001) [0.059]	-0.002 (0.001) [0.080]	0.001 (0.001) [0.096]
$\alpha_{1,n}$	0.017 (0.011) [0.107]	0.052 (0.014) [0.000]	0.018 (0.011) [0.109]	0.056 (0.015) [0.000]
$\beta_{1,n}$	0.814 (0.045) [0.000]	0.901 (0.021) [0.000]	0.797 (0.044) [0.000]	0.896 (0.022) [0.000]
β_{CP}	0.040 (0.015) [0.008]	0.002 (0.005) [0.706]	–	–
β_{CN}	0.059 (0.013) [0.000]	0.011 (0.005) [0.050]	–	–
β_{JP}	-0.033 (0.006) [0.000]	-0.008 (0.005) [0.077]	–	–
β_{JN}	0.024 (0.020) [0.225]	0.004 (0.008) [0.612]	–	–
β_C	–	–	0.055 (0.014) [0.000]	0.007 (0.005) [0.127]
β_C	0.024 (0.020) [0.225]	0.004 (0.008) [0.612]	0.055 (0.014) [0.000]	0.007 (0.005) [0.127]
LogL	-2006.181	-95.323	-2014.748	-100.196
Obs.	3800	3780	3800	3780

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	20.763	0.001	5.244	0.387	20.232	0.001	5.691	0.337
10	23.437	0.009	17.717	0.060	22.566	0.012	18.364	0.049
15	25.356	0.045	20.112	0.168	24.641	0.055	20.604	0.150
20	31.707	0.047	28.423	0.100	30.997	0.055	28.771	0.092

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	4.289	0.509	5.158	0.397	4.600	0.467	5.543	0.353
10	6.093	0.807	12.509	0.252	6.715	0.752	13.212	0.212
15	10.477	0.789	14.997	0.452	11.846	0.691	15.623	0.408
20	26.654	0.145	19.263	0.505	28.081	0.107	19.511	0.489

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	16.276	0.006	9.511	0.090	16.792	0.005	10.112	0.072
10	20.521	0.025	12.741	0.239	19.939	0.030	13.468	0.199
15	29.304	0.015	13.335	0.576	29.272	0.015	14.093	0.518
20	44.831	0.001	15.407	0.753	43.619	0.002	16.205	0.704

Table 2.24: Overnight GARCH-normal Model Estimates ($\alpha = 0.95$)

	Unrestricted		Restricted	
	SP	US	SP	US
μ	0.006 (0.006) [0.298]	0.004 (0.004) [0.296]	0.007 (0.006) [0.201]	0.004 (0.004) [0.272]
ω_n	-0.001 (0.001) [0.155]	0.002 (0.001) [0.055]	-0.002 (0.001) [0.086]	0.002 (0.001) [0.094]
$\alpha_{1,n}$	0.018 (0.011) [0.092]	0.051 (0.014) [0.000]	0.019 (0.011) [0.093]	0.056 (0.016) [0.000]
$\beta_{1,n}$	0.814 (0.044) [0.000]	0.900 (0.021) [0.000]	0.796 (0.044) [0.000]	0.894 (0.023) [0.000]
β_{CP}	0.042 (0.015) [0.006]	0.004 (0.006) [0.515]	–	–
β_{CN}	0.059 (0.013) [0.000]	0.010 (0.006) [0.071]	–	–
β_{JP}	-0.034 (0.006) [0.000]	-0.010 (0.004) [0.017]	–	–
β_{JN}	0.026 (0.020) [0.198]	0.005 (0.008) [0.565]	–	–
β_C	–	–	0.056 (0.014) [0.000]	0.008 (0.005) [0.111]
β_C	0.026 (0.020) [0.198]	0.005 (0.008) [0.565]	0.056 (0.014) [0.000]	0.008 (0.005) [0.111]
LogL	-2006.054	-94.006	-2014.839	-99.353
Obs.	3800	3780	3800	3780

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	20.590	0.001	5.281	0.383	19.975	0.001	5.621	0.345
10	23.311	0.010	17.796	0.058	22.362	0.013	18.347	0.049
15	25.253	0.047	20.226	0.163	24.468	0.058	20.641	0.149
20	31.631	0.047	28.671	0.094	30.853	0.057	28.893	0.090

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	4.069	0.539	5.272	0.384	4.476	0.483	5.679	0.339
10	5.829	0.829	12.715	0.240	6.473	0.774	13.396	0.202
15	10.259	0.803	15.316	0.429	11.603	0.709	15.934	0.386
20	26.169	0.160	19.683	0.478	27.384	0.125	20.012	0.457

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	15.897	0.007	9.569	0.088	16.626	0.005	10.341	0.066
10	20.162	0.028	12.757	0.238	19.834	0.031	13.704	0.187
15	28.893	0.017	13.357	0.575	29.072	0.016	14.341	0.500
20	44.076	0.001	15.384	0.754	42.934	0.002	16.477	0.687

Table 2.25: Overnight GARCH-t Model Estimates ($\alpha = 0.99$)

	Unrestricted		Restricted	
	SP	US	SP	US
μ	0.015 (0.005) [0.004]	0.006 (0.004) [0.121]	0.015 (0.005) [0.003]	0.006 (0.004) [0.104]
ω_n	-0.001 (0.001) [0.233]	0.002 (0.001) [0.014]	-0.001 (0.001) [0.199]	0.002 (0.001) [0.020]
$\alpha_{1,n}$	0.041 (0.012) [0.001]	0.045 (0.011) [0.000]	0.044 (0.012) [0.000]	0.046 (0.010) [0.000]
$\beta_{1,n}$	0.817 (0.024) [0.000]	0.852 (0.027) [0.000]	0.806 (0.025) [0.000]	0.854 (0.027) [0.000]
β_{CP}	0.040 (0.009) [0.000]	0.014 (0.006) [0.013]	–	–
β_{CN}	0.045 (0.007) [0.000]	0.023 (0.006) [0.000]	–	–
β_{JP}	-0.031 (0.012) [0.010]	-0.000 (0.011) [0.964]	–	–
β_{JN}	0.023 (0.022) [0.305]	0.005 (0.009) [0.574]	–	–
β_C	–	–	0.045 (0.007) [0.000]	0.019 (0.005) [0.000]
ν	5.004 (0.434) [0.000]	7.906 (0.747) [0.000]	4.944 (0.422) [0.000]	7.847 (0.730) [0.000]
LogL	-1863.415	-8.696	-1865.451	-10.300
Obs.	3799	3779	3799	3779

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	19.059	0.002	5.694	0.337	18.564	0.002	6.088	0.298
10	21.452	0.018	18.520	0.047	20.848	0.022	19.002	0.040
15	23.682	0.071	21.687	0.116	23.238	0.079	21.986	0.108
20	29.562	0.077	30.528	0.062	29.094	0.086	30.819	0.058

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	3.679	0.597	6.478	0.262	3.649	0.601	7.028	0.219
10	7.058	0.720	16.650	0.082	7.126	0.713	17.837	0.058
15	11.918	0.685	22.618	0.093	12.238	0.661	23.465	0.075
20	26.802	0.141	35.260	0.019	27.421	0.124	34.542	0.023

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	8.071	0.152	8.575	0.127	8.620	0.125	8.651	0.124
10	9.814	0.457	14.051	0.171	10.356	0.410	14.111	0.168
15	16.930	0.323	16.046	0.379	18.058	0.260	15.938	0.386
20	29.738	0.074	20.695	0.415	30.408	0.064	20.200	0.445

Table 2.26: Overnight GARCH-t Model Estimates ($\alpha = 0.95$)

	Unrestricted		Restricted	
	SP	US	SP	US
μ	0.015 (0.005) [0.004]	0.006 (0.004) [0.125]	0.015 (0.005) [0.003]	0.006 (0.004) [0.109]
ω_n	-0.001 (0.001) [0.275]	0.002 (0.001) [0.011]	-0.001 (0.001) [0.229]	0.002 (0.001) [0.018]
$\alpha_{1,n}$	0.042 (0.012) [0.001]	0.044 (0.011) [0.000]	0.044 (0.012) [0.000]	0.045 (0.011) [0.000]
$\beta_{1,n}$	0.816 (0.024) [0.000]	0.848 (0.028) [0.000]	0.806 (0.025) [0.000]	0.848 (0.028) [0.000]
β_{CP}	0.042 (0.009) [0.000]	0.018 (0.007) [0.007]	–	–
β_{CN}	0.045 (0.007) [0.000]	0.024 (0.006) [0.000]	–	–
β_{JP}	-0.032 (0.013) [0.011]	-0.006 (0.010) [0.519]	–	–
β_{JN}	0.024 (0.022) [0.283]	0.007 (0.010) [0.493]	–	–
β_C	–	–	0.046 (0.007) [0.000]	0.021 (0.005) [0.000]
ν	5.004 (0.434) [0.000]	7.934 (0.749) [0.000]	4.938 (0.421) [0.000]	7.851 (0.728) [0.000]
LogL	-1863.505	-7.389	-1865.527	-8.963
Obs.	3799	3779	3799	3779

Ljung-Box Q-statistics for $\epsilon_{t+1}/\sigma_{t+1}$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	18.936	0.002	5.674	0.339	18.396	0.002	5.959	0.310
10	21.362	0.019	18.533	0.047	20.720	0.023	18.996	0.040
15	23.621	0.072	21.772	0.114	23.142	0.081	22.110	0.105
20	29.523	0.078	30.784	0.058	29.041	0.087	31.131	0.053

Ljung-Box Q-statistics for $(\epsilon_{t+1}/\sigma_{t+1})^2$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	3.608	0.607	6.751	0.240	3.641	0.602	7.371	0.194
10	6.991	0.726	17.013	0.074	7.049	0.721	18.308	0.050
15	11.902	0.686	23.779	0.069	12.206	0.663	24.913	0.051
20	26.731	0.143	37.118	0.011	26.975	0.136	37.061	0.012

Ljung-Box Q-statistics for $|\epsilon_{t+1}/\sigma_{t+1}|$

	homoscedastic				GARCH(2,1)			
	SP		US		SP		US	
Lags	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value	Q stat.	P-Value
5	7.932	0.160	8.761	0.119	8.662	0.123	8.890	0.114
10	9.709	0.466	14.279	0.161	10.382	0.408	14.479	0.152
15	16.826	0.329	16.359	0.359	18.028	0.261	16.491	0.350
20	29.513	0.078	21.059	0.394	30.016	0.070	21.055	0.394

Table 2.27: Out-of-Sample Forecast Statistics (post 1/1/2003)

		RMSE			MAE		
Horizon		1	5	22	1	5	22
SP	GARCH	0.563(0.615)	0.306(0.947)	0.313(0.383)	0.343(0.061)	0.221(0.574)	0.228(0.352)
	HAR-RV	0.567(0.260)	0.329(0.186)	0.322(0.150)	0.324(0.973)	0.229(0.127)	0.250(0.079)
	HAR-CJN	0.555	0.304	0.280	0.324	0.212	0.204
US	GARCH	0.474(0.804)	0.228(0.825)	0.157(0.675)	0.238(0.000)	0.152(0.086)	0.105(0.875)
	HAR-RV	0.480(0.129)	0.234(0.453)	0.157(0.546)	0.239(0.000)	0.154(0.006)	0.107(0.683)
	HAR-CJN	0.476	0.230	0.149	0.222	0.141	0.103

Table 2.28: Out-of-Sample Mincer-Zarnowitz Regressions (post 1/1/2003)

Joint Regression

	SP			US		
Horizon	1	5	22	1	5	22
Const.	-0.182(0.138)	-0.361(0.206)	-0.886(0.422)	0.077(0.092)	0.060(0.076)	0.018(0.068)
GARCH	0.482(0.235)	0.568(0.210)	0.361(0.288)	0.566(0.338)	0.463(0.266)	-0.074(0.306)
HAR-RV	0.753(0.648)	1.367(0.878)	2.518(1.354)	-0.532(0.296)	-0.306(0.334)	0.194(0.173)
HAR-CJN	-0.032(0.588)	-0.543(0.664)	-1.016(0.677)	0.952(0.265)	0.870(0.293)	1.051(0.441)
R^2	0.494	0.785	0.793	0.087	0.291	0.527

Individual Regression

	SP			US		
Horizon	1	5	22	1	5	22
Const.	-0.035(0.075)	-0.047(0.066)	-0.035(0.107)	0.001(0.091)	0.004(0.093)	0.028(0.108)
GARCH	0.983(0.106)	0.980(0.097)	0.910(0.148)	1.099(0.207)	1.099(0.231)	1.063(0.267)
R^2	0.464	0.748	0.721	0.067	0.231	0.322
Const.	-0.201(0.082)	-0.328(0.084)	-0.602(0.140)	0.136(0.098)	0.084(0.111)	-0.000(0.103)
HAR-RV	1.263(0.124)	1.372(0.124)	1.581(0.195)	0.784(0.225)	0.922(0.274)	1.171(0.278)
R^2	0.472	0.750	0.773	0.048	0.198	0.373
Const.	-0.014(0.061)	-0.053(0.060)	-0.106(0.092)	0.119(0.077)	0.104(0.070)	0.034(0.081)
HAR-CJN	0.990(0.094)	1.020(0.094)	1.048(0.148)	0.885(0.183)	0.930(0.181)	1.130(0.224)
R^2	0.475	0.742	0.748	0.079	0.278	0.524

Table 2.29: In-Sample Forecast Statistics (α=0.95)

		RMSE			MAE		
Horizon		1	5	22	1	5	22
SP	GARCH	1.519(0.000)	0.995(0.000)	0.869(0.003)	0.626(0.000)	0.506(0.000)	0.504(0.000)
	HAR-RV	1.477(0.003)	0.943(0.003)	0.827(0.014)	0.556(0.041)	0.453(0.000)	0.466(0.002)
	HAR-CJN	1.413	0.856	0.746	0.543	0.417	0.420
US	GARCH	0.325(0.105)	0.170(0.474)	0.119(0.973)	0.176(0.821)	0.112(0.414)	0.087(0.236)
	HAR-RV	0.325(0.014)	0.169(0.527)	0.118(0.734)	0.175(0.452)	0.112(0.422)	0.086(0.060)
	HAR-CJN	0.322	0.168	0.119	0.176	0.114	0.093

Table 2.30: Out-of-Sample Forecast Statistics (post 1/1/2003)(α=0.95)

		RMSE			MAE		
Horizon		1	5	22	1	5	22
SP	GARCH	0.563(0.702)	0.306(0.976)	0.313(0.384)	0.343(0.027)	0.221(0.532)	0.228(0.366)
	HAR-RV	0.567(0.250)	0.329(0.126)	0.322(0.117)	0.324(0.437)	0.229(0.064)	0.250(0.070)
	HAR-CJN	0.557	0.305	0.279	0.320	0.210	0.204
US	GARCH	0.474(0.960)	0.228(0.903)	0.157(0.572)	0.238(0.000)	0.152(0.044)	0.105(0.795)
	HAR-RV	0.480(0.073)	0.234(0.220)	0.157(0.433)	0.239(0.000)	0.154(0.003)	0.107(0.593)
	HAR-CJN	0.475	0.227	0.147	0.221	0.138	0.102

Table 2.31: Out-of-Sample Forecast Statistics (post 1/1/2000)(α=0.95)

		RMSE			MAE		
Horizon		1	5	22	1	5	22
SP	GARCH	1.929(0.001)	1.269(0.004)	1.130(0.082)	0.836(0.000)	0.669(0.000)	0.694(0.021)
	HAR-RV	1.868(0.002)	1.234(0.005)	1.147(0.009)	0.717(0.153)	0.600(0.002)	0.642(0.004)
	HAR-CJN	1.791	1.127	1.057	0.702	0.556	0.587
US	GARCH	0.375(0.041)	0.199(0.086)	0.150(0.123)	0.193(0.330)	0.130(0.125)	0.105(0.424)
	HAR-RV	0.375(0.000)	0.198(0.007)	0.151(0.040)	0.192(0.297)	0.130(0.020)	0.108(0.141)
	HAR-CJN	0.367	0.187	0.131	0.190	0.123	0.098

Table 2.32: In-Sample Mincer-Zarnowitz Regressions (α=0.95)

	Joint Regression					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	-0.030(0.046)	0.031(0.055)	0.145(0.084)	-0.004(0.021)	-0.011(0.024)	-0.007(0.033)
GARCH	-0.071(0.105)	-0.115(0.105)	-0.016(0.147)	0.519(0.111)	0.449(0.109)	0.347(0.127)
HAR-RV	-0.115(0.083)	-0.212(0.126)	-0.474(0.242)	-0.252(0.144)	-0.010(0.185)	0.088(0.155)
HAR-CJN	1.248(0.150)	1.351(0.165)	1.415(0.232)	0.731(0.093)	0.578(0.117)	0.547(0.126)
R^2	0.397	0.600	0.568	0.123	0.313	0.413
	Individual Regression					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	0.044(0.046)	0.127(0.061)	0.257(0.073)	-0.023(0.019)	-0.009(0.025)	0.022(0.036)
GARCH	0.939(0.050)	0.868(0.068)	0.750(0.062)	1.093(0.059)	1.053(0.077)	0.963(0.109)
R^2	0.301	0.460	0.450	0.098	0.259	0.324
Const.	-0.066(0.081)	-0.098(0.083)	-0.083(0.104)	-0.007(0.021)	-0.018(0.027)	-0.031(0.037)
HAR-RV	1.150(0.089)	1.180(0.095)	1.169(0.111)	1.043(0.062)	1.076(0.080)	1.113(0.111)
R^2	0.346	0.523	0.473	0.095	0.265	0.345
Const.	-0.059(0.051)	-0.018(0.056)	0.039(0.065)	0.043(0.016)	0.046(0.019)	0.047(0.030)
HAR-CJN	1.088(0.058)	1.068(0.065)	1.031(0.071)	0.857(0.044)	0.832(0.053)	0.796(0.080)
R^2	0.396	0.596	0.561	0.116	0.295	0.391

Table 2.33: Out-of-Sample Mincer-Zarnowitz Regressions (post 1/1/2003) (α=0.95)

	Joint Regression					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	-0.198(0.134)	-0.341(0.195)	-0.765(0.390)	0.085(0.093)	0.073(0.076)	0.024(0.071)
GARCH	0.497(0.217)	0.553(0.214)	0.323(0.301)	0.532(0.335)	0.420(0.262)	-0.102(0.310)
HAR-RV	0.867(0.658)	1.286(0.833)	2.152(1.241)	-0.533(0.294)	-0.379(0.346)	0.174(0.191)
HAR-CJN	-0.140(0.564)	-0.482(0.652)	-0.747(0.561)	0.971(0.235)	0.957(0.286)	1.083(0.420)
R^2	0.494	0.785	0.789	0.090	0.309	0.549
	Individual Regression					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	-0.035(0.075)	-0.047(0.066)	-0.035(0.107)	0.001(0.091)	0.004(0.093)	0.028(0.108)
GARCH	0.983(0.106)	0.980(0.097)	0.910(0.148)	1.099(0.207)	1.099(0.231)	1.063(0.267)
R^2	0.464	0.748	0.721	0.067	0.231	0.322
Const.	-0.201(0.082)	-0.328(0.084)	-0.602(0.140)	0.136(0.098)	0.084(0.111)	-0.000(0.103)
HAR-RV	1.263(0.124)	1.372(0.124)	1.581(0.195)	0.784(0.225)	0.922(0.274)	1.171(0.278)
R^2	0.472	0.750	0.773	0.048	0.198	0.373
Const.	-0.020(0.062)	-0.058(0.062)	-0.122(0.091)	0.118(0.074)	0.100(0.068)	0.034(0.078)
HAR-CJN	1.014(0.097)	1.047(0.098)	1.075(0.148)	0.888(0.174)	0.938(0.174)	1.129(0.223)
R^2	0.471	0.740	0.748	0.083	0.296	0.546

Table 2.34: Out-of-Sample Mincer-Zarnowitz Regressions (post 1/1/2000) (α=0.95)

	Joint Regression					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	0.020(0.116)	0.127(0.167)	0.400(0.241)	-0.024(0.063)	-0.031(0.072)	-0.043(0.103)
GARCH	-0.172(0.268)	-0.176(0.261)	-0.085(0.296)	0.849(0.302)	0.764(0.279)	0.518(0.329)
HAR-RV	-0.277(0.605)	-0.863(0.772)	-2.534(1.542)	-0.674(0.373)	-0.429(0.413)	-0.102(0.455)
HAR-CJN	1.528(0.548)	2.051(0.709)	3.436(1.330)	0.975(0.225)	0.844(0.260)	0.814(0.371)
R^2	0.376	0.570	0.522	0.125	0.331	0.424

