Volatility proxies and GARCH models

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Chapter 4

Forecasting S&P 500 Daily Volatility using a Proxy for Downward Price Pressure

The way of modelling and forecasting financial volatility has evolved substantially over the past decade. GARCH and stochastic volatility models based on daily close-to-close returns are the classical time series models for daily volatility. The availability of large amounts of high-frequency data, recording prices tick-per-tick, has led to new ways of looking at volatility. In particular, one may use high-frequency data to calculate for each day a measure called realized volatility. Current practice is to model these realized volatilities directly by fitting AR(FI)MA models. These simple ARMA-type models outperform the GARCH-type models (based on daily returns) in out-of-sample forecasting, see for instance Andersen, Bollerslev, Diebold, and Labys (2003), and Koopman, Jungbacker, and Hol (2005).

Besides realized volatility there are other useful measures based on high-frequency data. Barndorff-Nielsen and Shephard (2004) estimated the contribution of jumps to daily price variability using the difference of realized volatility and bipower variation, and Andersen, Bollerslev, and Diebold (2007) used this jump component for forecasting. Brandt and Jones (2006) improved forecast accuracy by using the high-low range. Ghysels, Santa-Clara, and Valkanov (2006) found that the absolute power variation predicts volatility well. Engle and Gallo (2006) showed that a 3-dimensional multiplicative error model for the daily absolute return, the intraday high-low range, and the realized volatility is useful for forecasting.

One aspect of intraday prices that has received little attention in the literature is the effect of downward price pressure on future volatility. It is a stylized fact of equity market returns that declining prices go hand in hand with rising volatility. See, in the context of GARCH models, Nelson (1991), Engle and Ng (1993), and Glosten, Jagannathan, and
Runkle (1993). These papers showed that a large negative return today tends to raise tomorrow’s volatility more than a large positive return. This phenomenon is known as the leverage effect.

This chapter analyses the effect of downward price pressure by using high-frequency price movements. We shall sum the downward absolute five-minute returns, thus obtaining a measure termed downward absolute power variation, and use this measure for forecasting daily volatility.

The results in the chapter are both theoretical and applied. The main theoretical contribution is the introduction of a simple framework for incorporating statistics that use high-frequency data in a GARCH-type forecast equation. In the classical GARCH model only daily closing prices are used. We are in the position of observing high-frequency price movements, so it is natural to extend the GARCH framework, and replace the daily return by a proxy based on high-frequency data. Proxies that come to mind are for instance the realized volatility, the bipower variation, and the downward absolute power variation; a precise characterization of the proxies that we allow in the GARCH recursion is given below. Naturally, if volatility today is high, then these proxies tend to be large, and by the GARCH recursion this leads to high volatility tomorrow. So, formally, we have a stochastic system where each proxy in the GARCH recursion contributes to volatility persistence. We shall analyse this system and obtain easy-to-verify stationarity conditions on the parameters of the GARCH recursion, ensuring stability of the system.

The main empirical contribution of the chapter is to show a clear effect of high-frequency downward price pressure as a driving force of S&P 500 index volatility over 1988–2006, and to demonstrate its use in volatility forecasting. In a specification with several explanatory variables the downward absolute power variation has the most pronounced contribution to tomorrow’s volatility, whereas the upward absolute power variation adds almost no explanatory power. We find that measuring downward price pressure by high-frequency data improves forecast accuracy. Specifications that include the downward absolute power variation significantly outperform specifications that do not, both for in-sample and out-of-sample prediction. The Mincer-Zarnowitz $R^2$ for evaluating daily volatility forecasts yields a value 0.80.

In a recent paper Barndorff-Nielsen, Kinnebrock, and Shephard (2009) proposed to decompose the realized variance, which is given by the sum of squared intraday returns, into upward and downward components (called semivariances). They discussed the relation of these components to quadratic variation, and in line with our empirical results they found improved log-likelihood values for GARCH(1,1) models that include the downward component. We shall discuss the downward realized variance in our empirical analysis in Section 4.2.2.

The remainder of the chapter is organized as follows. Section 4.1 provides the theoretical framework. Section 4.2 introduces the downward absolute power variation and
evaluates the in-sample fit of the models, and Section 4.3 presents the out-of-sample forecasting results. Section 4.4 contains our main conclusions. Appendix 4.A describes the data; Appendix 4.B provides mathematical details on stationarity and invertibility.

### 4.1 Accounting for Intraday Price Movements in a Daily GARCH Model

#### 4.1.1 Continuous Time Extensions of Discrete Time Models

Only a decade ago, researchers of financial volatility would typically be analysing a series of daily close-to-close returns $r_n$. A commonly applied model for these returns is the GARCH(1,1) system, which consists of a return equation and a recursion for the scale factor $\sigma_n$,

$$
\begin{align*}
    r_n &= \sigma_n Z_n, \\
    \sigma_n^2 &= \kappa + \alpha r_{n-1}^2 + \beta \sigma_{n-1}^2.
\end{align*}
$$

(4.1)

(4.2)

Here, the $Z_n$ are iid, mean zero, unit variance innovations, and $\kappa, \alpha, \beta$ are positive parameters. For stationarity one may impose the condition $\alpha + \beta < 1$.

Nowadays we are in the fortunate position of having data on the price movements over the entire trading day. In formal terms, one observes for each trading day $n$ a process $R_n(\cdot)$, the continuous time log-return process for that day. This immediately raises questions of model consistency. Are the intraday return processes $R_n(\cdot)$ consistent with the daily returns in GARCH(1,1)? How does one incorporate the processes $R_n(\cdot)$ into this system?

For ease of notation we normalize the trading day to the unit time interval. A simple model for the intraday price movements is the scaled Brownian motion,

$$
R_n(u) = \sigma_n W_n(u), \quad 0 \leq u \leq 1,
$$

(4.3)

where intraday time $u$ advances from zero to one, see for instance Taylor (1987), and Brandt and Jones (2006). The standard Brownian motion $W_n(\cdot)$ captures intraday price movements, whereas $\sigma_n$ is a measure for the size of the intraday price fluctuations and is constant over the day. This chapter adopts the following generalization of equation (4.3). We allow for an arbitrary process $\Psi_n(\cdot)$, yielding the intraday extension of equations (4.1–4.2),

$$
\begin{align*}
    R_n(u) &= \sigma_n \Psi_n(u), \\
    \sigma_n^2 &= \kappa + \alpha \sigma_{n-1}^2 + \beta \sigma_{n-1}^2.
\end{align*}
$$

(4.4)

(4.5)
where $R_n(1) \equiv r_n$, and $\Psi_n(1) \equiv Z_n$. Specifically, the sample path of the standard process $\Psi_n(\cdot)$ is right-continuous and has left limits, one has the standardization $\mathbb{E}\Psi_n^2(1) = 1$, and the sequence of processes $\Psi_n(\cdot)$ is iid (for different days the standard processes $\Psi_k$ and $\Psi_n$, $k \neq n$, are independent and have the same probability distribution). Equation (4.4) reflects a scaling model for the return process over the day. While this framework does not impose severe constraints on the intraday price process, it does allow us to use high-frequency data in discrete time, daily models, as we shall see below.

4.1.2 Inserting Proxies Into a Log-GARCH Recursion

This section presents the GARCH recursion which forms the basis of the model used in this chapter. Let us first have a closer look at the GARCH(1,1) scale factors $\sigma_n$. The GARCH(1,1) recursion (4.5) states that the scale factor today ($\sigma_n$) is a function of the scale factor yesterday ($\sigma_{n-1}$) and what happened yesterday (reflected by $r_{n-1}$). In particular, a large price change yesterday, yields a large scale factor today (if $\alpha > 0$). In view of the intraday return process $R_n(\cdot)$, as it appears in the intraday extension (4.4–4.5), it is insightful to rephrase the GARCH(1,1) recursion as

$$\sigma^2_n = \kappa + \alpha H^2(R_n - 1) + \beta \sigma^2_{n-1}.$$  

In the classical situation one uses only the daily returns $r_{n-1}, r_{n-2}, \ldots$, so the statistic $H(R_n-1)$ is limited to functions of the close-to-close return $r_{n-1}$; in the case of GARCH(1,1)

$$H^2(R_{n-1}) = R^2_{n-1}(1) \equiv r^2_{n-1}.$$  

Given the price movements over the course of the day, $R_{n-1}(\cdot)$, there are many possible statistics that make use of this information. One could use a statistic that gives a good measurement of yesterday’s scale factor; another possibility is to focus on particular aspects of the sample path of $R_{n-1}$, such as jumps, or the role of the downward price movements.

