Oesterreichische Nationalbank

Working Paper 86

Testing for Longer Horizon Predictability of Return Volatility with an Application to the German DAX

Burkhard Raunig

Statement of Purpose

The Working Paper series of the Oesterreichische Nationalbank is designed to disseminate and to provide a platform for discussion of either work of the staff of the OeNB economists or outside contributors on topics which are of special interest to the OeNB. To ensure the high quality of their content, the contributions are subjected to an international refereeing process. The opinions are strictly those of the authors and do in no way commit the OeNB.

Imprint: Responsibility according to Austrian media law: Guenther Thonabauer, Secretariat of the Board of Executive Directors, Oesterreichische Nationalbank

Published and printed by Oesterreichische Nationalbank, Wien.

The Working Papers are also available on our website:

http://www.oenb.co.at/workpaper/pubwork.htm

Editorial

Volatility of financial returns as a measure of risk is a key parameter in asset pricing and risk management and holding periods for financial instruments of several weeks or month are common. Nevertheless, little is known about the predictability of return volatility at longer horizons. In the present paper, the author investigates the predictability of return volatility of the German DAX for forecasting horizons from one day to 45 days with a new model-free test procedure that avoids joint assessments of predictability and assumed volatility models. In Monte Carlo simulations the new test is compared with two alternative model-free test procedures. The simulations indicate that the new test has good statistical properties and is more powerful then the other two tests if the distribution of returns is fat tailed.

September 22, 2003

Testing for Longer Horizon Predictability of Return Volatility with an Application to the German DAX

Burkhard Raunig*

Abstract

Volatility of financial returns as a measure of risk is a key parameter in asset pricing and risk management and holding periods for financial instruments of several weeks or month are common. Nevertheless, little is known about the predictability of return volatility at longer horizons. This paper investigates the predictability of return volatility of the German DAX for forecasting horizons from one day to 45 days with a new model-free test procedure that avoids joint assessments of predictability and assumed volatility models. In Monte Carlo simulations the new test is compared with two alternative model-free test procedures. The simulations indicate that the new test has good statistical properties and is more powerful then the other two tests if the distribution of returns is fat tailed. Contrary to earlier findings according to which the return volatility of the DAX is only predictable for 10 to 15 trading days, the empirical evidence provided in this study suggests that the volatility of DAX returns is predictable for horizons of up to 35 trading days and may be forecastable at even longer horizons.

Key words: financial returns volatility, predictability, forecasting, interval forecast evaluation, density forecast evaluation

JEL codes: G 10, C 53

Burkhard Raunig
Oesterreichische Nationalbank
Economic Studies Division
Otto-Wagner-Platz 3
POB 61, A-1011 Vienna
Austria
Phone: (+43-1) 404 20-7219
Fax: (+43-1) 404 20-7299
Email: burkhard.raunig@oenb.co.at

*) The opinions expressed do not necessarily reflect those of the Oesterreichische Nationalbank.

1 Introduction

Volatility, defined as the standard deviation of financial returns, is an important measure of financial risk and forecasts of future volatility play a key role in the area of asset pricing, portfolio selection and risk management. For the accurate pricing, hedging and risk analysis of financial instruments traders and risk managers need accurate forecasts of volatility. Economists are also interested in volatility because volatility forecasts can serve as useful indicators of the future trend of the economy.[1] Volatility measures of major financial series are indeed routinely analyzed by Central Banks as for example in the monthly bulletin of the European Central Bank.

A number of studies have examined the forecasting performance of a variety of different volatility models, typically at short horizons (for a recent survey, see Poon and Granger, 2001). However, still little is known about the predictability of volatility over longer horizons such as weekly or monthly. This is unfortunate because the issue is important. For example, risk managers frequently have to deal with assets where the assumption of a holding period of one month or longer appears to be much more appropriate than the standard assumption of a one day- or ten day holding period (Chorafas, Ch. 11, 1998). In such a situation the longer horizon predictability of volatility becomes an important question. If volatility is predictable at longer horizons then more sophisticated models like GARCH, stochastic volatility or related approaches should be useful for forecasting volatility (for a survey of these models, see Campbell, Lo and McKinlay, 1997, Mills, 1999, Gourieroux and Jasiak, 2001). However, if volatility is unpredictable at longer horizons then an estimate of the unconditional standard deviation is probably the best that one can hope for and more complicated forecasting models may not be beneficial.[2]

---

[1] For example Annert, De Ceuster and Valckx (2001) find that estimates of recession probabilities improve when financial volatility is taken into account.

[2] If an option contract on the asset with a time to maturity equal to the desired forecasting horizon is available then the implicit volatility backed out of the theoretical formular for the option price could be used as an alternative forecast of the volatility of the underlying asset returns.

Some studies, including Pagan and Schwert (1990), Figlewski (1997) West and Cho (1995), Brailsford and Faff (1996), evaluate the forecasting performance of different volatility models over weekly, monthly or even longer horizons. Such model-based evaluations are informative but problematic if one is interested in the predictability of volatility per se because the results can vary not only with the forecasting horizon but also with the assumed model. To avoid this joint hypothesis problem, Christoffersen and Diebold (2000) examine the predictability of volatility of a number of financial return series for forecasting horizons of up to 20 trading days with the help of a *model-free* test procedure. They also ask how strong the predictability at different horizons might bee. Their main findings are that volatility is largely unpredictable for horizons beyond 10-15 trading days and that the degree of predictability decreases quickly with increasing horizon.

This paper proposes an alternative model-free test procedure to assess the predictability of return volatility at longer horizons using a definition of predictability developed in Clements and Hendry (1998). The new test procedure utilizes recent results from the density forecast evaluation literature (Crnkovic and Drachman, 1997, Diebold, Gunther and Tay, 1998 and Clements and Smith, 2000) and empirical distribution functions (EDF's) of nonoverlapping financial returns. Because the test procedure uses empirical distribution functions it is named EDF-predictability test. A simple measure of the strength of predictability is also proposed. In a simulation study the power and the size of the test procedure is examined and compared with the asymptotic version of the runs test of Christoffersen and Diebold (2000) and the classical ARCH test (Engle, 1982). The simulations suggest that the EDF-predictability test is more powerful than the runs test and virtually as powerful as the ARCH test if the returns are conditionally normally distributed. If the conditional return distributions are fat-tailed, the simulations indicate that the EDF-predictability test is more powerful then the other two tests. It is further pointed out that under certain distributional assumptions the EDF-predictability test is equivalent to the classical

ARCH test. In an empirical application, the three test procedures are used to examine the predictability and the strength of predictability of the German stock index DAX for forecasting horizons ranging from 1 day to 45 trading days. The empirical evidence from the EDF procedure points towards a predictability of volatility for horizons of up to 30-35 trading days.

The rest of the paper is organized as follows. Section 2 discusses the notion of predictability used in this paper. The new test procedure and its relationship to the classical ARCH test as well as a simple measure of the strength of predictability are described in Section 3. The results of a Monte Carlo Study concerning the power and the size of the EDF-predictability-, runs- and the classical ARCH test are reported in Section 4. The findings about the predictability- and the strength of predictability of the volatility of the DAX return series are presented in Section 5. Some conclusions are provided in section 6.

2 Predictability

This section introduces a notion of unpredictability developed in Clements and Hendry (1998). Unpredictability of a random variable y_t with distribution function F_{y_t} with respect to an information set Ω_{t-1} can be defined as follows:

Definition: A random variable y_t is unpredictable with respect to an information set Ω_{t-1} if the conditional and the unconditional distributions coincide:

$$F_{y_t}\left(y_t \middle| \Omega_{t-1}\right) = F_{y_t}\left(y_t\right). \tag{1}$$

This definition of unpredictability is intuitive and requires that the information set Ω_{t-1} does not improve the prediction of y_t. If Ω_{t-1} is assumed to be the history of y_t i.e. $\Omega_{t-1} = (y_{t-1}, y_{t-2},...)$ then the definition implies that the realizations of a stochastic process $\{y_t, t \in T\}$ up to time t-1 do not help to predict values of y_t for time t.[3] From this definition, a criterion for the predictability of volatility of a return series $\{r_t, t = 1,\ldots,n\}$ can be developed. Assume that a sample $\{e_t, t = 1,...,n\}$ of an already centered covariance stationary return process is available (i.e. $e_t = r_t - E[r_t \mid \Omega_{t-1}]$). The joint distribution $F(e_n, e_{n-1},\ldots,e_1)$ of this sample can always be factored into the product of n-1 conditional distributions and a marginal distribution:

$$F(e_n, e_{n-1}, ..., e_1) = \prod_{t=1}^{n} F_{e_t}(e_t | \Omega_{t-1}) . \tag{2}$$

Putting $\Omega_{t-1} = (e_{t-1},\ldots,e_1)$, it follows that $\{e_t, t = 1,\ldots,n\}$ is unpredictable with respect to its own past if the definition of unpredictability holds for each member of the series, i.e.

$$F(e_n, e_{n-1}, ..., e_1) = \prod_{t=1}^{n} F(e_t) , \tag{3a}$$

which is just the definition of statistical independence. This (strong) version of unpredictability assumes that the marginal distributions are the same for all e_t and equal to the unconditional distribution of the centered return series, hence the data should be independently and identically distributed (iid) with distribution function $F_h(.)$ and constant standard deviation σ_h if volatility is unpredictable at horizon h. Condition (3a) implies that all existing conditional moments are unpredictable from past observations. A weaker form of (3a) requires that the conditional variance of the centered returns e_t is constant and equal to the unconditional variance σ_h^2 at a forecasting horizon h, i.e.

$$Var(e_t | \Omega_{t-1}) = Var(e_h) \text{ for all t.} \tag{3b}$$

Note that (3b) does not rule out that higher moments than the second are predictable. Volatility is said to be predictable at horizon h if conditions (3a) or (3b) do not hold.