	Individual Regression					
		SP			US	
Horizon	1	5	22	1	5	22
Const.	0.077(0.124)	0.201(0.187)	0.487(0.259)	-0.049(0.060)	-0.034(0.079)	0.016(0.102)
GARCH	0.989(0.099)	0.915(0.154)	0.746(0.119)	1.282(0.166)	1.250(0.224)	1.137(0.288)
R^2	0.260	0.404	0.348	0.094	0.262	0.310
Const.	-0.128(0.150)	-0.043(0.202)	0.182(0.296)	0.025(0.070)	0.002(0.085)	-0.033(0.107)
HAR-RV	1.325(0.144)	1.300(0.200)	1.217(0.194)	1.062(0.183)	1.139(0.234)	1.286(0.304)
R^2	0.346	0.506	0.402	0.084	0.250	0.333
Const.	-0.070(0.145)	-0.004(0.167)	0.167(0.234)	0.055(0.056)	0.051(0.062)	0.020(0.095)
HAR-CJN	1.154(0.125)	1.159(0.155)	1.147(0.152)	0.926(0.132)	0.945(0.159)	1.040(0.251)
R^2	0.373	0.556	0.467	0.110	0.297	0.395

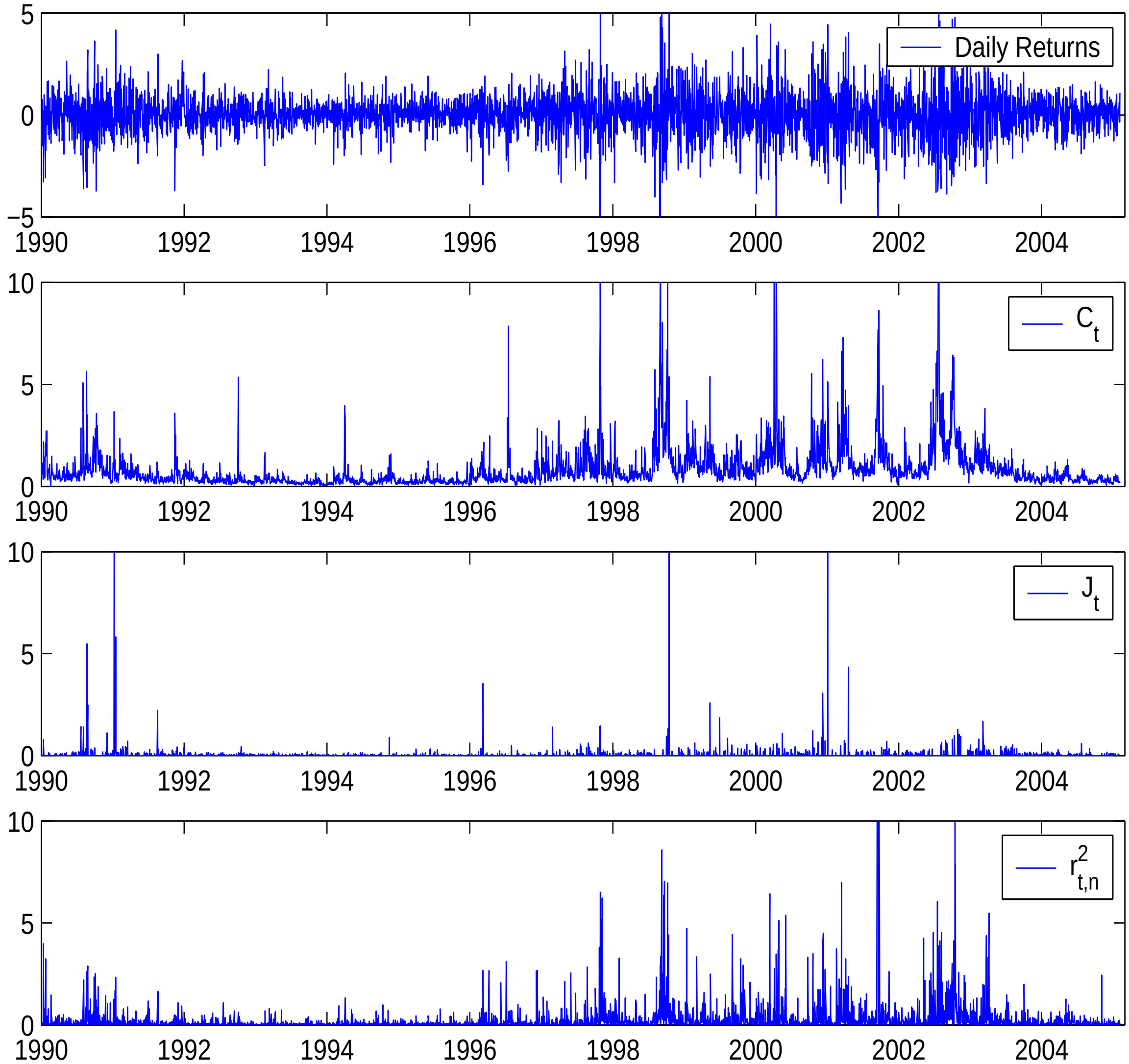

Figure 2.7: Daily Return and Variance Components for SP (α=0.95)

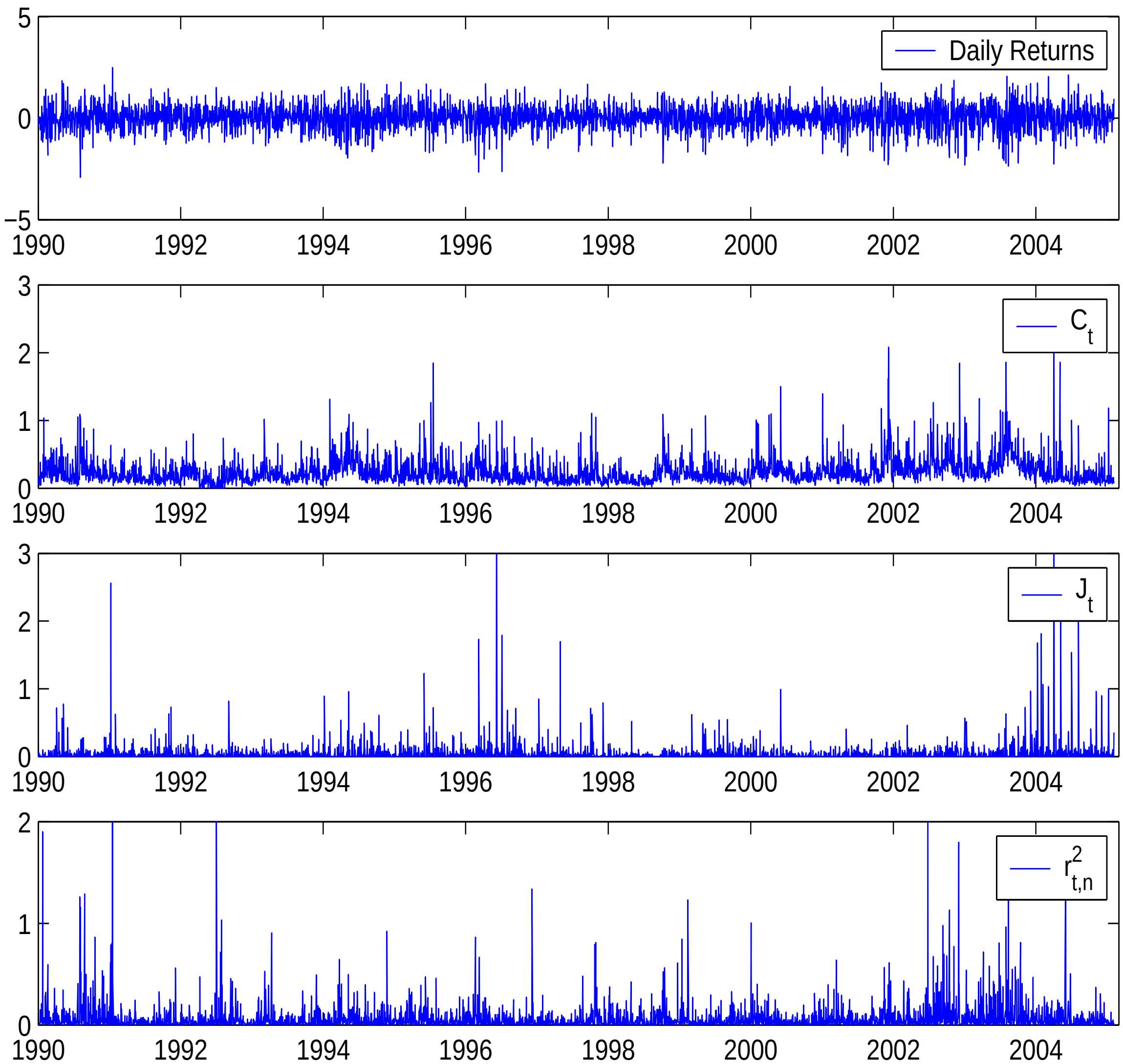

Figure 2.8: Daily Return and Variance Components for US (α=0.95)

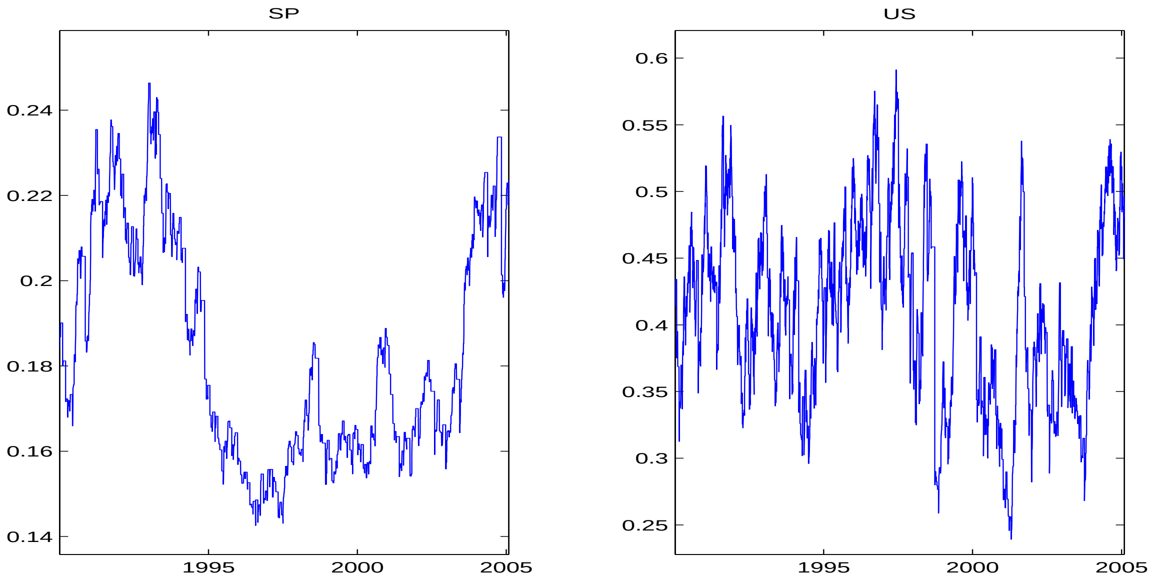

Figure 2.9: Extracted Conditional Hazard Rates from simple ACH Model (α=0.95)

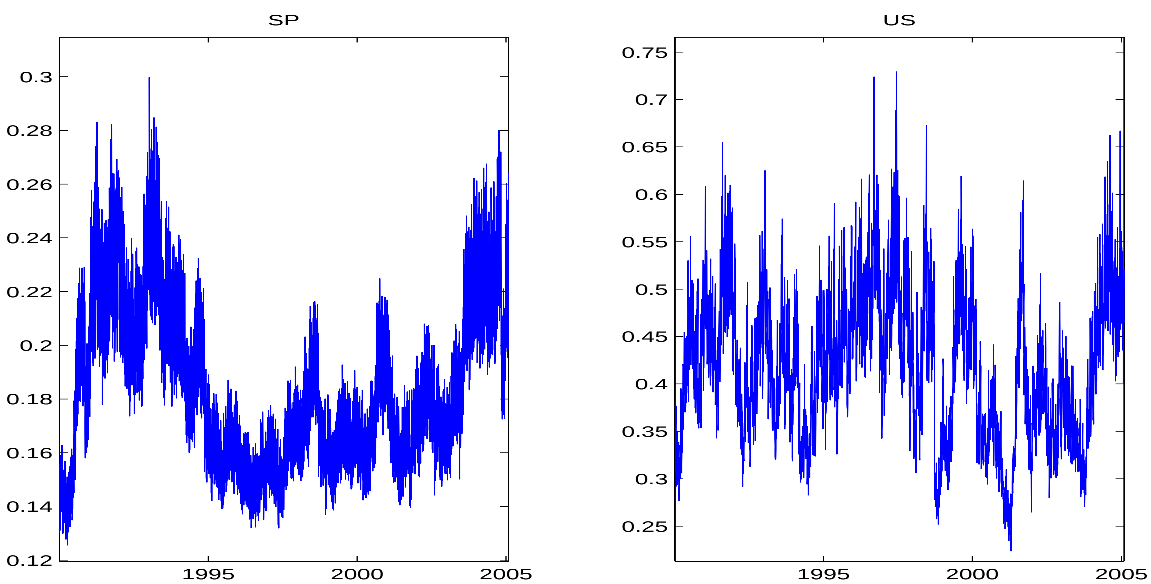

Figure 2.10: Extracted Conditional Hazard Rates from augmented ACH Model (α=0.95)