A number of statistics based on high-frequency data have appeared in the literature. A commonly applied statistic is the realized volatility (RV), see for instance Barndorff-Nielsen and Shephard (2002b), and Andersen, Bollerslev, Diebold, and Labys (2003). The statistic $RV$ is frequently used as a volatility proxy, and is given by the square root of the realized variance. The daily realized variance $RV^2_n(\Delta)$ is the sum of the squared returns
4.1 Accounting for Intraday Price Movements in a Daily GARCH Model

over intervals of length $\Delta$, so

$$RV_n(\Delta) = \left( \frac{1}{\Delta} \sum_{k=1}^{\Delta} r_{n,k}^2 \right)^{1/2}. \quad (4.6)$$

For ease of notation, and without loss of generality, we adopt the convention that $1/\Delta$ is an integer. The intraday returns on day $n$ are given by

$$r_{n,k} = R_n(k \Delta) - R_n((k - 1) \Delta). \quad (4.7)$$

Other statistics are the intraday high-low range (e.g. Parkinson, 1980), and the sum of absolute returns (see Barndorff-Nielsen and Shephard, 2003, 2004). These statistics all are positive and have the property of positive homogeneity: if the process $R_n(\cdot)$ is multiplied by a factor $\alpha \geq 0$, then so is the statistic:

$$H(\alpha R_n) = \alpha H(R_n), \quad \alpha \geq 0. \quad (4.8)$$

This chapter allows any positive and positively homogeneous statistic. In two recent papers (de Vilder and Visser, 2008, and Visser, 2008b), we studied this type of statistic and refer to both the random variable $H_n$, $H_n \equiv H(R_n)$,

as well as the functional $H$ as proxies.¹ This chapter uses the proxy $H_{n-1}$ as a driving force of the scale factors by incorporating it into the GARCH recursion. So $\sigma_n$ today depends on $\sigma_{n-1}$ yesterday, and a proxy $H_{n-1}$ that reflects specific aspects of yesterday’s trading. In particular, the empirical analysis below pays attention to the role of the downward price movements in forecasting volatility. We shall see that including proxies with the scaling property (4.8) leads to a tractable discrete time model.

We incorporate the proxy $H_{n-1}$ into a logarithmic GARCH recursion; for strictly positive $H$ one may adapt the GARCH(1,1) recursion as follows:

$$R_n(u) = \sigma_n \Psi_n(u), \quad 0 \leq u \leq 1, \quad (4.9)$$

$$\log(\sigma_n) = \kappa + \alpha \log(H_{n-1}) + \beta \log(\sigma_{n-1}), \quad (4.10)$$

where $\kappa$, $\alpha$, and $\beta$ are real-valued parameters. The system (4.9–4.10) constitutes the basic model in this chapter; we shall refer to it as the log-GARCH model. The recursion (4.10)

¹These papers use $H_n$ as a proxy for $\sigma_n$, show that one may improve GARCH parameter estimation using proxies, and show how to optimize proxies.
is new, but it has the same interpretation as the classical GARCH(1,1) equation for $\sigma_n^2$: the scale factor today ($\sigma_n$) depends on $\sigma_{n-1}$ yesterday, and on what happened yesterday (reflected by $H_{n-1}$). If the proxy $H_{n-1}$ is large, then $\sigma_n$ today is large (if $\alpha > 0$).

The use of the logarithm, $\log(\sigma_n)$, yields easy-to-verify stationarity conditions, as Section 4.1.3 shows. It also ensures positivity of the scale factors: one does not need to impose on the parameters positivity constraints that may be violated in practice. The parameter values $\alpha = 0$, $\beta = 0$ are not on the boundary of the parameter space. This has the important advantage that one can apply simple $t$-tests based on asymptotic normality of the parameter estimators for testing significance of the parameters.$^2$ Early accounts of using the logarithm in GARCH models are Geweke (1986) and Pantula (1986). Both propose a log-GARCH model. Their log-GARCH models are similar to equation (4.10), but apply the logarithm to the squared daily return $r_{n-1}^2$. That approach is infeasible in practice since daily returns may be zero. The system (4.9–4.10) does not suffer from this drawback, as our proxies $H_n$ shall be strictly positive.

### 4.1.3 Stationarity for the Log-GARCH Model

The log-GARCH model admits easy-to-verify stationarity conditions. Since a proxy $H_n$ is linear in $\sigma_n$, by $H_n = \sigma_n H(\Psi_n)$, the log of a strictly positive proxy satisfies

$$\log(H_n) = \log(\sigma_n) + U_n,$$

where the $U_n \equiv \log(H(\Psi_n))$ are iid random variables. Inserting relation (4.11) into the recursion (4.10) results in

$$\log(\sigma_n) = \kappa + (\alpha + \beta) \log(\sigma_{n-1}) + \eta_n,$$

where the $\eta_n \equiv \alpha U_{n-1}$ are iid innovations. Equation (4.12) is simply an autoregressive process of order one (AR(1)) for $\log(\sigma_n)$ with decay parameter $\alpha + \beta$, and mean $(\kappa + \alpha \mathbb{E} U_n)/(1 - \alpha - \beta)$. If $\eta_n$ has a finite second moment the AR(1) equation is well known to admit a stationary solution if

$$|\alpha + \beta| < 1.$$  

$^2$In the case of classical GARCH models the parameters are positive, and the limit distribution for the quasi-maximum likelihood estimator when some of the coefficients are zero does not satisfy the usual asymptotic normality, see Francq and Zakoian (2008).
One may also consider log-GARCH($p, q$) models that incorporate $j = 1, \ldots, d$ proxies:

\[
\log(\sigma_n) = \kappa + \sum_{i=1}^{p} \sum_{j=1}^{d} \alpha_i^{(j)} \log(H_n^{(j)}) + \sum_{i=1}^{q} \beta_i \log(\sigma_{n-i}), \tag{4.14}
\]

\[
= \kappa + \sum_{i=1}^{m} (\bar{\alpha}_i + \beta_i) \log(\sigma_{n-i}) + \eta_n, \tag{4.15}
\]

where $m \equiv \max\{p, q\}$, $\eta_n \equiv \sum_{i=1}^{p} \sum_{j=1}^{d} \alpha_i^{(j)} U_{n-i}^{(j)}$, and $\bar{\alpha}_i = \sum_{j=1}^{d} \alpha_i^{(j)}$. Here, $\bar{\alpha}_i \equiv 0$ for $i > p$ and $\beta_i \equiv 0$ for $i > q$. Equation (4.15) represents an AR($m$) process, but is non-standard since the $\eta_n$ are not independent if $p > 1$. The term $\eta_n$ can be seen as a standard MA($p$) component in the restrictive case that $\alpha_i^{(j)} = \alpha^{(j)}$ for all $i$. As we show in the appendix, one may establish stationarity by looking at the AR-polynomial: equation (4.15) has a unique stationary ergodic solution if the characteristic AR-polynomial $\phi(z)$,

\[
\phi(z) = 1 - (\bar{\alpha}_1 + \beta_1) z - \ldots - (\bar{\alpha}_m + \beta_m) z^m, \tag{4.16}
\]

has only roots outside the unit circle.\(^3\) By the triangle inequality it is sufficient that\(^4\)

\[
\sum_{i=1}^{m} |\bar{\alpha}_i + \beta_i| < 1. \tag{4.17}
\]

For details on stationarity, and invertibility, see Appendix 4.B. Invertibility is important, as it ensures that the scale factor $\sigma_n$ can be obtained from observed information.

### 4.1.4 Quasi Maximum Likelihood

One may estimate the parameters of a GARCH model by maximum likelihood. The traditional approach to GARCH parameter estimation is to determine the likelihood by assuming that the daily returns $r_n$ are conditionally Gaussian with mean zero and variance $\sigma_n^2$. If the true conditional distribution is not Gaussian, the maximizer of the Gaussian likelihood may still be consistent and asymptotically normal, with adjusted standard errors. It is then called a quasi maximum likelihood estimator (QMLE). For GARCH($p, q$) processes the QMLE has recently been shown to be consistent and asymptotically normal (Berkes, Horvath, and Kokoszka, 2003); for many other GARCH processes consistency and asymptotic normality of the QMLE are open problems. In our empirical analysis we proceed by simply calculating the QMLE and providing the Bollerslev and Wooldridge (1992) QML standard errors.

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\(^3\)This condition excludes non-causal stationary solutions, see Brockwell and Davis (1991).

\(^4\)Suppose $z_0$ is a root of $\phi$. Then $0 = \phi(z_0) = 1 - \sum_{i=1}^{m} (\bar{\alpha}_i + \beta_i) z_0^i$. And, $1 = \sum_{i=1}^{m} (\bar{\alpha}_i + \beta_i) z_0^m \leq \sum_{i=1}^{m} |\bar{\alpha}_i + \beta_i| |z_0^m|$. Condition (4.17) now implies $|z_0| > 1$. 
A likelihood for the daily returns $r_n$ does not make use of the information contained in the high-frequency data observed during the course of the day. It is intuitively clear that the use of high-frequency data by means of a suitable volatility proxy of the type given in Section 4.1.2 may improve the efficiency of parameter estimation: Visser (2008b) provided the formal details and introduced a log-Gaussian QMLE; the empirical analysis below uses the log-Gaussian QMLE for parameter estimation. We illustrate the principle for the log-GARCH(1,1) model.