[3] Unpredictability is defined relative to the information set used, therefore, unpredictability of y_t with respect to Ω_{t-1} does not imply that y_t could not be predicted with the help of another information set $\Psi_{t-1} \neq \Omega_{t-1}$. The volatility of a return series could, for example, be unpredictable from past returns but predictable from quoted option prices.

3 Methods

The test procedures and the measure of the strength of predictability outlined below assess the predictability of volatility at various horizons from observed returns without conditioning on specific models of volatility; thus they are model-free. All tests use nonoverlapping centered returns to avoid dependencies in the data induced by temporal aggregation of overlapping returns. For example, to investigate predictability for a 20 day forecasting horizon, nonoverlapping 20 day returns are used.

3.1 The EDF-Predictability Test

The proposed new test procedure utilizes recent ideas from density forecast evaluation developed in Crnkovic and Drachman (1997), Diebold, Gunther and Tay (1998), Clements and Smith (2000)-, and surveyed in Tay and Wallis (2000). A short digression into this literature is necessary to explain the procedure. The basic result on which density forecast evaluations are built dates back to Rosenblatt (1952) and is given by the probability integral transformation

$$z_t = \int_{-\infty}^{y_t} p(u)du = P_t(y_t), \quad t = 1,\ldots,n. \tag{4a}$$

In (4a) $P_t(y_t)$ denotes the predicted conditional distribution and $p_t(.)$ denotes the predicted conditional density of realization y_t of the stochastic process $\{y_t, t = 1,\ldots,n\}$. If conditioning is with respect to the past of y_t, Diebold et al. show that the resulting transformed series $\{z_t, t = 1,\ldots,n\}$ must be a sequence of independent and uniformly distributed U(0,1) random variables if the forecasted distributions $\{P_t(y_t), t = 1,\ldots,n\}$ and the true distributions $\{F_t(y_t), t = 1,\ldots,n\}$ coincide. Frühwirth-Schnatter (1996) and Berkowitz (2000) suggest a subsequent application of a quantile transformation, based on the inverse of a standard normal distribution

$$n_t = \Phi^{-1}(z_t), \quad t = 1,\ldots,n \tag{4b}$$

to the members of a z-series that yields a sequence $\{n_t,\ t = 1,\ldots,n\}$ of independent and identically distributed standard normal N(0,1) random variables provided the predicted conditional distributions are correct.

Condition (3a) suggests a direct test for predictability of volatility. Recall that unpredictability of volatility of a return series $\{e_t,\ t = 1,\ldots,n\}$ requires that the conditional distribution of each e_t is equal to the unconditional distribution of $\{e_t,\ t \in T)$. Hence, a series of nonoverlapping centered returns-, transformed with respect to its unconditional distribution P(.)

$$\{ n_t = \Phi_t^{-1}[P(e_t)], n_{t-1} = \Phi_{t-1}^{-1}[P(e_{t-1})], \ldots, n_1 = \Phi_1^{-1}[P(e_1)],\ t = 1,\ldots,n\} \tag{5}$$

should be iid N(0,1) if volatility is unpredictable at horizon h (i.e. $F_{e_t}(e_t | \Omega_{t-1}) = F(e_t) = P(e_t)$ holds for all t). Since the unconditional distribution P(.) is unknown, it can only be estimated. One strategy would be to assume a certain parametric family of distributions, to estimate the parameters from the data, and to transform the centered returns with respect to the estimated unconditional distribution. The properties of the transformed data would then crucially depend on the assumptions about the unconditional distribution of the return series, however.

A more attractive nonparametric alternative that requires no assumption about a particular family of distributions is the empirical distribution function (EDF) of a centered return series. The value $\hat{P}(e_i)$ of the EDF for a particular e_i, $i \in [t = 1,\ldots,n]$, is given by

$$\hat{P}(e_i) = n^{-1} \sum_{t=1}^{n} \mathbf{1}\{e_t \le e_i\}, \tag{6}$$

where **1** is an indicator function that takes on the value 1 if $e_t \le e_i$ and 0 otherwise. The empirical distribution function carries all the information about the sample, except the order of the observed data. Given a sample of nonoverlapping returns, the strategy of the testing procedure is:

a) to transform the centered returns via their empirical distribution function, i.e. to compute $z_t = \hat{P}(e_t)$ for each e_t. This computation is the empirical counterpart to the probability integral transformation (4a).
b) to create an n-series by transforming the z_t's resulting from step a) via the inverse of the standard normal distribution function (4b).
c) to examine the properties of the resulting n-series.

Note that the transformations always produce an unconditionally standard normally distributed n-series because an unconditional U(0,1) distribution is induced by the transformations via the empirical distribution function. However, if volatility is predictable, then the true *conditional* distributions differ from the unconditional distribution. The conditional distributions tend to be too wide during times of high volatility and too tight during times of low volatility. This means that the resulting n_t's will fall into certain regions of the unconditional standard normal distribution in a non-random fashion. In other words, the transformed data will not be independent if volatility is predictable. In particular, if volatility is predictable, then the sequence of *squared transformed returns* $\{n_t^2, t = 1,...,n\}$ will display clusters similar to the clusters observed in the original squared returns. On the other hand, if volatility is unpredictable then the n_t^2's must be uncorrelated and cannot be predictable from past squared transformed returns. This reasoning suggests an ARCH-type test applied to the squared transformed returns. In a regression

$$n_t^2 = \alpha_0 + \alpha_1 n_{t-1}^2 + ... + \alpha_d n_{t-d}^2 + \varepsilon_t, \qquad (7)$$

where the error term ε_t is assumed to be a martingale difference sequence and d denotes the specified lag length, an F-test should not reject the hypothesis $\alpha_1 = \alpha_2 = ... = \alpha_d = 0$ at conventional significance levels if volatility is unpredictable at horizon h.

3.2 Relationship Between the EDF-Predictability Test and the Classical ARCH Test

The well-known ARCH test for conditional heteroskedasticity-, developed in Engle (1982) uses the original centered squared returns. One version of the test consists of testing the null of homoskedasticity, implied by the restriction $\beta_1 = \beta_2 = \ldots = \beta_m = 0$ with an F-test against the alternative of heteroskedasticity in the regression

$$e_t^2 = \beta_0 + \beta_1 e_{t-1}^2 + \beta_2 e_{t-2}^2 + \ldots + \beta_m e_{t-m}^2 + \eta_t, \tag{8}$$

where e_t^2 denotes squared centered returns, m is the chosen lag length, and the error term η_t is assumed to have zero mean and constant variance. An F-statistic that does not reject the hypotheses of homoskedasticity at conventional significance levels can be interpreted as evidence against predictability of volatility.

Observe the similarity between equations (7) and (8). The EDF-predictability regression in equation (7) simply replaces the original squared centered returns by the corresponding n_t^2s and there is indeed a connection between (7) and (8) in the density forecast evaluation framework. Running the classical ARCH regression (8) is the same thing as running regression (7) if the original observations are transformed *under the assumption of an unconditional normal distribution*. To see this, assume that e_t can be written as the product $e_t = \sigma_t X_t$, where σ_t is the conditional standard deviation and the X_t's are uncorrelated random variables following some arbitrary distribution D(0,1) with zero mean and unit variance. Then under the assumption of unconditionally normally distributed density forecasts transformations (4a) and (4b) produce a series $n_t = (\sigma_t/\sigma)X_t$ via the relationship $n_t = \Phi^{-1}[\Phi(e_t/\sigma)] = e_t/\sigma$ where σ denotes the unconditional standard deviation. Hence, in this special case equation (7) is simply equation (8) scaled by $1/\sigma^2$. Both regressions produce exactly the same R-squares and hence exactly the same F-statistics under this particular distributional assumption.

