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Stock Market Volatility and Deviations from Macroeconomic Fundamentals: Evidence from GARCH and GARCH-X Models

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I. Introduction

It is known in the financial markets that asset prices react to fluctuations in macroeconomic variables. According to *Asprem* (1989), the literature does not provide certain asset pricing models that take into consideration these macroeconomic variables. For the purposes of this paper, the value of a firm can be expressed in terms of the simple present value formula as:

$$V_t = E_t \left[\sum_{k=0}^{\infty} C_{t+k} / (1 + r_{t+k})^k \right] \tag{1}$$

where C_{t+k} is the cash flow available to stockholders in period $t + k, r_{t+k}$ is the discount rate for income streams received in period $t + k$, and V_t is the value of the firm, all conditional on the information at time t. In addition, cash flow can be thought of as the difference between total sales (or total income), S, and total costs, K, i.e., $C \equiv S - K$. Total sales, in turn, can be thought of as a function of aggregate income (a proxy for economic activity), the exchange rate, money supply, and prices, while total costs can be thought of as a function of oil prices and the exchange rate (for input pricing). The above simple model for the evaluation of a firm, could also be considered as a simplified version of the intertemporal asset pricing model (I-CAPM), developed by *Merton* (1973), in which the return of an asset covaries not only with the return from the market portfolio, but also with a set of state variables. These state variables could be represented by certain macroeconomic factors.

One of the most important macroeconomic variables that seem to influence the behaviour of stock prices is money supply. A group of economists argues that money supply tends to exert a negative influence on stock prices. According to the quantity theory of money, higher money supply leads to higher inflation and next to lower stock prices. By contrast, others favour a positive association between money supply and stock prices through the liquidity effect. Higher liquidity in the economy leads to lower interest rates and, thus, to higher stock prices. In addition, money supply leads business cycles and since money supply and economic activity are positively associated, money supply and stock prices are also positively correlated. Econometric studies have provided empirical support to this (*Cooper,* 1974; *Grossman,* 1981; *Cornell,* 1983; *Wong,* 1986; *Calomiris* and *Hubbard,* 1987).

Other studies have concluded that exists a negative correlation between stock market data and inflation (*Fama* and *Schwert,* 1977; *Huizinga* and *Mishkin,* 1984; *Pearce* and *Roley,* 1985; *Summers,* 1986; *Kaul,* 1987). The effect of inflation works mostly through the impact of inflation on the discount factor (an interest rate) in the asset pricing model. The Fisher equation argues that higher inflation leads to higher nominal interest rates, which in turn, contribute to a lower value of the firm, and thus, to lower stock prices.

Real production can also affect stock market data through the real value of cash flows in the process of evaluating the value of a firm. (*Cecchetti* et al., 1990; *Kandel* and *Stambaugh,* 1990; *Campbell* and *Ammer,* 1993). Although it is future income that should be involved in the evaluation process, in an efficient financial market, realized income values are unbiased estimates of expected values. Therefore, actual income values are used as a proxy for the expected income values.

Very few studies have examined whether a relationship between the stock market and exchange rates exists. The value of firms, in particular those involved in international trade, is sensitive to exchange rate movements (*Bodnar* and *Gentry,* 1993). Moreover, the value of the firms that are not explicitly involved in international trade can also be affected by exchange rate fluctuations due to the impact of those fluctuations on foreign competitors, input costs, and aggregate demand. *Aggarwal* (1981), *Soenen* and *Hennigar* (1988), and *Asprem* (1989) have found that stock prices react to exchange rate changes. Movements in exchange rates convey additional information relevant to domestic markets. Exchange rate changes influence the value of a firm's foreign operations, which is reflected on the balance sheet as a profit or a loss.

Finally, oil price shocks could also be associated to output changes (*Hamilton,* 1983 and 1988; *Mork* 1989) and, therefore, to the behaviour of stock prices. In addition, changes in oil prices tend to directly change the value of a firm through its input cost performance.