First one has to pick a volatility proxy $H^{(0)}$ for which to determine the likelihood function. This does not have to be the same proxy as the proxy $H$ that appears in the recursion (4.10); all that is required is positivity, and positive homogeneity: if $\sigma_n$ satisfies a log-GARCH(1,1) model then the proxy $H_t^{(0)} = \sigma_t H^{(0)}(\Psi_t)$ satisfies

$$\log(H_t^{(0)}) = \log(\sigma_t) + U_t^{(0)},$$

$$= \kappa_{H^{(0)}} + \alpha \log(H_{t-1}) + \beta \log(\sigma_{t-1}) + \lambda \varepsilon_t,$$

where $\kappa_{H^{(0)}} = \kappa + \mathbb{E}U_t^{(0)}$, $\lambda$ is the standard deviation of $U_t^{(0)}$, and $\varepsilon_t$ is the standardized version of $U_t^{(0)}$, yielding a mean zero, unit variance iid sequence. The conditional mean and variance functions of $\log(H_t^{(0)})$ are

$$\mu_n(\theta) = \kappa_{H^{(0)}} + \alpha \log(H_{t-1}) + \beta \log(\sigma_{t-1}), \quad \text{and} \quad h_n(\theta) = \lambda^2,$$

where $\theta = (\kappa_{H^{(0)}}, \alpha, \beta, \lambda)$. The QMLE $\hat{\theta}_N$ is the maximizer of the Gaussian likelihood determined as if

$$\log(H_t^{(0)})|\mathcal{F}_{t-1} \overset{d}{\sim} \mathcal{N}(\mu_n(\theta), h_n(\theta)),$$

where $\mathcal{F}_{t-1}$ represents observable information until yesterday. One may use the Bollerslev and Wooldridge (1992) QML covariance matrix to obtain empirical standard deviations for the parameter estimates.

### 4.2 Full-Sample Analysis

This section provides an in-sample analysis of the daily price fluctuations of the S&P 500 index over the years 1988–2006, a total of 4575 trading days. For a description of the data see Appendix 4.A. Section 4.2.1 introduces the downward absolute power variation as a measure for downward price pressure. Section 4.2.2 analyses the explanatory power of the downward absolute power variation in a log-GARCH model specification.

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5The details are for the classical GARCH(1,1) model, though the principle applies widely to GARCH-type models.
4.2 Full-Sample Analysis

4.2.1 Downward Price Pressure and Volatility

Before starting to use high-frequency data, let us briefly say a few words on the need for volatility proxies to forecast daily volatility. There is a voluminous literature on GARCH models based on daily returns alone. One message from this literature for the empirical modelling of the daily volatility of equity indices and stocks, is the importance of including a leverage effect. The leverage effect refers to an asymmetry in the return-volatility relationship: declining prices typically go hand in hand with rising volatility, as already noted by Black (1976) and Christie (1982). More precisely one may distinguish between a leverage effect and a volatility feedback effect; the leverage effect then refers to declining prices that cause volatility, and the volatility feedback effect refers to rising volatility that causes declining prices.\(^6\) The analysis of Bollerslev, Litvinova, and Tauchen (2006) using S&P 500 index five-minute returns strongly suggests that the leverage effect is the more important of the two. A commonly used GARCH model that takes into account the leverage effect is the GJR(1,1) model (Glosten, Jagannathan, and Runkle, 1993), which weighs positive and negative returns differently. Estimation of this model on the S&P 500 data yields\(^7\)

\[
\sigma_n^2 = 1.34 \times 10^{-6} + 0.005 \left| r_{n-1} \right|^2 + 0.096 \left| r_{n-1}^- \right|^2 + 0.936 \sigma_{n-1}^2,
\]

(4.18)

where \(r_n^- = \min\{r_n, 0\}\) reflects downward price pressure. In accordance with the literature the estimates reflect that a downward price move yesterday tends to intensify price fluctuations today, more so than an upward price move. If only daily returns are available the GJR(1,1) model is hard to beat, see for instance Hansen and Lunde (2005a) and Awartani and Corradi (2005), and is quite successful at describing the in-sample returns. This is confirmed by Figures 4.1(a1) and (a2). Part (a1) depicts the first fifty autocorrelations of the absolute returns, which decay slowly and are significant at all lags shown. For GARCH models, the absolute returns standardized by the scale factor, \(|r_n|/\sigma_n\), are iid. Indeed, Figure 4.1(a2) shows that the estimated GJR(1,1) scale factors successfully remove the autocorrelation structure, leaving only residual autocorrelations of irregular size and sign.

If high-frequency data are available one may use other proxies to evaluate the scale

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\(^6\)An economic explanation for the leverage effect is that a lower stock price increases financial leverage, which entails a larger risk (Black, 1976, Christie, 1982). The volatility feedback effect may be caused by investors demanding a higher expected return, thus lower prices, in the case of increased volatility. Ang, Chen, and Xing (2006) looked at downside risk of stocks from a global market perspective, and argue that investors demand a risk premium for bearing downside risk if this risk has a positive correlation with the downside risk of the market portfolio.

\(^7\)Estimation by Gaussian QMLE using the daily returns \(r_n\) for \(n = 1, \ldots, 4575\), where the first 30 days do not contribute to the likelihood. QML standard errors in parentheses.
factors \( \hat{\sigma}_n \). In the scaling model from Section 4.1.1 proxies standardized by the scale factor,

\[
H_n/\sigma_n,
\]

form an iid sequence. Figure 4.1(c2) shows that the GJR(1,1) scale factors do not remove the autocorrelation structure of the five-minute realized volatility \( RV_5 \), where \( RV_5 \) denotes \( RV(\Delta = 5 \text{ min.}, \ 81 \text{ intervals}) \). A similar observation applies to the graphs of the high-low range \( hl \) and the proxy \( H(\hat{w}) \) in Figures 4.1(b2) and (d2), where the proxy \( H(\hat{w}) \) combines the sum of the ten-minute highs, the sum of the ten-minute lows and the sum of the ten-minute absolute returns as\(^8\)

\[
H_n^{(\hat{w})} = (RAV10HIGH_n)^{1.04}(RAV10LOW_n)^{0.72}(RAV10n)^{-0.76}, \tag{4.19}
\]

which is a good volatility proxy for the S&P 500 data, see de Vilder and Visser (2008).

We shall incorporate the intraday price movements in a log-GARCH model for \( \sigma_n \). A natural generalization of the absolute return \( |r_n| \) as a volatility proxy is the sum of the absolute returns over successive intervals of length \( \Delta \), yielding the absolute power variation \( RAV \),

\[
RAV_n(\Delta) = \sum_{k=1}^{1/\Delta} |r_{n,k}|,
\]

where as before \( 1/\Delta \) is assumed to be an integer. The intraday returns \( r_{n,k} \) on day \( n \) are given by (4.7). The absolute power variation is a good predictor of daily volatility, outperforming the standard realized volatility, see Ghysels, Santa-Clara, and Valkanov (2006), and Forsberg and Ghysels (2007). For a discussion of the theoretical properties of \( RAV \) for semimartingales, see Barndorff-Nielsen and Shephard (2003, 2004).

Likewise, a sensible proxy for downward price pressure is the sum of the negative returns, \( r_{n,k}^- = \min\{r_{n,k}, 0\} \), yielding a novel proxy termed the downward absolute power variation

\[
RAV_n^- (\Delta) = \sum_{k=1}^{1/\Delta} |r_{n,k}^-|.
\]

\(^8\)The ten-minute high is obtained by the difference of the maximum of \( R_n(\cdot) \) and the starting value of \( R_n(\cdot) \) over the ten-minute interval in question. The lows are obtained similarly, and made positive by taking absolute values. The coefficients \( \hat{w} = (\hat{w}_1, \hat{w}_2, \hat{w}_3) \) were optimized in de Vilder and Visser (2008) such that the proxy \( H(\hat{w}) \) has minimal measurement variance.
4.2 Full-Sample Analysis

Figure 4.1: Autocorrelations of four proxies for the days $n = 31, \ldots, 4575$; before and after standardization by $\sigma_n$. The volatility proxies change from top to bottom: daily absolute return, intraday high-low range, five-minute realized volatility, and $H^{(w)}$ as in (4.19). From left to right different standardization. Leftmost: no standardization. Middle: standardization by GJR(1,1) scale factors $\hat{\sigma}_n$ (equation (4.18)). Rightmost: standardization by log-GARCH where $\hat{\sigma}_n$ uses intraday based volatility proxies (equation (4.20)). The dotted lines give the standard 95% confidence bounds, $(\pm)2/\sqrt{N}$.