Having shown that the classical ARCH test and the EDF-predictability test are equivalent under the assumption of an unconditional normal distribution (this is the implicit assumption for the error process under the null hypothesis of homoskedasticity made in Engle (1982) in the original derivation of the ARCH-test, see also Bollerslev, Engle and Nelson, 1994, p 2974 ff) it can now be seen that *both procedures differ under alternative distributional assumptions*. Whereas the classical ARCH test assumes a normal distribution under the null of homoskedasticity, the EDF-predictability test takes the unconditional distribution of the data and compares it with the true conditional distributions. The distribution under the null of unpredictability of volatility in the EDF-predictability test is therefore given by a nonparametric estimate of the unconditional distribution of centered returns. The auxiliary regression (7) based on squared n_t's then examines whether the variances of the conditional distributions of the centered returns differ in a predictable way from the variance of the unconditional distribution of the centered returns.

3.3 Strength of Predictability

It is not only important to know whether volatility is predictable or not, but also whether the predictability of volatility at different horizons is strong or weak. Equation (7) suggests a simple measure s_h of the strength of predictability of return volatility at a particular horizon h by summing up the values of the coefficients α_i from the lagged n_t^2's considered in the regression, i.e.

$$s_h = \sum_{i=1}^{d} \alpha_i \ . \qquad (9)$$

This measure is easy interpreted. If predictability of volatility from past returns is strong then the sum of coefficients of the lagged n_t^2's should be large because the lagged n_t^2's should then be highly correlated with current n_t^2's. On the other hand, this sum should be close to zero if volatility is unpredictable at horizon h because past n_t^2's should then not help to predict current n_t^2's which implies coefficients close to zero.[4] Confidence intervals for s_h are very easy to simulate for any sample size and forecasting horizon. Any desired confidence interval at horizon h for a sample of size T can be obtained from the appropriate quantiles of a simulated distribution of s_h, obtained from the coefficients from regressions (7) based on samples of size T of randomly generated squared n_t's where the n_t's are drawn from a standard normal distribution.

4 Simulation Study

The power and the size of the EDF-predictability test at different horizons is investigated in a Monte Carlo experiment and compared with the power and size of the classical ARCH test and the asymptotic version of the runs test proposed in Christofersen and Diebold (2000).[5] Four standard models of daily returns that have been examined in Christoffersen and Diebold are considered. To analyze the power of the tests, a GARCH(1,1)-n process with Gaussian innovations and a GARCH(1,1)-t process with innovations that follow a fat tailed t-distribution with five degrees of freedom are specified for
daily returns.

$$e_t = \sqrt{\sigma_t^2}\, x_t \tag{10a}$$

$$\sigma_t^2 = \gamma + \alpha e_t^2 + \beta \sigma_{t-1}^2 \tag{10b}$$

$$x_t \sim \text{iid } N(0,1), \text{ for GARCH(1,1)-n} \tag{10c}$$

[4] A similar measure of the strength of predictability could also be defined from the ARCH test regression (9) and a measure in the same spirit is developed in Christoffersen and Diebold (2000) for the runs test.

[5] The runs test for the predictability of volatility is based on the theory of interval forecast evaluation (Christoffersen, 1998) and considers a pre specified (symmetric) interval [-c, c] of the unconditional return distribution where c is a multiple of the standard deviation of the unconditional return distribution. In this test an indicator sequence $\{I_t\}$ defined as $I_t = 1$, if $e_t \in [-c, c]$, and $I_t = 0$, otherwise, is examined. Unpredictability of volatility implies an independent indicator sequence. The independence of the indicator sequence is assessed with a runs test that can be derived from combinatorial arguments (Wolfowitz,1943, Feller, 1968). For further details, see Christoffersen an Diebold (2000).

$$x_t \sim \text{iid } t_5, \text{ for GARCH(1,1)-t} \quad (10d)$$

In the simulations the same parameters (α = 0.06 and β = 0.93) as in Christoffersen and Diebold are used. These parameters generate a highly persistent volatility dynamics of daily returns ($\alpha + \beta = 0.99$) with non trivial volatility persistence at longer horizons.[6] To asses the size of the test statistics the processes $x_t \sim$ iid N(0,1) and $x_t \sim$ iid t_5 with zero mean and constant volatility are simulated.

The experiments are carried out as follows. First, 10,000 observations of logarithmic daily returns (which is close to the number of available daily observations of the DAX in the empirical analysis) are generated with each process. Then the daily returns are aggregated to nonoverlapping h-day returns, h = 1,…,45. On each aggregated return series the runs-, EDF-predictability-, and ARCH tests are carried out assuming a 5% significance level. For the runs test a fixed +/- 1σ_h interval, where σ_h denotes the estimated unconditional standard deviation at horizon h, is assumed. In the ARCH- and EDF-predictability tests 10 lags of the squared returns and squared n-transformed returns are considered at each horizon, respectively. This procedure is repeated 10,000 times. Figure 1 and Figure 2 show the estimated power of the tests for the GARCH-n and the GARCH-t model.

INSERT FIGURES 1 AND 2 ABOUT HERE

As to be expected, the power of the three tests decreases with horizon due to the diminishing persistence in volatility at longer horizons and the declining number of observations involved in the test procedures. The power of all tests is quite high for short horizons and still acceptable at longer horizons. However, figures 1 and 2 show that for both GARCH models the power of the runs test is lower then the power of the other tests at horizons between 10 to

---

[6] The theoretical persistence in variance for the GARCH(1,1) process, computed with the aggregation formulars in Drost and Nijman (1993) assuming a kurtosis of 3 for x_t , after 45 trading days is still $\alpha + \beta$ =0.636.

30 days.[7] The ARCH test and the EDF-predictability test have virtually the same power to detect volatility predictability in the GARCH-n model. Note that for the GARCH-t model the power of the EDF-predictability test clearly exceeds the power of the ARCH test and the runs test at all but the shortest horizons. Hence, the EDF-predictability test appears to be more powerful then the other two tests at all but the shortest horizons for data that are characterized by fat-tailed conditional distributions, the latter being rather the norm than the exception for many financial return series.

The estimated size of the test statistics for aggregated returns from the homoskedastic processes $x_t \sim$ iid N(0,1) and $x_t \sim$ iid t_5, based on 10,000 simulations and computed at a significance level of 5%, are displayed in figures 3 and 4.

INSERT FIGURES 3 AND 4 ABOUT HERE

In the case of the iid N(0,1) process the size of the ARCH test and the EDF-predictability test is virtually identical and in general quite close to the theoretical level of 5% with a slight downward trend in size with growing horizon. The size of the runs test appears to be correct only at very short horizons and compared to the size of the other test the size of the runs test decreases much more at longer horizons. The size patterns are somewhat different for the simulated iid t_5 process. The size of the EDF-predictability test is again invariably very close to the theoretical level at all investigated horizons (albeit a slight downward trend is again visible). The same is true for the size of the ARCH test at horizons beyond 10 to 15 trading days. At shorter horizons the estimated rejection rates for the ARCH test tend to be somewhat too conservative. The size pattern of the runs test for the iid t_5 model again displays significant size distortions at longer forecasting horizons.

[7] The results for the runs-test are quite similar to the simulation results for the exact version of the runs test investigated in Christoffersen and Diebold (2000) over a period of 20 trading days for the same parameters in the GARCH(1,1)-n and GARCH(1,1)-t models.

5 Empirical Analysis of Volatility Predictability of DAX returns

This section reports the results from the three model-free tests about the predictability of the return volatility of the German stock market index DAX for forecasting horizons ranging from 1 to 45 trading days. Daily values of the index starting at 12/31/1964 and ending at 09/05/2001, obtained from Datastream, are used to calculate daily logarithmic returns which results in a sample of 9484 observations. The daily returns are then used to compute nonoverlapping h-day returns for h = 1,…, 45 trading days. Since the focus of this study is on conditional volatility, possible predictability in the conditional mean is removed by first estimating a sixth order autoregression for each of the 45 return series. The residuals resulting from these regressions are then called centered returns, or simply returns, and are used to assess predictability. To verify whether the procedure has successfully removed predictability in mean the correlograms of the individual centered return series are examined. The correlograms indicate no sign of autocorrelation. To gain some information about the distributional properties of the nonoverlapping return series at different horizons the skewness- and kurtosis coefficients of the return distributions are computed. The results of these calculations are displayed in figure 5 and 6. It is easy to see that the return distributions are negatively skewed and fat-tailed at all horizons.[8]

INSERT FIGURES 5 AND 6 ABOUT HERE

Let us now turn to the results about the predictability of volatility. Figure 7 displays the p-values resulting from the runs test. It also contains lines that indicate 5% and 10% significance levels.

