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Empirical Evidence on Feedback Trading in Mature and Emerging Stock Markets

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Empirical Evidence on Feedback Trading in Mature and Emerging Stock Markets*

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Empirical Evidence on Feedback Trading in Mature and Emerging Stock Markets

Abstract: We investigate the hypothesis that some participants in mature and emerging capital markets engage in feedback trading. The analysis is based on the Shiller-Sentana-Wadhwani noise trader model. It has the attractive property that it yields testable implications about the presence of positive and negative feedback traders in stock markets. This theoretical framework, together with an asymmetric GARCH-type model, allows us to draw conclusions about whether differences exist between mature and emerging capital markets in terms of the degree of feedback trading. The empirical results show that positive and negative feedback trading strategies exist in both types of markets but are more pronounced in emerging stock markets than in their mature counterparts. Hence, non-fundamental trading strategies seems to play a more important role in emerging relative to mature stock markets.

Keywords: Feedback Trading, Return Autocorrelation, Emerging Capital Markets in Central and Eastern European Countries, Asymmetric GARCH Models

JEL Classification: G14, C22

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1. Introduction

There is a widely held belief that some investors seek trends in past stock prices and base their portfolio decisions on the expectation that such trends will persist. In the behavioral finance literature this type of investor is usually called a feedback trader. Consequently, one expects that if there is sufficiently large numbers of feedback traders in the stock market this would be reflected in the autocorrelation of stock returns. If feedback trading is of the positive kind, stock prices overshoot levels based on fundamentals and exhibit excess volatility. Hence, the activities of positive feedback traders in stock markets may potentially destabilize stock prices (DeLong et al., 1990). In contrast, negative feedback traders buy when prices are low and sell when prices are high and thereby may stabilize stock markets.

The Shiller-Sentana-Wadhwani model (Shiller, 1984; Sentana and Wadhwani, 1992) captures the behavior of feedback traders and rational investors. The presence of both groups in the stock market, and their specific behavior, provides the theoretical rationale for serially correlated stock returns and the importance of volatility for stock return autocorrelation characteristics. The model has testable implications. In particular, when stock return volatility is low, stock returns exhibit positive autocorrelation, while during periods of high volatility the autocorrelations of stock returns turns negative. The reversal in the sign of stock return autocorrelations is consistent with the presence of positive feedback traders in the stock market.

The present paper contributes to the literature by providing new empirical evidence on the importance of feedback trading in highly developed versus ones in emerging stock markets. Using the Shiller-Sentana-Wadhwani model as a theoretical basis, asymmetric GARCH type models (Glosten, Jagannathan and Runkle, 1993;

Nelson, 1991; Taylor, 1986; Schwert, 1989) are estimated for daily stock index returns beginning in the mid 1990s, and ending December 30, 2003. Comparing the empirical results for stock markets in Central and Eastern Europe (Czech Republic, Hungary, Poland and Russia) with mature markets (Germany, the UK and the US) we examine the question of whether differences exist between both types of stock markets in terms of the degree and type of feedback trading.

In turn, evidence on the existence of feedback traders provides information about their potential impact in destabilizing stock prices in mature relative to emerging markets. Because feedback traders rely on information other than fundamentals our paper provides indirect evidence on the extent of differences in the amount of noisy information affecting the stock markets considered. Since stock returns are often interpreted as containing a significant forward looking component the empirical results shown here may be useful to policymakers since our paper indirectly addresses the forecasting ability of stock returns in both types of markets.

Although our findings reveal some similarities between mature and emerging stock market returns, there is evidence of more pronounced positive and negative feedback trading strategies in emerging stock markets relative to mature ones. Hence, non-fundamental trading strategies seem to play a more important role among investors and in the stock price formation process in emerging stock markets relative to mature capital markets. This empirical evidence is fairly robust across different stock market indices and with respect to the various models of conditional volatility estimated.

The paper proceeds as follows. Section 2 outlines the theoretical model and its testable implications. In section 3, we discuss the econometric methodology. Section 4 describes the data and the empirical results. Section 5 summarizes and concludes.

