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# The Effects of Exchange-Rate Exposures on Equity Asset Markets

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# Abstract

This paper analyzes the relationship between stock returns and exchange rate changes in international markets and examines how well exchange rate volatility explains movements in stock market returns. The model-based predictions are evaluated on several cost functions. Results from such analysis can be used to appraise the need for hedging.
Of the three examined stock indexes, the FTSE was found to be the only robust index, while the S&P 500 and the Nikkei indexes reacted to the dollar/yen exchange rates. The dollar/yen rate also improved risk prediction for the Standard&Poor futures, while the gains in forecasting from using bivariate models remained small otherwise.

## Keywords
Exchange rate futures, index futures, conditional heteroskedasticity, forecasting

## JEL Classifications
C32, C53, G15

**Comments**

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# Contents

# 1 Introduction

Traditionally, investors with international portfolios rely on two approaches to manage their assets. The …rst assumes that the bene…ts from asset diversi…cation in international markets cannot be enhanced by hedging the exchange risk (see Akdogan 1996). Thus, investors are supposed to ignore foreign exchange risk. This argument is also supported by Hauser et al. (1994) who show that the presence of negative correlation between changes in stock and currency prices produces decreased stock variability. The second posits all assets to be hedged completely. This stems from the fact that in an era of ‡oating exchange rates, exchange rate expectations and, hence, exchange risk premiums di¤er across countries.

Although it may be true that currencies eventually return to equilibrium, implying that returns from hedging foreign exchange exposures are slight in the long run, the …rst option has been disproved (at least in the short to medium term) by the impacts on asset prices of the recent currency crises and the fall of the Euro since its inception at the beginning of 1999. The second option can also be very expensive, as the cost of hedging certain currency risk exposures often outweighs the gain in yield.

The stock market plays an important role in the whole process of …nancial intermediation. Particularly, in most industrialized countries, the shattering e¤ect of a market crash on an economy is immense because of the reaction of foreign investors. Furthermore, globalization has a¤ected monetary policy by changing the channel through which interest rates a¤ect demand. Increasingly, changing exchange rate patterns signify changing investor sentiments. Thus, asset return volatility conceived as being induced by changes in exchange rates may imply rebalancing of risks in portfolios. A better understanding as to how well exchange rate volatility explains movements in stock market indexes could be helpful in identifying structural rigidities and ine¢ciencies that discourage smooth arbitrage between di¤erent …nancial markets.

This paper analyses the relationship between stock returns and exchange rate changes in international markets and examines how well exchange rate volatility explains movements in stock market returns. The relationship can be interpreted as the measure of a stock market's exposure to currency movements.

Some recent related studies have used regression analysis based on stock returns to estimate a …rm's exposure to its various uncertainties (see, e.g., Smith et al. 1989; Oxelheim and Wihlborg 1987; and Khoo 1994). We provide empirical evidence on the dynamic effects of the dollar exchange rate (i.e., the Deutschmark-US Dollar (DM/$); the Sterling-US Dollar (£/$); and the Yen-US Dollar (¥/$)) volatility on several stock indexes (DAX, FTSE, Nikkei, and Standard & Poor 500) traded on the corresponding stock exchanges by means of multivariate GARCH models. These are, respectively, the most actively traded and quoted foreign currencies and stock indexes in the world. The model-based predictions are then evaluated on several cost functions. Results from such analysis can be used to appraise the need for hedging.

The plan of the paper is as follows. Section 2 outlines the econometric techniques and provides a description of the data. Section 3 presents and analyzes the results of the time-series model estimation. Section 4 focuses on forecasting experiments. Section 5 concludes.

# 2 Methodology

## 2.1 Bivariate ARCH models

The investigation of autoregressive conditional heteroskedasticity (ARCH) was motivated by the empirical observation of temporal clustering of volatility in financial time series that otherwise follow the theory-based martingale property for prices in efficient markets. The original ARCH model by Engle (1982) makes a Gaussian assumption for the underlying distribution and specifies a lag polynomial for second-order dependence:

$$\varepsilon_t = \xi_t \sqrt{h_t} \quad ; \quad h_t = c + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 \quad ; \quad \xi_t \sim \text{i.i.d. } N(0;1):$$

The GARCH model ('general ARCH') of Bollerslev (1986) generalizes the lag polynomial form to a rational function. The most common GARCH model is GARCH(1,1) with $p = 1$ and one lag of $h_t$ as a further explanatory variable added to the r.h.s. Multivariate extensions are almost exclusively restricted to this specification. In the following, we use a notation similar to Gourieroux (1997). From his work, we also adopt the view that ARCH models are descriptions of the conditional-moments structure of the variables ('weak ARCH') and hence we will not explicitly specify distributional assumptions. This also implies that estimation by Gaussian maximum-likelihood (ML) methods is to be seen as 'quasi–ML'.

For scalar martingale-difference $\varepsilon_t$, the GARCH(1,1) model reads

$$\begin{aligned} E(\varepsilon_t|F_{t-1}) &= 0 \quad ; \\ E(\varepsilon_t^2|F_{t-1}) &= h_t = c + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad . \end{aligned}$$

The filtration $F_t$ is built from information sets that typically are generated by the past of the process $\varepsilon_t$ and hence include the past of $h_t$ if the model is stable. Coefficients are subject to the admissibility restrictions $c > 0; \alpha \geq 0; \beta \geq 0; (\alpha;\beta) \in \{0\} \times (0;\infty)$. The stability conditions are more involved (see Nelson, 1990), and most researchers focus on the case where $\alpha + \beta \leq 1; \beta < 1$, which guarantees the existence of the unconditional second moment $E(\varepsilon_t^2)$ if $\alpha + \beta < 1$ and includes the interesting borderline 'IGARCH' case with $E(|\varepsilon_t|\delta) < \infty$ for $\delta \in (0;2)$ if $\alpha + \beta = 1$.