INSERT FIGURE 7 ABOUT HERE

The p-values are quite low for horizons of up to 14 trading days suggesting that the volatility of the DAX is forecastable within this horizon. The pattern of the p-values is quite erratic for

[8] Statistical tests (not reported but available upon request) reveal that the skewness coefficients are virtually always significantly different from 0 at conventional significance levels and that the kurtosis coefficients are always strongly significantly different from 3.

horizons from 15 to 34 trading days, however. High p-values-, rejecting predictability-, are frequently followed by p-values below conventional significance levels of 5% and 10%, again suggesting predictability. Given the erratic behavior of the p-values for horizons beyond 14 trading days, the evidence from the runs test does not lead to a clear conclusion as to whether volatility is predictable or not at these longer horizons. Beyond 34 trading days the p-values from the runs test never hit the conventional significance levels, however. Hence, it seems somewhat safer to conclude that volatility is unlikely to be predictable at horizons longer than 35 to 40 trading days. The results from the ARCH test summarized in Figure 8 are qualitatively similar to the findings obtained with the runs test and lead to the same conclusions.

INSERT FIGURE 8 ABOUT HERE

A much clearer picture emerges from figure 7, where the p-values from the EDF-predictability tests are plotted against the number of trading days. For horizons shorter then 25 trading days the p-values never cross the 5% line and for horizons between 25 and 35 trading days the p-values are only three times slightly above the 10% level of significance and well below the 20% level. Thus, in contrast to the runs- and ARCH tests, the EDF-predictability test provides much stronger evidence for predictability of volatility for holding periods of up to 34 trading days. At horizons larger than 34 trading days the p-values stay above the 10% line pointing towards potential unpredictability of volatility.

INSERT FIGURE 9 ABOUT HERE

It is interesting that the p-values of the runs- and ARCH tests behave quite erratic for horizons between 15-35 days whereas the p-values of the EDF-predictability test do not. Possible explanations are lower power of both tests and additionally in the case of the classical ARCH test the sensitivity of the test against violations of the normal distribution assumption. To gain some insights into these issues the p-values for the period from 15-35 trading days obtained from the different tests are regressed on the corresponding skewness-and kurtosis coefficients of the return distributions. If a test is robust against skewed and/or fat-tailed data then one would expect that the skewness- and kurtosis coefficients do not help to explain the p-values of the test statistic. Table 1 shows the results from the regressions.

INSERT TABLE 1 ABOUT HERE

The estimated regression coefficients for skewness and kurtosis are clearly statistically insignificant in the case of the EDF-predictability test and the runs test and both variables have no explanatory power as indicated by the low R^2's. This finding supports the conjecture that low power might be a possible explanation for the erratic behavior of the runs test. Things are different for the ARCH test. The coefficient for skewness is negative and significant at the 5% level implying that the p-values tend to rise with more negative skewness. Moreover, the rather high R^2 of 0.62 (the adjusted R^2 is 0.58) indicates that the results from the classical ARCH test are driven by violations of the symmetry of the return distributions to a substantial degree.[9]

Let us finally discuss the results about the strength of the predictability of return volatility. Figure 10 contains the sums of the estimated coefficients s_h for the forecasting horizons of h = 1,…,45 trading days, obtained from the EDF-predictability test regressions based on 10 lags of squared transformed returns. The figure also shows simulated 95%- and 90% confidence intervals (10,000 simulations) for unpredictability based on the exact number of available nonoverlapping returns for the corresponding forecasting horizons with the method described in section 3.3.

INSERT FIGURE 10 ABOUT HERE

The pattern of s_h indicates that the degree of predictability of the return volatility of the DAX decreases rather slowly with horizon. As expected, predictability appears to be quite strong at short horizons, more interestingly, the moderate decline in the strength of predictability

[9] This finding is consistent with the Monte Carlo evidence provided in Gregory (1989). He finds that the ARCH test is fairly robust against leptokurtic error distributions but sensitive to departures from symmetry of the error distribution.

suggests that the predictability of volatility is not weak on average for much longer forecasting horizons such as 25 to 35 days. Beyond 38 trading days volatility predictability seems to diminish significantly.

6 Conclusions

This paper introduced a model-free test procedure that avoids joint assessments of predictability and assumed forecasting models to examine two questions of vital importance in finance. Is the volatility of financial returns predictable for forecasting horizons beyond a few trading days? If yes, to what a degree is it predictable? The model-free test procedure makes it possible to assess predictability of volatility without postulating any particular volatility model. A simple measure of the strength of volatility predictability was also defined. In a simulation experiment the new test, named the EDF-predictability test, was compared with two alternative model-free test procedures, namely the classical ARCH test and a runs test. The results point towards better statistical properties of the EDF-predictability test (more power, more accurate size) if the conditional distributions of the data are fat-tailed. It was also shown that the classical ARCH test arises as a special case in the density forecast evaluation framework underlying the EDF-predictability test if one assumes unconditionally normally distributed density forecasts.

The three tests where then applied to nonoverlapping centered returns of the DAX for horizons from 1 to 45 trading days. The empirical results about the predictability of the DAX return volatility from the runs- and ARCH tests are qualitatively similar and suggest that the volatility of the DAX returns is at least predictable for forecasting horizons below 15 to 17 trading days. Both tests provide no clear answer for horizons between 15 to 35 days, however. Predictability is sometimes rejected and sometimes not. A simple regression analysis suggests that lower power in the case of the runs test and a combination of lower power and sensitivity to departures from normality in the case of the ARCH test might be responsible for these results. In contrast, the evidence from the EDF-predictability test strongly suggests that the volatility of DAX returns is predictable from past returns for horizons of up to 35 trading days and the proposed measure of the strength of predictability indicates that the degree of predictability of the DAX return volatility decreases rather slowly, implying some predictability even at horizons of 30 to 35 trading days. From the practitioners point of view, the findings suggest that better forecasts of the DAX return volatility than estimates of the unconditional standard deviation can potentially be made for holding periods beyond two or three weeks.

An obvious extension to this study would be to apply the EDF-predictability test to other financial series to gain a more comprehensive body of empirical evidence concerning the predictability of return volatility as well as it's strength at longer horizons. It might also be interesting to compare longer horizon volatility forecasts from more sophisticated forecasting models with simple unconditional volatility forecasts using alternative statistical and economic metrics. Finally, the EDF-predictability test could also be used as a diagnostic test for ARCH effects in time series data. It might therefore be interesting to explore the usefulness of the EDF-prdictability test under non standard distributions of the error terms and different volatility processes along the lines of Van Dijk, Fransens and Lucas (1999) and Peguin-Feissolle (1999). These are issues for future research.

References

Annaert, J., De Ceuster, M. J.K. & Valckx, N. (2001). Financial Market Volatility : Informative in Predicting Recessions. Bank of Finland Discussion Paper No. 14.

Berkowitz, J. (2000). Testing Density Forecasts, with Applications to Risk Management. Working Paper, University of California, Irvine (forthcoming in the Journal of Business and Economic Statistics).

Bollerslev, T., Chou, R. Y. & Kroner, K. F. (1992). ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence. Journal of Econometrics, 52, 5-60.

Bollerslev T., Engle, R. F. & Nelson, D. B. (1994). ARCH Models. In Handbook of Econometrics, Volume 4, Engle R. F. and McFadden D. L. eds.

Brailsford, T. J. & Faff, R. W. (1996). An Evaluation of Volatility Forecasting Techniques. Journal of Banking and Finance, 20, 419-438.

Campbell, J. Y., Lo, A. W. & McKinlay, A. C. (1997). The Econometrics of Financial Markets. Princeton. Princeton University Press

Clements, M. P. & Hendry, D. F. (1998). Forecasting Economic Time Series. Cambridge. Cambridge University Press.

Clements, M. P., & Smith, J. (2000). Evaluating the Forecast Densities of Linear and Non-linear Models: Applications to Output Growth and Unimployment. Journal of Forecasting, 19, 255-276.

Chorafas, D. N. (1998). The Market Risk Amendment: Understanding the Marking-to-Model and Value-at-Risk.McGraw-Hill: New York, Chicago, etc.

Christoffersen, P. F. (1998). Evaluating Interval Forecasts. International Economic Review, 39, 841-862.

Christoffersen, P. F. & Diebold, F. X. (2000). How Relevant is Volatility Forecasting for Financial Risk Management. The Review of Economics and Statistics, 82(1), 12-22.

Crnkovic, C., & Drachman, J. (1997). Quality Control. In VaR: Understanding and Applying Value-at-Risk. London: Risk Publications.

Diebold, F. X., Gunther, T. A., & Tay, A. S. (1998). Evaluating Density Forecasts, with Applications to Financial Risk Management. International Economic Review, 39, 863-883.