2. Feedback Trading, Autocorrelated Stock Returns and Volatility

The Shiller-Sentana-Wadhwani model (Shiller, 1984; Sentana and Wadhwani, 1992) captures the behavior of two distinct types of investors in the stock market. Feedback traders or trend chasers, as a group, do not base their asset decisions on fundamental values, reacting instead to stock price changes. Their demand for stocks is based on the history of past stock returns rather than on expected fundamentals. The second group, smart money investors, responds rationally to expected stock returns subject to their wealth limitation. The presence of both groups in the stock market and their specific behavior provides the theoretical rationale for serially correlated stock returns and the importance of volatility as a characteristic of stock returns.

The relative demand for stocks by feedback traders, F_t, is modeled as:

$$F_t = \gamma R_{t-1}, \tag{1}$$

where R_{t-1} denotes the stock return in the previous period. The value of the parameter γ permits differentiation between the two types of feedback traders. When $\gamma > 0$, this refers to the case of positive feedback traders who buy stocks after a price rise and sell stocks after a price fall. In contrast, $\gamma < 0$ indicates the case of negative feedback trading. Unlike a positive feedback trader, the negative feedback trader sells stocks after price increases and buys stocks after price declines. While (1) is the usual way of defining demand for stocks by feedback traders it is, arguably, a rather simplistic model. In particular, it may be argued that individuals and institutions may react to somewhat longer run patterns in the data. In the empirical exercise that follows we consider one variant of (1) that proxies such behavior.

The proportionate demand for stocks by smart money traders, S_t, is determined by a mean-variance model:

$$S_t = (E_{t-1}R_t - \alpha)/\mu_t, \quad (2)$$

where E_{t-1} denotes the expectation operator and α the return on a risk free asset. In this model smart money traders hold a higher proportion of stocks, the higher the expected excess return, $E_{t-1}R_t - \alpha$, and the smaller the risk of holding stocks, μ_t. The risk measure is modeled as a positive function of the conditional variance, σ_t^2, of stock prices $\mu_t = \mu(\sigma_t^2)$. Equilibrium in the stock market requires that all stocks are held:

$$S_t + F_t = 1. \quad (3)$$

Allowing the presence of both groups in the stock market and substituting (1) and (2) in (3) yields, after rearranging and assuming rational expectations in the determination of stock returns, i.e., $R_t = E_{t-1}R_t + \upsilon_t$:

$$R_t = \alpha + \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} + \varepsilon_t. \quad (4)$$

As seen from equation (4), in a stock market with feedback traders, the return function contains the additional term R_{t-1} indicating that stock returns exhibit autocorrelation of order one. The pattern of autocorrelation in stock returns depends on the type of feedback traders captured by the parameter γ. The presence of positive feedback traders ($\gamma > 0$) leads to negatively autocorrelated stock returns while negative feedback trading ($\gamma < 0$) implies positively autocorrelated stock returns.

Furthermore, the extent to which stock returns exhibit autocorrelation varies with volatility, σ_t^2. Relying on a linear form, $\gamma\mu(\sigma_t^2)$ in equation (4) can be reformulated as:

$$R_t = \alpha + \mu(\sigma_t^2) - (\gamma_0 + \gamma_1\sigma_t^2)R_{t-1} + \varepsilon_t \,. \tag{5}$$

Following Sentana and Wadhwani (1992) negative feedback trading dominates at low volatility levels and positive feedback trading dominates at high levels of volatility. At a low risk level σ_t^2, the direct impact of feedback traders is given by the sign of γ_0. Negative feedback trading, $\gamma_0 < 0$, results in positively autocorrelated stock returns. With a rising risk level, the influence of a positive γ_1 increases and might induce negatively autocorrelated stock returns due to the dominance of positive feedback trading. Thus, the model predicts that the interaction of smart money traders and positive feedback traders can induce negative autocorrelation in stock returns during periods of high volatility.

Generally, positive feedback trading activities are associated with positive stock return autocorrelation because positive feedback traders move stock prices away from fundamental values in the short-run (DeLong et al., 1990). However, Shiller (1989) points out that positive feedback trading may induce negligible and even negative stock return autocorrelation. As shown in LeBaron (1992) and Campbell, Grossman and Wang (1993) the autocorrelation pattern of stock returns is more complex than a simple first order autocorrelation coefficient is able to capture. LeBaron's empirical findings show significant non-linear dependencies between autocorrelation and volatility. Campbell, Grossman and Wang find an inverse relationship between trading volume and stock return autocorrelation. Furthermore, previous empirical evidence on the Shiller-Sentana-Wadhwani model shows that the finding of negative autocorrelations in stock index returns during periods of high volatility is a fairly robust result (Sentana and Wadhwani, 1992; Koutmos, 1997; Koutmos and Saidi, 2001).