In principle, an extension of the GARCH(1,1) model to higher dimensions is straightforward, as all scalar coefficients are simply replaced by matrix coefficients

$$\begin{aligned} E(\varepsilon_t|F_{t-1}) &= 0 \quad ; \\ E(\varepsilon_t\varepsilon_t'|F_{t-1}) &= H_t \\ \mathrm{vech}(H_t) &= \mathrm{vech}(C) + \tilde{A}\,\mathrm{vech}(\varepsilon_{t-1}\varepsilon_{t-1}') + \tilde{B}\,\mathrm{vech}(H_{t-1}) \quad ; \qquad (1) \end{aligned}$$

where we use the notation $\varepsilon_t = (\varepsilon_{t1}; \ldots; \varepsilon_{tn})'$ for the vector of white-noise observations. Again, system stability depends on the properties of the $\{n(n+1)/2\} \times \{n(n+1)/2\}$–matrices $\tilde{A}$ and $\tilde{B}$, though such conditions are now becoming increasingly complicated.

The application of such multivariate GARCH models faces two main problems. First, the joint estimation of the matrix coefficients quickly exhausts the degrees of freedom, particularly if the system dimension $n$ becomes large. Second, the imposition of the admissibility conditions during estimation is extremely difficult. Therefore, various restricted models with simplified admissibility conditions have been considered in the literature, see, e.g., Baba et al., Bollerslev (1990), or Holt and Aradhyula (1990).

Alternatively, we will focus on the case of the ARCH(1) model with $\tilde{B} = 0$. This restriction is supported by the fact that, in tentative estimation for our data sets (unreported), the two GARCH parameters $\alpha$ and $\beta$ turned out to be poorly identified even in the univariate models. In the following, we also exclusively consider the case $n = 2$.

We adopt a variant of the block-diagonal design of Gourieroux that allows for heteroskedasticity in conditional covariances and was suggested by Kunst and Saez (1994). Because returns show substantial serial correlation, a first-order MA term is added to the specification for the conditional expectation. In detail, we use the MA-ARCH model

$$\begin{aligned} X_t &= \mu + \varepsilon_t + \Theta \varepsilon_{t-1} \quad , \\ E(\varepsilon_t \varepsilon_t') &= H_t \quad , \\ H_t &= C + L \operatorname{diag}(\varepsilon_{t-1}' A \varepsilon_{t-1}, \varepsilon_{t-1}' B \varepsilon_{t-1}) L' \quad . \end{aligned} \tag{2}$$

The matrix $L$ is a triangular matrix with a unit diagonal. Imposing symmetry and definiteness of the matrices $A, B, C$, the model has 16 parameters: 2 intercepts in $\mu$, 4 entries in the $2 \times 2$–matrix $\Theta$, 1 off-diagonal entry in $L$, and each 3 elements in the positive definite matrices $A, B, C$. The (2,1) element of $L$ will be denoted by $\tau$. It can be viewed as 'rotating' the two factors to the two components and hence we will also refer to it as the 'rotation parameter'.

In order to impose definiteness restrictions in calculation, the matrices $A$, $B$, $C$ are re-parameterized in a Choleski form. For example, $A = L_A' L_A$, where $L_A$ is a lower triangular matrix with a positive diagonal, i.e., $L_A = (\tilde{a}_{11}^2, 0 | \tilde{a}_{12}, \tilde{a}_{22}^2)$. Hence, numerical optimization of the likelihood is conducted for technical parameters $\tilde{a}_{11}, \tilde{a}_{12}, \tilde{a}_{22}, \tilde{b}_{11}, \ldots$, from which estimates of the elements $a_{11}, \ldots$ can be calculated by algebraic transformations.

The system model has its 'normal' form when $L = I$ and $C$ is diagonal. Then, covariances are 0 and the ARCH effects decompose into two independent variates. Another interesting case occurs if, e.g., $B = 0$ and the variation of volatility in both variates is explained by a single factor. The latter case and similar events of degeneration deserve special attention, as they cause non-identifiability of some parameters and, in practice, numerical problems. A third case of special interest is $A = \operatorname{diag}(a_{11}, 0)$, $B = \operatorname{diag}(0, b_{22})$. Then, conditional heteroskedasticity is fully described by squared past errors. Otherwise, more general quadratic forms are needed. A slight generalization of this special case occurs if $A$ or $B$ are singular. If $A$ has rank one, it can be represented as $(a_1, a_2)'(a_1, a_2)$ and conditional variance in the first error is explained by a single lagged 'factor' $(a_1 \varepsilon_{t-1,1} + a_2 \varepsilon_{t-1,2})^2$.

If both $A$ and $B$ have full rank, volatility in the system is described by four different combinations of past errors. It follows that the model can be poorly identified for many parameter values. We have experimented with some general-to-specific backward elimination of insignificant parameters. In most cases, point estimates turned out very similar to those reported for the unrestricted variants. Unfortunately, t–values are usually strongly inflated for these pre-test estimates and can become unreliable for further inference.

## 2.2 Causality

The investigated AR-ARCH models involve dynamic relationships among variables that indicate causal structures in the sense of Granger causation. The concept of Granger causality (Granger 1969) was originally developed in a linear framework. Several extensions to non-linear models have been suggested.

In the original definition, a variable $X$ is defined as causing a variable $Y$ if the linear prediction $P(Y|X_-;Y_-;Z_-)$ differs from the linear prediction $P(Y|Y_-;Z_-)$ that involves only the past of $Y$, denoted by $Y_-$, and the past of some other variables of potential relevance $Z_-$, assuming that $Z$ does not contain $X$. In some non-linear models, linear prediction and optimum prediction differ and it may well be that $X$ does not cause $Y$ in the linear Granger sense whereas there may be causation if the linear prediction operator $P(.|.)$ is replaced by conditional expectation $E(.|.)$. This is a non-linear extension that was suggested by some authors, see also Granger (1988). The most general and obvious extension would be to replace prediction and expectation by the conditional distribution. This definition is too general for empirical usage, hence workable definitions are based on conditional moment characteristics.