Drost, F. & Nijman, T. (1993). Temporal Aggregation of GARCH processes. Econometrica, 61, 909-927.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasicity with Estimates of the Variance of United Kingdom Inflation. Econometrica, 50(4), 987-1007.

Figlewski, S. (1997). Forecasting Volatility. Financial markets, Institutions and Instruments. Monograph. New York University Salomon Center.

Frühwirth-Schnatter, S. (1996). Recursive residuals and model diagnostics for normal and non-normal state space models. Environmental and Ecological Statistics, 3, 291-309.

Gourieroux, C. & Jasiak, J. (2001). Financial Econometrics. Princeton University Press. Princeton and Oxford.

Gregory, A. W. (1989). A Nonparametric Test for Autoregressive Conditional Heteroscedasticity: A Markov-Chain Approach. Journal of Business and Economic Statistics, 7(1), 107-115.

Mills, T. C. (1999). The Econometric Modelling of Financial Time Series. 2nd Edition. Cambridge University Press.

Pagan, A. R. & Schwert, W. G. (1990). Alternative Models for Conditional Volatility. Journal of Econometrics, 45, 267-290.

Peguin-Feissolle, A. (1999). A Comparison of the Power of some Tests for Conditional Heteroscedasticity. Economics Letters, 63, 5-17.

Poon, S.H. & Granger, C. (2001). Forecasting Financial Market Volatility. Working Paper.

Rosenblatt, M. (1952). Remarks on a Multivariate Transformation. Annals of Mathematical Statistics, 23, 470-472.

Feller, W. (1968). An Introduction to Probability Theory and its Applications. New York, etc., John Wiley & Sons.

Tay, A. S. & Wallis, K. F. (2000). Density forecasting: A Survey. Journal of Forecasting, 19 (4), 235-254.

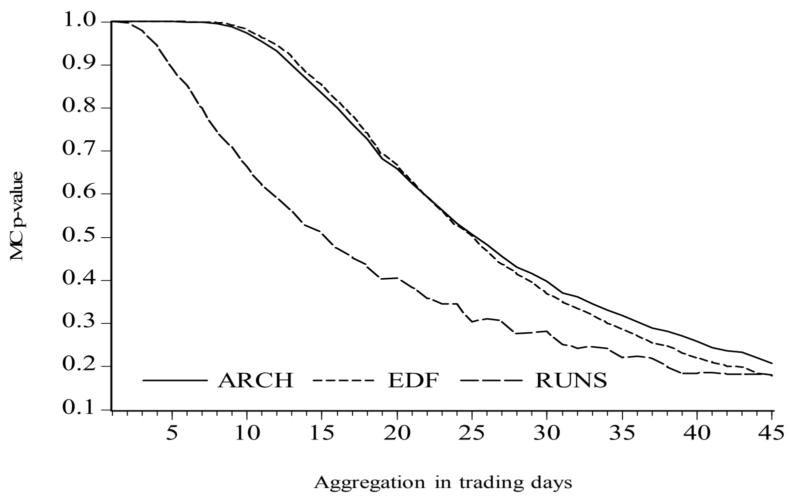
Van Dijk, D., Fransens, P. H. & Lucas, A. (1999). Testing for ARCH in the Presence of Additive Outliers. Journal of Applied Econometrics, 14, 539-562.

West. K. D. & Cho, D. (1995). The Predictive Ability of Several Models of Exchange Rate Volatility. . Journal of Econometrics, 69, 367-391

Wolfowitz, J. (1943). On the Theory of Runs with some Applications to Quality Control. Annals of Mathematical Statistics, 14, 280-288.

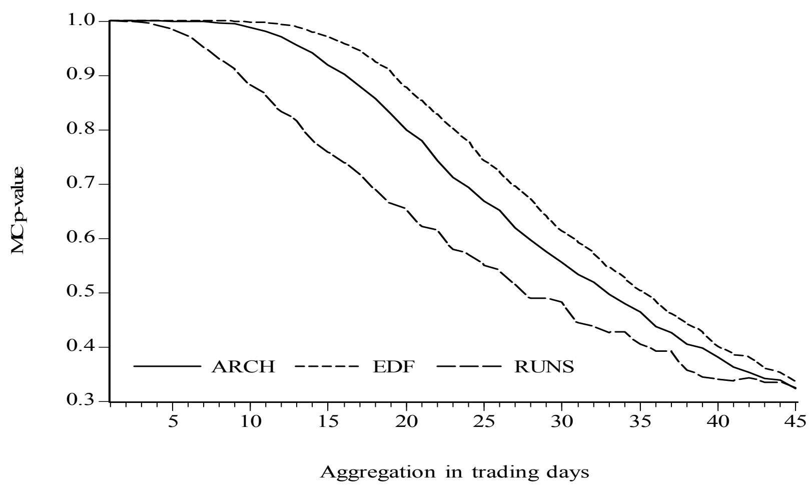
Figures

Figure 1: Power of runs-, EDF-predictability- and ARCH tests, GARCH(1,1)-n model.



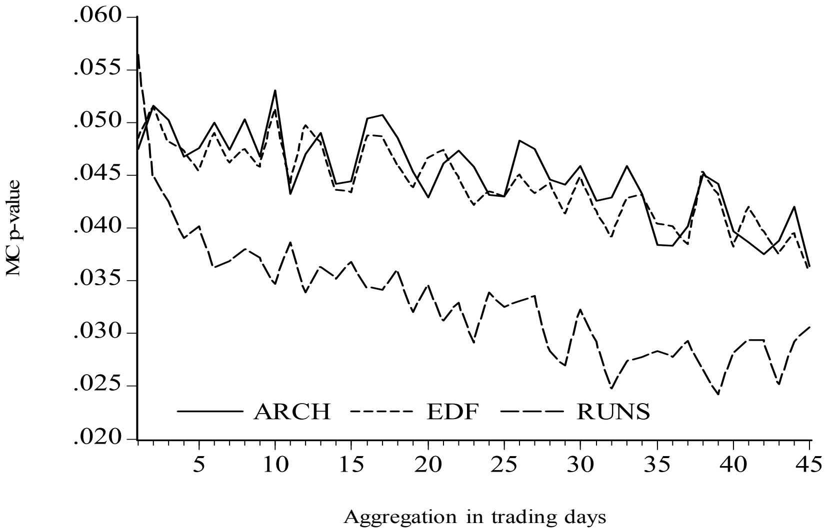
The graph shows rejection rates (MC p-value) of the null hypothesis of unpredictability of volatility with significance level of 5% based on 10,000 replications. In the runs test the interval defining the indicator sequence is +/- $2\sigma_h$, where σ_h denotes the estimated unconditional standard deviation at horizon h. In the EDF-predictability- and ARCH tests the first 10 lags of the dependent variable are used as regressors. For further details, see text.

Figure 2: Power of runs-, EDF-predictability- and ARCH tests, GARCH(1,1)-t model.



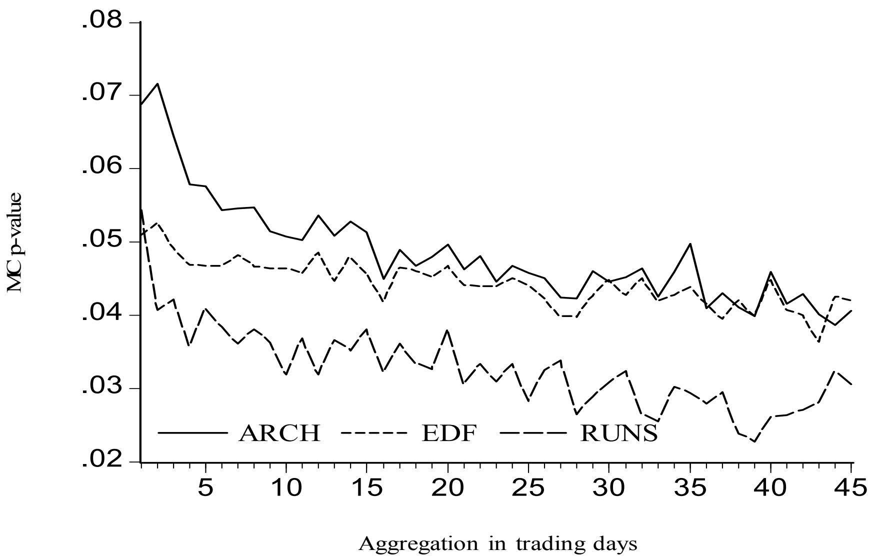
The graph shows rejection rates (MC p-value) of the null hypothesis of unpredictability of volatility with significance level of 5% based on 10,000 replications. In the runs test the interval defining the indicator sequence is +/- $2\sigma_h$, where σ_h denotes the estimated unconditional standard deviation at horizon h. In the EDF-predictability- and ARCH tests the first 10 lags of the dependent variable are used as regressors. For further details, see text.