The objective of this paper is to investigate how short-run deviations from the relationship (if any) between stock prices and certain macroeconomic fundamentals tend to affect stock market volatility. A significant positive effect would imply that prediction of stock prices may become harder as these data move apart from macroeconomic variables in the short-run. The methodology followed in this paper is that of the Generalised Autoregressive Conditional Heteroskedastic (GARCH) models. GARCH models, introduced by *Bollerslev* (1986), are capable of capturing certain features observed in stock market data, such as leptokyrtosis and volatility clustering[1] (*French* et al., 1987; *Akgiray,* 1989; *Baillie* and *DeGennaro,* 1990; *Funke,* 1994, among others). Moreover, *Chou* (1988) argues in favour of GARCH models on the grounds that they are capable of capturing various dynamic structures of conditional variance, of incorporating heteroskedasticity into the estimation procedure, and of allowing simultaneous estimation of several parameters under examination.

The GARCH-X model is an extension of the standard GARCH model (*Lee,* 1994), and allows the link between short-run deviations (captured by the error-correction term from an Error Correction (EC) model) from a long-run cointegrated relationship and volatility. This paper applies the GARCH-X model to examine the predictive power of the short-run deviations between stock market data and macroeconomic fundamentals in predicting the volatility of those stock market data. The empirical work presented in this paper is conducted by means of the Johansen's multivariate cointegration methodology and the GARCH and GARCH-X approaches. The empirical analysis finds evidence in favour of a positive as well as significant effect of the short-run deviations on the conditional variance.

The rest of the paper is organised as follows. Section II. presents the methodology of the GARCH and GARCH-X models, while section III. performs the empirical analysis. Finally, section IV. contains concluding remarks.

[1] According to *Akgiray* (1989), volatility clustering can be attributed to certain features of the stock market, such as, irregularities in the rate of information arrivals as well as in the level of trading activity, and financial and operating leverage decisions.

II. The methodology of the GARCH and GARCH-X models

Let ξ_t be a model's prediction error, b a vector of parameters, x_t a vector of predetermined explanatory variables in the equation for the conditional mean:

$$y_t = x_t b + \xi_t \quad \xi_t \sim N(0, h_t) \tag{2}$$

and h_t the variance of ξ_t, given information at time t. The GARCH specification, as it was developed by *Bollerslev* (1986), makes h_t defined as:

$$h_t = v + \sum_{i=1}^{q} b_i h_{t-i} + \sum_{j=1}^{w} a_j \xi_{t-j}^2 \tag{3}$$

with v, a_j, and b_i being nonnegative parameters. According to (3), the conditional variance h_t is specified as a linear function of its own lagged q conditional variances and the lagged w squared residuals. *Engle* and *Bollerslev* (1986) have argued that if $\Sigma b_i + \Sigma a_j = 1$, then the GARCH process turns into an integrated GARCH (IGARCH) process, implying that current shocks persist indefinitely in conditioning the future variance. Maximum likelihood techniques are used to estimate the parameters of the GARCH model (the algorithm was developed by *Berndt* et al., 1974).

The GARCH-X model takes into consideration the effects of the short-run deviations on the conditional variance. In this respect, the specification (3) becomes:

$$h_t = u + \sum_{i=1}^{q} b_i h_{t-i} + \sum_{j=1}^{w} a_j \xi_{t-j}^2 + \gamma_1 z_{t-1}^2 \tag{4}$$

The short-run deviations are represented by the squared and lagged error-correction term z_{t-1}^2. The error-correction term z_t, the residuals from a cointegrating vector, is believed to have important predictive powers for the conditional mean as well as the conditional variance of stock prices (*Lee,* 1994). The parameter γ_1 indicates the effects of the short-run deviations from a long-run cointegrated relationship on the conditional variance. If γ_1 is positive, this implies that stock market data become more volatile and harder to predict as the deviation of those data and certain economic factors gets larger.