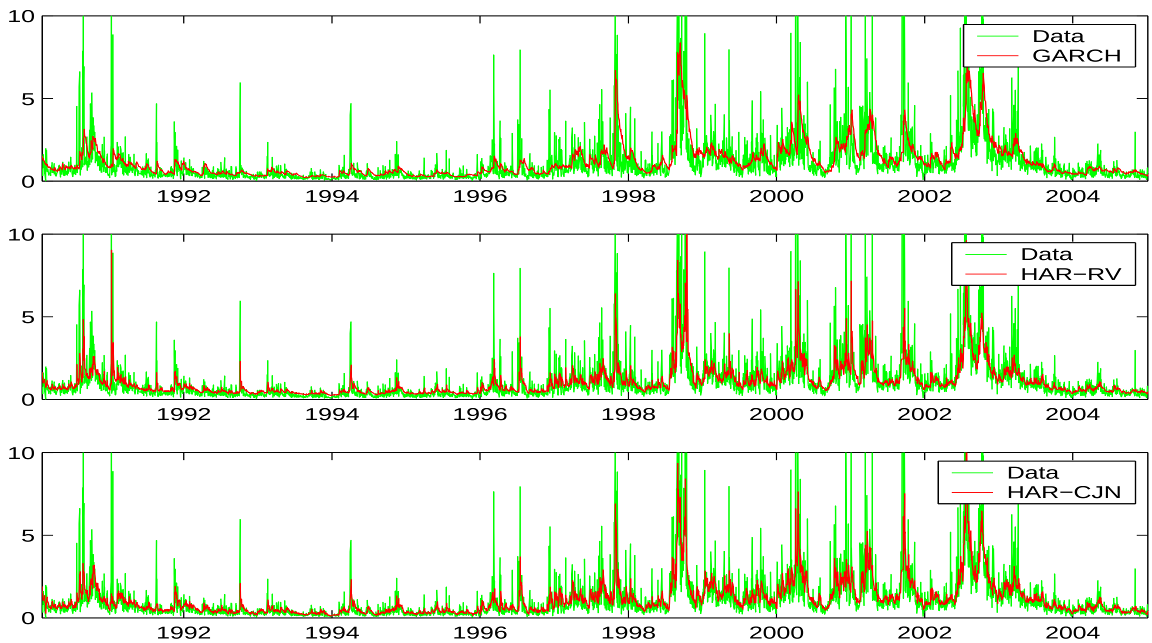

Figure 2.11: In-Sample 1-Day Ahead Forecast for SP

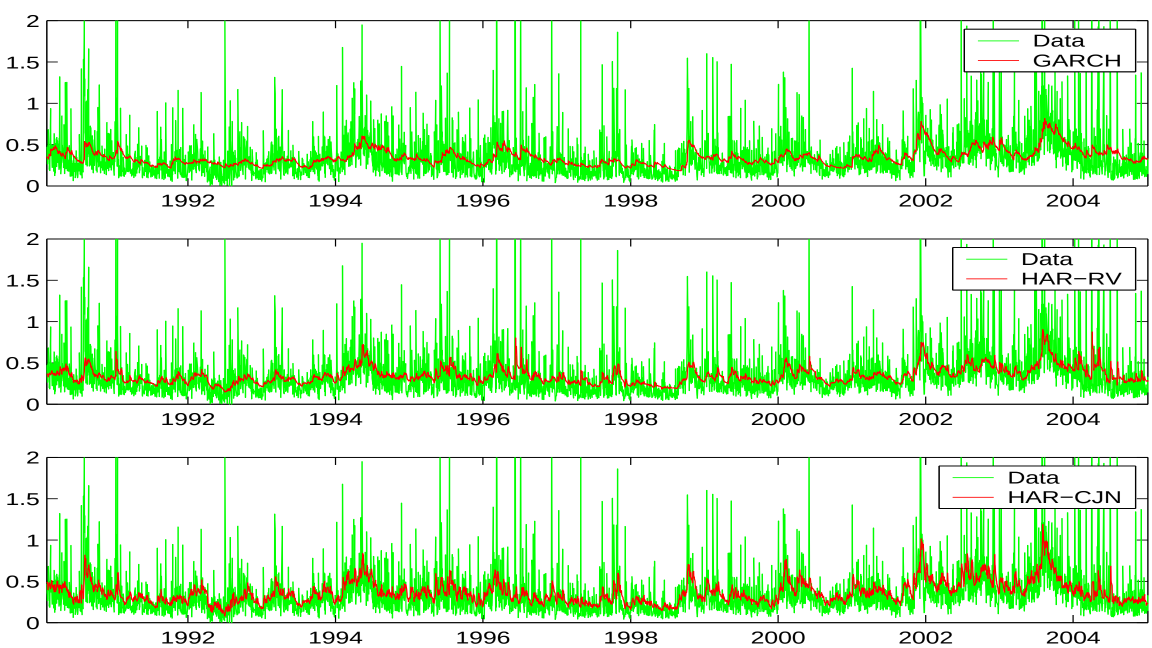

Figure 2.12: In-Sample 1-Day Ahead Forecast for US

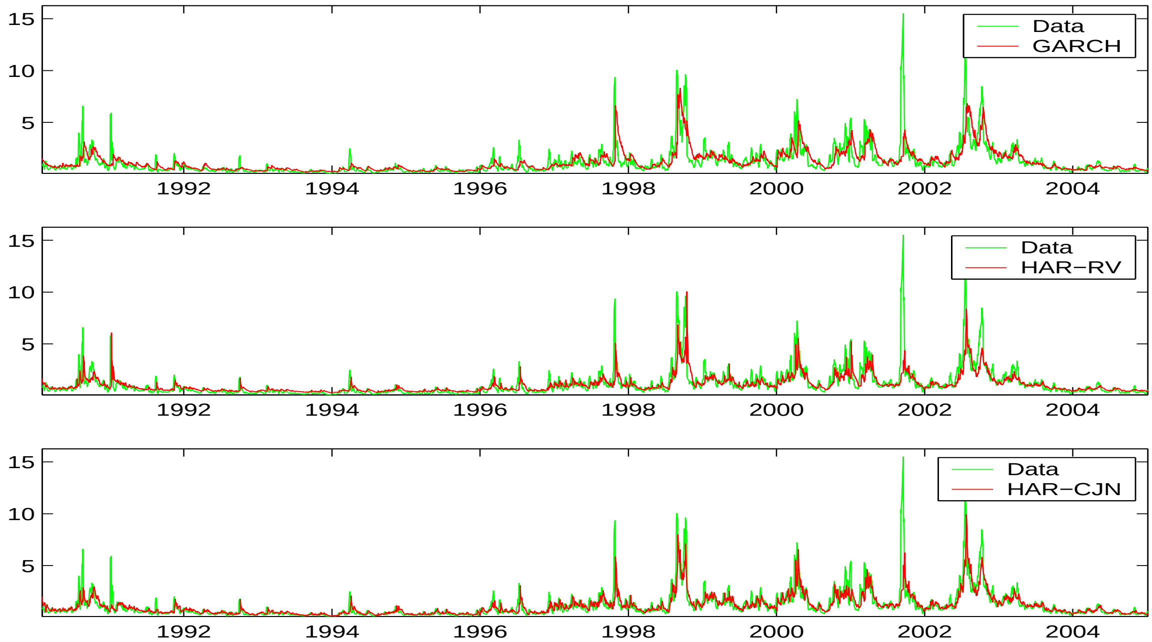

Figure 2.13: In-Sample 1-Week Ahead Forecast for SP

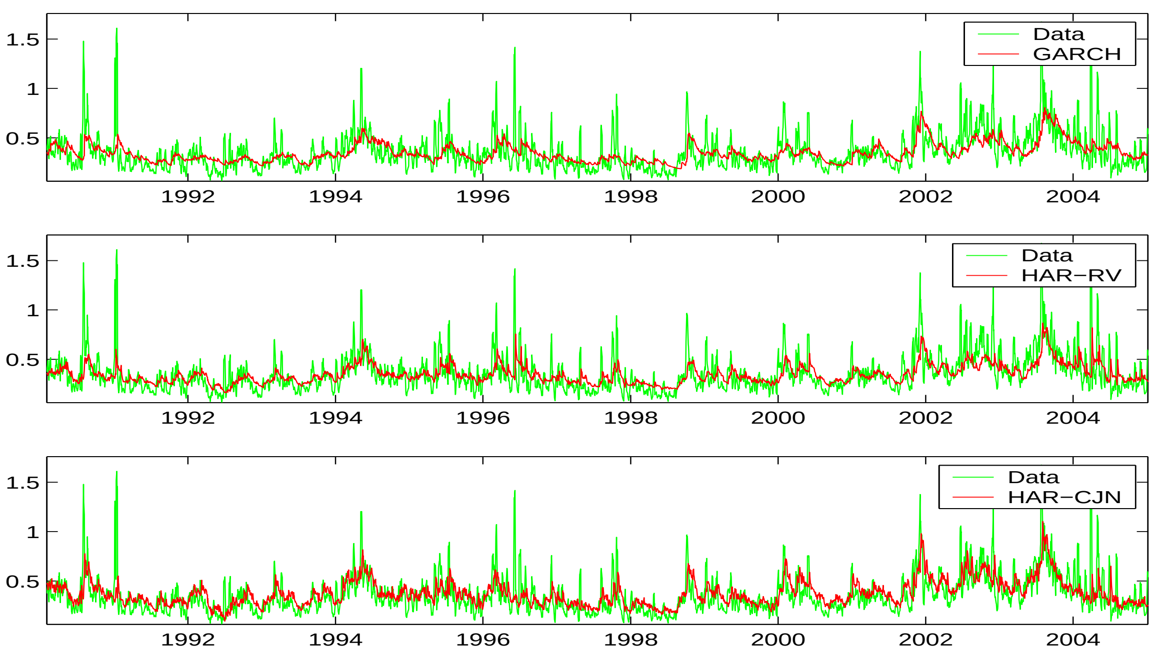

Figure 2.14: In-Sample 1-Week Ahead Forecast for US

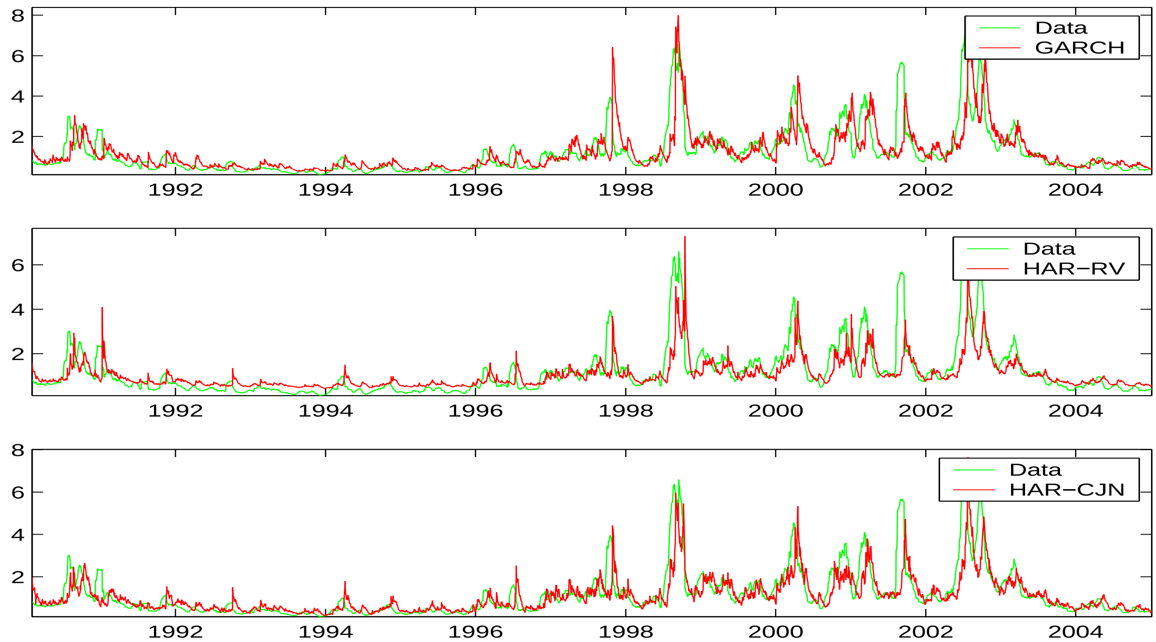

Figure 2.15: In-Sample 1-Month Ahead Forecast for SP

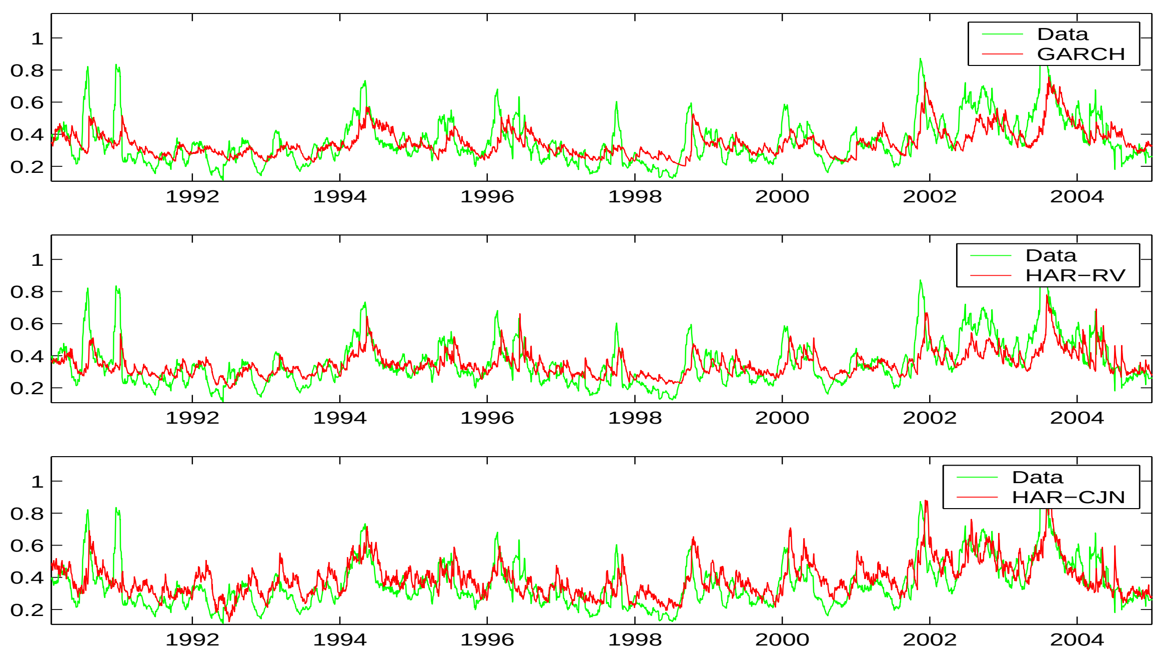

Figure 2.16: In-Sample 1-Month Ahead Forecast for US

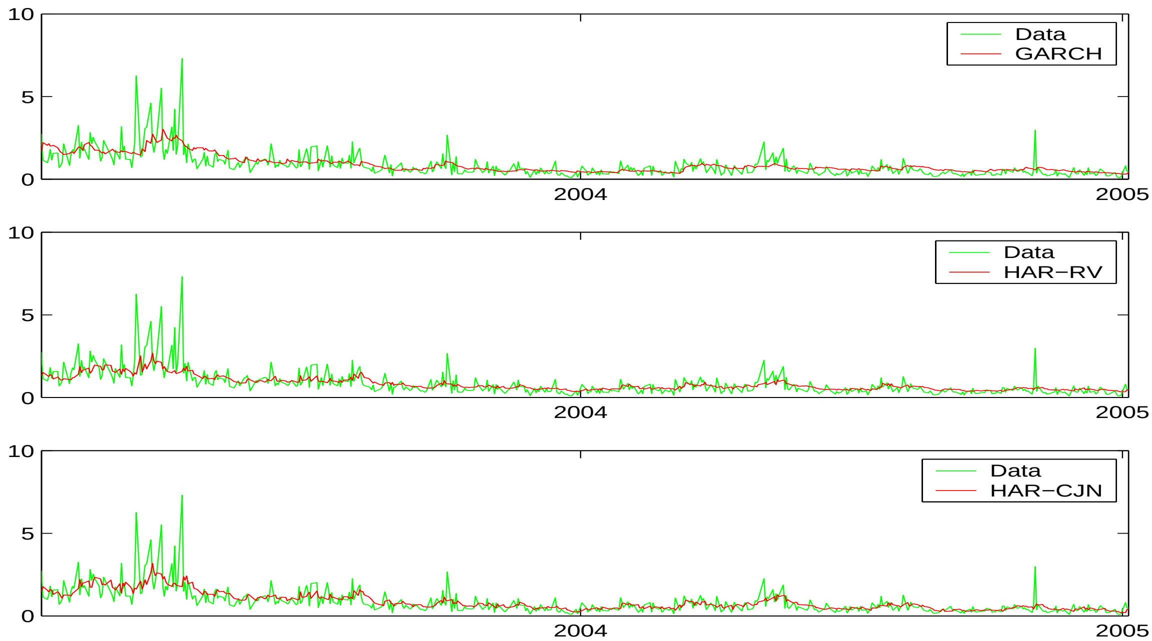

Figure 2.17: Out-of-Sample 1-Day Ahead Forecast for SP (post 1/1/2003)

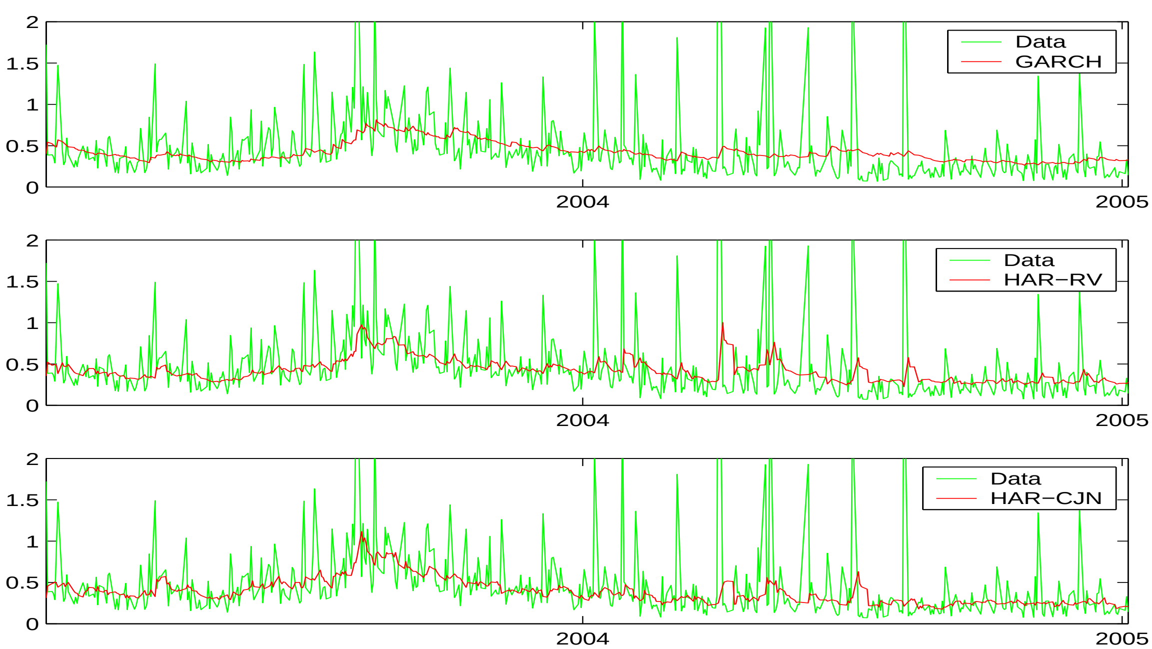

Figure 2.18: Out-of-Sample 1-Day Ahead Forecast for US (post 1/1/2003)

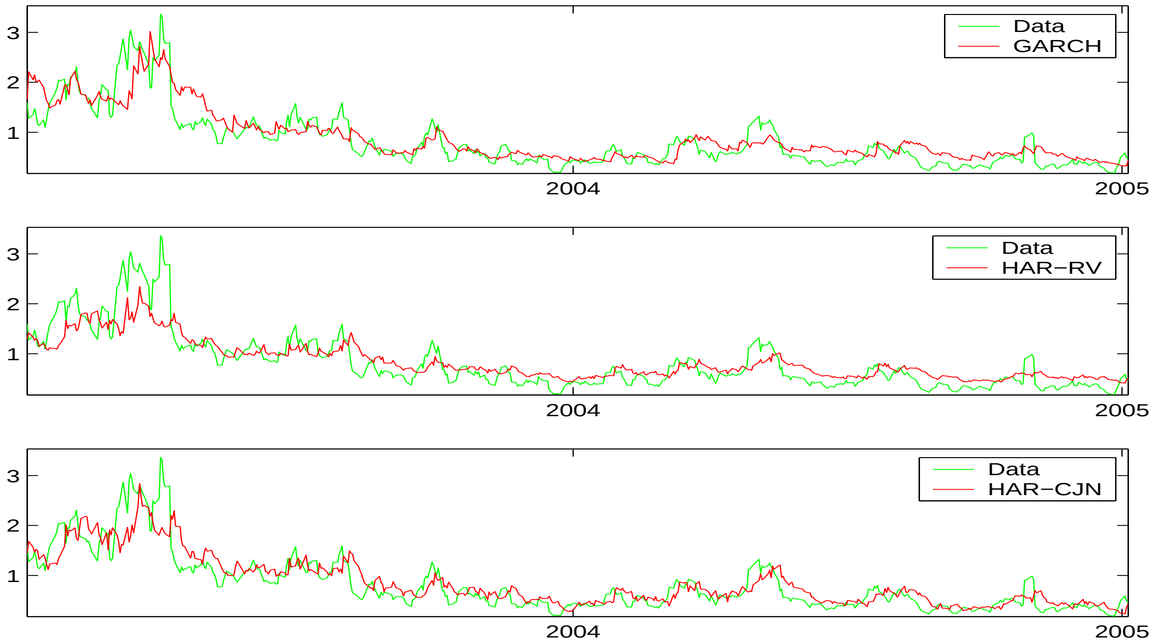

Figure 2.19: Out-of-Sample 1-Week Ahead Forecast for SP (post 1/1/2003)

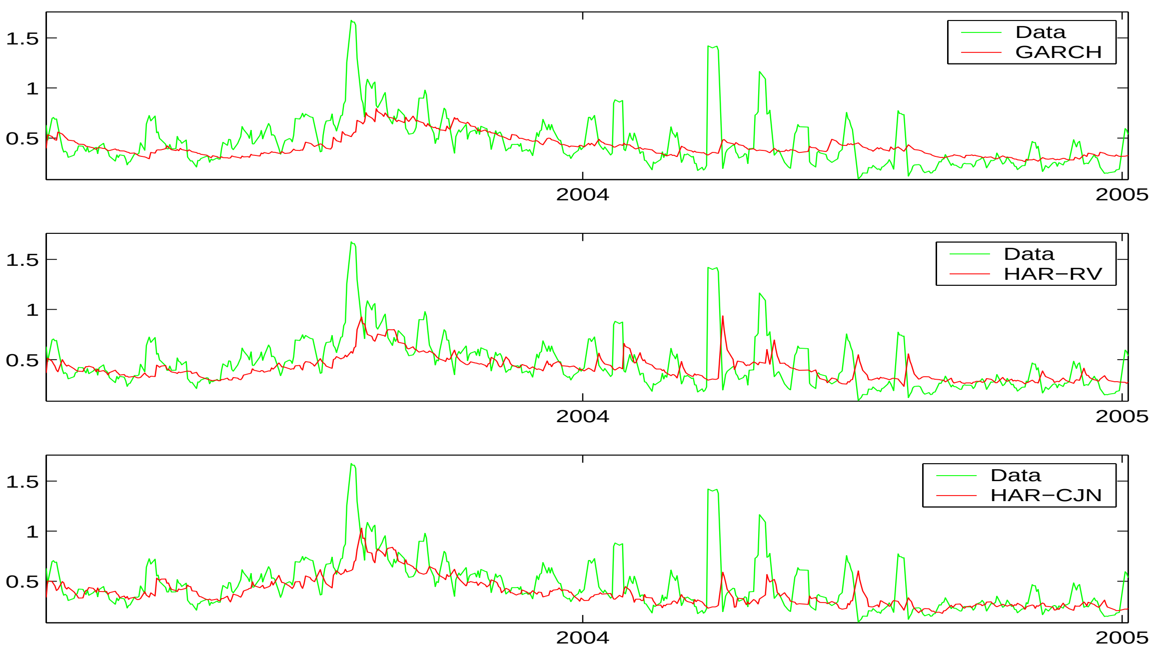

Figure 2.20: Out-of-Sample 1-Week Ahead Forecast for US (post 1/1/2003)

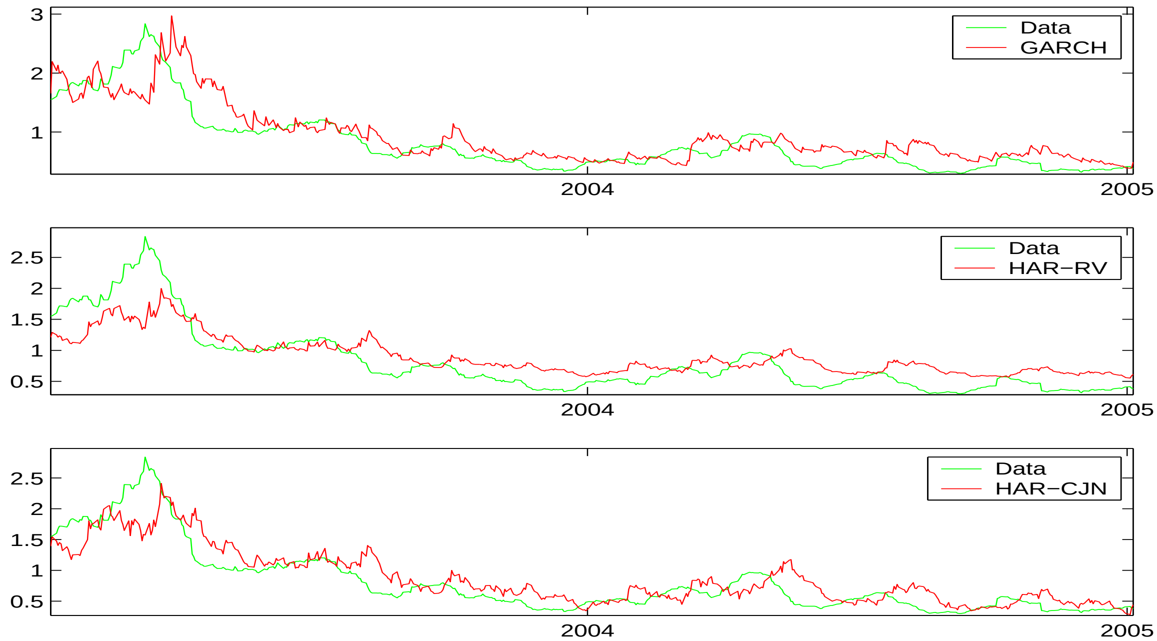

Figure 2.21: Out-of-Sample 1-Month Ahead Forecast for SP (post 1/1/2003)

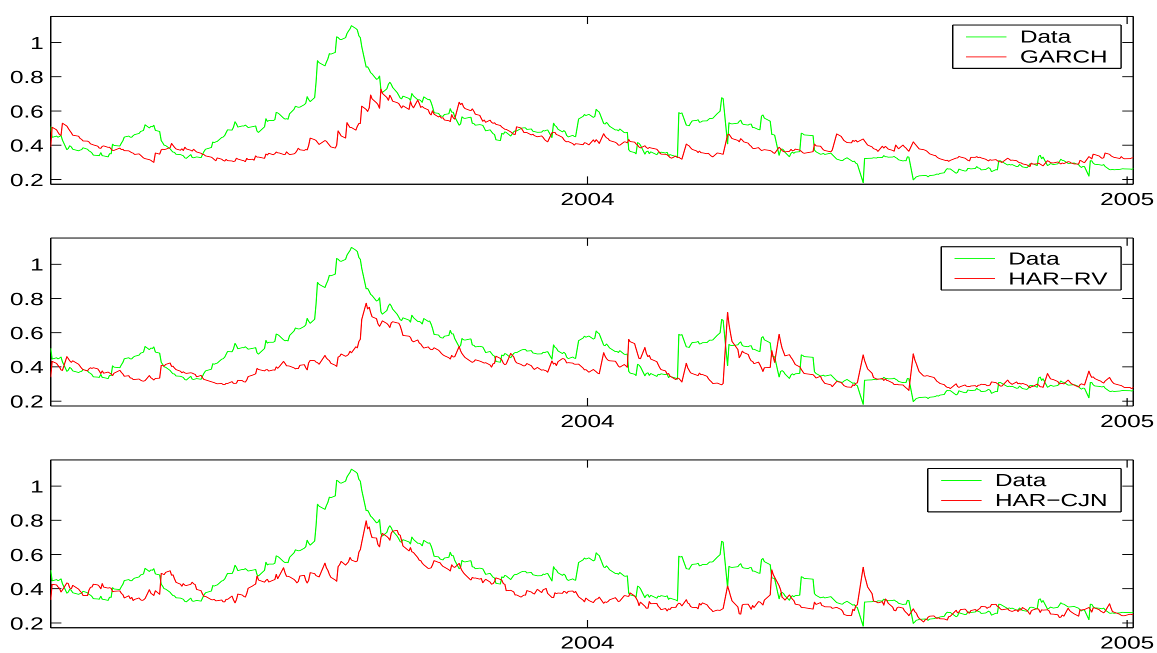

Figure 2.22: Out-of-Sample 1-Month Ahead Forecast for US (post 1/1/2003)