Figure 3: Size of runs-, EDF-predictability- and ARCH tests, iid N(0,1) model.



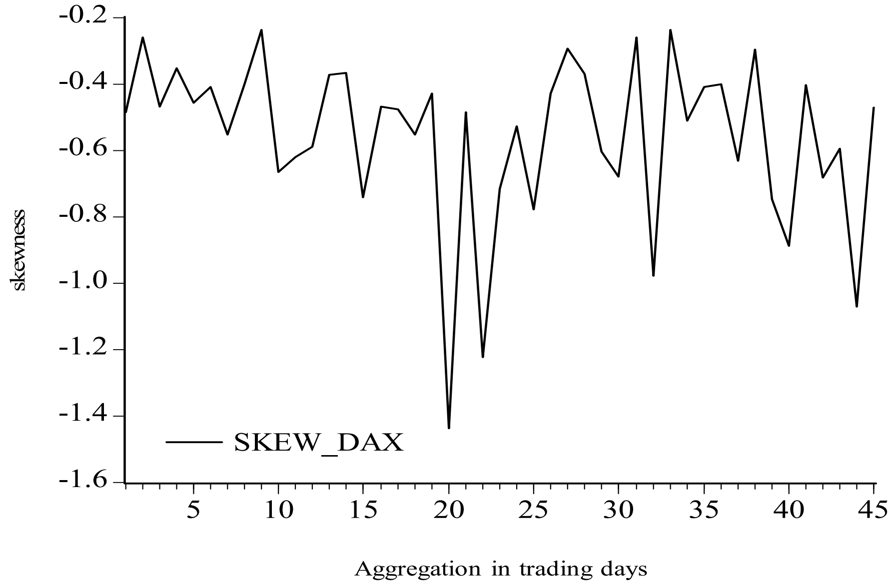
The graph shows rejection rates (MC p-values) of the null hypothesis of unpredictability of volatility with significance level of 5% based on 10,000 replications. In the runs test the interval defining the indicator sequence is +/- $2\sigma_h$, where σ_h denotes the estimated unconditional standard deviation at horizon h. In the EDF-predictability- and ARCH tests the first 10 lags of the dependent variable are used as regressors. For further details, see text.

Figure 4: Size of runs-, EDF-predictability- and ARCH tests, iid t_5 model.



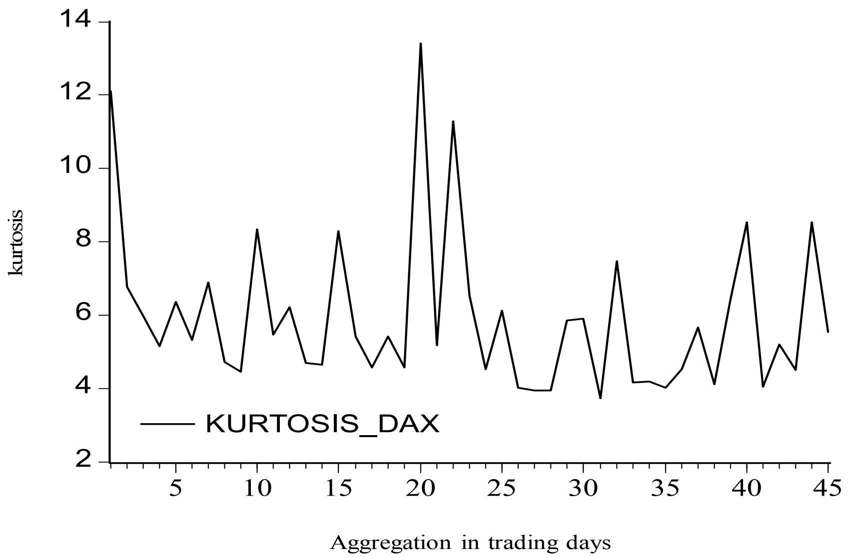
The graph shows rejection rates (MC p-value) of the null hypothesis of unpredictability of volatility with significance level of 5% based on 10,000 replications. In the runs test the interval defining the indicator sequence is +/- $2\sigma_h$, where σ_h denotes the estimated unconditional standard deviation at horizon h. In the EDF-predictability- and ARCH tests the first 10 lags of the dependent variable are used as regressors. For further details, see text.

Figure 5: Skewness coefficients of centered DAX return series



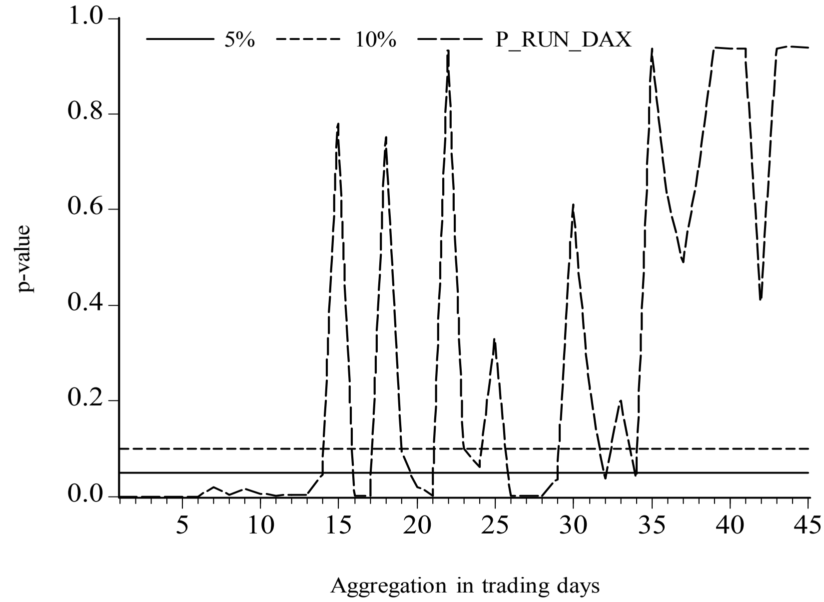
Skewness is defined by $SK = m_3/m_2^{3/2}$, where $m_j = n^{-1}\Sigma_n e^j$ and n is the number of effective observations.

Figure 6: Kurtosis of centred DAX returns



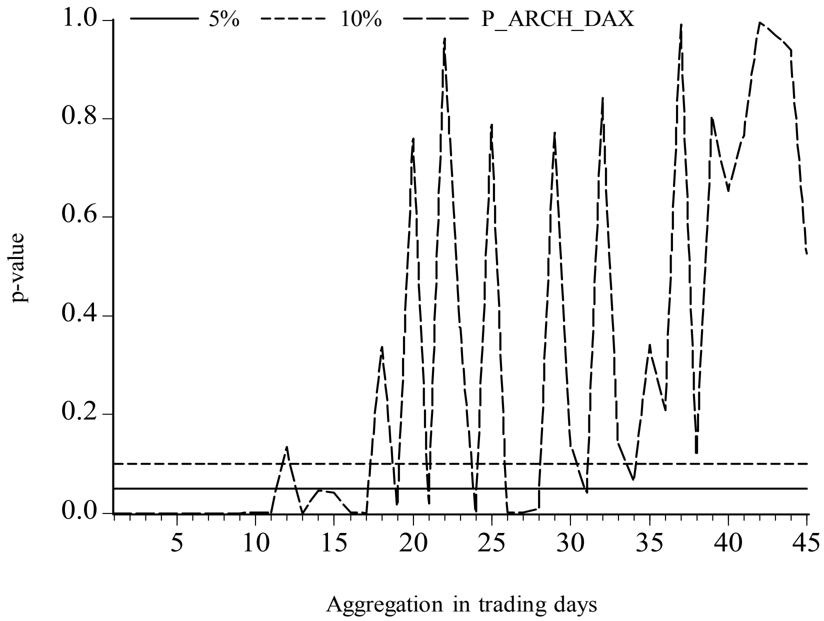
Kurtosis is defined by $K = m_4/m_2^2$, where $m_j = n^{-1}\Sigma_n e^j$ and n is the number of effective observations.

Figure 7: P-values from runs tests of volatility predictability of centred DAX return series.