In the AR-ARCH model, mean prediction is linear and the linear prediction and conditional expectation operator coincide, as do linear and non-linear Granger causality in the above sense. However, variance prediction may be affected by a source variable even when there is no Granger causality. A special feature of ARCH models is that all potential dynamic influences of this sort are reflected in linear variance prediction in the sense of Comte and Lieberman (2000) who define linear causality in variance by

$$P\left[\{Y - P(Y|X_-;Y_-;Z_-)\}^2 | X^2_-;Y^2_-;Z^2_-\right] \neq P\left[\{Y - P(Y|Y_-;Z_-)\}^2 | Y^2_-;Z^2_-\right]$$

where the conditioning set $X^2_-$ is defined as the linear space containing squares and cross-products of $X_-$. Evaluation of this feature requires a comparison between two models. In contrast, multivariate AR-ARCH models and some other non-linear models permit a direct assessment of the alternative definition of linear second-order causality, i.e.,

$$P\left(\{Y - P(Y|X_{-};Y_{-};Z_{-})\}^2 | X_{-}^2; Y_{-}^2; Z_{-}^2\right) \neq P\left(\{Y - P(Y|X_{-};Y_{-};Z_{-})\}^2 | Y_{-}^2; Z_{-}^2\right) : \quad (3)$$

Here, both variances are calculated conditional on the full multivariate history. Events of causality and non-causality can be read off the $H_t$ matrices of the ARCH model. Comte and Lieberman (2000) show that linear causality in variance is essentially equivalent to either linear Granger causality or to linear second-order causality (or both). In the present application, second-order causality can be given a natural interpretation as the spill-over of volatility from $X$ to $Y$.

In the present paper, we are interested in investigating linear Granger causality as well as linear causality in variance. Granger causality corresponds to the aim of mean prediction and causality in variance to risk prediction. Estimated parametric models convey information on Granger causality and on second-order causality. Forecasting experiments admit a direct evaluation of Granger causality as well as of variance causality. The sampling variation of parameter estimates often implies an apparent contradiction between the theoretical evaluation and the prediction evaluation, as we will show in the empirical part.

## 2.3 Data characteristics

The first set of data consists of index futures for the DAX, FTSE, Nikkei, and Standard & Poor 500 index series. These series are available from November 1990 to May 2000 on a daily basis. Continuous series have been constructed officially in the following form. In March, June, September, and December 3-months futures were used for contracts ending three months later. In April, July, October, and January 2-months futures are used, and in the remaining months 1-month futures are compiled.

The second set of data consists of exchange rate futures for four main currencies: the rate of US dollars per pound sterling, the rate of US dollars per German mark, and the rate of Japanese yen per US dollar. While the first two rates are available on a daily basis for the whole time span that was defined by the availability of the index futures, i.e., November 1990 to May 2000, the yen/dollar rate is only available from the beginning of

1997. In order to obtain comparable futures series for exchange rates, where only 1-month and 3-months futures were available on a daily basis, we used 3-months exchange rate futures for the contract months of March, June, September, December. For the months preceding these months we used the 1-month exchange rate futures. For the intermediate months, we used simple arithmetic averages of the 1-month and 2-months series in order to approximate the unavailable 2-months futures variable.

# 3 The results

## 3.1 Univariate ARCH models

We estimate univariate ARCH models for the four stock futures series and report the result in Table 1. We estimate univariate ARCH models for the three exchange rate futures series and report the results in Table 2. All variables have been transformed into logarithmic differences in order to obtain return series.

Note that the exchange rate futures pass the efficient-markets criterion, as their MA coefficients are insignificant, whereas the futures returns show significant serial correlation. All series show significant ARCH effects. It appears that the t–values are inflated, due to a downward bias in variance estimates that is often observed in nonlinear time-series models. However, the importance of ARCH effects is confirmed by visual inspection of second-order correlograms (cf. Weiss, 1986). In spite of the statistical significance of conditional heteroskedasticity, we note that the coefficients $\alpha_1$ are comparatively small and that hence the implied data-generating processes have finite variance and kurtosis.

## 3.2 Bivariate ARCH models

As outlined in Section 2.1, the formal model with all its parameters is given as

$$
\begin{aligned}
X_t &= \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \varepsilon_t + \begin{pmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{pmatrix} \varepsilon_{t-1} ; \\
E(\varepsilon_t \varepsilon_t') &= H_t ; \\
H_t &= \begin{pmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ \tau & 1 \end{pmatrix}
\end{aligned}
$$

$$\Theta \, \mathrm{diag}\left(\varepsilon'_{t-1}\begin{bmatrix} a_{11} & a_{12} \\ a_{12} & a_{22}\end{bmatrix}\varepsilon_{t-1}; \varepsilon'_{t-1}\begin{bmatrix} b_{11} & b_{12} \\ b_{12} & b_{22}\end{bmatrix}\varepsilon_{t-1}\right)\begin{bmatrix} 1 & \tau \\ 0 & 1\end{bmatrix} \quad (4)$$

in which the matrices C, A, B are estimated in their Choleski form in order to guarantee their positive definiteness. Estimates for the 'model parameters' $c_{11}; c_{12}; c_{22}$ can be retrieved from estimates for the 'technical parameters' $\tilde{c}_{11}$, $\tilde{c}_{22}$, $\tilde{c}_{12}$ in a second step. Estimation in the technical parameterization is conducted by a quasi–ML algorithm that imposes normality on the errors $\varepsilon_t$. Optimization of the likelihood function uses the BFGS algorithm of GAUSS that also calculates numerical standard errors and t–values. Due to near-singularities of some matrices, many of these standard errors appear fragile. Hence, we refrain from calculating t–values for the transformed model parameter estimates. Therefore, whereas we give point estimates of both model and technical parameters, t–values are shown for technical parameters only.

Table 3 gives the results for a bivariate model that contains the FTSE index returns and the sterling/dollar exchange rate. The insignificant value of $\mu_2$ indicates that the sterling has been on a par against the dollar in the longer run, whereas the positive $\mu_1$ represents the positive long-run return for the FTSE index. The moving-average coefficients matrix $\Theta$ contains insignificant values only, which supports market efficiency. Only the (1,2) entry is marginally significant, hence there is weak evidence on Granger causal effects from the exchange rate to the FTSE returns. Two ARCH factors govern the series. The first factor is rooted primarily in the FTSE index series, though it also contains a small weight from the exchange rate. The second factor depends on the exchange rate only. The insignificant rotation parameter $\tau$ indicates that either ARCH factor just causes the volatility in its own series and that the covariance is time-constant. In short, the amount of second-order causality from the exchange rate to the FTSE is small. Curiously, the effect from the dollar/mark exchange rate is slightly stronger, as we learned from a further unreported experiment.