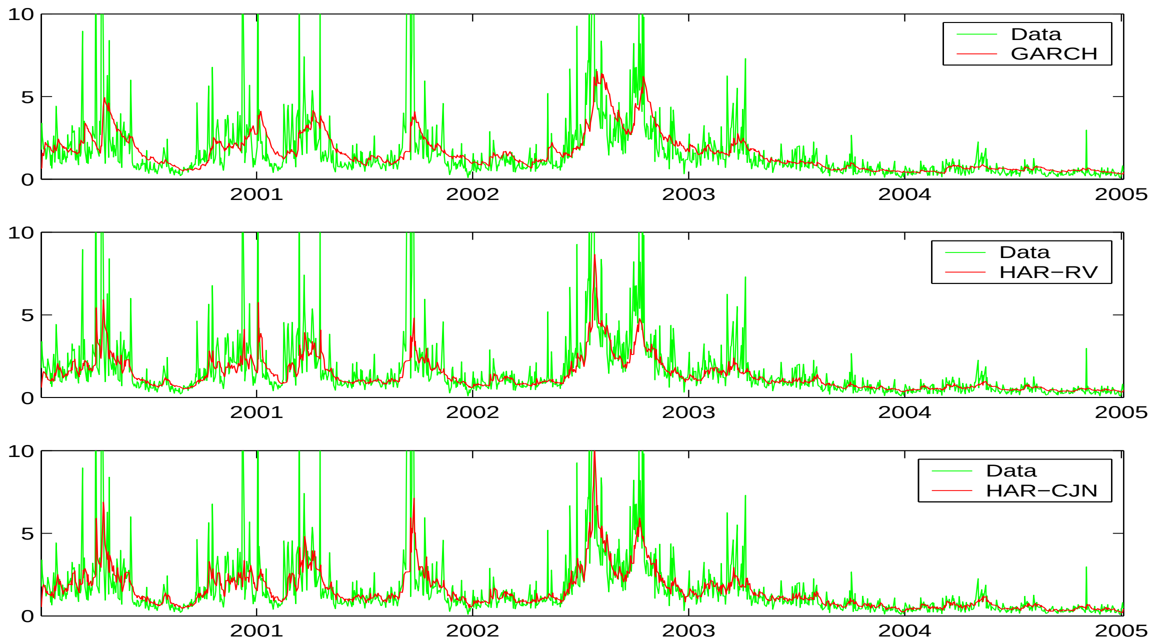

Figure 2.23: Out-of-Sample 1-Day Ahead Forecast for SP (post 1/1/2000)

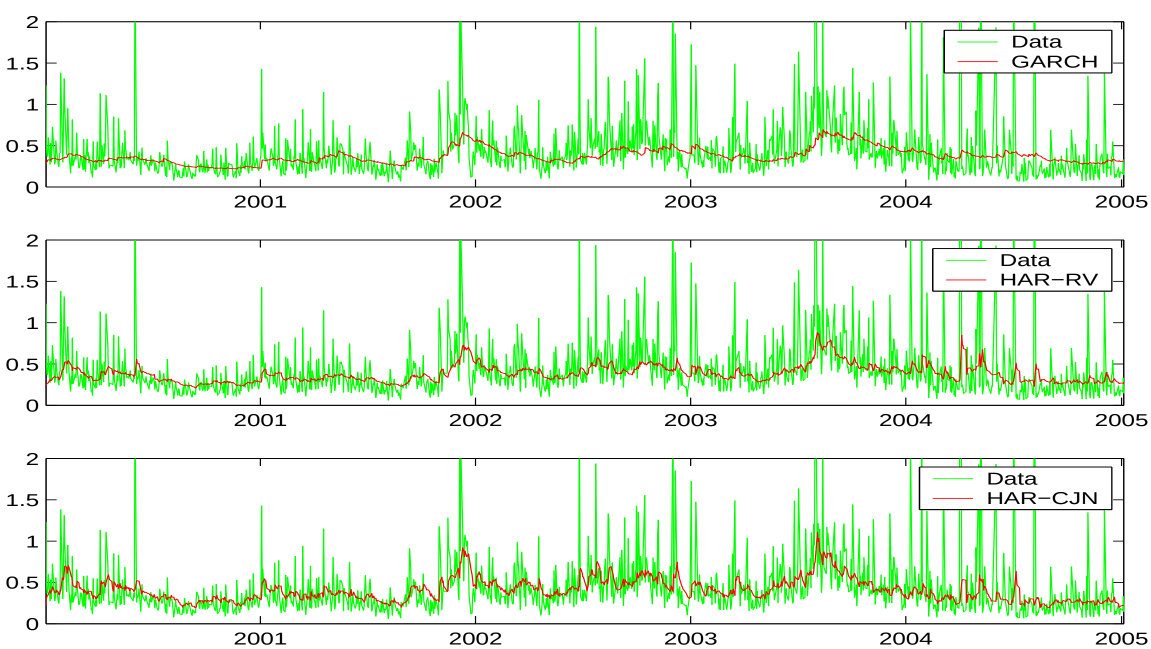

Figure 2.24: Out-of-Sample 1-Day Ahead Forecast for US (post 1/1/2000)

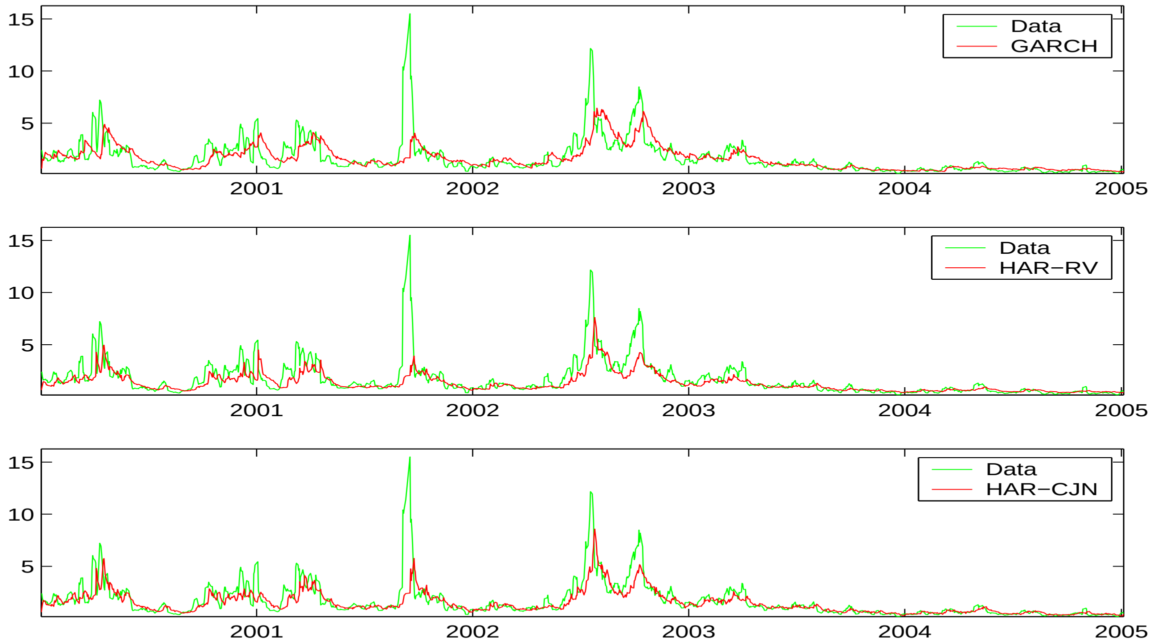

Figure 2.25: Out-of-Sample 1-Week Ahead Forecast for SP (post 1/1/2000)

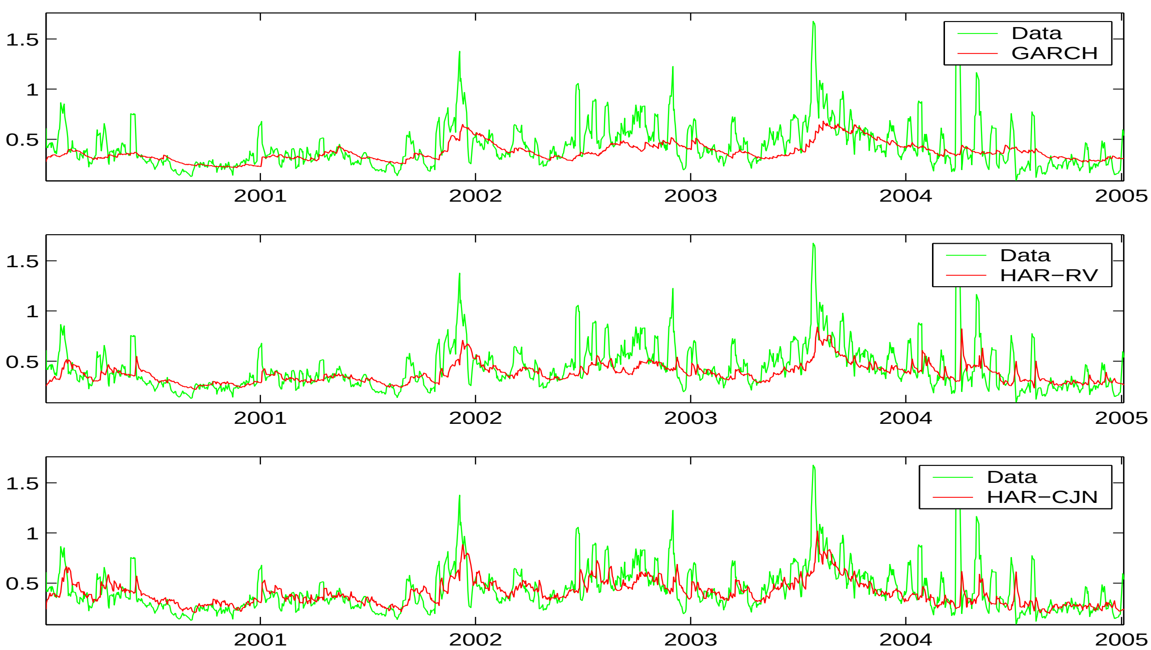

Figure 2.26: Out-of-Sample 1-Week Ahead Forecast for US (post 1/1/2000)

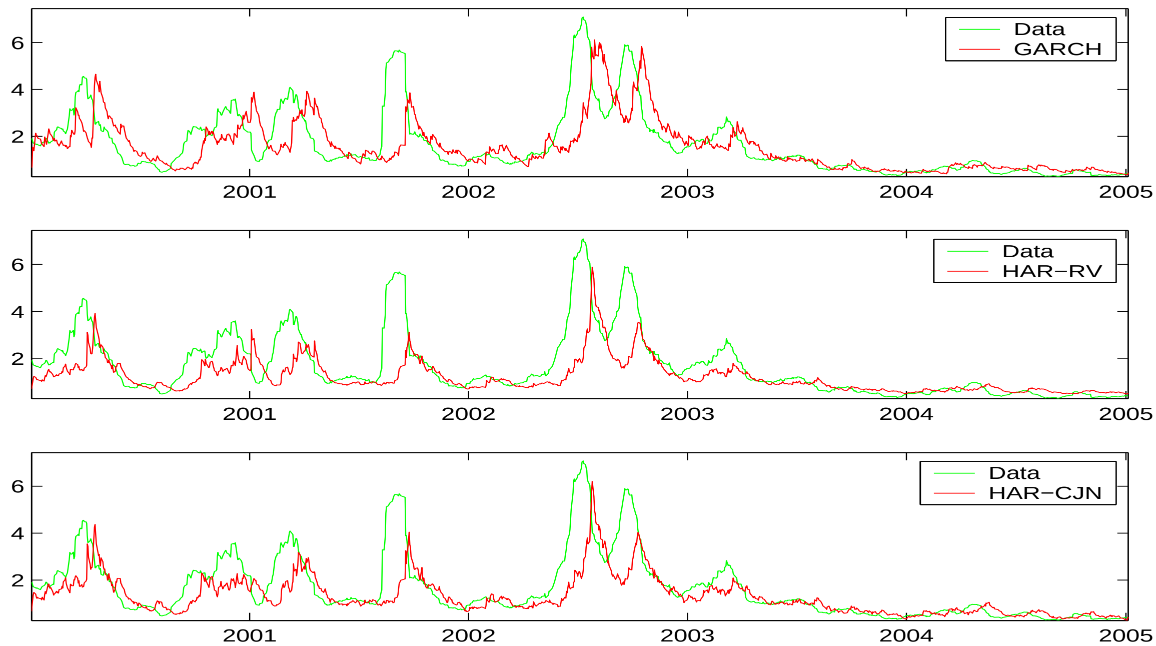

Figure 2.27: Out-of-Sample 1-Month Ahead Forecast for SP (post 1/1/2000)

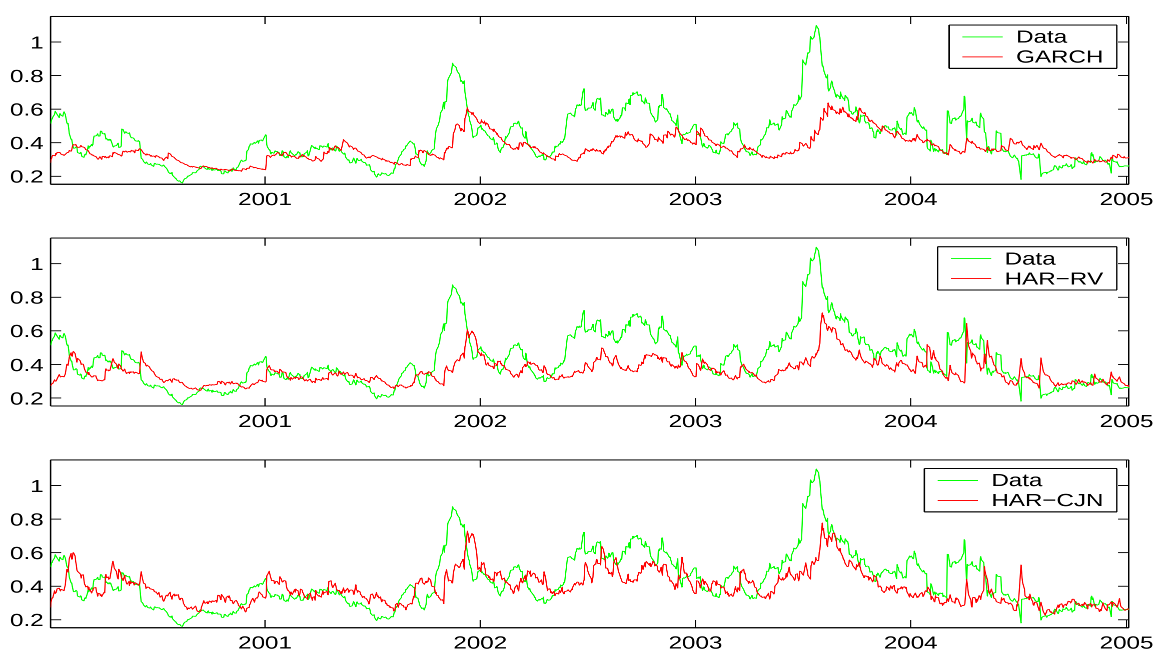

Figure 2.28: Out-of-Sample 1-Month Ahead Forecast for US (post 1/1/2000)

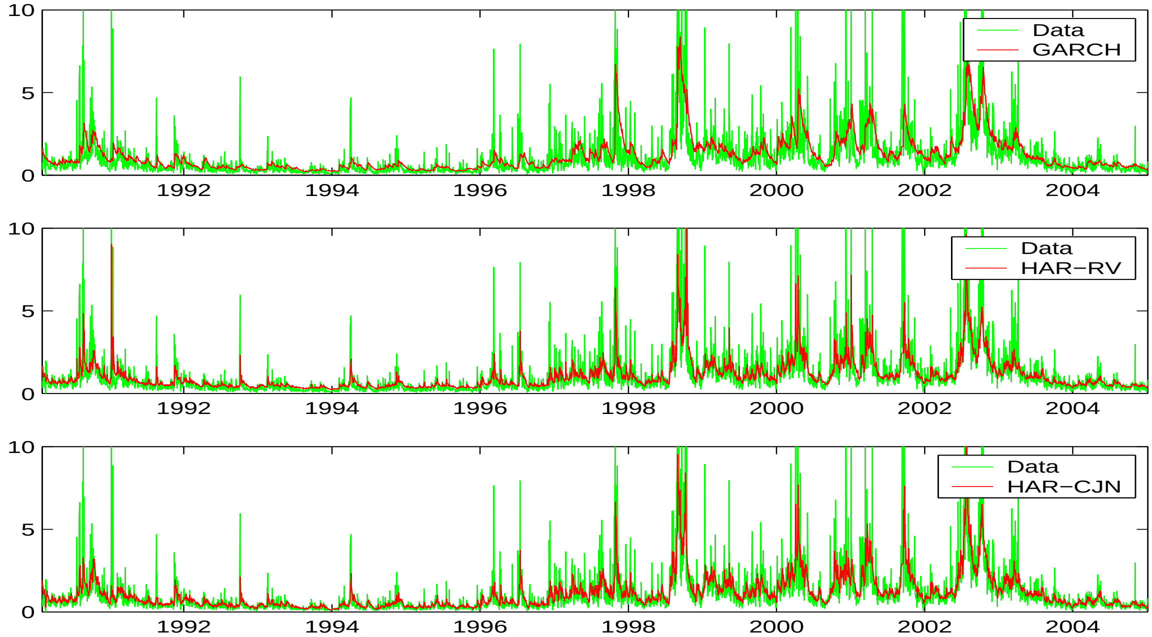

Figure 2.29: In-Sample 1-Day Ahead Forecast for SP (α=0.95)

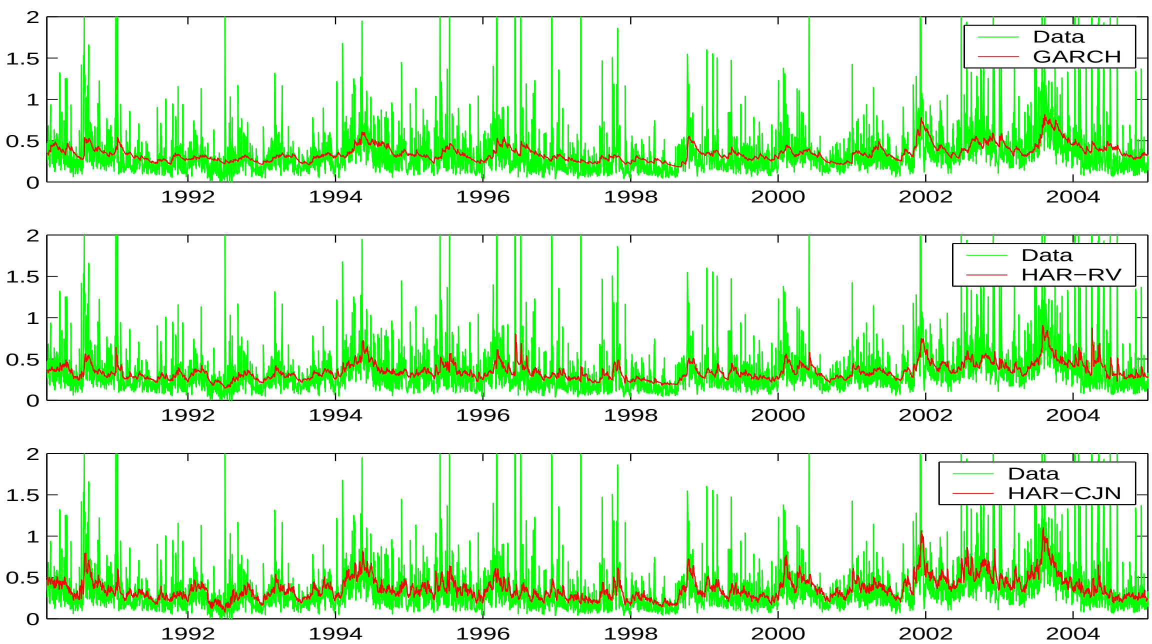

Figure 2.30: In-Sample 1-Day Ahead Forecast for US (α=0.95)