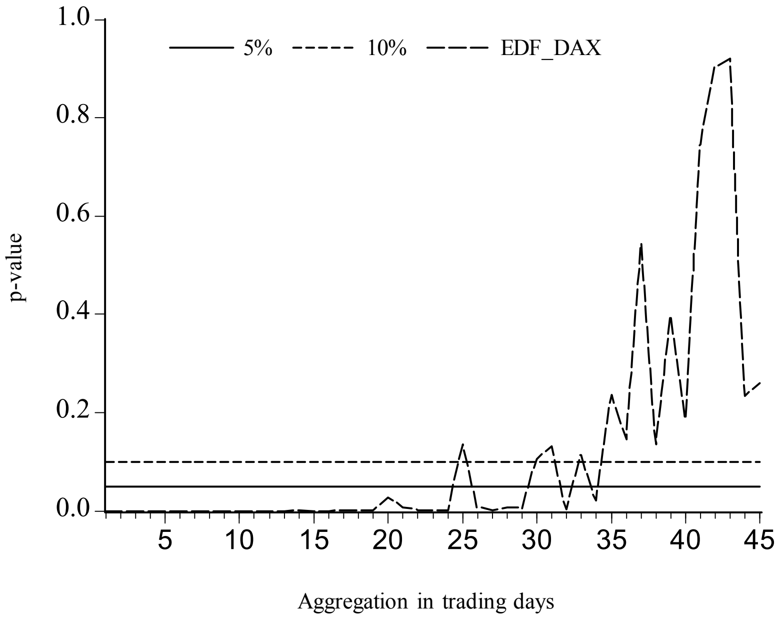
In the runs test the interval defining the indicator sequence is +/- $1\sigma_h$, where σ_h denotes the estimated unconditional standard deviation at horizon h.

Figure 8: P-values from ARCH tests of volatility predictability of centred DAX return series.



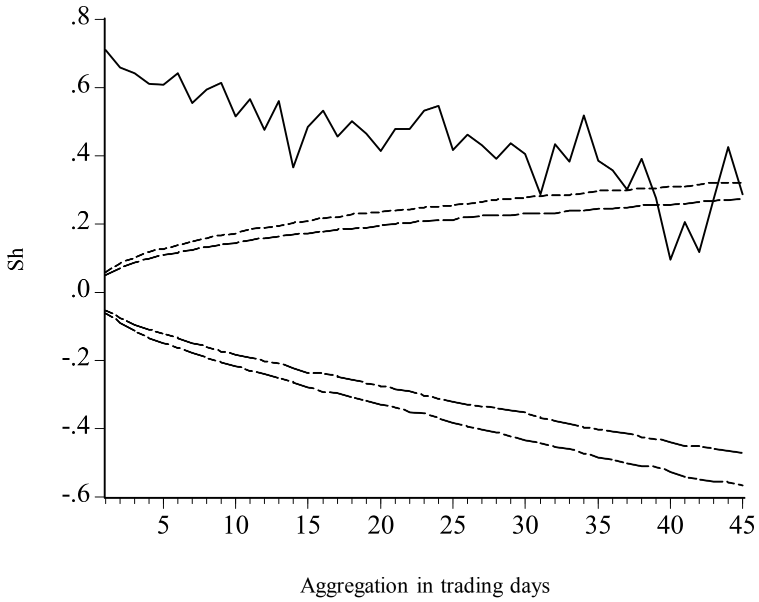
In the ARCH tests the first 10 lags of the dependent variable are used as regressors. For further details, see text.

Figure 9: P-values from EDF-predictability tests of volatility predictability of centred DAX return series.



In the EDF-predictability tests the first 10 lags of the dependent variable are used as regressors. For further details, see text.

Figure 10: Strength of predictability of volatility of centered DAX return series



The Figure shows the sum of estimated coefficients (Sh) from equation (8) assuming 10 lags together with simulated 95%- and 90% confidence intervals (10,000 simulations) of unpredictability. For further details, see text.

Table 1: Regression of p-values from predictability tests for 15-35 trading days on skewness- and kurtosis measures.

No. of observations: 21

dependent variable	regression coefficients			
	intercept	skewness	kurtosis	R^2
p-EDF-pred.	0.072 (0.091)	-0.013 (0.941)	-0.010 (0.736)	0.046
p-runs	0.022 (0.917)	0.322 (0.711)	0.072 (0.500)	0.073
p-ARCH	-0.164 (0.230)	-1.472 (0.017)	-0.077 (0.269)	0.620

Notes: p-values of t statistics in brackets below coefficients.

Index of Working Papers:

August 28, 1990	Pauer Franz	1 [1)]	Hat Böhm-Bawerk Recht gehabt? Zum Zusammenhang zwischen Handelsbilanzpassivum und Budgetdefizit in den USA [2)]
March 20, 1991	Backé Peter	2 [1)]	Ost- und Mitteleuropa auf dem Weg zur Marktwirtschaft - Anpassungskrise 1990
March 14, 1991	Pauer Franz	3 [1)]	Die Wirtschaft Österreichs im Vergleich zu den EG-Staaten - eine makroökonomische Analyse für die 80er Jahre
May 28, 1991	Mauler Kurt	4 [1)]	The Soviet Banking Reform
July 16, 1991	Pauer Franz	5 [1)]	Die Auswirkungen der Finanzmarkt- und Kapitalverkehrsliberalisierung auf die Wirtschaftsentwicklung und Wirtschaftspolitik in Norwegen, Schweden, Finnland und Großbritannien - mögliche Konsequenzen für Österreich [3)]
August 1, 1991	Backé Peter	6 [1)]	Zwei Jahre G-24-Prozess: Bestandsaufnahme und Perspektiven unter besonderer Berücksichtigung makroökonomischer Unterstützungsleistungen [4)]
August 8, 1991	Holzmann Robert	7 [1)]	Die Finanzoperationen der öffentlichen Haushalte der Reformländer CSFR, Polen und Ungarn: Eine erste quantitative Analyse
January 27, 1992	Pauer Franz	8 [1)]	Erfüllung der Konvergenzkriterien durch die EG-Staaten und die EG-Mitgliedswerber Schweden und Österreich [5)]
October 12, 1992	Hochreiter Eduard (Editor)	9 [1)]	Alternative Strategies For Overcoming the Current Output Decline of Economies in Transition
November 10, 1992	Hochreiter Eduard and Winckler Georg	10 [1)]	Signaling a Hard Currency Strategy: The Case of Austria

1) vergriffen (out of print)
2) In abgeänderter Form erschienen in Berichte und Studien Nr. 4/1990, S 74 ff
3) In abgeänderter Form erschienen in Berichte und Studien Nr. 4/1991, S 44 ff
4) In abgeänderter Form erschienen in Berichte und Studien Nr. 3/1991, S 39 ff
5) In abgeänderter Form erschienen in Berichte und Studien Nr. 1/1992, S 54 ff

March 12, 1993	Hochreiter Eduard (Editor)	11	The Impact of the Opening-up of the East on the Austrian Economy - A First Quantitative Assessment
June 8, 1993	Anulova Guzel	12	The Scope for Regional Autonomy in Russia
July 14, 1993	Mundell Robert	13	EMU and the International Monetary System: A Transatlantic Perspective
November 29, 1993	Hochreiter Eduard	14	Austria's Role as a Bridgehead Between East and West
March 8, 1994	Hochreiter Eduard (Editor)	15	Prospects for Growth in Eastern Europe
June 8, 1994	Mader Richard	16	A Survey of the Austrian Capital Market
September 1, 1994	Andersen Palle and Dittus Peter	17	Trade and Employment: Can We Afford Better Market Access for Eastern Europe?
November 21, 1994	Rautava Jouko	18[1)]	Interdependence of Politics and Economic Development: Financial Stabilization in Russia
January 30, 1995	Hochreiter Eduard (Editor)	19	Austrian Exchange Rate Policy and European Monetary Integration - Selected Issues
October 3, 1995	Groeneveld Hans	20	Monetary Spill-over Effects in the ERM: The Case of Austria, a Former Shadow Member
December 6, 1995	Frydman Roman et al	21	Investing in Insider-dominated Firms: A Study of Voucher Privatization Funds in Russia
March 5, 1996	Wissels Rutger	22	Recovery in Eastern Europe: Pessimism Confounded ?
June 25, 1996	Pauer Franz	23	Will Asymmetric Shocks Pose a Serious Problem in EMU?
September 19, 1997	Koch Elmar B.	24	Exchange Rates and Monetary Policy in Central Europe - a Survey of Some Issues
April 15, 1998	Weber Axel A.	25	Sources of Currency Crises: An Empirical Analysis