Table 4 gives parallel results for the DAX index and the dollar/mark exchange rate. The structure of the estimated model is similar, although now there is significant Granger causality from exchange rate shocks to the DAX index, thus violating market efficiency in the DAX futures, in slight conflict with the univariate evidence. Again, the evidence on second-order causality is very small.

Tables 5 to 7 consider the Standard & Poor 500 index and all three di¤erent exchange rates versus the US dollar. There appears to be little spill-over from the German mark. In contrast, the British pound and the Japanese yen are statistically signi…cant carriers of information for the S&P futures. For both of these cases, the rotation parameter ¿ is also signi…cant, which implies that volatility in the exchange rates not only a¤ects the S&P volatility via the …rst factor but also via the second factor. For the dollar/sterling rate, the …rst factor is dominated by the S&P volatility and the parameter ¿ is still small, although statistically signi…cant. For the dollar/yen rate, the …rst factor mixes squared shocks in both series with similar weights and the rotation parameter ¿ opens a second strong channel for the volatility spill-over. We note, however, that the dollar/yen results were obtained from a shortened time range and are therefore more likely to re‡ect the patterns of a particular episode than the other experiments. There is also strong evidence against market e¢ciency in the dollar/yen rate, which corroborates the univariate results. In the remaining cases, direct evidence on ine¢ciency remains weak, thus also enhancing the univariate models (see Tables 1 and 2).

Table 8 shows that the bilateral yen/dollar exchange rate also incurs a signi…cant volatility spill-over to the Japanese Nikkei index. The Nikkei returns are signi…cantly autocorrelated and thus do not conform to market e¢ciency. The rotation parameter ¿ is only marginally signi…cant. The main spill-over e¤ect to the Nikkei futures stems from the …rst ARCH factor that re‡ects a weighted average of the innovations from both series. Conditional heteroskedasticity in the covariance across both types of shocks is weaker than in the S&P experiment.

# 4 Forecasting experiments

As is well known, the predictive quality of an econometric model is an issue that is largely separate from other checks on its validity. Slightly misspeci…ed models can prove to be good workhorses for forecasting, whereas otherwise acceptable speci…cations can fail completely with regard to predictive accuracy. The latter feature has been often reported for models of the ARCH type (see, e.g. Jorion, 1995). It is possible that the predictive quality is of more concern to an investor than other statistical properties of the entertained model, hence we consider forecasting experiments to be of major relevance.

We assess the relative predictive accuracy of the reported models as follows. We estimate the univariate and bivariate models iteratively from the starting point of the available sample to a fixed end point $T_0 = T - s$ and then predict the next observation at time $T_0 + 1$. We then update the parameter estimates of the models and predict the observation at time $T_0 + 2$. Thus, $s$ one-step forecasts are generated that can be gauged against the known realizations. Because the procedure of updating the complex non-linear structures is computationally intensive, we restrict ourselves to predicting the last $s = 22$ observations in the available sample. We note that the value of $s = 22$ was chosen to represent one business month.

We consider mean predictions as well as risk predictions. Because of the speculative nature of the data and the closeness of the market structure to theoretical assumptions of efficiency—which were not too hardly rejected in the reported estimations—we expected that the relative results of risk predictions would be more interesting. The known difficulty of evaluating risk predictions is that the true volatility is unknown, hence one must be satisfied with the poor approximation of forecasting squared mean-corrected observations instead. We note that the indispensable mean correction is the main problem, as a poor forecast of the local mean may ruin a correct prediction of local volatility.

The following evaluation criteria will be used: firstly, the mean squared error as the traditional measure of prediction accuracy; secondly, the more robust mean absolute error; thirdly, the even more robust median absolute error. The latter criterion successfully mitigates the role of local outliers that otherwise dominate the relative evaluation. All three criteria are applied to the two cases of mean and of risk prediction, hence we report six numbers for each experiment.

The results for index futures predictions based on univariate and bivariate ARCH models—in all cases for the stock futures indexes and not for the exchange rates—are summarized in Table 9. The comparison is disappointing. Most of the bivariate forecasts are dominated by the corresponding univariate forecast. On the whole, the bivariate predictions appear to be slightly worse, with the noteworthy exceptions of the risk forecast for the Nikkei index and of the risk forecast for the US S&P index on the basis of the dollar/yen exchange rate. These two experiments share the common feature that they are based on a shorter sample that is dictated by the range of available yen futures. A small overall improvement relative to the univariate prediction points to the possibility that the time-series structure may have been subjected to longer-run changes. Therefore, we re-ran all other prediction experiments basing all estimates of model parameters on the same shortened time range that was dictated by availability in the yen case. These results are marked by asterisks in Table 9. Indeed, the quality of the Standard&Poor forecasts generally increases for the shortened estimation range but this e¤ect is more pronounced for the mean prediction. For risk prediction, the model that uses the dollar/yen exchange rate still dominates and that based on the dollar/sterling rate even deteriorates by shortening the estimation range. This e¤ect is similar for the DAX and FTSE predictions. While mean prediction is slightly improved by shortening the estimation range, no such improvement is felt for predicting the risk.

# 5 Summary and conclusion

We have analyzed the relationship between stock returns and exchange rate changes in international markets and examined how well exchange rate volatility explains movements in stock market returns. The model-based predictions were evaluated on several cost functions.