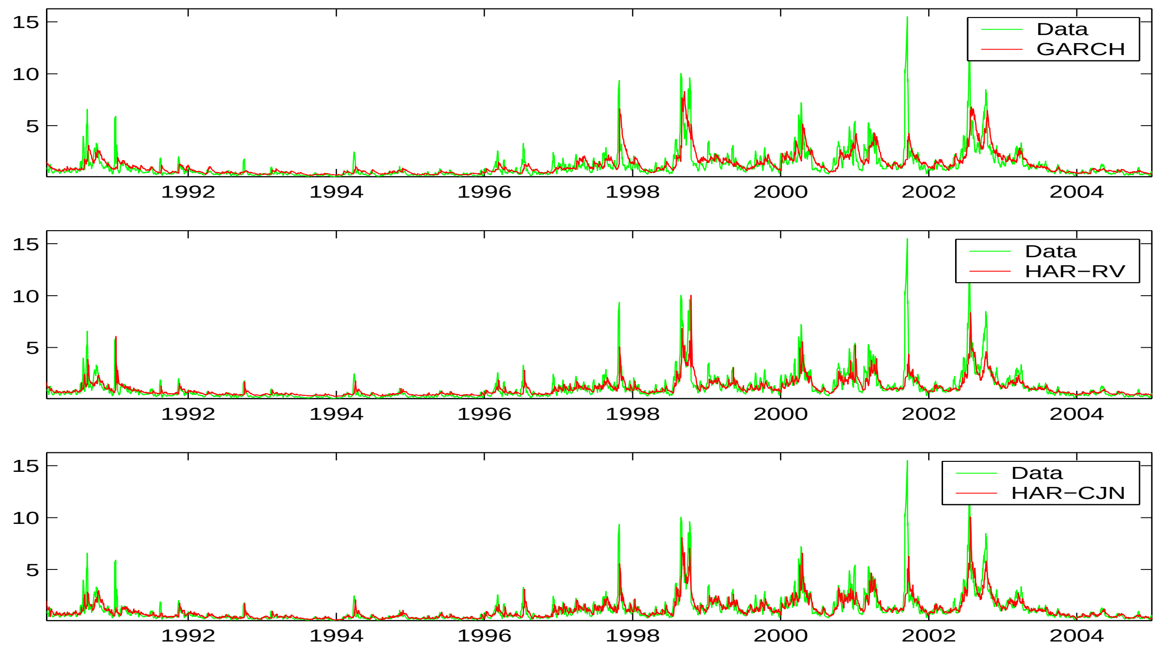

Figure 2.31: In-Sample 1-Week Ahead Forecast for SP (α=0.95)

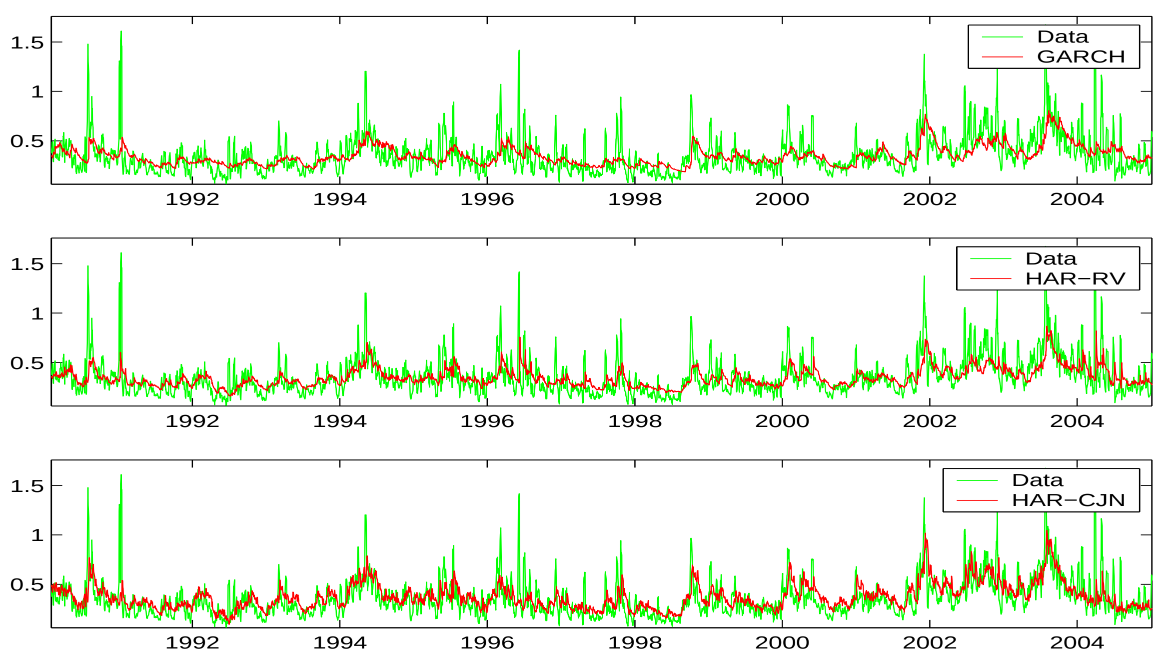

Figure 2.32: In-Sample 1-Week Ahead Forecast for US (α=0.95)

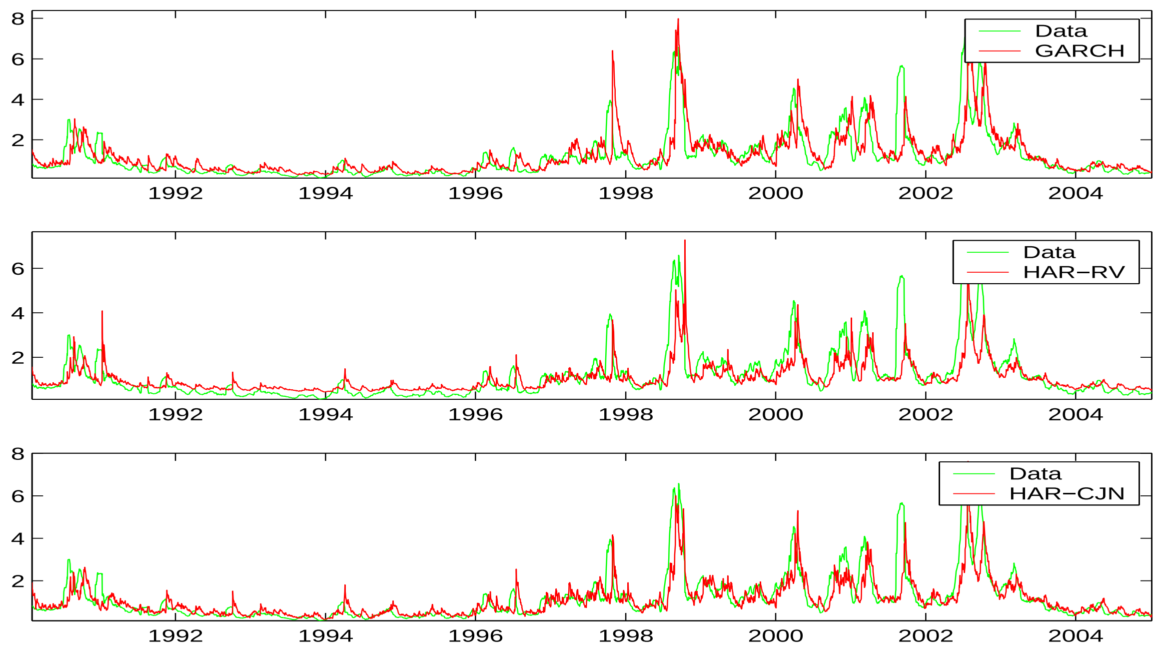

Figure 2.33: In-Sample 1-Month Ahead Forecast for SP (α=0.95)

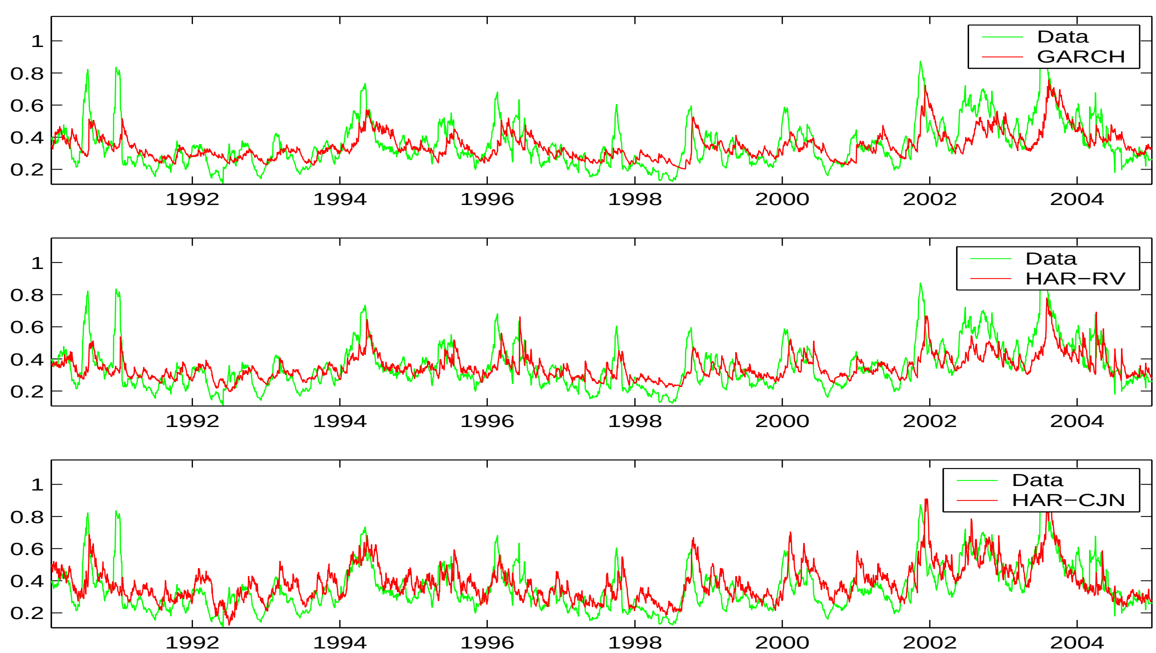

Figure 2.34: In-Sample 1-Month Ahead Forecast for US (α=0.95)

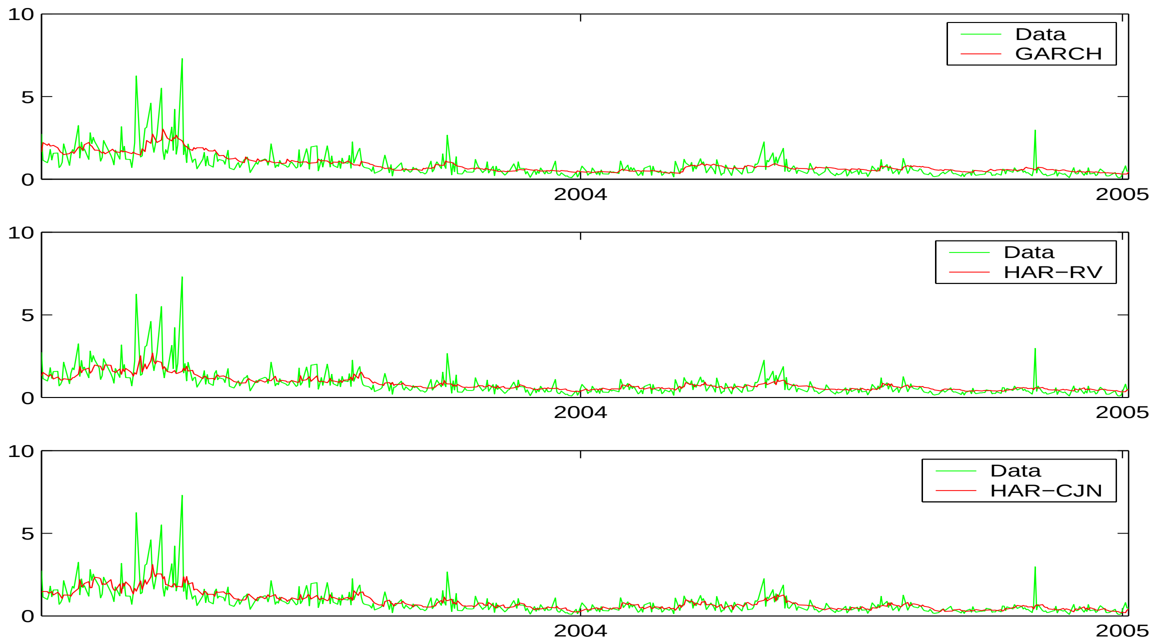

Figure 2.35: Out-of-Sample 1-Day Ahead Forecast for SP (post 1/1/2003) (α=0.95)

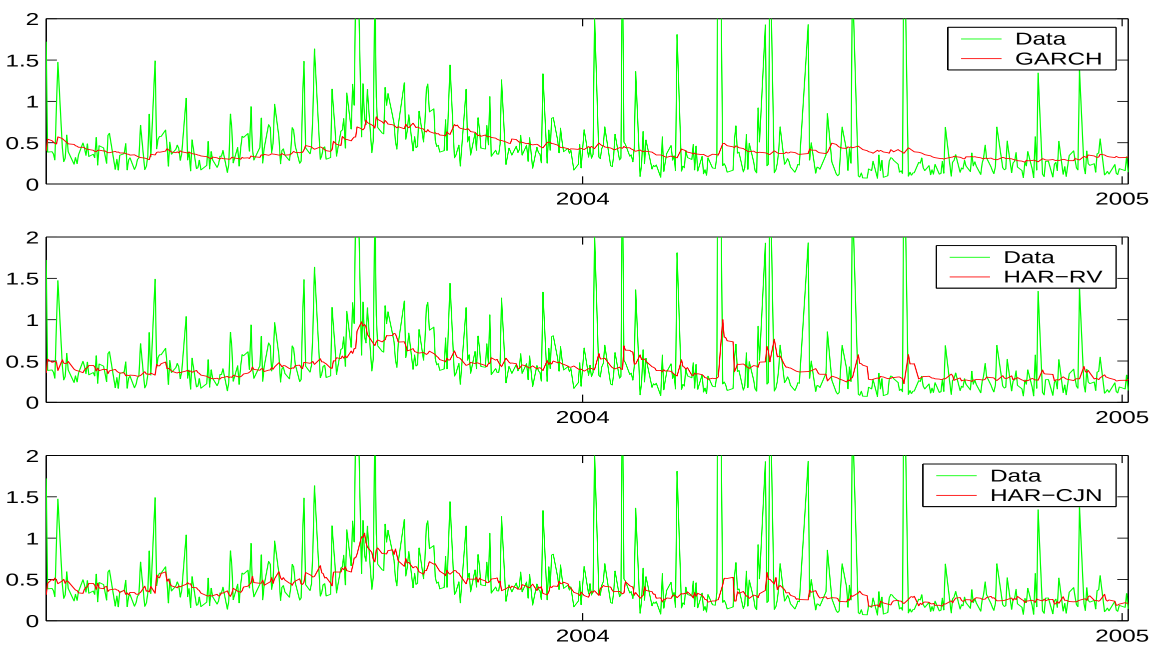

Figure 2.36: Out-of-Sample 1-Day Ahead Forecast for US (post 1/1/2003) (α=0.95)

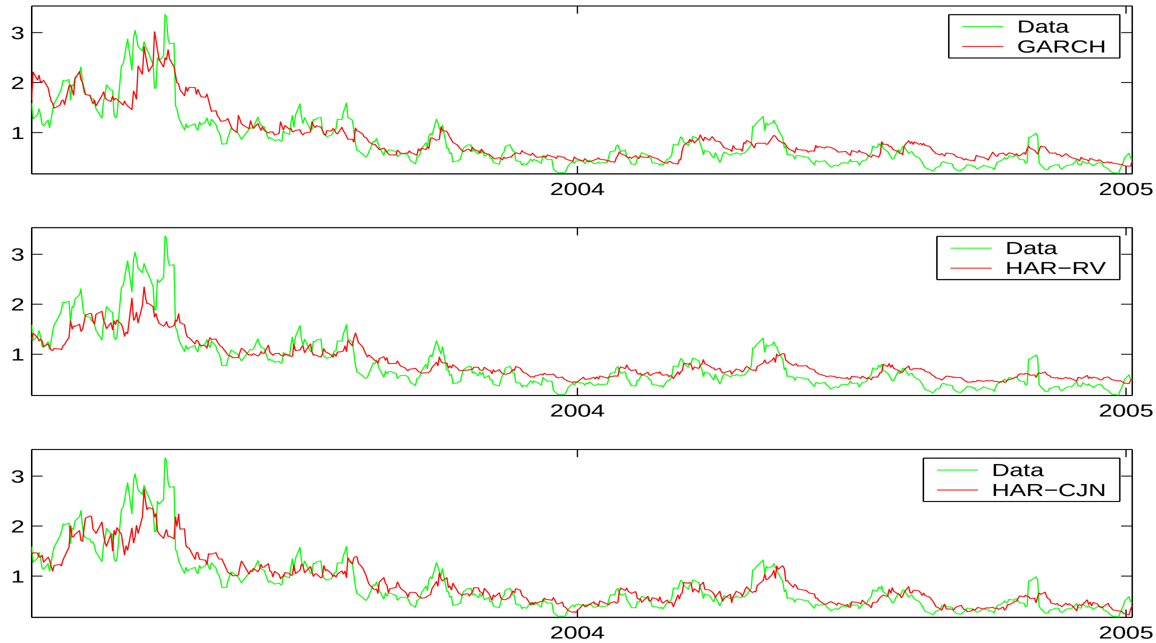

Figure 2.37: Out-of-Sample 1-Week Ahead Forecast for SP (post 1/1/2003) (α=0.95)

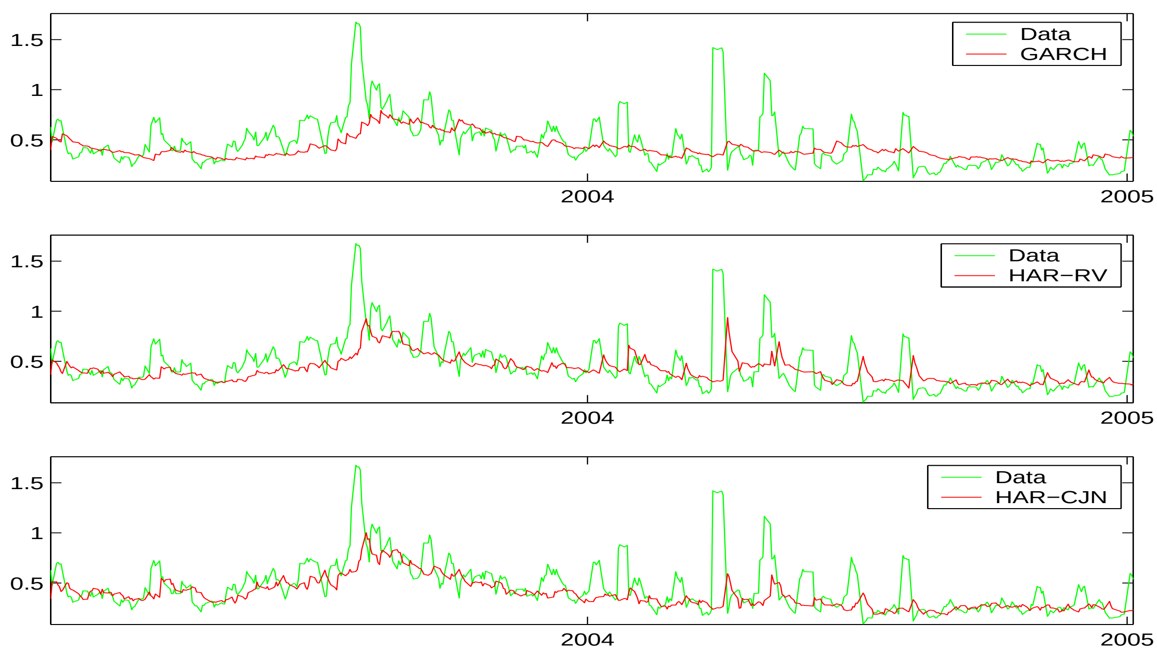

Figure 2.38: Out-of-Sample 1-Week Ahead Forecast for US (post 1/1/2003) (α=0.95)

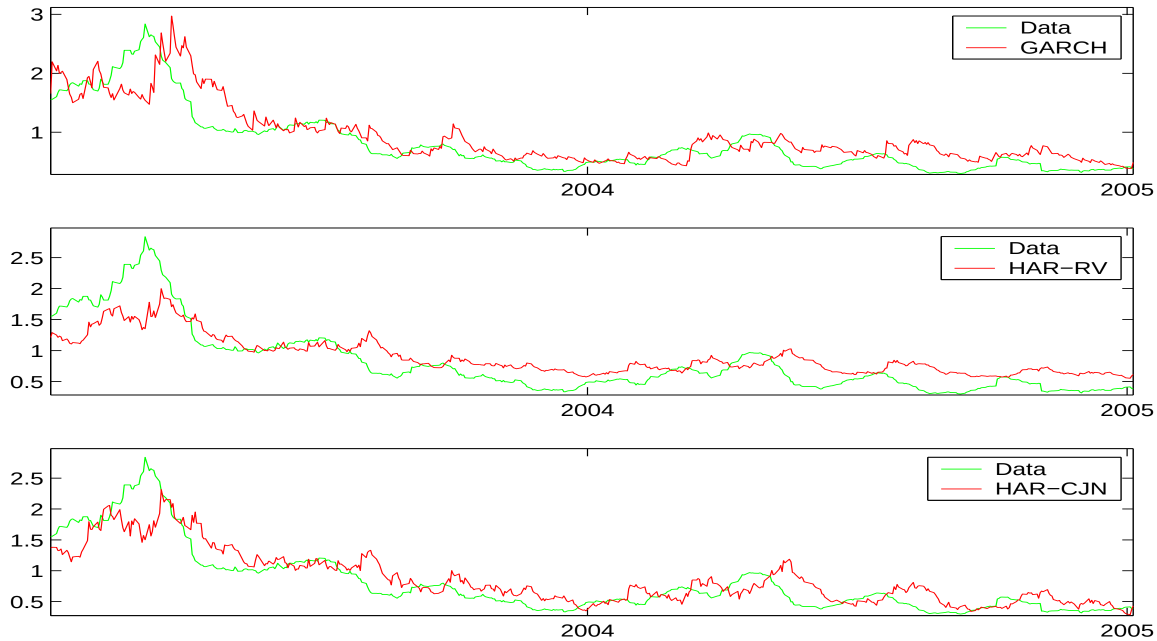

Figure 2.39: Out-of-Sample 1-Month Ahead Forecast for SP (post 1/1/2003) (α=0.95)