III. Empirical analysis

1. Data

The empirical analysis is carried out using monthly data on the stock-price general index (S), measured by the Standard and Poor's 500 industrial index, money supply (M) defined as $M1$, prices (P) measured by the consumer price index ($1990 = 100$), income (Y) defined as the industrial production index ($1990 = 100$), and the exchange rate (E) measured as the effective exchange rate index ($1990 = 100$), which represents the ratio of an index of the period average exchange rate of the dollar to a weighted geometric average of exchange rates for the currencies of selected partner countries. An increase in the index reflects an appreciation. Data on crude oil prices (O) were also obtained. From this point on, oil prices have been divided by consumer prices. Data cover the period 1978: 1 to 1996: 12 and were obtained from the OECD Main Economic Indicators CD-ROM. Data on stock prices were obtained from DATASTREAM, while those on crude oil prices from the McGraw-Hill Research Department. Finally, lower case letters indicate variables expressed in logarithms.

2. Integration and cointegration analysis

Unit root tests, developed by *Fuller* (1976), *Phillips* (1987) and *Perron* (1988), reported in Table 1, indicated that the log of all the series under examination is stationary only after first differencing. Next, Likelihood Ratio tests, developed by *Sims* (1980), determined the number of lags in a six-variable VAR system, i.e., a system that involves s, y, m, p, e, and o as endogenous variables. A maximum number of twelve lags was considered and the restriction that a lower-order system is as good as a higher-order system was tested. The results provided evidence in favour of a 5-lag VAR. Cointegration tests, developed by *Johansen* and *Juselius* (1990), revealed evidence in favour of cointegration (Table 2). Both the maximum eigenvalue statistic and the trace statistic suggest the presence of one cointegrating relationship between stock prices and macroeconomic fundamentals concerned.[2] In other words, stock prices and the macroeconomic series involved share a common stochastic trend, a piece of evidence against the semi-strong form of market efficiency (*Choudhry,*

[2] The MFIT software assisted with the empirical analysis.

1994). The cointegration estimations yielded the following cointegrating vector:[3]

$$s = 0.607\,y - 0.47\,p + 0.172\,m - 0.118\,o - 0.458\,e + 3.08$$

t-statistics: (2.97)* (−4.49)* (2.14)* (−2.34)* (−3.04)* (4.65)*

$R^2 = 0.49$, LM: $x^2\,(36) = 33.88\,[p\text{-value} = 0.57]$,
NO: $x^2\,(12) = 46.38\,[p\text{-value} = 0.39]$

where LM is a Langrance Multiplier serial correlation test and NO is a normality test. An asterisk denotes that a variable is statistically significant at 5 %.

Table 1: **Unit root tests**

Variable	ADF levels	ADF 1st differences	PP1 levels	PP1 1st differences	PP2 levels	PP2 1st differences
m	−1.50	−4.48*	−1.87	−15.23*	−1.65	−15.41*
e	−1.96	−5.17*	−1.43	−12.85*	−1.72	−12.85*
y	−2.17	−4.76*	−0.31	−14.78*	−2.58	−14.84*
p	−2.22	−9.99*	−1.21	−15.36*	−1.45	−11.68*
s	−1.21	−5.77*	−1.15	−15.03*	−1.40	−15.08*
o	−1.88	−6.21*	−1.49	− 8.32*	−2.31	− 8.31*

Notes: m is the log of money supply, e is the log of the exchange rate, y is the log of income, p is the log of consumer prices, s is the log of stock prices, and o is the log of oil prices divided by consumer prices.

ADF is the Augmented Dickey-Fuller test. The regression involved is:

$$\Delta x_t = a_1 + a_2\,\text{TIME} + a_3\,x_{t-1} + \sum_{i=1}^{k} b_i\,\Delta x_{t-i} + u_t$$

with u being a random term. A 6-lag length was used for the ADF test to ensure white noise residuals. The null hypothesis of nonstationarity tested is $H_0: a_3 = 0$ through the τ_τ-statistic. PP1 is the Phillips-Perron test and the regression involved is:

$\Delta x_t = m + (a-1)\,x_{t-1} + u_{1t}$. The null hypothesis of nonstationarity is $H_0: a = 1$ and it is tested through the τ_μ statistic. PP2 is the Phillips-Perron test and the regression involved is:

$\Delta x_t = m^* + d^*\,T + (a^* - 1)\,x_{t-1} + u_{2t}$. The null hypothesis of nonstationarity is $H_0: a^* = 1$ and it is tested through the τ_τ statistic. u_{1t} and u_{2t} are random terms with different serial correlation.