Results from time-series model estimation vary considerably across countries. Whereas, in a bivariate model for the FTSE index returns and the sterling/dollar exchange rate, market e¢ ciency is supported, strong evidence on violation of market e¢ ciency was found for most other series. For the FTSE index and the sterling/dollar case, two ARCH factors govern the series. The rotation parameter remains insigni…cant, hence either ARCH factor just causes the volatility in its own series and the covariance is time-constant. In short, the amount of second-order causality from the exchange rate to the FTSE is small. This also turned out to be true for the DAX index and the dollar/mark exchange rate. We also considered joint models of the Standard & Poor 500 index and the three di¤erent exchange rates versus the US dollar. Whereas there appears to be little spill-over from the German mark, the British pound and the Japanese yen are statistically signi…cant carriers of information for the S&P futures. For both of these cases, volatility in the exchange rates a¤ects the S&P volatility via several channels. Finally, the bilateral yen/dollar exchange rate also incurs a signi…cant volatility spill-over to the Japanese Nikkei index.

With regard to the prediction experiments, we can summarize that the di¤erences in performance are too small and fragile to allow any general recommendation. For the case of the Standard&Poor futures, it seems that only the dollar/yen rate improves risk prediction. This e¤ect cannot be explained by the shorter estimation time range that was dictated by the availability of the dollar/yen rate. For all other cases, it was found that risk prediction and mean prediction do not necessarily coincide with regard to suggesting a speci…c optimum prediction model and that signi…cant in-sample dynamic structures do not necessarily imply links that can be used systematically for forecasting.

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# Tables and Figures

Table 1: Univariate MA–ARCH models for the stock futures series 23/11/1990-15/5/00.

| parameter | DAX | FTSE | Nikkei | S&P 500 |
|---|---|---|---|---|
| $\delta$ | 0.080 | 0.053 | -0.005 | 0.064 |
| | [3.60] | [3.45] | [0.81] | [3.61] |
| $\theta$ | -0.038 | -0.016 | 0.049 | 0.022 |
| | [1.98] | [1.04] | [2.80] | [1.29] |
| $\alpha_0$ | 1.384 | 0.912 | 1.702 | 0.773 |
| | [58.03] | [58.53] | [73.57] | [49.55] |
| $\alpha$ | 0.176 | 0.174 | 0.161 | 0.189 |
| | [13.31] | [12.55] | [22.60] | [24.53] |

Note: Fitted models are of the form $x_t = \delta + \varepsilon_t + \theta\varepsilon_{t-1}$ with conditional variance equation $h_t = \alpha_0 + \alpha\varepsilon^2_{t-1}$. Figures in squared brackets are t–values.

Table 2: Univariate MA–ARCH models for the exchange rate futures series. Time range is 23/11/1990–15/5/00, except for the Yen series with the range 1/1/1997–15/5/00.

| parameter | UK£ to US$ | US$ to G.Mark | Yen to US$ |
|---|---|---|---|
| ¹ | 0.004 | -0.019 | 0.017 |
| | [0.28] | [1.42] | [0.59] |
| µ | 0.003 | 0.026 | -0.103 |
| | [0.10] | [1.26] | [2.65] |
| ®$_0$ | 0.350 | 0.426 | 0.594 |
| | [57.98] | [56.40] | [33.03] |
| ® | 0.179 | 0.122 | 0.276 |
| | [12.08] | [9.35] | [10.24] |

Note: see Table 1

Table 3: Bivariate model for the FTSE index and the US dollar / sterling exchange rate. Time range is 23/11/1990–15/5/2000.

| technical parameter | estimated | t–value | model parameter | estimated |
|---|---|---|---|---|
| $^{1}{}_{1}$ | 0.053 | 2.68 | | |
| $^{1}{}_{2}$ | 0.005 | 0.39 | | |
| $\mu_{11}$ | -0.006 | 0.22 | | |
| $\mu_{12}$ | -0.049 | 1.62 | | |
| $\mu_{21}$ | 0.000 | 0.02 | | |
| $\mu_{22}$ | 0.003 | 0.13 | | |
| $\tilde{c}_{11}$ | 0.976 | 109.20 | $c_{11}$ | 0.906 |
| $\tilde{c}_{21}$ | 0.097 | 6.34 | $c_{21}$ | 0.092 |
| $\tilde{c}_{22}$ | 0.763 | 114.74 | $c_{22}$ | 0.348 |
| $\tilde{a}_{11}$ | 0.645 | 23.64 | $a_{11}$ | 0.173 |
| $\tilde{a}_{21}$ | 0.073 | 1.36 | $a_{21}$ | 0.030 |
| $\tilde{a}_{22}$ | 0.020 | 0.99 | $a_{22}$ | 0.005 |
| $\tilde{b}_{11}$ | 0.070 | 0.24 | $b_{11}$ | 0.000 |
| $\tilde{b}_{21}$ | 0.425 | 13.42 | $b_{21}$ | 0.002 |
| $\tilde{b}_{22}$ | 0.025 | 1.24 | $b_{22}$ | 0.181 |
| ¿ | 0.043 | 1.02 | | |

Note: The (unsigned) t–values in the third column correspond to the parameters and their point estimates in the first and second column. In those cases where model parameters are transforms of technical parameters, these are indicated in the fourth column and point estimates are given without t–values in the fifth column.

Table 4: Bivariate model for the DAX index and the US dollar / German mark exchange rate. Time range is 23/11/1990–15/5/2000.

| technical parameter | estimated | t–value | model parameter | estimated |
|---|---|---|---|---|
| ¹$_1$ | 0.081 | 3.42 | | |
| ¹$_2$ | -0.018 | 1.28 | | |
| $\mu_{11}$ | -0.029 | 1.30 | | |
| $\mu_{12}$ | 0.099 | 2.76 | | |
| $\mu_{21}$ | -0.004 | 0.36 | | |
| $\mu_{22}$ | 0.028 | 1.21 | | |
| $\tilde{c}_{11}$ | 1.085 | 110.12 | $c_{11}$ | 1.383 |
| $\tilde{c}_{21}$ | -0.108 | 6.94 | $c_{21}$ | -0.128 |
| $\tilde{c}_{22}$ | 0.801 | 113.75 | $c_{22}$ | 0.424 |
| $\tilde{a}_{11}$ | 0.649 | 24.28 | $a_{11}$ | 0.178 |
| $\tilde{a}_{21}$ | 0.041 | 0.54 | $a_{21}$ | 0.017 |
| $\tilde{a}_{22}$ | 0.020 | 1.19 | $a_{22}$ | 0.002 |
| $\tilde{b}_{11}$ | 0.109 | 1.04 | $b_{11}$ | 0.000 |
| $\tilde{b}_{21}$ | 0.361 | 9.47 | $b_{21}$ | 0.004 |
| $\tilde{b}_{22}$ | 0.025 | 1.51 | $b_{22}$ | 0.130 |
| ¿ | -0.045 | 1.10 | | |

Note: See Table 3.