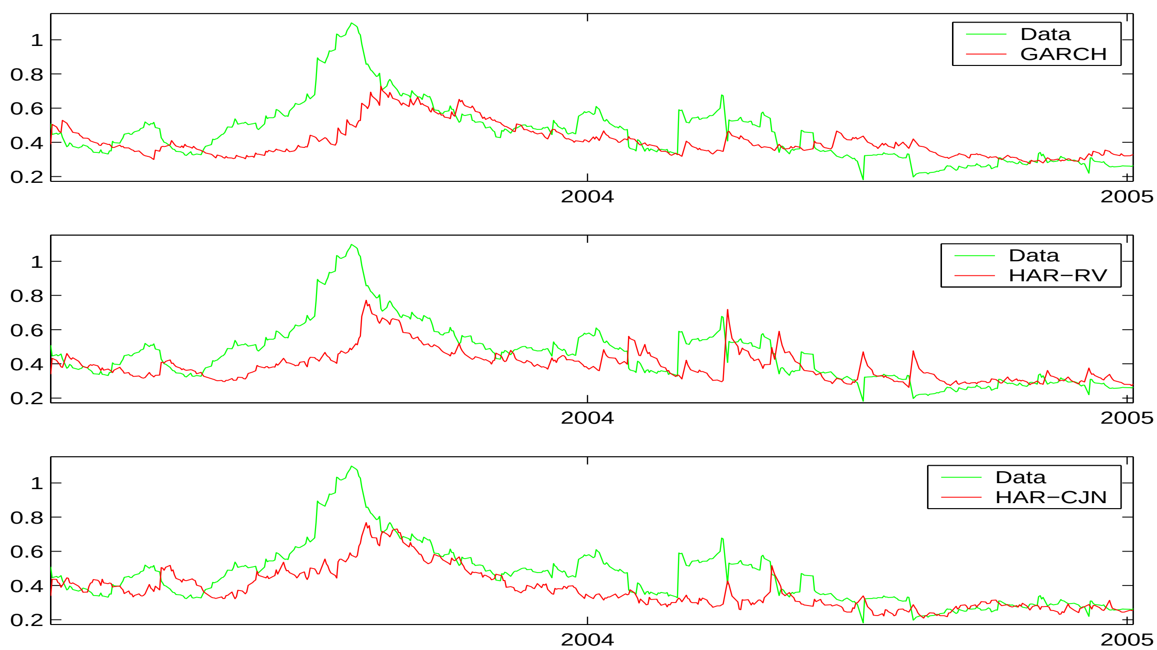

Figure 2.40: Out-of-Sample 1-Month Ahead Forecast for US (post 1/1/2003) (α=0.95)

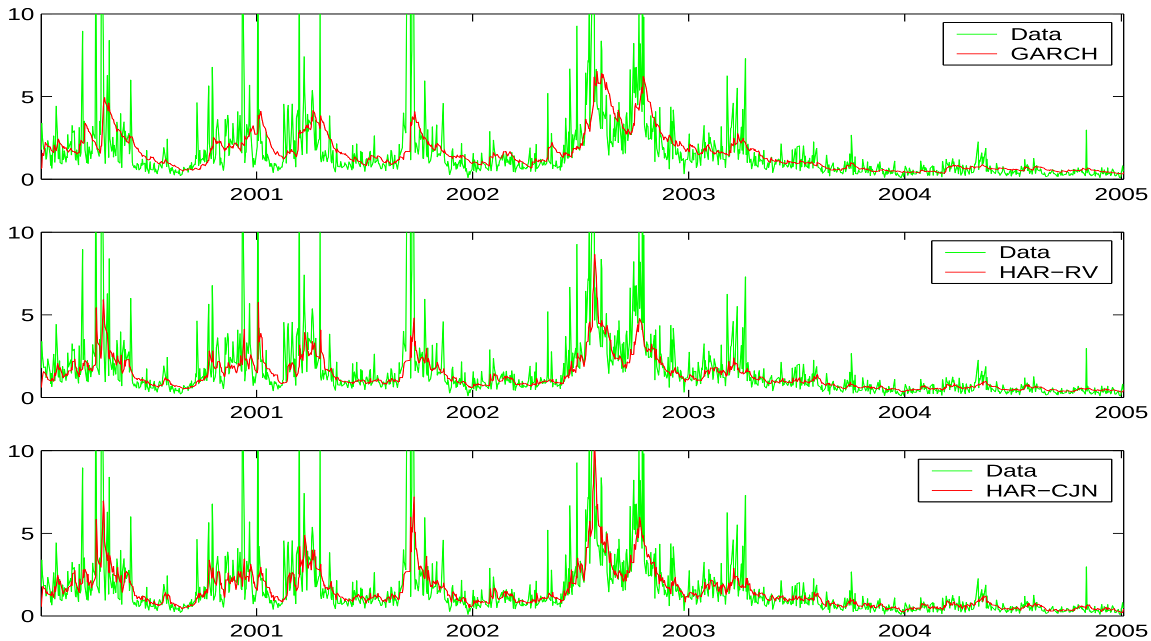

Figure 2.41: Out-of-Sample 1-Day Ahead Forecast for SP (post 1/1/2000) (α=0.95)

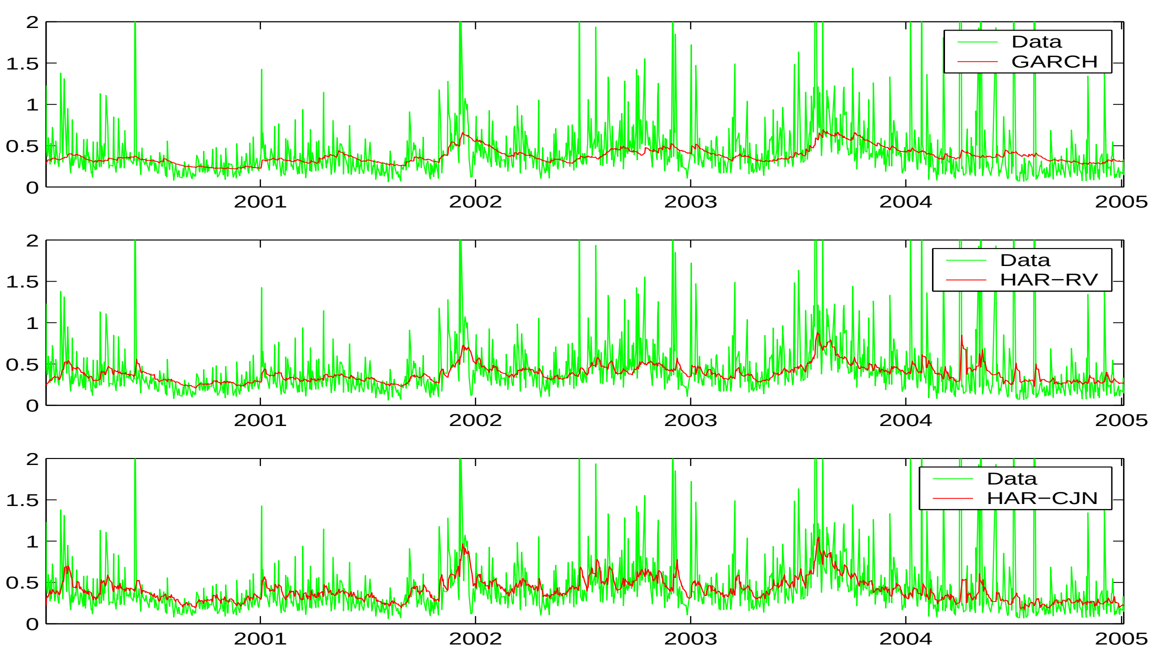

Figure 2.42: Out-of-Sample 1-Day Ahead Forecast for US (post 1/1/2000) (α=0.95)

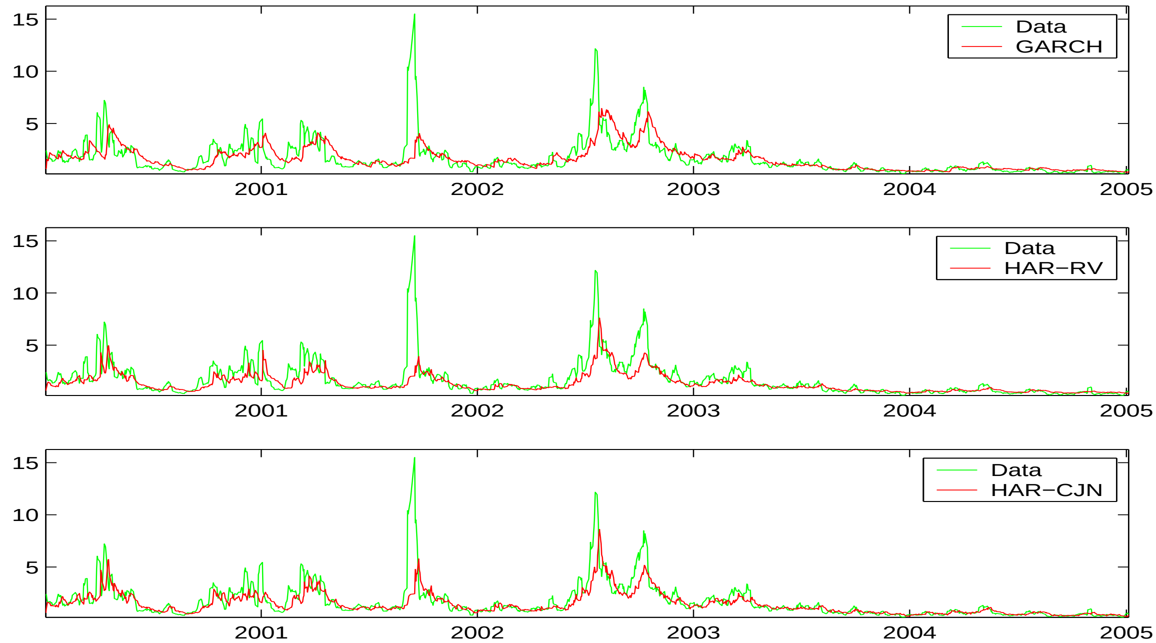

Figure 2.43: Out-of-Sample 1-Week Ahead Forecast for SP (post 1/1/2000) (α=0.95)

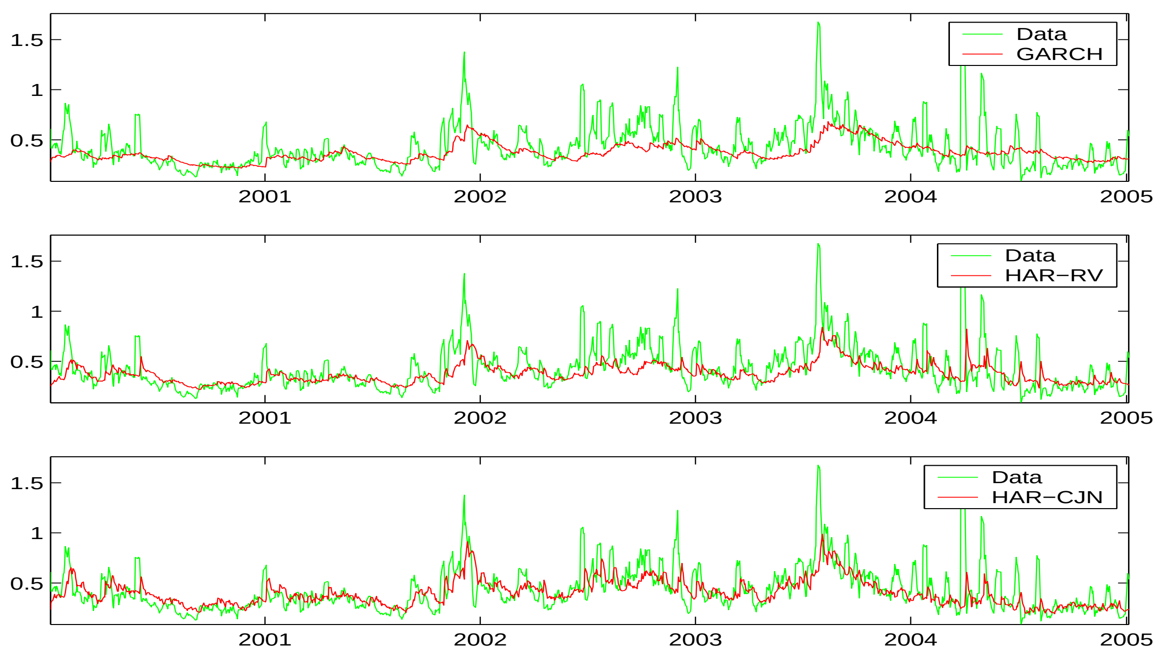

Figure 2.44: Out-of-Sample 1-Week Ahead Forecast for US (post 1/1/2000) (α=0.95)

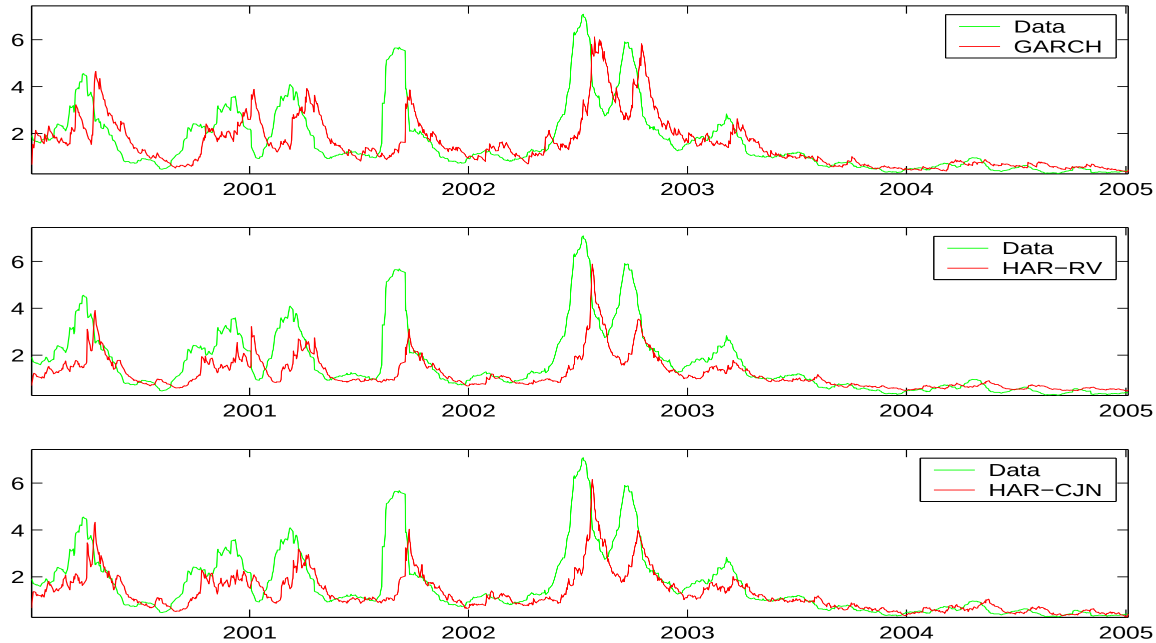

Figure 2.45: Out-of-Sample 1-Month Ahead Forecast for SP (post 1/1/2000) (α=0.95)

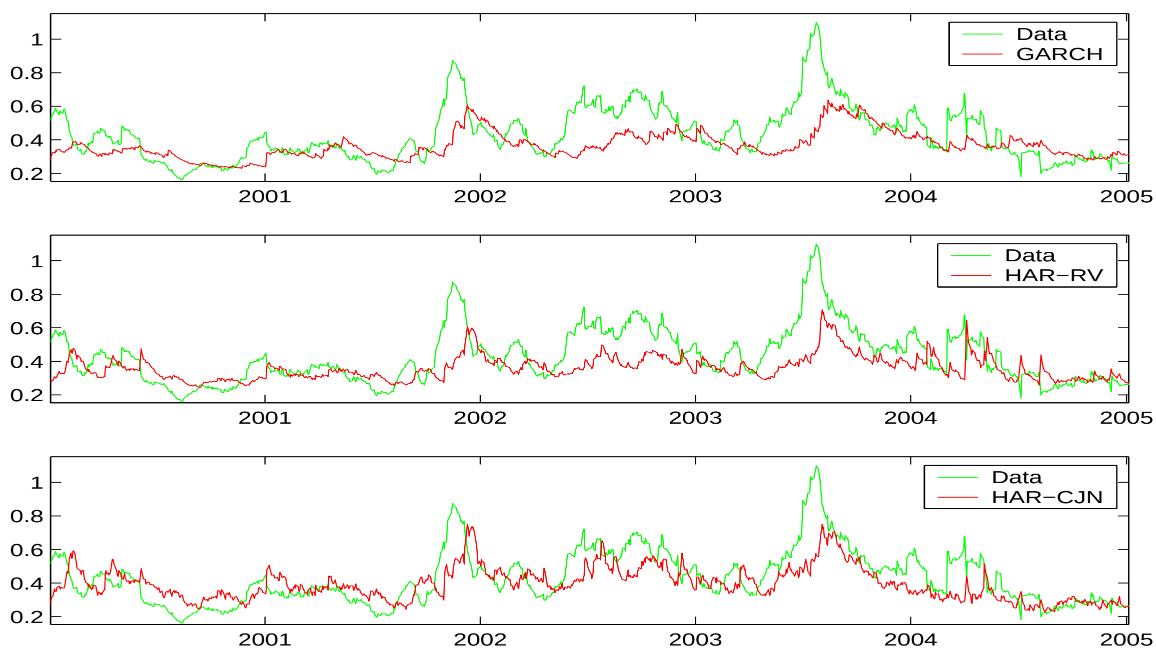

Figure 2.46: Out-of-Sample 1-Month Ahead Forecast for US (post 1/1/2000) (α=0.95)

Chapter 3

Macroeconomic News Announcements, Financial Market Volatility and Jumps

This chapter studies the financial market responses to macroeconomic news announcements, in the form of volatility and jumps.

3.1 Introduction

When macroeconomic news announcements bring new information to the financial market, will the market respond? If so, how does it respond? If not, what are the likely reasons? Answers to these questions not only are of great theoretical interest, as they can directly buttress or falsify the efficient market hypothesis in financial economics, and may be useful for studying various macroeconomic questions, but also have important practical implications.

There is a vast literature studying macroeconomic news announcements and the financial market responses. I summarize the literature into Tables 3.1 and 3.2. The general findings in the literature are that it is relatively easier to detect the bond market response to news announcements than that of the equity market, and intraday high-frequency data help to reveal stronger links between news and market responses.

This chapter extends the above literature in two directions. First, it differentiates market responses into volatility coming from the continuous price movements often known as diffusion, and jumps from the discrete price movements, and studies them at the same time. In particular, jumps in this chapter are defined in the formal statistical sense, instead of price movements over certain threshold, as traditionally used in literature. As diffusion and jumps are two distinct dynamic processes, they exhibit quite different patterns in response to news releases.

Of course, when we model the price movement as a jump-diffusion process, both volatility and jumps are unobservable. The powerful toolkit of jump detection test statistics introduced by Barndorff-Nielsen and Shephard (2004b, 2006) makes it possible to separate the jump component from the continuous volatility. Then using realized measures based on high-frequency data, we can turn the latent volatility and jumps into observable time series, and study their dynamics during the announcement periods.

The second direction is to differentiate the market's disagreement based on survey data and uncertainty based on economic derivatives, which are options on the future values of some macroeconomic data releases. Disagreement measures the degree that the heterogeneous market forecasters differ from each other on their forecasts of future macroeconomics news announcement values. Uncertainty, on the other hand, aggregates the market participants into a homogenous agent, and measures his or her uncertainty about his or her own forecast of future release values.

The traditional literature uncovers the market's expectation about future announcement release values using survey data, mostly from Money Market Services (MMS), an independent agent asking professional forecasters what their expectation of future release values are. This data set also provides the variance of the surveys. However, such variance conveys only the disagreement among economic agents, rather than the uncertainty. The two concepts may be related, but can be quite different, too, because it is possible that the distribution of the representative agent is quite centered, but the surveyed forecasters are selected from very different points of the distribution curve, resulting in a large survey variance. See Gürkaynak and Wolfers (2006) for further evidence on the difference between disagreement and uncertainty. Therefore, it will be interesting to see how these two different measures affect market responses.