* indicates statistical significance at 5 %

[3] *Hansen-Johansen* (1993) recursive analysis tests for stability of the cointegration vector was also used with the assistance of the CATS in RATS 4.0 software. The October 1987 crash event was examined as a starting point. The results (available upon request) suggested that there was no break in the cointegrating vector, and thus, there was no evidence of temporal instability in the long-run.

Table 2: **Johansen-Juselius cointegration tests**

Variables included: s m p y e intercept. Lags = 5					
Null	Alternative	m. λ.	95 %	Tr.	95 %
$r = 0$	r = 1	54.9296	46.4550	167.8091	131.7000
$r <= 1$	r = 2	36.3282	40.3030	100.8795	102.1390
$r <= 2$	r = 3	25.3250	34.2000	66.5513	76.0690
$r <= 3$	r = 4	19.1987	28.1380	44.2262	53.1160
$r <= 4$	r = 5	10.1831	22.0020	25.0276	34.9100
$r <= 5$	r = 6	5.1383	9.2430	5.1383	9.2430

Notes: m. λ. = maximum eigenvalue statistic, Tr. = trace statistic

The coefficients in the cointegrating vector are shown with signs consistent to certain theoretical arguments. In particular, a lower exchange rate (a currency depreciation) tends to improve the competitive position of domestic industries, resulting in higher profitability and higher stock prices. A higher value of income (higher economic activity) is accompanied by higher stock prices. Higher oil prices lead to lower stock prices, while a higher value of money supply is positively correlated to stock prices, a piece of evidence in accordance with the liquidity effect as well as with the argument that money supply leads business cycles. Finally, stock prices are shown to be bad hedges against inflation.

3. A mean equation for stock prices

Having established the presence of a cointegrating relationship between stock prices, on one hand, and income, money supply, prices, oil prices, and the exchange rate, on the other hand, the associated EC mechanism (the proxy for the mean equation), which describes the short-run dynamics, is employed. The EC mechanism has the following form:

$$\Delta s = 0.0086 + 0.225\,\Delta s(-1) + 0.124\,\Delta s(-3) - 0.165\,\Delta e(-1) - 0.355\,\Delta o(-3)$$

t-statistics: (2.5)* (3.44)* (2.88)* (−2.47)* (−3.66)*

$$-0.306\,\Delta m(-2) - 0.477\,\Delta p(-4) + 0.555\,\Delta y(-4) - 0.0567\,z(-1)$$

t-statistics: (2.17)* (−3.07)* (3.35)* (−3.6)*

$R^2 = 0.61$ SEE $= 0.033$ LM $= 35.53\,[0.02]$ RESET $= 1.2\,[0.27]$ HE $= 0.4\,[0.53]$
ARCH(12) $= 1.56\,[0.02]$

where z are the residuals from the cointegrating vector, while all statistically insignificant terms have been omitted. Numbers in brackets denote p-values. Once again, the asterisk denotes that a variable is statistically significant at 5 %. The coefficient of z is negative, implying that stock returns adjust to restore long-run equilibrium after a short-run disturbance. The estimated equation satisfies certain econometric criteria, namely, absence of functional misspecification (RESET) and absence of heteroskedasticity (HE). However, serial correlation tests (LM) indicate the presence of serial correlation, while ARCH tests indicate the presence of ARCH effects at 12 lags. Both of these latter tests suggest the presence of volatility clustering in stock prices and the employment of ARCH or GARCH techniques as the approach to generate consistent estimates of the mean equation seems to be appropriate.