One may now decompose the absolute power variation as

$$RAV_n(\Delta) = RAV_n^-(\Delta) + RAV_n^+(\Delta),$$
where $RAV^+$ is the sum of the positive returns. The proxies $RAV^-$ and $RAV^+$ are positively homogeneous; below we shall analyse their use in a log-GARCH model.

4.2.2 A log-GARCH Model for the S&P 500 Index

In empirical applications volatility processes are typically associated with slowly decaying autocorrelations. One way to deal with the slow decay is to apply a long memory model.\(^9\)

We deal with the memory structure by incorporating volatility proxies over the past week and the past month. Such a combination of shorter and longer horizons has been successfully employed in heterogeneous volatility models, such as the HAR-RV specifications for realized volatility in Andersen, Bollerslev, and Diebold (2007), and in Corsi (2009), and the HARCH model in Müller et al. (1997), which ascribes the relevance of such components to the coexistence of market participants with different trading horizons. In particular we use the weekly and monthly logarithmic moving averages

$$H_n^{(\hat{w}), \text{log Week}} = \frac{1}{5} \sum_{i=0}^{4} \log(H_{n-i}^{(\hat{w})}), \quad \text{and} \quad H_n^{(\hat{w}), \text{log Month}} = \frac{1}{22} \sum_{i=0}^{21} \log(H_{n-i}^{(\hat{w})}),$$

where $H_n^{(\hat{w})}$ is given by (4.19), and 22 is the typical number of trading days in a month.

We specify a log-GARCH model that is autoregressive of order one ($q = 1$). The recursion for the log scale factor $\log(\sigma_n)$ includes four kinds of indicators of price fluctuations (with parameters $\alpha^{(i)}$, $i = 1, \ldots, 4$):

$$\log(\sigma_n) = \kappa + \alpha^{(1)} H_{n-1, \text{Week}}^{(\hat{w}), \text{log}} + \alpha^{(2)} H_{n-1, \text{Month}}^{(\hat{w}), \text{log}} + \alpha^{(3)} \log(hl_{n-1}) + \alpha^{(4)} \log(RAV^5_{n-1}) + \beta \log(\sigma_{n-1}), \quad (4.20)$$

where $RAV^5_-$ denotes $RAV^-(\Delta = 5 \text{ min.}, \ 81 \text{ intervals})$, and $hl$ denotes the intraday high-low range. In the terminology from Section 4.1.3, equation (4.20) describes a log-GARCH($p = 22$, $q = 1$) model with $d = 3$ proxies.

The top three rows of Table 4.1 give the full-sample parameter estimates and in parentheses the standard errors and $t$-values. The estimation uses the log-Gaussian quasi-likelihood for $H_n^{(\hat{w})}$, see Section 4.1.4. All parameters are highly significant with $t$-values far outside the 95% region ($-2, 2$). The estimate $\hat{\beta} = 0.34$ is much smaller than the typical values around 0.9 for traditional GARCH; much of the persistence in fluctuations is already captured by the explanatory variables. Fluctuations over the past week ($\alpha^{(1)}$) and over the past month ($\alpha^{(2)}$) are of similar importance. In line with Engle and Gallo (2006) we find that the high-low range ($\alpha^{(3)}$) has explanatory power in addition to

\(^9\)See for instance the log-ARFIMA model for realized volatility in Andersen, Bollerslev, Diebold, and Labys (2003).
other high-frequency measures of price fluctuations. The most striking effect is the positive and highly significant effect $\alpha^{(4)}$ for the downward absolute power variation $RAV^5_{n-1}$. The downward price movements appear an important driving force of the daily volatility process.

Would the parameter $\alpha^{(4)}$ have been as dominant if we had included $RAV$ or $RAV^+$ in the specification? The inclusion of $RAV$ leads to a small increase in $\hat{\alpha}^{(4)}$ to 0.242 with a $t$-value 13.56, whereas the parameter value for $RAV$ is slightly negative, $-0.056$, with a $t$-value $-1.98$. The inclusion of $RAV^+$ yields similar results. This confirms the relevance of distinguishing between upward and downward price movements, and provides an additional sign of a pronounced effect of downward price pressure.\(^{10}\) One could alternatively capture downward price pressure by the downward five-minute realized volatility\(^{11}\) $RV^5_{-}$, cf. equation (4.6). Indeed, if we replace $RAV^5_{-}$ by $RV^5_{-}$, we find that the coefficient for $RV^5_{-}$ is large and significant: 0.210 with a $t$-value of 17.3. It is also interesting to see what happens if we include both $RAV^5_{-}$ and $RV^5_{-}$: we observe a small increase in the

\(^{10}\)Our model (4.20) does not include $RAV$, or $RAV^+$, since their coefficients are small, and change sign in subsamples.

\(^{11}\)For a discussion of the downward realized volatility, and its relation to quadratic variation, see Barndorff-Nielsen, Kinnebrock, and Shephard (2009). One theoretical difference between summing absolute and squared returns, i.e. $RAV(\Delta)$ or $RV(\Delta)$, is that in the context of semimartingales with a finite activity jump process the measure $RV$ includes the jumps as $\Delta \downarrow 0$, whereas $RAV$ does not (after appropriate scaling). See Barndorff-Nielsen and Shephard (2004).
parameter $\hat{\alpha}^{(4)}$ for $RAV^-$ to 0.234 ($t$-value 7.45), while the parameter value for $RV^-$ is slightly negative, $-0.023$, with an insignificant $t$-value $-0.66$. Though the quality of the specification that uses $RV^-$ instead of $RAV^-$ does not decrease much (the likelihood decreases by roughly 34 points), the parameter estimates favour $RAV^-$. To check for the effect of $RAV^-$ over separate time periods, Table 4.1 gives the parameter estimates for four subsamples spanning the full sample ($n = 1, \ldots, 1143$ and $1144:2287$, $2288:3431$, $3432:4575$). We find that $RV^-$ does not significantly add explanatory power in any of the subsamples. Moreover, in each subsample the downward absolute power variation is the predominant explanatory variable in (4.20). We also contrast low with high volatility periods. As a low volatility period we use the days 1003 to 2003 (the four years 1992–1995), and as a high volatility period the days 2600–3700 (the period 1998–05–26 to 2002–11–19). The estimated coefficient $\alpha^{(4)}$ is larger in the high volatility period (as the 2nd and 3rd subsamples in Table 4.1 also suggest), and $RAV^-$ is the most pronounced variable in both periods.

The downward absolute power variation and the downward realized volatility are special cases ($r = 1$ and $r = 2$) of the downward $r$-power variation ($r > 0$),

$$RPV^{-}_n(\Delta) = \left( \frac{1}{\Delta} \sum_{k=1}^{1/\Delta} |r^{-}_{n,k}|^r \right)^{1/r}.$$ 

It is natural to ask for which power $r$ the downward power variation yields the largest likelihood. For this purpose we reestimate the model (4.20) where $RAV^-$ is replaced by the five-minute $RPV^-$ for various powers $r$. Figure 4.2 shows full-sample log-likelihood values when we vary the power $r$ over $[0.5, 3]$. The curve in Figure 4.2 is striking. There is a clear maximum at $r = 1$. The downward absolute power variation gives the best fit.

Taking the power $r = 1$ in $r$-power variation has a specific interpretation. Since the upward and downward absolute power variations are the sums of returns, their difference equals the open-to-close return,

$$RAV^+_n(\Delta) - RAV^-_n(\Delta) \equiv R_n(1) - R_n(0). \tag{4.21}$$

The difference in explanatory power of $RAV^+$ and $RAV^-$ may accordingly be attributed to the open-to-close return $R_n(1) - R_n(0)$. The return over the trading day is apparently an important determinant of future volatility, also after taking into account intraday high-frequency data. To see that this result is subtle, the direct use of the open-to-close return, upon replacing $\log(RAV^-)$ in equation (4.20) by $R_n(1) - R_n(0)$, yields a significantly lower likelihood.$^{12}$

$^{12}$One may note that such a change of specification does not formally fit into the framework from Section 4.1.3, so we cannot rely on the stationarity condition provided in equation (4.16).
4.2 Full-Sample Analysis

One should be careful with pushing $\Delta \downarrow 0$ in applying downward absolute power variation. The values of $RAV^+$ and $RAV^-$ are large and increasing for smaller $\Delta$, so by equation (4.21) the ratio $RAV^+/RAV^-$ tends to one for small intervals: for small sampling intervals $RAV^+$ and $RAV^-$ are approximately equal. This implies (somewhat counter intuitively) the existence of an optimal sampling interval of positive length $\Delta > 0$ on which to base the downward absolute power variation. The log-likelihood based on $RAV^-$ for two, five, ten, and thirty-minute intervals is 1372, 1376, 1368, and 1329. It is maximal for the $\Delta =$five-minute sampling interval.