Table 5: Bivariate model for the S&P 500 index and the US dollar / German mark exchange rate. Time range is 23/11/1990–15/5/1990.

| technical parameter | estimated | t–value | model parameter | estimated |
|---|---|---|---|---|
| $^{1}{}_{1}$ | 0.068 | 3.45 | | |
| $^{1}{}_{2}$ | 0.009 | 0.84 | | |
| $\mu_{11}$ | 0.031 | 1.33 | | |
| $\mu_{12}$ | 0.014 | 0.70 | | |
| $\mu_{21}$ | 0.009 | 0.87 | | |
| $\mu_{22}$ | 0.001 | 0.03 | | |
| $\tilde{c}_{11}$ | 0.932 | 105.90 | $c_{11}$ | 0.754 |
| $\tilde{c}_{21}$ | 0.042 | 2.90 | $c_{21}$ | 0.037 |
| $\tilde{c}_{22}$ | 0.767 | 112.41 | $c_{22}$ | 0.347 |
| $\tilde{a}_{11}$ | 0.641 | 21.72 | $a_{11}$ | 0.169 |
| $\tilde{a}_{21}$ | 0.254 | 6.95 | $a_{21}$ | 0.104 |
| $\tilde{a}_{22}$ | 0.020 | 0.99 | $a_{22}$ | 0.064 |
| $\tilde{b}_{11}$ | 0.099 | 0.97 | $b_{11}$ | 0.000 |
| $\tilde{b}_{21}$ | -0.432 | 12.35 | $b_{21}$ | -0.004 |
| $\tilde{b}_{22}$ | -0.025 | 1.22 | $b_{22}$ | 0.186 |
| ¿ | -0.045 | 1.34 | | |

Note: See Table 3.

Table 6: Bivariate model for the S&P 500 index and the US dollar / pound sterling exchange rate. Time range is 23/11/1990–15/5/2000.

| technical parameter | estimated | t–value | model parameter | estimated |
|---|---|---|---|---|
| $^{1}{}_{1}$ | 0.064 | 3.19 | | |
| $^{1}{}_{2}$ | -0.022 | 1.08 | | |
| $\mu_{11}$ | 0.026 | 1.30 | | |
| $\mu_{12}$ | -0.020 | 1.01 | | |
| $\mu_{21}$ | -0.019 | 0.94 | | |
| $\mu_{22}$ | 0.024 | 1.20 | | |
| $\tilde{c}_{11}$ | 0.935 | 46.46 | $c_{11}$ | 0.763 |
| $\tilde{c}_{21}$ | -0.087 | 4.32 | $c_{21}$ | -0.076 |
| $\tilde{c}_{22}$ | 0.803 | 39.92 | $c_{22}$ | 0.424 |
| $\tilde{a}_{11}$ | 0.650 | 32.32 | $a_{11}$ | 0.179 |
| $\tilde{a}_{21}$ | -0.133 | 6.59 | $a_{21}$ | -0.056 |
| $\tilde{a}_{22}$ | 0.020 | 0.97 | $a_{22}$ | 0.018 |
| $\tilde{b}_{11}$ | 0.000 | 0.02 | $b_{11}$ | 0.000 |
| $\tilde{b}_{21}$ | 0.359 | 17.85 | $b_{21}$ | 0.000 |
| $\tilde{b}_{22}$ | 0.025 | 1.22 | $b_{22}$ | 0.129 |
| ¿ | -0.045 | 2.22 | | |

Note: See Table 3.

Table 7: Bivariate model for the S&P 500 index and the US dollar / Japanese yen exchange rate. Time range is 1/1/1997–15/5/2000

| technical parameter | estimated | t–value | model parameter | estimated |
|---|---|---|---|---|
| $^{1}{}_{1}$ | 0.080 | 2.16 | | |
| $^{1}{}_{2}$ | 0.039 | 1.50 | | |
| $\mu_{11}$ | 0.009 | 0.56 | | |
| $\mu_{12}$ | 0.024 | 0.60 | | |
| $\mu_{21}$ | 0.020 | 1.11 | | |
| $\mu_{22}$ | -0.086 | 2.31 | | |
| $\tilde{c}_{11}$ | 1.117 | 70.54 | $c_{11}$ | 1.557 |
| $\tilde{c}_{21}$ | 0.141 | 4.80 | $c_{21}$ | 0.176 |
| $\tilde{c}_{22}$ | 0.854 | 63.25 | $c_{22}$ | 0.551 |
| $\tilde{a}_{11}$ | 0.500 | 10.83 | $a_{11}$ | 0.060 |
| $\tilde{a}_{21}$ | 0.292 | 2.89 | $a_{21}$ | 0.072 |
| $\tilde{a}_{22}$ | 0.020 | 0.75 | $a_{22}$ | 0.085 |
| $\tilde{b}_{11}$ | 0.179 | 1.60 | $b_{11}$ | 0.001 |
| $\tilde{b}_{21}$ | 0.486 | 8.75 | $b_{21}$ | 0.016 |
| $\tilde{b}_{22}$ | 0.026 | 0.99 | $b_{22}$ | 0.237 |
| ¿ | -0.584 | 3.88 | | |

Note: See Table 3.