To measure the uncertainty of a representative agent, this chapter uses the economic derivatives, first introduced by Goldman Sachs and Deutsche Bank in October 2002, and now traded in Chicago Mercantile Exchange as well as some online markets. In fact, by taking the difference of put or call prices on adjacent strike prices, we can recover the whole risk-neutral forecast probability density curve of the possible outcomes of the future release value.

The empirical findings of this chapter are based on more than a decade of high-frequency futures data for the S&P 500 index and US 30-Year Treasury Bond, together with MMS survey data and economic derivative data. This chapter finds that there are statistically significantly more large jumps on news days than on no-news days, with the fixed-income market being more responsive than the equity market, and nonfarm payroll employment being the most influential news. Surprises in forecasts impact volatility and jumps in the bond market more than the equity market, while disagreement and uncertainty influence both markets with different effects on volatility and jumps.

The rest of this chapter is organized as follows. Section 3.2 sets up the notation, and defines volatility and jumps studied in this chapter. Section 3.3 describes the data used in this chapter. Section 3.4 provides initial empirical evidence of market responses to news announcements. Section 3.5 compares the market volatility and jump responses to news surprises when market forecasts are measured by survey and economic derivative data respectively. Finally, Section 3.6 concludes the chapter and provides some directions for future research.

3.2 Volatility and Jumps Definitions

To understand how market volatility and jump respond to news announcements, it is necessary to give proper definitions for these two components of the price process first. In this chapter, the logarithmic asset price $p(\tau)$ is assumed to follow the jump-diffusion process defined by the following stochastic differential equation:

$$dp(\tau) = \mu(\tau)d\tau + \sigma(\tau-)dw(\tau) + \kappa(\tau)dq(\tau), \tag{3.1}$$

where $\tau \in \mathbb{R}^+$. The time scale is normalized such that one time unit corresponds to one trading day. $\mu(\tau)$ is the drift term with a continuous and locally finite variation sample path. $\sigma(\tau) > 0$ is the spot volatility process, assumed to be càdlàg. $w(\tau)$ is a standard Brownian motion. $\kappa(\tau)dq(\tau)$ refers to the pure jump part, where $dq(\tau) = 1$ if there is a jump at time τ and 0 otherwise, and $\kappa(\tau)$ represents the jump size.

Correspondingly, the within-day geometric returns are defined as

$$r_{t,j} = p(t-1+j/M) - p(t-1+(j-1)/M), \quad j = 1, 2, \ldots, M \tag{3.2}$$

where $t \in \mathbb{N}^+$ represents the trading day, and M refers to the number of intraday returns over a trading day.

The volatility over the trading day t is measured by the quadratic variation of the price process

$$QV_t = \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2. \tag{3.3}$$

The first term is the integrated variance term from the continuous-sample-path part, and the second term is the quadratic variation from the discrete jump part, with N_t equal the number of jumps on day t.

As QV_t and its different components are not directly observable, some model-free non-parametric consistent measures based on high frequency data are used in this chapter. The first one is the now familiar realized variance, which consistently estimates the QV_t when the sampling interval goes to zero, as noted in Andersen and Bollerslev (1998), Comte and Renault (1998), Andersen, Bollerslev, Diebold, and Labys (2001, 2003), and Barndorff-Nielsen and Shephard (2002a,b), among others.

$$RV_t(M) = \sum_{j=1}^{M} r_{t,j}^2 \xrightarrow[M\to\infty]{P} \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2. \tag{3.4}$$

To separately measure the volatility and the jump parts, Barndorff-Nielsen and Shephard (2004b, 2006) introduce the realized bipower variation

$$RBV(M)_{1,t} = \mu_1^{-2} \left(\frac{M}{M-2}\right) \sum_{j=3}^{M} |r_{t,j-2}||r_{t,j}| = \frac{\pi}{2} \left(\frac{M}{M-2}\right) \sum_{j=3}^{M} |r_{t,j-2}||r_{t,j}|. \tag{3.5}$$

where

$$\mu_a = E(|Z|^a), \quad Z \sim N(0,1),\, a > 0.$$

There is an additional staggering term in the above bipower variation formula, relative to the one initially introduced by Barndorff-Nielsen and Shephard (2004b). It helps to make the RBV measure together with the following jump detection test statistics robust under the influence of i.i.d. normal market microstructure noise. See Huang and Tauchen (2005) for some initial analytical investigations and Monte Carlo evidence. Under the assumption that the logarithmic price process is a continuous-time stochastic volatility semimartingale ($SVSM^c$) plus a finite-activity jump process, $RBV_{i,t}$ converges to the integrated variance as the sampling frequency goes to infinity

$$RBV_{1,t}(M) \xrightarrow[M\to\infty]{P} \int_{t-1}^{t} \sigma^2(s)ds. \tag{3.6}$$

Consequently, the difference between the realized variance and the realized bipower variation consistently estimates the quadratic variation of the jump component in the log price process

$$RV_t(M) - RBV_{1,t}(M) \xrightarrow[\mathrm{M}\to\infty]{\mathrm{P}} \sum_{j=1}^{N_t} \kappa_{t,j}^2. \tag{3.7}$$

Moreover, under the same regularity conditions, the test statistic

$$z_{RTQ,rm,t} = \frac{\frac{RV(M)_t - RBV(M)_{1,t}}{RV(M)_t}}{\sqrt{((\frac{\pi}{2})^2 + \pi - 5)\frac{1}{M}\max(1, \frac{RTQ(M)_t}{RBV(M)_{1,t}^2})}}. \tag{3.8}$$

where

$$RTQ(M)_{1,t} = M\mu_{4/3}^{-3}\left(\frac{M}{M-6}\right)\sum_{j=}^{M} |r_{t,j-4}|^{4/3}|r_{t,j-2}|^{4/3}|r_{t,j}|^{4/3}, \tag{3.9}$$

is asymptotically standard normally distributed under the null of no within-day jumps, and consequently may be used to test for significant jumps.[1]

Based on the above jump detection test statistic, the realized quadratic variation of the jump components is measured by

$$J_t(M) = I(z_{RTQ,rm,t} > \Phi_\alpha) \cdot (RV_t(M) - RBV_{i,t}(M)), \tag{3.10}$$

where $I(\cdot)$ is the indicator function, equal to 1 if its argument is evaluated to be true, and 0 otherwise, while Φ_α refers to the critical value from the standard normal distribution in the upper α quantile. Accordingly, the realized measure for the integrated variance is defined as

$$C_t(M) = I(z_{RTQ,rm,t} \leq \Phi_\alpha) \cdot RV_t(M) + I(z_{RTQ,rm,t} > \Phi_\alpha) \cdot RBV_{i,t}(M), \tag{3.11}$$

which automatically ensures that the non-parametric measures for the jump and continuous components add up to $RV_t(M)$. This same decomposition of the within

[1] Huang and Tauchen (2005) report extensive simulation evidence showing that the particular jump detection test statistic used here exhibits excellent size and power properties for a one-factor logarithmic stochastic volatility plus Compound Poisson jump process.

day variance is first studied by Andersen, Bollerslev, and Diebold (2006). The actual implementation requires a choice of α. In most of the results reported below, I use the critical value of $\alpha = 0.99$, but very similar results were obtained for other critical values, which are available upon request.

3.3 Data

To study the market responses to news announcements, two types of data are needed. The first one is the market response data, and the second one is the news release values and the corresponding market forecasts or expectations.

3.3.1 High-frequency Futures Data for Market Responses

This chapter studies both the U.S. equity and fixed-income markets, and the corresponding market responses data are five-minutes returns on the S&P 500 index futures (SP, traded in Chicago Mercantile Exchange (CME)) and 30-year U.S. treasury bond futures (US, traded in Chicago Board of Trade (CBOT)).

The choice of five-minute sampling frequency is based on the balance between sampling as finely as possible for the asymptotic theory to work, and minimizing the impact of the market microstructure noise usually found in very high-frequency data. Tick data are converted into five-minute prices using the previous-tick method, that is, the last price observation in the previous five-minute interval is taken as the price of this five-minute mark; see Wasserfallen and Zimmermann (1985) and Dacorogna, Gençay, Müller, Pictet, and Olsen (2001) for details on the previous-tick method.

As CME opens from 8:30 to 15:15 Central Time, or 9:30 to 16:15 Eastern Time, while many important news announcements, such as nonfarm payroll employment, are released at 8:30 Eastern Time, I extend the pit-traded price data by Globex to 8:25 Eastern Time. Hence there are 94 five-minute returns on each day for the S&P

500 index futures. Since Globex data became available from January 1994, the sample period for the S&P 500 index futures ranges from 1/3/1994 to 6/30/2005, for a total of 2857 x 94 = 268558 five-minute returns. On the other hand, as CBOT opens from 8:20 to 15:00 Eastern Time, the exchange-traded data is sufficient to cover the news announcements periods, so the sample period for US 30-year TB is relatively longer, from 11/7/1988 to 6/30/2005, for a total of 4108 x 79 = 324532 five-minute returns. The data source for the exchange-traded data is Price-Data before February 2005, Globex and all the futures data from February 2005 on are from TickData.

Four different futures contracts mature every year, in March, June, September and December respectively, and each futures contract exists for no more than two years, so the different futures contracts have to be rolled over to construct a single futures price time series. I always use the most actively traded futures contracts, usually the one closest to its maturity, and roll over to the next contract five business days before the expiration day for the S&P 500 index futures, and the first business day in the delivery month for the US 30-Year treasury bonds. The same rollover method is also implemented in Andersen, Bollerslev, and Huang (2007).

3.3.2 News Announcements and Survey Data

Data on macroeconomic news announcement release values and the corresponding survey values are from the International Money Market Services (MMS). I collect 26 announcements as listed in Table 3.3, covering the 25 announcements studied in Andersen, Bollerslev, Diebold, and Vega (2005), plus retail sales excluding autos, as it is one of the four major announcements that the economic derivatives are traded on. In this chapter, different announcements have slightly different sampling periods, according to the availability of the MMS survey data, but the four major announcements for the economic derivatives cover the full sample period of the 30-Year TB futures data.

3.3.3 Economic Derivatives

Economic derivatives were first introduced by Goldman Sachs and Deutsche Bank in October 2002, and are now traded in Chicago Mercantile Exchange as well as some online markets. They are digital options whose payoff depends on news announcements: the digital call (put) pays $1 if the announcement value is above (below) the strike. Most auctions take place on the announcement day before the announcement data are released.

Just like the vanilla options on stock prices, we can construct a risk-neutral density for the possible outcomes of the future release values, by taking the difference of put or call prices of the economic derivatives on adjacent strike prices. Figure 3.2 plots the implied probability density for the nonfarm payroll employment release on 6/3/2006. From this density, we can obtain various moments, so the economic derivatives provide richer information than the MMS survey data do.

More importantly, the standard deviation from the density based on the economic derivatives measures the uncertainty of the representative market participant, instead of the disagreement among the market forecasters as revealed by the standard deviation in the MMS survey data. They play a different role in determining the impact of the news announcements on the financial markets, as shown in Section 3.5.

Since the economic derivatives started trading only in October 2002, their sample period is relatively short, ranging from 10/2002 to 6/2005. In this chapter, I focus on four announcements: nonfarm payroll employment (NFPAY), the Institute of Supply Managements (formerly known as National Association of Purchasing Managers) manufacturing diffusion index (NAPM or ISM), percentage change in retail sales excluding autos (RSXAUT), and initial unemployment claims (ICLM), as they are the four announcements that the economic derivatives were traded on when they were launched in October 2002.

The economic derivatives data can be collected from the web page of Goldman Sachs, who initiated the auction trading of the economic derivatives together with Deutsche Bank.

3.4 Initial Evidence Linking Announcements and Jumps

To visualize the financial market responses to macroeconomic news announcements, figure 3.1 plots a typical announcement day. It is June 6, 1996, when the nonfarm payroll employment value was released at 340, while the survey expectation was only 170 with standard deviation 56.5. This news was quite out of the market expectation, and both S&P and US T-Bond reacted quickly and their price slumped right at the announcement time. Meanwhile, the jump detection test statistic discussed in Section 3.2 signals this day as a jump day for both markets. So we can be quite sure that the economic factor behind this jump day is the unexpected nonfarm payroll employment news release.

Of course, convincing evidence for the significant link between announcements and jumps comes from formal statistical tests. There are two directions we can approach this question, both of which have been used in the literature.

First, given each and all the news announcements, we can compute the proportion of the jump days. If news has no impact on jumps, then it is equally likely to observe jump days on news and no-news days. Consequently, we can use these two probabilities to form a test statistics. Specifically, let p_1 be the probability of jump days on the news days, and p_2 be the probability of jump days on the no-news days. Under the null of no link between news and jumps, $\hat{p_1} - \hat{p_2} \sim N(0, p_1(1-p_1)/n_1 +$

$p_2(1-p_2)/n_2)$, where n_1 is the number of news days, and n_2 is the number of no news days, and the hat above p's denotes estimated probabilities using sample proportions.

Table 3.4 reports the proportion of jump days in each of the news announcement days, as well as in the total news days and no-news days, together with the above test statistics computed from the two probability estimates, and one-sided p-values. The jump days are detected at the 99% significance level. It is apparent from the table that the proportions of jump days in many news announcement days are statistically significantly larger than those in no-news days for both S&P and US T-Bond markets, showing the significant impact of these news on jumps, especially nonfarm payroll employment, PPI, CPI, retail sales, initial unemployment claims, consumer credit and business inventories. Nonfarm payroll employment turns out to be the most influential news across different markets. The last column in Table 3.4 is based on the cojump of S&P and US T-Bond, and the same significant impacts of news show up when the two markets jump together. Moreover, US T-Bond exhibits more sensitivity to news announcements than S&P does.

The second direction is to pick out the jump days, and find out how many of them can be associated with news announcement days. If news has no impact on jumps, then this proportion will be equal to the proportion of news days in the whole sample. Similar test statistics can be constructed as the above jump-on-news-days test. Table 3.5 reports such test statistics for jump days signaled at the 99% and 999% levels of significance. Again we can see strong evidence that there are statistically significantly larger proportions of news days in jump days than that in the whole sample, either for the individual equity or fixed-income market jumps, or for the co-jumps of the two markets.

3.5 News Surprises, Volatility and Jumps

It may be noticeable that although the news impacts on jumps are statistically significant, the proportions of jump days in the news announcement days are not very high in Table 3.4, and the proportions of news days in the jump days are not much larger than the overall proportions of news days in Table 3.5. This does not mean that the news impact is not economically significant. Rather, we have not fully explored the relationship between news and market responses.

There are a lot of news releases, around two-third of the days are news days, as can be seen from Table 3.5. However, many of them are within market expectations, and thus introduce not much new information to the market. As price is the discounted expected future cash flow, it is not supposed to move much at the expected news announcements. So we have to translate news announcements into surprises, and link surprises in news announcements to market responses, and see how volatility and jumps change during the announcement periods.

Following Balduzzi, Elton, and Green (2001), and Andersen, Bollerslev, Diebold, and Vega (2003, 2005), I define the standardized news surprise as

$$S_{kt} = \frac{A_{kt} - E_{kt}}{\hat{\sigma_k}} \tag{3.12}$$

where A_{kt} is the released value for news k on day t, E_{kt} is the mean of survey forecast or market-based forecast from the economic derivative, $\hat{\sigma_k}$ is the sample standard deviation of surprise $A_{kt} - E_{kt}$. The numerator translates announcements into surprises, while the denominator standardizes the surprises to ensure the comparability of coefficient estimates across different news and markets.

To study how volatility and jumps react to the surprises in news, the realized continuous volatility C_t and jump quadratic variation J_t discussed in Section 3.2 are regressed on the standardized news surprises:

$$\begin{aligned} log(C_t^h + 1) &= \alpha_{C,k}^h + \beta_{C,k}^h S_{kt}^{ED} + \gamma_{C,k}^h S_{kt}^S + \epsilon_{C,t}^h \\ log(J_t^h + 1) &= \alpha_{J,k}^h + \beta_{J,k}^h S_{kt}^{ED} + \gamma_{J,k}^h S_{kt}^S + \epsilon_{J,t}^h \end{aligned}$$

I take logarithmic transformation of C and J so that the left-hand-side variables can cover the whole real line instead of only the positive quadrant, and their finite sample distribution can be better approximated by the normal distribution. The ED superscript means economic derivative, and S superscript means survey.

These regressions can be run on individual news as above. They can also be run on all the news jointly as follows:

$$\begin{aligned} log(C_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{C,k}^h + \beta_{C,k}^h S_{kt}^{ED} + \gamma_{C,k}^h S_{kt}^S + \epsilon_{C,t}^h \\ log(J_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{J,k}^h + \beta_{J,k}^h S_{kt}^{ED} + \gamma_{J,k}^h S_{kt}^S + \epsilon_{J,t}^h \end{aligned}$$

Table 3.6 reports the coefficient estimates together with their White heteroskedastic robust standard error for the individual news surprise regression. As economic derivatives were traded only on four economic news announcements in October 2002, I only compare the regression results on the four corresponding survey data. The last column of Table 3.6 reports the p-value of the joint test that all the news surprise coefficients are zero in the joint regression.

In line with the findings in Section 3.4, news surprises impact the bond market statistically significantly, both in terms of volatility and jumps, even though each individual news announcement may not always be significant. In comparison, the equity market is not very significantly affected by the news surprises, as any factor influencing either cash flow or discount rate can affect the equity market.

The above analysis uses the first moment of the market forecast for the news release values. However, market response to news surprise can be affected by the second moment, that is the disagreement among the individual economic agents measured by the standard deviation of the survey forecast, and the uncertainty of the representative agent measured by the standard deviation of the probability distribution recovered from the economic derivative prices. So I run similar individual regressions of C and J on these standard deviations. The individual regressions are:

$$\begin{aligned} log(C_t^h + 1) &= \alpha_{C,k}^h + \beta_{C,k}^h SD_{kt}^{ED} + \gamma_{C,k}^h SD_{kt}^S + \epsilon_{C,t}^h \\ log(J_t^h + 1) &= \alpha_{J,k}^h + \beta_{J,k}^h SD_{kt}^{ED} + \gamma_{J,k}^h SD_{kt}^S + \epsilon_{J,t}^h \end{aligned}$$

and the joint regressions are:

$$\begin{aligned} log(C_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{C,k}^h + \beta_{C,k}^h SD_{kt}^{ED} + \gamma_{C,k}^h SD_{kt}^S + \epsilon_{C,t}^h \\ log(J_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{J,k}^h + \beta_{J,k}^h SD_{kt}^{ED} + \gamma_{J,k}^h SD_{kt}^S + \epsilon_{J,t}^h \end{aligned}$$

where SD is the standard deviation from economic derivatives or survey.

Table 3.7 reports the coefficient estimates together with their White heteroskedastic robust standard error for the individual uncertainty and disagreement regressions. The last column of Table 3.7 reports the p-value of the joint test that all the coefficients are zero in the joint regression. Interestingly, uncertainty and disagreement turn out to be statistically significant for both equity and fixed-income markets, with slightly different roles for different markets' volatility and jumps. Uncertainty is significant for both volatility and jumps in the equity market, while uncertainty affects the fixed-income market's volatility, and disagreement significantly influences its jumps.

The impacts of disagreement or uncertainty on market responses make economic sense. When the news release values are different from market forecast expectation, but the representative economic agent is not very sure about his or her expectation, or the individual agents disagree quite a lot on their forecasts, then the news surprises are not likely to increase volatility or induce big jumps in the prices. The effect of news surprises is the biggest, when the market players are quite sure about their expectation or there is strong consensus among themselves, while the release value turns out to be different from the market forecast. Of course, different markets can exhibit different ways of responses, either in volatility or in jumps, depending on the characteristics of the particular markets.

3.6 Conclusion

This chapter studies the financial market responses to macroeconomics news announcements. It extends the literature in two directions. First, it differentiates market responses into continuous volatility and discontinuous jumps, and studies them at the same time. Second, in addition to news surprises in the first moment of the market forecast, this chapter introduces disagreement and uncertainty in the second moment of the market forecast.

Based on high-frequency futures data of the U.S. equity and fixed-income markets, this chapter detects a statistically significant link between news announcements and financial market jump responses, with the fixed-income market being the more responsive one and nonfarm payroll employment being the most influential news. Surprises in news releases also affect the fixed-income market more, while disagreement and uncertainty influence both markets with different effects on volatility and jumps.

There are several directions for future research. First, jumps detected in this chapter are on a daily basis. As jumps are defined to be short-lived events, it will be of both theoretical and practical interest to discover the particular interval(s) within the trading day in which jumps occur. The sequential test proposed by Andersen, Bollerslev, Frederiksen, and Nielsen (2006) provides a good starting point. Discovering the jump interval can reaffirm the link between the news announcement and market jump response if the jump takes place right after the announcement time.

Second, as jumps are controlled by jump occurrence and jump size, it will be interesting to see how news surprises impact these two components separately. Will big surprises in news announcements increase the jump hazard rate for the future jump occurrence? Are jump sizes positively related to the sizes of the news surprises? Answers to these questions will help portfolio hedging and other risk management applications.