One may wonder whether other variables contribute to equation (4.20). We test this for a few commonly applied proxies, by separately including the five-minute realized volatility $RV5_{n-1}$, the ten-minute realized range (the square root of the sum of the squared 10-minute high-low ranges, see e.g. Martens and van Dijk, 2007), and the proxy $H_{n-1}^{(w)}$. None of these measures yields a significant $t$-value. One may test for the significance of a separate jump component by simultaneously including the five-minute realized volatility and the square root of the five-minute realized bipower variation, where the bipower variation is given by $\sum_{k=2}^{1/\Delta} |r_{n,k}| r_{n,k-1}$. The bipower variation does not include jumps, at least asymptotically for $\Delta \downarrow 0$, under fairly mild regularity conditions. Whereas Andersen, Bollerslev, and Diebold (2007) found that the bipower variation contributes significantly

---

Figure 4.2: Full-sample log-likelihood values for equation (4.20) where $RAV5^-$ is replaced by the downward $r$-power variation, $RPV5^-$, for various powers $r$. The power $r$ is varied over $[0.5, 3]$.
to their forecast equation, we obtain insignificant \( t \)-values. This insignificance is in line with the property that the sum of absolute values (instead of squared values) is robust to jumps (again asymptotically), i.e. jumps in the price process have a relatively minor contribution to the indicators in equation (4.20).

Table 4.2 lists the in-sample performance of the six specifications for the scale factor \( \sigma_n \).

The first two columns concern the standard GARCH(1,1) and GJR(1,1) models based on daily returns. The third and fourth columns extend the GJR(1,1) model by including the five minute (downward) absolute power variation. The third column, for instance, represents the model

\[
\sigma_n^2 = \kappa + \alpha(1)r_{n-1}^2 + \alpha(2)(r_{n-1}^-)^2 + \alpha(3)(\text{RAV}5_{n-1}^-)^2 + \beta\sigma_{n-1}^2.
\]

The last two columns give the results for the log-GARCH model (4.20) without \( \alpha(4) \equiv 0 \) and with the downward absolute power variation \( \text{RAV}5^- \). The estimation of each specification uses the log-Gaussian quasi-likelihood for \( H^{(a)} \). The first row gives the full-

<table>
<thead>
<tr>
<th>criterion</th>
<th>GARCH(1,1)</th>
<th>GJR(1,1)</th>
<th>GJR(1,1) + RAV5^-</th>
<th>GJR(1,1) + RAV5^- + RAV5^-</th>
<th>log-GARCH no RAV5^-</th>
<th>log-GARCH (eq. 4.20)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogL</td>
<td>329.61</td>
<td>419.20</td>
<td>1123.24</td>
<td>1141.06</td>
<td>1145.25</td>
<td>1375.55</td>
</tr>
<tr>
<td>( R^2_{\log RV5} )</td>
<td>0.595</td>
<td>0.610</td>
<td>0.679</td>
<td>0.680</td>
<td>0.666</td>
<td>0.689</td>
</tr>
<tr>
<td>( R^2_{\log H} )</td>
<td>0.678</td>
<td>0.691</td>
<td>0.773</td>
<td>0.775</td>
<td>0.775</td>
<td>0.797</td>
</tr>
</tbody>
</table>

Table 4.2: In-sample model comparison for full sample, \( n = 31, \ldots, 4575 \). Model comparison criteria are the log-likelihood and the \( R^2 \)'s from the logarithmic Mincer-Zarnowitz regression (4.22), where the volatility proxy is either \( RV5 \) or \( H^{(a)} \). The two leftmost columns concern the classical GARCH(1,1) and GJR(1,1) models. The 3rd and 4th columns extend GJR(1,1) by (downward) absolute power variation. The final two columns concern the log-GARCH model (eq. 4.20) without and with downward absolute power variation. The estimation of each specification uses the log-Gaussian quasi-likelihood for \( H_n^{(a)} \), using all observations \( (n = 1, \ldots, 4575) \) to determine the scale factors \( \hat{\sigma}_n \), but leaving the first 30 days out of the likelihood.

sample log-likelihoods. If the Gaussian density used for determining the likelihood is in fact the true innovations density, then one may use the likelihood ratio statistic (LR) for comparing likelihoods. In the case of QML estimation one may use the QML likelihood ratio statistic given by

\[
LR_{\text{qml}} = \frac{4}{\text{var}(\hat{\varepsilon}^2)} (L_1 - L_0),
\]
where $\varepsilon$ denotes the quasi standard-Gaussian innovation (see Section 4.1.4), $L_1$ and $L_0$ are Gaussian likelihood values, and the factor $4/\text{var}(\varepsilon^2)$ replaces the conventional factor 2 for the standard LR statistic. The statistic $LR_{qml}$ has the usual chi-square asymptotics, see Busch (2005). Using the full-sample residuals of the log-GARCH model (4.20) we estimate $4/\text{var}(\varepsilon^2) \approx 1.26$. So a 3 point change in the likelihood is significant $\left(\frac{3.84}{1.26} \approx 3\right)$; here 3.84 is the 95% quantile of the chi-square distribution. Comparing the first two likelihoods, one sees that the GJR(1,1) model clearly outperforms the standard GARCH(1,1) model. This is due to its additional term $(r_{n-1}^-)^2$. The inclusion of the more refined measure $RAV5^-$ greatly raises the log-likelihood value from 419 to 1123. Such a large increase in likelihood signals a statistically highly significant improvement. The large sample size makes it possible to have such a clear statistical significance. The fourth likelihood value confirms that the absolute power variation $RAV5^-$ contributes only modestly to the specification, reinforcing the relative importance of the downward price movements captured by $RAV5^-$. The final two columns concern the log-GARCH specification, and show that also if one accounts for week and month effects the downward price pressure is a highly powerful predictor of one-day ahead volatility. In addition to likelihood values, Table 4.2 gives the coefficients of determination $R^2$ for two Mincer-Zarnowitz (1969) forecast regressions, based on the log of the standard five-minute realized volatility $\log(RV5_n)$ and $\log(H_n^{(w)})$. The regression equation is given by

$$\log(\text{proxy}_n) = a + b \log(\hat{\sigma}_n) + \varepsilon_n,$$

where we either set $\text{proxy}_n = RV5_n$, or $\text{proxy}_n = H_n^{(w)}$. In the evaluation of forecasts one has to deal with the complication that the scale factor is not observed. So even if one has perfect forecasts, $\hat{\sigma}_n \equiv \sigma_n$, one obtains an $R^2 < 1$, since $RV5_n \neq \sigma_n$ in general. Unfortunately, the upper bound for $R^2$ is not known. Of course, the larger the $R^2$ of the regression (4.22), the larger the predictive ability of $\hat{\sigma}_n$. The full-sample $R^2$s show the same pattern as the likelihood values: specifications that include the proxy $RAV5^-$ have larger in-sample forecast accuracy. The log-GARCH specification outperforms the other specifications, attaining a value of $R^2 \approx 0.80$.

Finally, let us return to Figure 4.1. From top to bottom, the four rightmost subfigures depict the autocorrelation structure of the proxies $|r|$, $hl$, $RV5$, and $H^{(w)}$ after standardization by the log-GARCH scale factors $\hat{\sigma}_n$. The log-GARCH specification (4.20) outperforms the GJR(1,1) model in removing the autocorrelation structure for each of the four volatility proxies.

\footnote{Formally, for nested models.}

\footnote{Including $RAV5^-$ in the GARCH(1,1) specification yields a log-likelihood 1118, so taking account of the negative daily return $r^-$ adds almost no explanatory power in the presence of $RAV5^-$.}
4.3 Out-of-Sample Volatility Forecasts

The main practical requirement for a volatility model is that it should be able to forecast volatility (Engle and Patton, 2001). The ultimate test of forecast accuracy is an out-of-sample forecast comparison. We shall apply a number of out-of-sample forecasting criteria to the different models. More specifically, our aim is to gain insight into the out-of-sample predictive ability of $RAV^5^-$. We shall consider the six specifications of Table 4.2, and refer to these models as M1 to M6. The forecasts use parameter estimates from rolling samples with a fixed sample size of 1000 days. For each specification we thus generate out-of-sample forecasts

$$\hat{\sigma}_n, \quad \text{for } n = 1001, \ldots, 4575.$$ 

The parameter estimates are obtained by log-Gaussian QMLE based on observations $n - 1000, \ldots, n - 1$. For each model the likelihood is determined for the proxy $H^{(0)} = H^{(e)}/c$, where $c$ simply rescales $H^{(e)}$ such that $\log(H^{(0)}_n)$ has the same full-sample average $(n = 1, \ldots, 4575)$ as the log five-minute realized volatilities $\log(RV_5^n)$. This ensures that we can compare the forecasts $\hat{\sigma}_n$ with $RV_5$. To evaluate predictive accuracy we compare the forecasts with two measures of daily price fluctuations: $\log(RV_5^n)$, and $\log(H^{(0)}_n)$. We use these measures in forecast regressions, $\log(\text{proxy}_n) = a + b \log(\hat{\sigma}_n) + \varepsilon_n$, see (4.22) above. Unbiasedness corresponds to $a = 0$ and $b = 1$. We shall also compare the regression $R^2$s with those obtained from in-sample forecasts.