4. *Statistical analysis of stock market data*

Table 3 reports the summary statistics for the stock returns series defined as $r_t = \Delta s_t = s_t - s_{t-1}$. The stock returns series does not include any measure on dividends. This is not expected to have any influence on the empirical findings (*French* et al., 1987). The relatively large value of the kurtosis statistic suggests that the series is leptokurtic or heavily tailed and sharply peaked about the mean when compared with the normal distribution. Since GARCH models feature this property of leptokurtosis, the use of a GARCH model would seem appropriate to describe the leptokurtosis type in this time series. In addition, the Ljung-Box statistic $Q(10)$ provides a test for the presence of autocorrelation. The significant value of the statistic suggests the rejection of the null hypothesis of no serial correlation, i.e., there is evidence for autocorrelation. Moreover, the value of the $Q^2(10)$ statistic rejects the null hypothesis of homoskedastic stock returns, implying volatility clustering. Overall, the above evidence suggests that the use of a GARCH model seems appropriate to describe the evolution of the variance for this time series.

5. *GARCH and GARCH-X estimates*

Having estimated the form of the mean equation, the variance equation must also be estimated. On the basis of parsimony criteria, GARCH models can be seen as a special case of an ARMA process (*Tsay,* 1987). Therefore, through a Box-Jenkins methodological procedure, a

Table 3 : **Summary statistics of the return series**

No. of Obs.	Mean	Standard Deviation	Kurtosis	Q (10)	Q^2 (10)
228	0.00397	0.02	6.56	41.30	175.71
p-value			0.00	0.011	0.00

Notes: $Q(10)$ is the Box-Ljung statistic identifying the presence of autocorrelation. $Q^2(10)$ is the Box-Ljung statistic identifying the presence of autocorrelation in the squared returns.

GARCH(1,1) model showed the best fit. Higher order GARCH formulations added no significant improvements in goodness-of-fit. The results obtained from fitting the GARCH model to the data are as follows:

$$\underset{}{\Delta s} = \underset{(2.1)^*}{0.0074} + \underset{(2.44)^*}{0.171}\,\Delta s(-1) + \underset{(2.89)^*}{0.067}\,\Delta s(-3) - \underset{(-3.41)^*}{0.272}\,\Delta e(-1) - \underset{(-2.44)^*}{0.154}\,\Delta o(-3)$$

$$\underset{(2.39)^*}{0.429}\,\Delta m(-2) - \underset{(-2.58)^*}{0.111}\,\Delta p(-4) + \underset{(2.91)^*}{0.434}\,\Delta y(-4) - \underset{(-2.85)^*}{0.0167}\,\mathrm{EC}(-1)$$

$$h_t = \underset{(7.06)^*}{0.0011} + \underset{(3.14)^*}{0.427}\,h_{t-i} + \underset{(3.21)^*}{0.197}\,\xi^2_{t-i}$$

Function Value (the log likelihood) = 357.82

with ξ_t being the residuals from the EC model.

(t statistic values are in parentheses, while the asterisk denotes significance at 5 %). The persistence measurement $(0.427 + 0.197)$ is well below unity, which first, suggests that the GARCH(1,1) is stationary and second, indicates the transitory character of shocks to volatility.

Similarly, a GARCH-X(1,1) model was identified. The estimation method provided the following results:

$$\Delta s = \underset{(2.22)^*}{0.0084} + \underset{(2.73)^*}{0.139}\,\Delta s(-1) + \underset{(3.05)^*}{0.077}\,\Delta s(-3) - \underset{(-3.87)^*}{0.341}\,\Delta e(-1) - \underset{(-4.07)^*}{0.266}\,\Delta o(-3)$$

$$\underset{(2.14)^*}{0.349}\,\Delta m(-2) - \underset{(-3.07)^*}{0.099}\,\Delta p(-4) + \underset{(2.61)^*}{0.361}\,\Delta y(-4) - \underset{(-3.26)^*}{0.0116}\,z(-1)$$

$$h_t = \underset{(5.56)^*}{0.0012} + \underset{(3.52)^*}{0.234}\,h_{t-i} + \underset{(4.68)^*}{0.619}\,\xi^2_{t-i} + \underset{(5.01)^*}{0.083}\,z^2_{t-1}$$

Function Value (the log likelihood) = 656.22

with ξ_t being the residuals from the EC model and z the residuals from the cointegrating vector.[4]

(t statistic values in parentheses while the asterisk denotes significance at 5 %). This time, the persistence measurement $(0.234 + 0.619 + 0.083)$ is close to unity, implying that shocks to volatility may be permanent. The coefficient on the error-correction term is positive and significant. This positive and significant relationship implies a direct relationship between volatility and short-run deviations, which in turn indicate that prediction of stock market data will become a difficult task as the deviation of those data series from macroeconomic fundamentals increases in the short-run.