May 28,1998	Brandner Peter, Diebalek Leopold and Schuberth Helene	26	Structural Budget Deficits and Sustainability of Fiscal Positions in the European Union
June 15, 1998	Canzeroni Matthew, Cumby Robert, Diba Behzad and Eudey Gwen	27	Trends in European Productivity: Implications for Real Exchange Rates, Real Interest Rates and Inflation Differentials
June 20, 1998	MacDonald Ronald	28	What Do We Really Know About Real Exchange Rates?
June 30, 1998	Campa José and Wolf Holger	29	Goods Arbitrage and Real Exchange Rate Stationarity
July 3,1998	Papell David H.	30	The Great Appreciation, the Great Depreciation, and the Purchasing Power Parity Hypothesis
July 20,1998	Chinn Menzie David	31	The Usual Suspects? Productivity and Demand Shocks and Asia-Pacific Real Exchange Rates
July 30,1998	Cecchetti Stephen G., Mark Nelson C., Sonora Robert	32	Price Level Convergence Among United States Cities: Lessons for the European Central Bank
September 30, 1998	Christine Gartner, Gert Wehinger	33	Core Inflation in Selected European Union Countries
November 5, 1998	José Viñals and Juan F. Jimeno	34	The Impact of EMU on European Unemployment
December 11, 1998	Helene Schuberth and Gert Wehinger	35	Room for Manoeuvre of Economic Policy in the EU Countries – Are there Costs of Joining EMU?
December 21, 1998	Dennis C. Mueller and Burkhard Raunig	36	Heterogeneities within Industries and Structure-Performance Models
May 21, 1999	Alois Geyer and Richard Mader	37	Estimation of the Term Structure of Interest Rates – A Parametric Approach
July 29, 1999	José Viñals and Javier Vallés	38	On the Real Effects of Monetary Policy: A Central Banker´s View
December 20, 1999	John R. Freeman, Jude C. Hays and Helmut Stix	39	Democracy and Markets: The Case of Exchange Rates

March 01, 2000	Eduard Hochreiter and Tadeusz Kowalski	40	Central Banks in European Emerging Market Economies in the 1990s
March 20, 2000	Katrin Wesche	41	Is there a Credit Channel in Austria? The Impact of Monetary Policy on Firms' Investment Decisions
June 20, 2000	Jarko Fidrmuc and Jan Fidrmuc	42	Integration, Disintegration and Trade in Europe: Evolution of Trade Relations During the 1990s
March 06, 2001	Marc Flandreau	43	The Bank, the States, and the Market, A Austro-Hungarian Tale for Euroland, 1867-1914
May 01, 2001	Otmar Issing	44	The Euro Area and the Single Monetary Policy
May 18, 2001	Sylvia Kaufmann	45	Is there an asymmetric effect of monetary policy over time? A Bayesian analysis using Austrian data.
May 31, 2001	Paul De Grauwe and Marianna Grimaldi	46	Exchange Rates, Prices and Money. A Long Run Perspective
June 25, 2001	Vítor Gaspar, Gabriel Perez-Quiros and Jorge Sicilia	47	The ECB Monetary Strategy and the Money Market
July 27, 2001	David T. Llewellyn	48	A *Regulatory Regime* For Financial Stability
August 24, 2001	Helmut Elsinger and Martin Summer	49	Arbitrage Arbitrage and Optimal Portfolio Choice with Financial Constraints
September 1, 2001	Michael D. Goldberg and Roman Frydman	50	Macroeconomic Fundamentals and the DM/$ Exchange Rate: Temporal Instability and the Monetary Model
September 8, 2001	Vittorio Corbo, Oscar Landerretche and Klaus Schmidt-Hebbel	51	Assessing Inflation Targeting after a Decade of World Experience
September 25, 2001	Kenneth N. Kuttner and Adam S. Posen	52	Beyond Bipolar: A Three-Dimensional Assessment of Monetary Frameworks

October 1, 2001	Luca Dedola and Sylvain Leduc	53	Why Is the Business-Cycle Behavior of Fundamentals Alike Across Exchange-Rate Regimes?
October 10, 2001	Tommaso Monacelli	54	New International Monetary Arrangements and the Exchange Rate
December 3, 2001	Peter Brandner, Harald Grech and Helmut Stix	55	The Effectiveness of Central Bank Intervention in the EMS: The Post 1993 Experience
January 2, 2002	Sylvia Kaufmann	56	Asymmetries in Bank Lending Behaviour. Austria During the 1990s
January 7, 2002	Martin Summer	57	Banking Regulation and Systemic Risk
January 28, 2002	Maria Valderrama	58	Credit Channel and Investment Behavior in Austria: A Micro-Econometric Approach
February 18, 2002	Gabriela de Raaij and Burkhard Raunig	59	Evaluating Density Forecasts with an Application to Stock Market Returns
February 25, 2002	Ben R. Craig and Joachim G. Keller	60	The Empirical Performance of Option Based Densities of Foreign Exchange
February 28, 2002	Peter Backé, Jarko Fidrmuc, Thomas Reininger and Franz Schardax	61	Price Dynamics in Central and Eastern European EU Accession Countries
April 8, 2002	Jesús Crespo-Cuaresma, Maria Antoinette Dimitz and Doris Ritzberger-Grünwald	62	Growth, Convergence and EU Membership
May 29, 2002	Markus Knell	63	Wage Formation in Open Economies and the Role of Monetary and Wage-Setting Institutions
June 19, 2002	Sylvester C.W. Eijffinger (comments by: José Luis Malo de Molina and by Franz Seitz)	64	The Federal Design of a Central Bank in a Monetary Union: The Case of the European System of Central Banks

July 1, 2002	Sebastian Edwards and I. Igal Magendzo (comments by Luis Adalberto Aquino Cardona and by Hans Genberg)	65	Dollarization and Economic Performance: What Do We Really Know?
July 10, 2002	David Begg (comment by Peter Bofinger)	66	Growth, Integration, and Macroeconomic Policy Design: Some Lessons for Latin America
July 15, 2002	Andrew Berg, Eduardo Borensztein, and Paolo Mauro (comment by Sven Arndt)	67	An Evaluation of Monetary Regime Options for Latin America
July 22, 2002	Eduard Hochreiter, Klaus Schmidt-Hebbel and Georg Winckler (comments by Lars Jonung and George Tavlas)	68	Monetary Union: European Lessons, Latin American Prospects
July 29, 2002	Michael J. Artis (comment by David Archer)	69	Reflections on the Optimal Currency Area (OCA) criteria in the light of EMU
August 5, 2002	Jürgen von Hagen, Susanne Mundschenk (comments by Thorsten Polleit, Gernot Doppelhofer and Roland Vaubel)	70	Fiscal and Monetary Policy Coordination in EMU
August 12, 2002	Dimitri Boreiko (comment by Ryszard Kokoszczyński)	71	EMU and Accession Countries: Fuzzy Cluster Analysis of Membership
August 19, 2002	Ansgar Belke and Daniel Gros (comments by Luís de Campos e Cunha, Nuno Alves and Eduardo Levy-Yeyati)	72	Monetary Integration in the Southern Cone: Mercosur Is Not Like the EU?
August 26, 2002	Friedrich Fritzer, Gabriel Moser and Johann Scharler	73	Forecasting Austrian HICP and its Components using VAR and ARIMA Models

September 30, 2002	Sebastian Edwards	74	The Great Exchange Rate Debate after Argentina
October 3, 2002	George Kopits (comments by Zsolt Darvas and Gerhard Illing)	75	Central European EU Accession and Latin American Integration: Mutual Lessons in Macroeconomic Policy Design
October 10, 2002	Eduard Hochreiter, Anton Korinek and Pierre L. Siklos (comments by Jeannine Bailliu and Thorvaldur Gylfason)	76	The Potential Consequences of Alternative Exchange Rate Regimes: A Study of Three Candidate Regions
October 14, 2002	Peter Brandner, Harald Grech	77	Why Did Central Banks Intervene in the EMS? The Post 1993 Experience
October 21, 2002	Alfred Stiglbauer, Florian Stahl, Rudolf Winter-Ebmer, Josef Zweimüller	78	Job Creation and Job Destruction in a Regulated Labor Market: The Case of Austria
October 28, 2002	Elsinger, Alfred Lehar and Martin Summer	79	Risk Assessment for Banking Systems
November 4, 2002	Helmut Stix	80	Does Central Bank Intervention Influence the Probability of a Speculative Attack? Evidence from the EMS
June 30, 2003	Markus Knell, Helmut Stix	81	How Robust are Money Demand Estimations? A Meta-Analytic Approach
July 7, 2003	Helmut Stix	82	How Do Debit Cards Affect Cash Demand? Survey Data Evidence
July 14, 2003	Sylvia Kaufmann	83	The business cycle of European countries. Bayesian clustering of country-individual IP growth series.
July 21, 2003	Jesus Crespo Cuaresma, Ernest Gnan, Doris Ritzberger-Gruenwald	84	Searching for the Natural Rate of Interest: a Euro-Area Perspective
July 28, 2003	Sylvia Frühwirth-Schnatter, Sylvia Kaufmann	85	Investigating asymmetries in the bank lending channel. An analysis using Austrian banks' balance sheet data

September 22, 2003	Burkhard Raunig	86	Testing for Longer Horizon Predictability of Return Volatility with an Application to the German DAX