Last but not least, understanding how financial markets respond to news surprises has important policy implications, too. From the results reported in this chapter, it is obvious that different news announcements have different levels of impact on jumps and volatilities. Further analysis along this line, such as how the direction of market responses changes over the business cycle, will provide guidance for the policy makers as they choose different fiscal and monetary policies to affect the economy during different phases of the economy.

3.7 Tables

Table 3.1: Announcements (In)Significantly Affect Equity Market

Money supply	PPI	IP	NFP
Pearce and Roley	Cutler, Poterba and	Cutler, Poterba and	Pearce and
(1983)(-)	Summers (1989)(-)	Summers (1989)(+)	Roley (1985) (0)
Pearce and Roley	Pearce and Roley	Pearce and Roley	Hardouvelis
(1985)(-)	(1985)(-/0)	(1985) (0)	(1987) (-)
Hardouvelis (1987) (-)	G. William Schwert	McQueen and Roley	McQueen and
Jain(1988)(-)	(1981)(-/0)	(1993) (-.+)	Roley(1993)(+.-)
McQueen and Roley	McQueen and Roley		
(1993)(-)	(1993)(-)		
	Nelson (1976) (-)		
	Geske and Roll (1983) (-)		
	Jain(1988,CPI) (-)		

Positive sign means the news has positive impact on the market, negative sign means negative impact and 0 means insignificant impact.

Table 3.2: Announcements Significantly Affect Bond Market

Money supply	PPI	IP	NFP
Berkman (1978)	Urich and Wachtel	Roley and Troll (1983)	Cook and Korn (1991)
Grossman (1981)	(1984)	Harvey and Huang	McQueen and Roley
Urich and Wachtel (1981)	Smirlock (1986)	(1993)	(1993)
Cornell (1982, 1983)	Hardouvelis (1988)	McQueen and Roley	Edison (1996)
Roley (1982, 1983)	Dwyer and Hafer (1989)	(1993)	Krueger (1996)
Roley (1983)	McQueen and Roley	Edison (1996)	Fleming and Remolona
Roley and Troll (1983)	(1993)	ABDV(2005)	(1997)
Urich and Wachtel (1984)	Edison (1996)		ABDV(2005)
Roley and Walsh (1985)	ABDV(2005)		
Hardouvelis (1988)	Fleming and Remolona		
Dwyer and Hafer (1989)	(1997)		
Thornton (1989)			
Strongin and Tarhan (1990)			
McQueen and Roley (1993)			

Table 3.3: List of Macroeconomics News Announcements

Announcement	Dates	Time	Frequency
BUSINV(Business Inventories)	3/14/1988-9/15/2005	10:00/8:30[1]	Monthly
CAPA(Capacity Utilization)	4/18/1988-9/14/2005	9:15	Monthly
CCONF(Consumer Confidence)	7/30/1991-9/27/2005	10:00	Monthly
CONST(Construction Spending)	4/1/1988-10/3/2005	10:00	Monthly
CPI(Consumer Price Index)	2/22/1980-9/15/2005	8:30	Monthly
CREDIT(Consumer Credit)	4/8/1988-9/8/2005	3:00[2]	Monthly
DGORD(Durable Goods Orders)	2/22/1980-9/28/2005	8:30/9:00/10:00[3]	Monthly
FACORD(Factory Orders)	3/2/1988-10/4/2005	10:00	Monthly
FFR(Average Fed Funds Rate)	4/11/1984-1/31/2001	14:15[4]	Six-Week
GDPADV(GDP Advance)	4/23/1987-7/29/2005	8:30	Quarterly
GDPPRE(GDP Preliminary)	5/27/1999-8/31/2005	8:30	Quarterly
GDPFIN(GDP Final)	3/31/1999-9/29/2005	8:30	Quarterly
HSTART(Housing Starts)	2/15/1980-9/20/2005	8:30	Monthly
ICLM(Initial Unemployment Claims)	7/18/1991-9/29/1005	8:30	Weekly
INDPRD(Industrial Production)	2/15/1980-9/14/2005	9:15	Monthly
LDERS(Leading Economic Indicators)	2/29/1980-9/22/2005	8:30	Monthly
NAPM(National Association of Purchasing Managers)	2/1/1990-10/3/1005	10:00	Monthly
NFPAY(Nonfarm Payroll Employment)	2/1/1985-9/2/1005	8:30	Monthly
NHOMES(New Home Sales)	3/29/1988-9/27/1005	10:00	Monthly
PCE(Personal Consumption Expenditures)	7/17/1985-9/30/1005	10:00/8:30[5]	Monthly
PERINC(Personal Income)	3/17/1981-9/30/2005	10:00/8:30[6]	Monthly
PPI(Producer Price Index)	2/15/1980-9/13/2005	8:30	Monthly
RETLS(Retail Sales)	2/13/1980-9/14/2005	8:30	Monthly
RSXAUT(Retail Sales excluding Auto)	8/11/1989-9/14/2005	8:30	Monthly
TRDBAL(Trade Balance)	2/28/1980-9/18/1996	8:30	Monthly
TREBUD(Treasury Budget)	2/22/1988-9/13/2005	14:00	Monthly

1. BUSINV announcement was moved from 10:00 to 8:30 in 1/1997.
2. Before 1/1996, CREDIT release time varied.
3. DGORD announcement is moved to 10:00 whenever there is a GDP release on the same day. DGORD announcement was released at 9:00 on 7/1996.
4. Before 3/28/1994, FFR release time varied.
5. PCE announcement time was moved from 10:00 to 8:30 in 12/1993.
6. PERINC announcement time was moved from 10:00 to 8:30 in 1/1994.

Table 3.4: Proportion of Jump Days in Announcement Days

Announcement	SP	US	Cojump
BUSINV	0.181<116>(1.633)[0.051]*	0.339<174>(3.193)[0.001]**	0.061<115>(1.632)[0.051]*
CAPA	0.162<136>(1.250)[0.106]	0.316<193>(2.750)[0.003]**	0.045<133>(1.154)[0.124]
CCONF	0.139<137>(0.593)[0.277]	0.323<164>(2.727)[0.003]**	0.044<135>(1.133)[0.129]
CONST	0.104<134>(-0.545)[0.707]	0.263<194>(1.311)[0.095]*	0.030<132>(0.429)[0.334]
CPI	0.232<138>(2.982)[0.001]**	0.307<199>(2.534)[0.006]**	0.080<138>(2.379)[0.009]**
CREDIT	0.244<131>(3.181)[0.001]**	0.326<193>(3.020)[0.001]**	0.107<131>(3.034)[0.001]**
DGORD	0.150<133>(0.924)[0.178]	0.298<188>(2.242)[0.012]**	0.039<129>(0.858)[0.195]
FACORD	0.170<135>(1.476)[0.070]*	0.249<193>(0.901)[0.184]	0.052<134>(1.443)[0.074]*
GDPADV	0.143< 42>(0.414)[0.339]	0.435< 62>(3.385)[0.000]**	0.119< 42>(1.901)[0.029]**
GDPFIN	0.217< 23>(1.123)[0.131]	0.182< 22>(-0.446)[0.672]	0.000< 22>(-4.637)[1.000]
GDPPRE	0.091< 22>(-0.468)[0.680]	0.286< 21>(0.674)[0.250]	0.095< 21>(1.116)[0.132]
HSTART	0.176<136>(1.639)[0.051]*	0.221<195>(0.052)[0.479]	0.052<134>(1.443)[0.074]*
ICLM	0.179<581>(3.068)[0.001]**	0.258<705>(1.963)[0.025]**	0.064<575>(3.572)[0.000]**
INDPRD	0.162<136>(1.250)[0.106]	0.311<193>(2.614)[0.004]**	0.045<133>(1.154)[0.124]
LDERS	0.094<138>(-0.953)[0.830]	0.246<195>(0.830)[0.203]	0.029<137>(0.371)[0.355]
NAPM	0.119<134>(-0.021)[0.509]	0.243<181>(0.716)[0.237]	0.030<132>(0.429)[0.334]
NFPAY	0.356<132>(5.482)[0.000]**	0.547<192>(8.705)[0.000]**	0.200<130>(4.978)[0.000]**
NHOMES	0.118<136>(-0.081)[0.532]	0.241<191>(0.667)[0.253]	0.023<133>(-0.071)[0.528]
PCE	0.126<127>(0.189)[0.425]	0.267<187>(1.414)[0.079]*	0.049<123>(1.257)[0.104]
PERINC	0.125<128>(0.159)[0.437]	0.266<188>(1.378)[0.084]*	0.048<124>(1.247)[0.106]
PPI	0.228<136>(2.873)[0.002]**	0.411<192>(5.165)[0.000]**	0.137<131>(3.733)[0.000]**
RETLS	0.243<136>(3.200)[0.001]**	0.368<193>(4.080)[0.000]**	0.106<132>(3.025)[0.001]**
RSXAUT	0.250<136>(3.361)[0.000]**	0.364<184>(3.900)[0.000]**	0.114<132>(3.208)[0.001]**
TRDBAL	0.091< 33>(-0.569)[0.715]	0.232< 95>(0.284)[0.388]	0.030< 33>(0.223)[0.412]
TREBUD	0.138<130>(0.573)[0.283]	0.208<192>(-0.335)[0.631]	0.038<130>(0.847)[0.198]
FFR	0.108<120>(-0.386)[0.650]	0.270<248>(1.687)[0.046]**	0.042<118>(0.979)[0.164]
News	0.169<1949>	0.290<2783>	0.063<1924>
No-news	0.120< 908>	0.219<1325>	0.024< 892>
Total	0.154<2857>	0.267<4108>	0.051<2816>

The four elements in each cell are: the proportion of jump days in each of the news announcement days, the number of the news announcement or no-news days inside the angle brackets, the t-statistic inside the parentheses, and the one-sided p-value inside the square brackets. The t-statistic is computed under the null that news has no impact on jumps, thus the probability of the jump days in the respective news day is equal to the probability of the jump days in no-news days. Two asterisks mean the t-statistic is statistically significant at the 5% level, and one asterisk denotes statistical significance at the 10% level.

Table 3.5: Proportion of News Days in Jump Days

Asset	0.99 Sig. Jumps	0.999 Sig. Jumps	Overall
SP	0.752< 439>(3.106)[0.001]**	0.775< 231>(3.216)[0.001]**	0.682<2857>
US	0.735<1096>(3.815)[0.000]**	0.795< 575>(6.392)[0.000]**	0.677<4108>
Cojump	0.853< 143>(5.504)[0.000]**	0.939< 49>(7.228)[0.000]**	0.683<2816>

The four elements in each cell are: the proportion of the news days in the jump or co-jump days, the number of the jump or co-jump days inside the angle brackets, the t-statistic inside the parentheses, and the one-sided p-value inside the square brackets. The t-statistic is computed under the null that news has no impact on jumps, thus the probability of the news days in the jump days is equal to the overall probability of the news days. Two asterisks mean the t-statistic is statistically significant at the 5% level, and one asterisk denotes statistical significance at the 10% level.

Table 3.6: News Surprises, Volatility and Jumps

	NFPAY	NAPM	RSXAUT	ICLM	Joint
			Panel 1: S&P 500, C		
Econ. Deriv.	0.481	-0.078	0.554	-0.013	p=0.381
	(0.307)	(0.245)	(0.272)	(0.134)	
Survey	-0.504	-0.073	-0.406	0.009	p=0.407
	(0.301)	(0.189)	(0.224)	(0.124)	
			Panel 2: S&P 500, J		
Econ. Deriv.	-0.037	0.059	-0.120	0.014	p=0.448
	(0.171)	(0.106)	(0.051)	(0.019)	
Survey	-0.032	-0.043	0.138	-0.017	p=0.268
	(0.189)	(0.092)	(0.068)	(0.021)	
			Panel 3: US 30-Year TB, C		
Econ. Deriv.	-0.199	-0.108	0.060	0.019	p=0.008**
	(0.194)	(0.126)	(0.130)	(0.046)	
Survey	0.187	0.127	-0.046	-0.027	p=0.027**
	(0.224)	(0.120)	(0.109)	(0.044)	
			Panel 4: US 30-Year TB, J		
Econ. Deriv.	-0.614	0.006	-0.082	-0.015	p=0.000**
	(0.265)	(0.030)	(0.040)	(0.031)	
Survey	0.664	0.004	0.085	0.016	p=0.000**
	(0.270)	(0.027)	(0.036)	(0.029)	

This table reports the regression coefficients of C and J on standardized news surprise, together with the White standard deviations inside the parentheses. The p-value is from the joint test that all the news surprises coefficients are zero.

Table 3.7: Disagreement v.s. Uncertainty

	NFPAY	NAPM	RSXAUT	ICLM	Joint
			Panel 1: S&P 500, C		
Econ. Deriv.	-1.126	0.639	-0.025	0.324	p=0.035**
	(0.395)	(0.707)	(0.539)	(0.251)	
Survey	0.744	-0.746	0.145	-0.108	p=0.238
	(0.524)	(0.348)	(0.349)	(0.145)	
			Panel 2: S&P 500, J		
Econ. Deriv.	-0.454	0.358	0.132	0.002	p=0.001**
	(0.293)	(0.269)	(0.222)	(0.076)	
Survey	0.350	0.051	-0.152	-0.009	p=0.057*
	(0.453)	(0.088*)	(0.145)	(0.043)	
			Panel 3: US 30-Year TB, C		
Econ. Deriv.	-0.616	0.284	-0.239	-0.108	p=0.000**
	(0.370)	(0.399)	(0.145)	(0.116)	
Survey	-0.455	-0.604	-0.012	-0.031	p=0.166
	(0.512)	(0.383)	(0.211)	(0.060)	
			Panel 4: US 30-Year TB, J		
Econ. Deriv.	0.773	0.086	-0.115	0.104	p=0.727
	(0.466)	(0.148)	(0.133)	(0.077)	
Survey	-0.434	-0.006	0.014	0.025	p=0.003**
	(0.793)	(0.113)	(0.117)	(0.042)	

This table reports the regression coefficients of C and J on uncertainty from the economic derivative data, or disagreement from survey data, together with the White standard deviations inside the parentheses. The p-value is from the joint test that all the coefficients are zero.

3.8 Figures

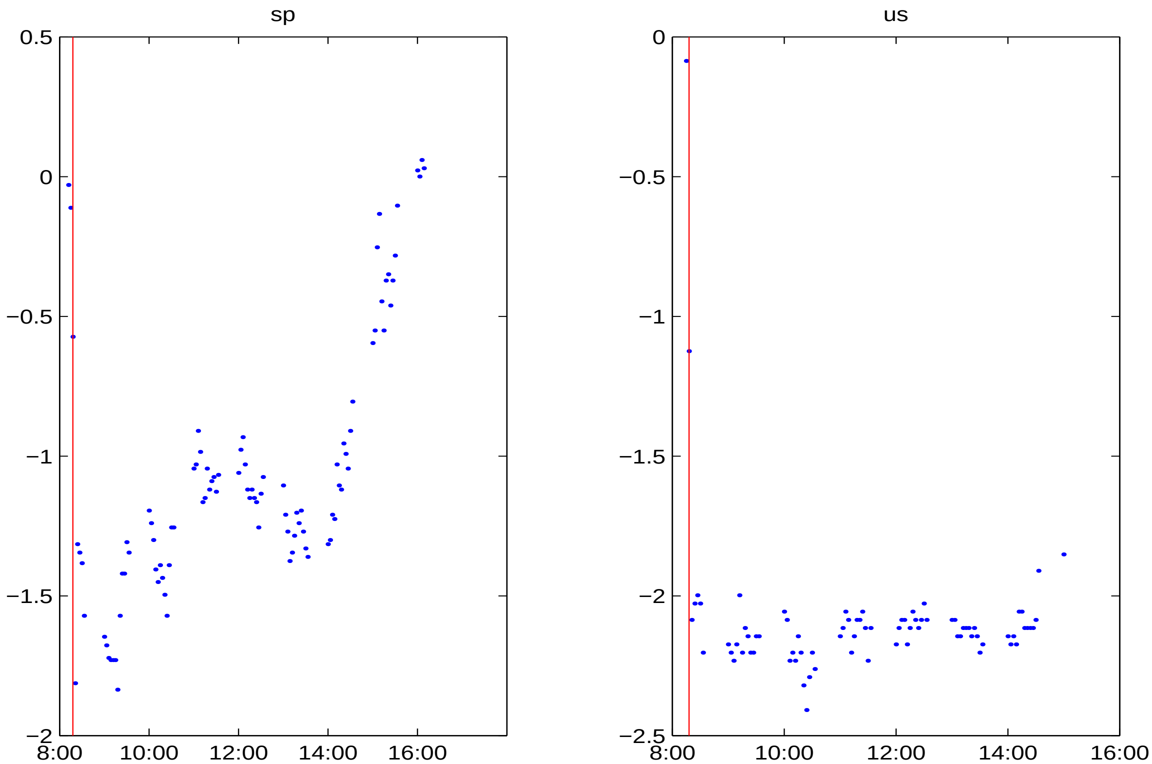

Figure 3.1: Logarithmic Price Plot on 6/7/1996. NFPAY
Release value is 340, survey expectation is 170 with standard deviation 56.5. The dots are the prices, and the line is at 8:30 when the announcement was released.

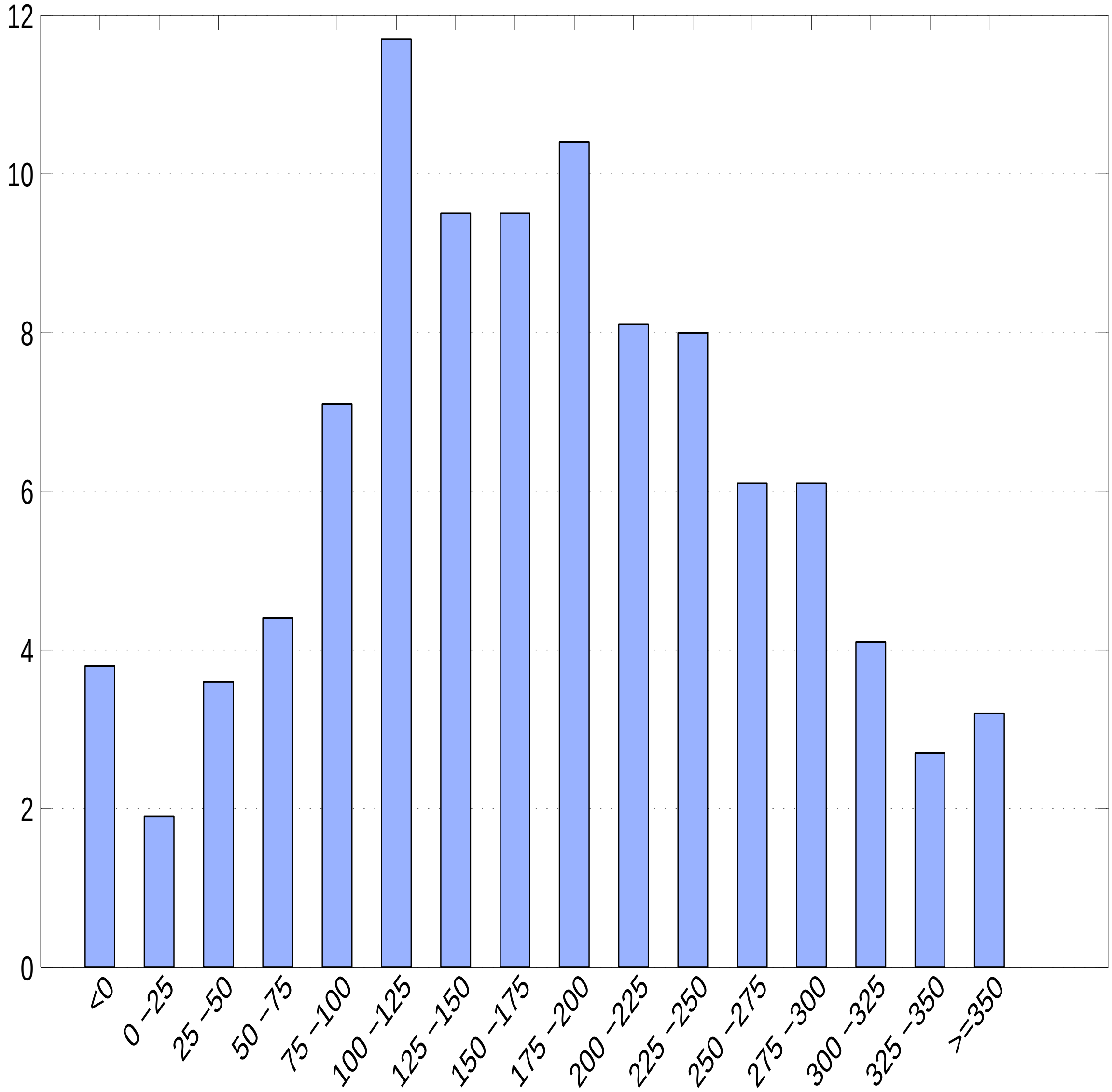

Figure 3.2: Implied PDF for NFP, 6/3/2006

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Biography

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