Table 4.3 gives estimates of the forecast regression coefficients as well as heteroscedasticity and autocorrelation adjusted $t$-statistics for testing $a = 0$ and $b = 1$. All estimated intercepts $\hat{a}$ are positive, which is (partially) offset by the slopes $\hat{b}$ that all are larger than one (since $\log(RV_5^n) < 0$). In the case of the GJR(1,1) model and its extensions with $RAV_5$ and $RAV_5^-$ the $t$-values lie outside the 95% confidence region ($-2, 2$), indicating a significant departure from unbiasedness; for the other specifications they are not significant.

The first two rows of Table 4.4 give the $R^2$s for the out-of-sample forecast regressions. For comparison, the bottom two rows of Table 4.4 provide values for predictive accuracy by giving forecast equation $R^2$s for in-sample predictions based on parameter estimates over the period $n = 1001, \ldots, 4575$ (cf. the full-sample values in Table 4.2). The out-of-sample forecasts are practically as good as the in-sample forecasts, which suggests that the observed high predictive accuracy is not merely an in-sample artifact, or the result of overfitting. It also indicates that estimation error in the parameters plays a minor role in these forecasts. Consistent with full-sample analysis the specifications that include a measure for downward price pressure have larger $R^2$s than those without downward price pressure.
4.3 Out-of-Sample Volatility Forecasts

Table 4.3: Out-of-sample forecast regression intercepts and slopes for the regression (4.22), where $\hat{\sigma}_n$, $n = 1001, \ldots, 4575$, are out-of-sample forecasts. The forecasts use parameter estimates from moving windows of 1000 days. Newey-West $t$-values for $a = 0$ and $b = 1$ in parentheses. The models M1 to M6 are those of Table 4.2.

<table>
<thead>
<tr>
<th></th>
<th>$\log(RV5)$</th>
<th></th>
<th>$\log(H^{(0)})$</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>intercept</td>
<td>slope</td>
<td>intercept</td>
<td>slope</td>
</tr>
<tr>
<td>M1</td>
<td>0.218</td>
<td>1.045</td>
<td>0.188</td>
<td>1.038</td>
</tr>
<tr>
<td></td>
<td>(1.92)</td>
<td>(1.97)</td>
<td>(1.85)</td>
<td>(1.86)</td>
</tr>
<tr>
<td>M2</td>
<td>0.219</td>
<td>1.046</td>
<td>0.164</td>
<td>1.033</td>
</tr>
<tr>
<td></td>
<td>(2.13)</td>
<td>(2.18)</td>
<td>(1.73)</td>
<td>(1.73)</td>
</tr>
<tr>
<td>M3</td>
<td>0.277</td>
<td>1.057</td>
<td>0.215</td>
<td>1.043</td>
</tr>
<tr>
<td></td>
<td>(4.79)</td>
<td>(4.80)</td>
<td>(3.93)</td>
<td>(3.88)</td>
</tr>
<tr>
<td>M4</td>
<td>0.262</td>
<td>1.054</td>
<td>0.203</td>
<td>1.041</td>
</tr>
<tr>
<td></td>
<td>(4.60)</td>
<td>(4.61)</td>
<td>(3.80)</td>
<td>(3.75)</td>
</tr>
<tr>
<td>M5</td>
<td>0.056</td>
<td>1.012</td>
<td>0.039</td>
<td>1.008</td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(0.91)</td>
<td>(0.80)</td>
<td>(0.76)</td>
</tr>
<tr>
<td>M6</td>
<td>0.100</td>
<td>1.021</td>
<td>0.067</td>
<td>1.013</td>
</tr>
<tr>
<td></td>
<td>(1.85)</td>
<td>(1.90)</td>
<td>(1.62)</td>
<td>(1.55)</td>
</tr>
</tbody>
</table>

Table 4.4: Forecast regression $R^2$s for the regression (4.22), and $\hat{\sigma}_n$, $n = 1001, \ldots, 4575$. The out-of-sample forecasts correspond to those of Table 4.3. The in-sample forecasts are produced by estimating the parameters over the sample $n = 971, \ldots, 4575$, leaving the first 30 days out of the likelihood. The models M1 to M6 are those of Table 4.2.

<table>
<thead>
<tr>
<th></th>
<th>out-of-sample</th>
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<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2_{\log(RV5)}$</td>
<td>M1</td>
<td>M2</td>
<td>M3</td>
<td>M4</td>
<td>M5</td>
</tr>
<tr>
<td></td>
<td>0.641</td>
<td>0.664</td>
<td>0.721</td>
<td>0.720</td>
<td>0.704</td>
<td>0.728</td>
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<td>$R^2_{\log(H^{(0)})}$</td>
<td>0.726</td>
<td>0.744</td>
<td>0.806</td>
<td>0.806</td>
<td>0.802</td>
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<td>in-sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$R^2_{\log(RV5)}$</td>
<td>0.649</td>
<td>0.672</td>
<td>0.727</td>
<td>0.727</td>
<td>0.708</td>
</tr>
<tr>
<td></td>
<td>$R^2_{\log(H^{(0)})}$</td>
<td>0.727</td>
<td>0.747</td>
<td>0.807</td>
<td>0.807</td>
<td>0.803</td>
</tr>
</tbody>
</table>

Finally, Tables 4.5 and 4.6 provide for each pair of models a Diebold and Mariano (1995) and West (1996) (DMW) test for the predictive superiority of one model over the other. First, define model $i$’s forecast errors (using a volatility proxy as stand-in for $\sigma_n$)

$$e_{i,n} = \log(\text{proxy}_n) - \log(\hat{\sigma}_{i,n}).$$

Better forecasts have smaller mean squared errors (MSE). One may test for the superiority of model $i$ over model $j$ by testing the significance of the difference in MSE, as given by the $t$-test for the $\mu_{i,j}$ coefficient in the regression

$$e_{j,n}^2 - e_{i,n}^2 = \mu_{i,j} + \varepsilon_n, \quad (4.23)$$
where $\mu_{i,j} > 0$ supports superiority of model $i$. In both tables the bottom row of each table gives the root mean squared error (RMSE), setting the proxy to either $RV5_n$ or $H_{n}^{(0)}$. The first five rows give the $t$-statistics, calculated using standard-errors with the Newey-West adjustment for heteroscedasticity and autocorrelation. The log-GARCH specification (4.20) outperforms the other models. In all cases the inclusion of $RAV5_n^-$ as a measure for downward price pressure significantly improves forecast accuracy.

log realized volatility: $\log(RV5_n)$

<table>
<thead>
<tr>
<th>model</th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
</tr>
</thead>
<tbody>
<tr>
<td>M2</td>
<td>-7.80</td>
<td>-7.79</td>
<td>-5.52</td>
<td>-8.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M3</td>
<td>0.38</td>
<td>3.41</td>
<td>-2.97</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M4</td>
<td>3.43</td>
<td>-3.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-9.02</td>
</tr>
</tbody>
</table>

RMSE  | 0.272 0.263 0.241 0.241 0.247 0.237

Table 4.5: Pairwise tests for superior out-of-sample predictive ability, for $n = 1001, \ldots, 4575$. The $(i,j)$-th entry in the top five rows gives the $t$-value for $\mu_{i,j} = 0$ in the regression (4.23), where proxy $n$ is the five-minute realized volatility $RV5_n$. A $t$-value outside the 95% confidence interval $(-2, 2)$ represents statistical significance. The $t$-value $=-5.28$ for entry (1,2) supports superiority of model M2 over model M1. The $t$-values are based on Newey-West adjusted standard errors. The bottom row gives the root mean squared error for each model. The models M1 to M6 are those of Table 4.2.

log combined proxy: $\log(H_{n}^{(\hat{w})})$

<table>
<thead>
<tr>
<th>model</th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>M5</th>
<th>M6</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>-4.30</td>
<td>-9.49</td>
<td>-9.54</td>
<td>-9.82</td>
<td>-11.28</td>
<td></td>
</tr>
<tr>
<td>M2</td>
<td>-8.66</td>
<td>-8.70</td>
<td>-7.92</td>
<td>-10.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M3</td>
<td>-0.61</td>
<td>0.87</td>
<td>-6.57</td>
<td></td>
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<tr>
<td>M4</td>
<td>0.99</td>
<td>-6.56</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>M5</td>
<td></td>
<td></td>
<td>-9.10</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

RMSE  | 0.222 0.214 0.187 0.187 0.189 0.178

Table 4.6: Pairwise tests for superior out-of-sample predictive ability as in Table 4.5, but now with proxy $n = H_{n}^{(0)}$.