Table 8: Bivariate model for the Nikkei index and the US dollar / Japanese yen exchange rate. Time range is 1/1/1997–15/5/2000

| technical parameter | estimated | t–value | model parameter | estimated |
|---|---|---|---|---|
| $^{1}{}_{1}$ | -0.013 | 2.16 | | |
| $^{1}{}_{2}$ | 0.014 | 1.50 | | |
| $\mu_{11}$ | 0.120 | 3.24 | | |
| $\mu_{12}$ | 0.038 | 0.52 | | |
| $\mu_{21}$ | 0.010 | 0.63 | | |
| $\mu_{22}$ | -0.111 | 2.92 | | |
| $\tilde{c}_{11}$ | 1.208 | 65.64 | $c_{11}$ | 2.128 |
| $\tilde{c}_{21}$ | -0.096 | 2.78 | $c_{21}$ | -0.141 |
| $\tilde{c}_{22}$ | 0.871 | 67.30 | $c_{22}$ | 0.585 |
| $\tilde{a}_{11}$ | 0.459 | 6.80 | $a_{11}$ | 0.044 |
| $\tilde{a}_{21}$ | -0.647 | 4.90 | $a_{21}$ | -0.136 |
| $\tilde{a}_{22}$ | 0.020 | 0.82 | $a_{22}$ | 0.418 |
| $\tilde{b}_{11}$ | 0.000 | 0.00 | $b_{11}$ | 0.000 |
| $\tilde{b}_{21}$ | -0.519 | 10.62 | $b_{21}$ | -0.000 |
| $\tilde{b}_{22}$ | 0.025 | 1.02 | $b_{22}$ | 0.269 |
| ¿ | -0.188 | 1.94 | | |

Note: See Table 3.

Table 9: Prediction from univariate and bivariate ARCH models.

| variable | | mean prediction | | | risk prediction | | |
|---|---|---|---|---|---|---|---|
| predicted | explanatory | MSE | MAE | medAE | MSE | MAE | medAE |
| DAX | - | 6.354 | 1.954 | 1.413 | 13.605 | 2.598 | 1.538 |
| DAX | US-$/mark | 6.414 | 1.962 | 1.414 | 13.698 | 2.612 | 1.528 |
| DAX | US-$/mark ¤ | 6.341 | 1.963 | 1.330 | 13.274 | 2.834 | 2.150 |
| FTSE | - | 4.547 | 1.648 | 1.167 | 17.086 | 2.519 | 0.998 |
| FTSE | US-$/Sterling | 4.591 | 1.657 | 1.168 | 17.149 | 2.526 | 1.003 |
| FTSE | US-$/Sterling ¤ | 4.563 | 1.654 | 1.184 | 16.094 | 2.657 | 1.186 |
| Nikkei | - | 10.900 | 2.230 | 1.684 | 181.239 | 5.865 | 1.886 |
| Nikkei | US-$/yen ¤ | 11.759 | 2.326 | 1.713 | 176.745 | 5.480 | 2.123 |
| S&P | - | 9.751 | 2.175 | 1.444 | 78.716 | 3.905 | 1.536 |
| S&P | US-$/Sterling | 9.829 | 2.183 | 1.443 | 78.920 | 3.849 | 1.547 |
| S&P | US-$/Sterling ¤ | 9.591 | 2.151 | 1.435 | 77.600 | 4.014 | 1.552 |
| S&P | US-$/mark | 9.802 | 2.177 | 1.434 | 79.647 | 3.944 | 1.752 |
| S&P | US-$/mark ¤ | 9.564 | 2.161 | 1.413 | 77.488 | 4.146 | 1.716 |
| S&P | US-$/yen ¤ | 9.663 | 2.166 | 1.400 | 76.157 | 3.923 | 1.704 |

* estimated for the shorter time range 1997–2000.

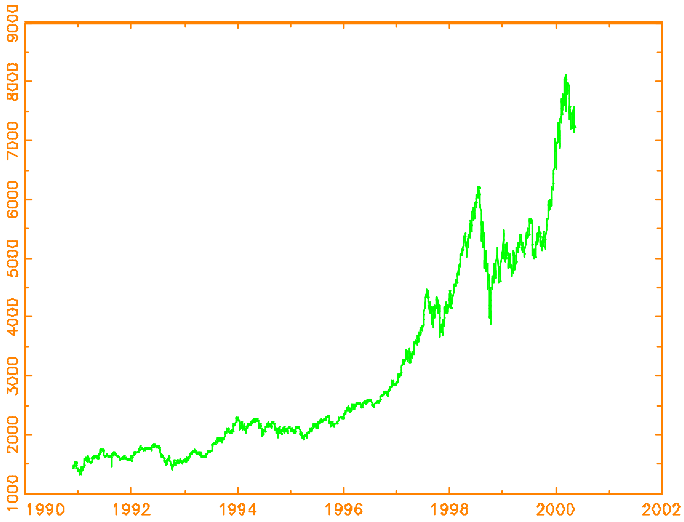


Figure 1: DAX futures series.

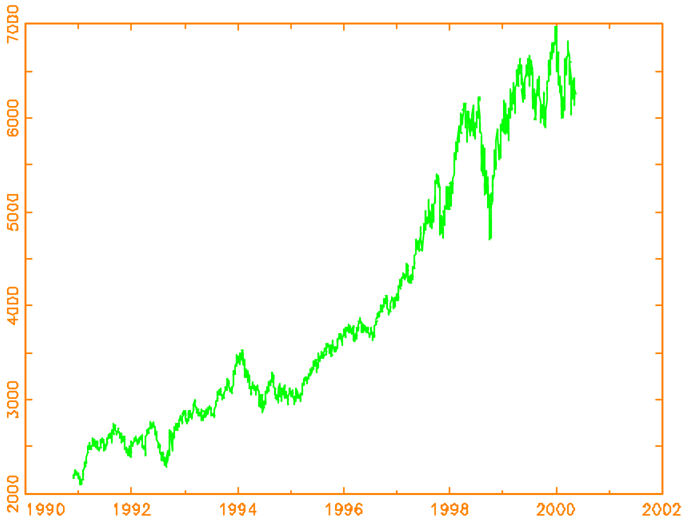


Figure 2: FTSE futures series.