Comparing the GARCH versus the GARCH-X results, based on the likelihood function value, the GARCH-X(1,1) model outperforms substantially the standard GARCH(1,1) model. In other words, the GARCH-X(1,1) model fits the data substantially better than the GARCH(1,1) process. In addition, the sum of the coefficients in the GARCH-X model has increased, indicating that the persistence of shocks to volatility has considerably increased. The latter results are in accordance with those reached by *French* et al. (1987), *Baillie* and *Bollerslev* (1989), and *Nelson* (1991) for the US stock market.

IV. Concluding remarks

This paper investigated the behaviour of the stock market data volatility and the effects of the short-run deviations between stock market data and certain macroeconomic fundamentals on stock returns volatility in the US market. The empirical analysis used the methodology of the GARCH and GARCH-X models. Short-run deviations were indicated by the error-correction term from the cointegration relationship between stock prices and certain macroeconomic variables, such as money supply, commodity prices, oil prices, income, and the exchange rate. Results from a GARCH-X(1,1) model indicated a significant and positive effect imposed by the deviations on the volatility of the US stock market. The empirical findings imply that the forecasting business of stock market behaviour is expected to become a harder task. Additionally, the GARCH-X results demonstrated a more persistent pattern for volatility, i.e., there is evidence of permanent shocks to volatility. Finally, future research could also consider other or more macroeconomic fundamentals that could exert an effect on financial aggregates, such as, stock prices.

4 Both the GARCH and the GARCH-X estimates were obtained with the assistance of the RATS 4.0 software.

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Summary

Stock Market Volatility and Deviations from Macroeconomic Fundamentals: Evidence from GARCH and GARCH-X Models

This paper investigates volatility in the US stock market and the effects of short-run deviations between stock prices and certain macroeconomic fundamentals over the period 1978: 1 1996: 12. The methodology followed is that of the GARCH and GARCH-X models. The results show that the GARCH-X model outperforms the standard GARCH model, while they indicate a significant effect of the short-run deviations on volatility. (JEL G10)

Zusammenfassung

Aktienmarkt-Volatilität und Abweichungen von den makroökonomischen Fundamentalfaktoren: Beweise auf der Grundlage der Modelle GARCH und GARCH-X

In diesem Beitrag werden die Volatilität des US-Aktienmarktes und die Auswirkungen kurzfristiger Abweichungen zwischen Aktienkursen und bestimmten makroökonomischen Fundamentalfaktoren in der Zeit von Januar 1978 bis Dezember 1996 untersucht. Die angewandte Methodik ist die der Modelle GARCH und GARCH-X. Die Ergebnisse zeigen, daß das Modell GARCH-X dem Standardmodell GARCH überlegen ist, obwohl sie auf eine signifikante Auswirkung der kurzfristigen Abweichungen auf die Volatilität hindeuten.

Résumé

La volatilité du marché boursier et les déviations des paramètres fondamentaux macroéconomiques: Résultats des modèles de GARCH et X-GARCH

Dans cet article, l'auteur analyse la volatilité du marché boursier des EU et les effets de déviations à court terme entre les prix des titres et certains paramètres macroéconomiques fondamentaux. Son examen se base sur la période allant du début de 1978 jusqu'à la fin de 1996. La méthodologie utilisée est celle du modèle de GARCH et de GARCH-X. Les résultats montrent que le modèle de GARCH-X est meilleur que le modèle standard de GARCH puisqu'ils indiquent un effet significatif des déviations à court terme sur la volatilité.