4.4 Conclusions

This chapter has analysed the effect of downward price pressure, which is measured using high-frequency downward price movements, as a driving force of daily volatility. Its main
4.4 Conclusions

Theoretical contribution is the introduction of a GARCH-type discrete time model that incorporates statistics based on high-frequency data into a forecast equation for daily volatility. The chapter incorporated intraday price movements in a GARCH model for daily volatility. This was achieved by adopting a scaling model for the intraday return process, without imposing severe constraints on the intraday price process. The scaling model offers a continuous time model that yields daily close-to-close returns that satisfy a GARCH model. The chapter then introduced a GARCH-type forecast equation for incorporating statistics such as the realized volatility, and the absolute power variation. The resulting stochastic system leads to easy-to-verify stationarity conditions.

The main empirical result is that the sum of downward absolute five-minute returns (downward absolute power variation), reflecting downward price pressure, is an effective predictor of daily volatility. There is a distinction between explanatory power of upward and downward high-frequency price movements. In a model with several explanatory variables the upward absolute power variation adds almost no explanatory power, whereas the downward movements have the predominant effect. For the S&P 500 index tick data over 1988–2006, taking into account the downward absolute power variation yields a model that achieves a value $R^2 \approx 0.80$ for evaluating daily volatility forecasts, both for in-sample and out-of-sample prediction. The likelihoods for models that use the more general downward $r$-power variation (summing the $r$-th power of downward absolute five-minute returns for various $r$) yield a likelihood plot that is unimodal with a clear maximum at $r = 1$, i.e. the downward absolute power variation yields the best fit for the S&P data.
Appendices

4.A Data

Our data set is the U.S. Standard & Poor’s 500 stock index future, traded at the Chicago Mercantile Exchange (CME), for the period 1st of January, 1988 until May 31st, 2006. The data were obtained from Nexa Technologies Inc. (www.tickdata.com). The futures trade from 8:30 A.M. until 15:15 P.M. Central Standard Time. Each record in the set contains a timestamp (with one second precision) and a transaction price. The tick size is $0.05 for the first part of the data and $0.10 from 1997–11–01. The data set consists of 4655 trading days. We remove sixty four days for which the closing hour is 12:15 P.M. (early closing hours occur on days before a holiday). Sixteen more days are removed, either because of too late first ticks, too early last ticks, or a suspiciously long intraday no-tick period. These removals leave us with a data set of 4575 days with nearly 14 million price ticks, on average more than 3 thousand price ticks per day, or 7.5 price ticks per minute.

There are four expiration months: March, June, September, and December. We use the most actively-traded contract: we roll to a next expiration as soon as the tick volume for the next expiration is larger than for the current expiration.

4.B Stationarity and Invertibility

Stationarity and invertibility of a time series are properties that concern the stability of the stochastic system. They play a central role in parameter estimation. Let us first address the question of stationarity. We consider a log-GARCH\((p, q)\) model that includes proxies, cf. (4.14–4.15):

\[
\log(\sigma_n) = \kappa + \sum_{i=1}^{m} \left( \sum_{j=1}^{d} \alpha_i^{(j)} \log(H_{n-i}^{(j)}) + \sum_{i=1}^{q} \beta_i \log(\sigma_{n-i}) \right),
\]

where \(m \equiv \max\{p, q\}\), \(\eta_n \equiv \sum_{i=1}^{p} \sum_{j=1}^{d} \alpha_i^{(j)} U_{n-i}^{(j)}\), \(U_{n}^{(j)} = \log(H^{(j)}(\Psi_n))\), and \(\bar{\alpha}_i = \sum_{j=1}^{d} \alpha_i^{(j)}\). As before, \(\bar{\alpha}_i \equiv 0\) for \(i > p\) and \(\bar{\beta}_i \equiv 0\) for \(i > q\). Proposition 4.1 gives conditions that ensure stationarity. The function \(\log^+(\cdot)\) is given by \(\log^+(x) = \log(\max\{x, 1\})\). If a random variable \(X\) has a finite \(r\)-th moment, \(\mathbb{E}|X|^r < \infty\) for some \(r > 0\), then \(\mathbb{E}\log^+(|X|) < \infty\). Let \((G_n)\) denote the filtration generated by the processes \(\Psi_n(\cdot)\), given by \(G_n = \sigma\{\Psi_n, \Psi_{n-1}, \ldots\}\).
Proposition 4.1 Suppose \( E\log^+(|\eta_n|) < \infty \), and define the polynomial \( \phi(z) \),

\[
\phi(z) = 1 - (\bar{\alpha}_1 + \beta_1) z - \ldots - (\bar{\alpha}_m + \beta_m) z^m.
\] (4.26)

If all roots of \( \phi(z) \) lie outside the unit circle, then equation (4.24) admits a unique stationary solution \((\log(\sigma_n))\). The stationary solution \( \log(\sigma_n) \) is ergodic, and is \( G_{n-1} \)-measurable for all \( n \). Moreover, if \( E|\eta_n| < \infty \), then \( E|\log(\sigma_n)| < \infty \). If \( E\eta_n^2 < \infty \), then \( E|\log(\sigma_n)|^2 < \infty \).

Proof. First, the sequence \( U_{d,n} \equiv (U^{(1)}_n, \ldots, U^{(d)}_n) \), \( n \in \mathbb{Z} \), is iid, hence stationary ergodic. The sequence \( \eta_n \) is stationary ergodic, since it is a causal transformation of the stationary ergodic \( U_{d,n} \) (Straumann and Mikosch, Proposition 2.5, 2006).

One may write equation (4.25) in matrix form. Let \( A^T \) denote the transpose of \( A \). Let us define an \( m \)-dimensional system where \( Y_n = (\log(\sigma_n), \ldots, \log(\sigma_n-m+1))^T \) and \( B_n = (\eta_n, 0, \ldots, 0)^T \). Equation (4.25) may now be expressed as

\[
Y_n = AY_{n-1} + B_n,
\]

where \((B_n)\) is a stationary ergodic sequence, and the \( m \times m \) matrix \( A \) is given by

\[
A = \begin{pmatrix}
(\bar{\alpha}_1 + \beta_1) & \ldots & (\bar{\alpha}_m + \beta_m) \\
1 & 0 & \ldots & 0 \\
0 & 1 & 0 & \ldots & 0 \\
\vdots & \ddots & \ddots & \ddots & \vdots \\
0 & \ldots & 0 & 1 & 0
\end{pmatrix}.
\]

The eigenvalues of \( A \) are central to the existence of a stationary solution. As is frequently used in standard ARMA theory, the largest absolute eigenvalue \( |\lambda_i| \) (i.e. the spectral radius) of \( A \) is smaller than one if the polynomial (4.26) has only roots outside the unit circle. For a non-stochastic matrix the top-Lyapunov exponent equals the logarithm of the spectral radius, so one may now apply Theorem 1.1 from Bougerol and Picard (1992): \( Y_n \) admits the almost sure representation

\[
Y_n = \sum_{k=0}^{\infty} A^k B_{n-k},
\]

which is the unique stationary solution to (4.24). Here \( A^0 \) represents the identity matrix. The solution \( Y_n \) is ergodic, since it is the almost sure limit of a causal transformation of the stationary ergodic sequence \((B_n)\), see Proposition 2.6, Straumann and Mikosch (2006). This proves the claim that \( \log(\sigma_n) \) admits a unique stationary and ergodic solution. The \( B_n, B_{n-1}, \ldots \) all are \( G_{n-1} \)-measurable. So \( Y_n \) is \( G_{n-1} \)-measurable, since it is the limit of
By ARMA theory one may express \( \log(\sigma_n) \) as

\[
\log(\sigma_n) = \sum_{i=0}^{\infty} c_i \eta_{n-i},
\]

where the \( c_i \) are given by \( \sum_{i=0}^{\infty} c_i z^i = 1/\phi(z) \), and \( \sum_{i=0}^{\infty} |c_i| < \infty \), see for instance Brockwell and Davis (1991). The existence of the first two moments of \( \log(\sigma_n) \) now follows from standard arguments, see for instance Proposition 3.1.1 in Brockwell and Davis.