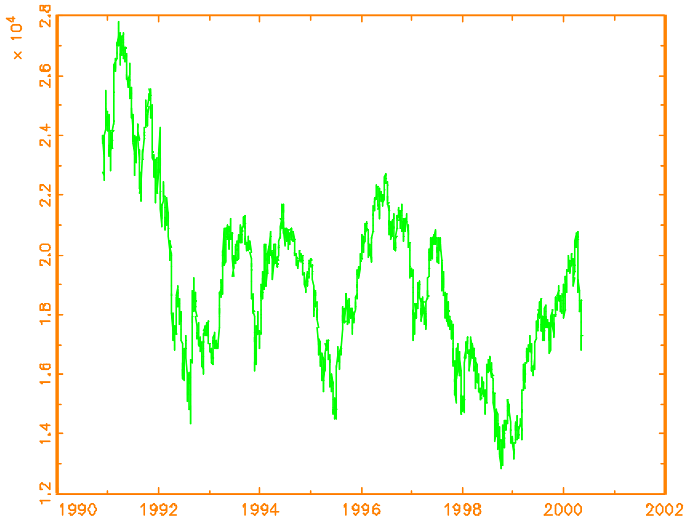


Figure 3: Nikkei futures series.

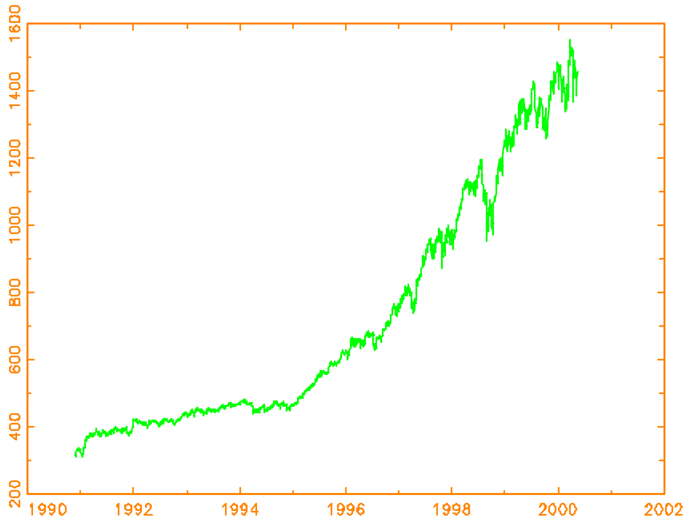


Figure 4: Standard & Poor 500 futures series.

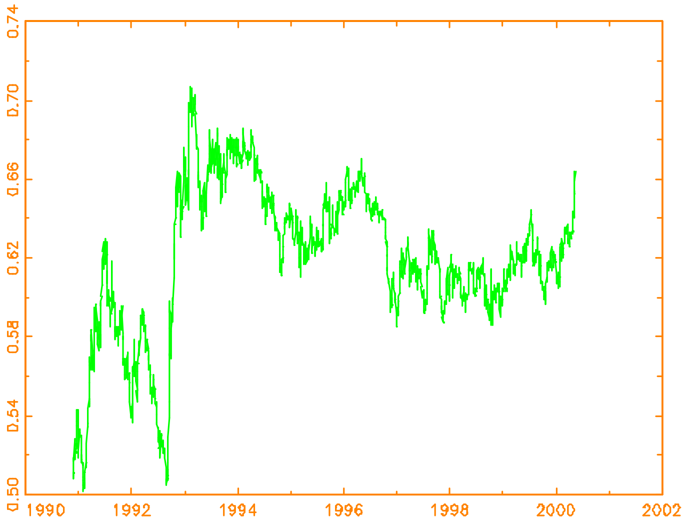


Figure 5: Continuous forward exchange rate pound sterling per US dollar.

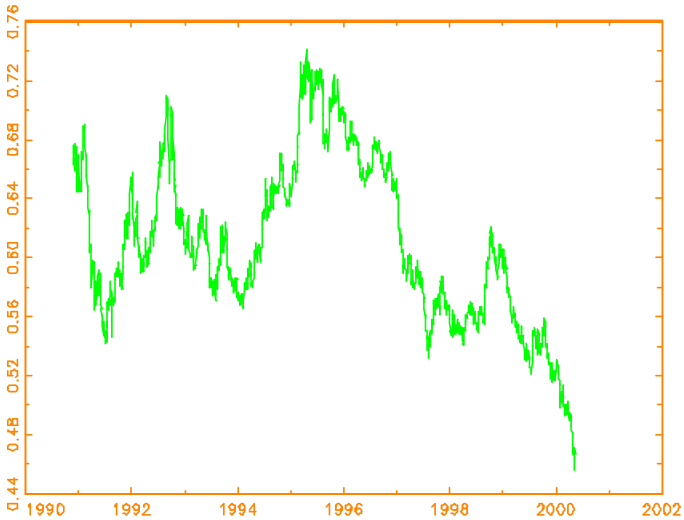


Figure 6: Continuous forward exchange rate US dollars per German mark.

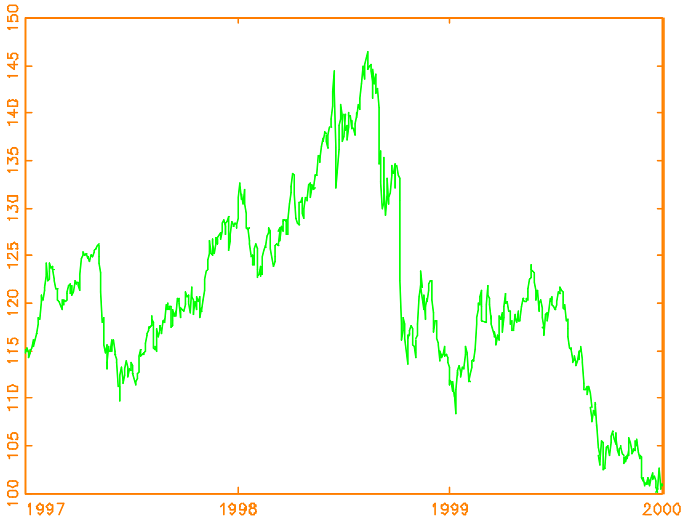


Figure 7: Continuous forward exchange rate Japanese yen per US dollar.

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