Let us now turn to the question of invertibility. Algorithms for estimating parameters and forecasting are typically only effective under invertibility. Consider the log-GARCH(1,1) specification (4.10), and suppose that \( \log(\sigma_n) \) is a stationary solution. One does not observe \( \sigma_0 \), and in practice one typically replaces this value by a starting value \( \hat{\sigma}_0 > 0 \), and simply iterates the recursion

\[
\log(\hat{\sigma}_n) = \kappa + \alpha \log(H_{n-1}) + \beta \log(\hat{\sigma}_{n-1}),
\]

for \( n = 1, \ldots, N \). Following Straumann and Mikosch (2006), we say that the process \( \log(\sigma_n) \) is invertible\(^{16}\) if

\[
\lim_{n \to \infty} \mathbb{P}[|\log(\hat{\sigma}_n) - \log(\sigma_n)| \to 0, n \to \infty],
\]

i.e. the approximation becomes arbitrarily precise (given the true parameter values).

Application of the invertibility definition to the general specification (4.24) reveals that invertibility concerns only the parameters \( \beta \). Let the filtration \( (\mathcal{F}_n) \) represent the observed information given by the intraday return processes \( R_n(\cdot) \), so \( \mathcal{F}_n = \sigma\{R_n, R_{n-1}, \ldots\} \).

**Proposition 4.2** Let the process \( (\log(\sigma_n)) \) be a stationary solution to the log-GARCH equation (4.24). Define the polynomial \( \phi_\beta(z) \),

\[
\phi_\beta(z) = 1 - \beta_1 z - \ldots - \beta_q z^q.
\]

If \( q = 0 \) then \( (\log(\sigma_n)) \) is invertible. If \( q > 0 \) and all roots of \( \phi_\beta(z) \) lie outside the unit circle then \( (\log(\sigma_n)) \) is invertible. An invertible solution \( \log(\sigma_n) \) is \( \mathcal{F}_{n-1} \)-measurable for all \( n \).

**Proof.** If there are no autoregression parameters \( (q = 0) \), then the approximation scheme is exact, hence the process is invertible, and is \( \mathcal{F}_{n-1} \)-measurable.

\(^{16}\)The usual ARMA invertibility ensures that the ARMA innovations may be expressed in terms of the present and past of the observables; the concept of invertibility here may be seen as a generalization, see Straumann and Mikosch (2006, Section 3.2).
Consider the case \( q > 0 \). In analogy to the proof of Proposition 4.1 define the \( q \)-dimensional vector \( Y_n = (\log(\sigma_n), \ldots, \log(\sigma_{n-q+1}))^T \), and the \( d \)-dimensional vector \( B_n = (\log(H_n^{(1)}), \ldots, \log(H_n^{(d)}))^T \). By definition, the stationary solution \( Y_n \) satisfies the recursion

\[
Y_n = AY_{n-1} + \sum_{i=1}^{p} A_i B_{n-i},
\]

for all \( n \). Here, the \( q \times q \) matrix \( A \) and the \( q \times d \) matrices \( A_i \) are given by

\[
A = \begin{pmatrix}
\beta_1 & \cdots & \beta_q \\
1 & 0 & \cdots & 0 \\
0 & 1 & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \ddots & \vdots \\
0 & \cdots & 0 & 1 & 0
\end{pmatrix}, \quad \text{and} \quad A_i = \begin{pmatrix}
\alpha_i^{(1)} & \cdots & \alpha_i^{(d)} \\
0 & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \ddots \\
0 & \cdots & 0 & 0
\end{pmatrix}.
\]

To obtain the reconstruction vector \( \hat{Y}_n \), start with arbitrary values \( n \) days back, \( \log(\hat{\sigma}_0) = \hat{y}_0, \ldots, \log(\hat{\sigma}_{-q+1}) = \hat{y}_{-q+1} \), and iterate

\[
\hat{Y}_n = A\hat{Y}_{n-1} + \sum_{j=1}^{d} A_j B_{n-j}, \quad n \geq 1.
\]

One has

\[
Y_n - \hat{Y}_n = A(Y_{n-1} - \hat{Y}_{n-1}) = \ldots = A^n(Y_0 - \hat{Y}_0), \quad n = 1, 2, \ldots
\]

So \( \|Y_n - \hat{Y}_n\| \leq \|A^n\|_{op} \|Y_0 - \hat{Y}_0\| \) almost surely, where \( \|B\|_{op} \) denotes the operator norm for a matrix \( B \), given by \( \|B\|_{op} = \sup_{x \neq 0} \frac{\|Bx\|}{\|x\|} \). Let \( \rho(A) \) denote the spectral radius of \( A \). One has, in general, \( \lim_{n \to \infty} \|A^n\|_{op}^{1/n} = \rho(A) \), so

\[
\lim_{n \to \infty} \|Y_n - \hat{Y}_n\| \overset{\text{a.s.}}{=} 0,
\]

if \( \rho(A) < 1 \). In analogy to the proof of Proposition 4.1, one has \( \rho(A) < 1 \) if the roots of \( \phi_{\beta}(z) \) lie outside the unit circle.

In general one could start the reconstruction iteration \( k \) days back, and obtain the \( k \)-th backward iterate \( \hat{Y}_{n,k} \) (in particular, \( \hat{Y}_{n,n} \equiv \hat{Y}_n \)). Note that \( \hat{Y}_{n,k} \) is \( \mathcal{F}_{n-1} \)-measurable for all \( k > 0 \). By stationarity \( Y_n - \hat{Y}_{n,k} \overset{d}{=} Y_k - \hat{Y}_{k,k} = Y_k - \hat{Y}_k \). So invertibility of the \( Y_k \) (i.e. \( Y_k - \hat{Y}_k \) converges to zero in probability) is equivalent to \( Y_n - \hat{Y}_{n,k} \to 0 \) in probability for \( k \to \infty \). Convergence in probability implies the existence of a subsequence \( k_i \) such
that

\[ Y_n = \lim_{i \to \infty} \hat{Y}_{n,k}, \]

almost surely, hence an invertible \( Y_n \) is \( \mathcal{F}_{n-1} \)-measurable.

\[ \blacksquare \]

**Remark 4.1** If the conditions of Proposition 4.1 hold for \( r = 2 \) then \( \log(\sigma_n) \) is covariance stationary.

**Remark 4.2** If \( q = 1 \) in Proposition 4.2 one has invertibility if \( -1 < \beta < 1 \).

**Remark 4.3** One may think of parameter configurations that satisfy the conditions for stationarity, but not those for invertibility. An example is a log-GARCH(1,1) model with \( |\alpha + \beta| < 1 \) and \( \beta > 1 \).

**Remark 4.4** Under the conditions of both Proposition 4.1 and Proposition 4.2 one has \( \mathcal{F}_n \equiv \mathcal{G}_n \). This may be seen by the following arguments. If the conditions of Proposition 4.1 are satisfied, then \( \mathcal{F}_n \subset \mathcal{G}_n \), since \( R_n(\cdot) = \sigma_n \Psi_n(\cdot) \), and \( \sigma_n \) is \( \mathcal{G}_n \)-measurable. If the conditions of Proposition 4.2 are satisfied, then \( \mathcal{G}_n \subset \mathcal{F}_n \), since \( \Psi_n(\cdot) = R_n(\cdot)/\sigma_n \), and \( \sigma_n \) is \( \mathcal{F}_n \)-measurable.

**Remark 4.5** One can include positive proxies that are positively homogeneous of a degree \( r > 0 \) in the log-GARCH recursion. The focus on \( r \equiv 1 \) in this chapter is without loss of generality. Suppose that \( \hat{H} \) is positively homogeneous of degree \( r \). Then \( \hat{H} \equiv (\hat{H})^{1/r} \) is positively homogeneous of degree 1. Then, \( \log(\hat{H}(R_n)) = r \log(H(R_n)) \), so the effect of \( \hat{H} \) may simply be captured by \( H \).

**Remark 4.6** It is fairly easy to extend the log-GARCH model by the following class of intraday statistics. Let \( R_n \) denote, as before, the intraday return process. Consider a statistic \( D_n \equiv D(R_n) \) that is positively homogeneous of degree zero,

\[ D(\alpha R_n) = D(R_n), \quad \alpha \geq 0. \]

Examples of such a statistic are the ratio of two proxies, the ratio of the daily return and the realized volatility, or the time of the intraday high. The statistic \( D_n \) satisfies

\[ D_n = D(\sigma_n \Psi_n) = D(\Psi_n), \]

so the \( D_n \) form an iid sequence. Inclusion of a term \( \delta D_{n-1} \) in equation (4.24) only alters the innovation \( \eta_n \) in (4.25). The conditions for stationarity and invertibility of the log-GARCH model, as given by Propositions 4.1 and 4.2, remain unchanged.