A related question is the sampling frequency over which the autocorrelation patterns described above will appear in the data. The finding that there is autocorrelation in daily stock returns may be spurious because trading is non-synchronous (Lo and MacKinlay, 1990). However, as significant autocorrelations remain at lower frequencies (e.g., weekly stock returns) it is not clear that the non-synchronous trading problem is empirically meaningful. While the models specified below are also estimated at the weekly frequency only the results using daily data are reported to facilitate comparisons with the literature. It should be noted, however, that the autocorrelations found at the daily frequency remain at the weekly frequency and, indeed, the weekly results reinforce the ones reported based on daily data.

3. Econometric Methodology

A characteristic of stock return volatility often found in the empirical finance literature is asymmetry in the conditional variance. Therefore, the threshold GARCH model, or TGARCH, proposed by Glosten, Jagannathan and Runkle (1993) and Zakoïan (1994) is implemented. This result in equation (5) being jointly estimated with:

$$\sigma_t^2 = \omega + \beta_0 \sigma_{t-1}^2 + \beta_1 I_{t-1} \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2, \tag{6}$$

where the indicator variable is defined as:

$$I_{t-1} = \begin{cases} 1, \text{ if } \varepsilon_{t-1} < 0 \\ 0, \text{ if } \varepsilon_{t-1} \geq 0 \end{cases}. \tag{7}$$

In (6) and (7) the conditional variance is a function of the last period's squared innovations and the last period's conditional volatility. Stationarity requires that $\beta_0 + \beta_1 + \beta_2 < 1$ while the condition for non-negativity is that β_0, β_1, β_2 each be positive and $\beta_1 + \beta_2 \geq 0$.

Moreover, the conditional volatility may be an asymmetric function of last period's squared innovations in the sense that past negative innovations increase volatility more than positive ones of equal magnitude. If the asymmetry parameter is significantly positive, conditional volatility rises more after a negative shock than a positive shock. The degree of volatility persistence is measured by $\beta_0 + \beta_2$. Since we consider the possibility that stock return information may be transmitted across markets, we permit additional exogenous terms in both the mean and variance equations, if these can improve our estimated specifications. The TGARCH(1,1) model has the additional advantage that it nests the GARCH(1,1) model as a special case. This allows to perform a test of the validity of a key restriction, namely the null hypothesis that $\beta_1 = 0$. If we are not able to reject this null hypothesis then conditional volatility does not possess the asymmetric feature.

A popular alternative to the TGARCH(1,1) model is Nelson's (1991) EGARCH(1,1) model:

$$\ln(\sigma_t^2) = \omega + \beta_0 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta_1 \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) + \beta_2 \ln \sigma_{t-1}^2, \tag{8}$$

where $|\varepsilon_{t-1}/\sigma_{t-1}|$ is the absolute value of the standardized innovations. Asymmetry is indicated by a statistically significant value for β_1. An arguably more general formulation, the Power GARCH or PGARCH model, is able to nest many varieties of ARCH and GARCH models (Brooks et al., 2000). Introduced by Taylor (1986) and Schwert (1989), and generalized by Ding, Granger and Engle (1993), the standard deviation is modeled instead of the variance. The model is written as:

$$\sigma_t^d = \omega + \beta_0 \left(|\varepsilon_{t-1}| - \beta_1 \varepsilon_{t-1} \right)^d + \beta_2 \sigma_{t-1}^d, \tag{9}$$

where asymmetry is given by β_1. The PGARCH model (9) nests the conventional GARCH family of models when $d = 2$ which is a testable restriction.

4. Data and Empirical Results

Our sample consists of daily data for three indices for mature stock markets and four indices for emerging capital markets in Central and Eastern European countries. The stock markets indices are the DAX (Germany), the FTSE (UK) and the S&P500 (US). The PX50 (Czech Republic), the BUX (Hungary), the WIG (Poland) and the RTS (Russia) are the indices for the emerging stock markets. These indices are from the largest stock markets in West Europe, Central and Eastern Europe and the US. The time series are available on the daily frequency at the close of trading day at the Web site http://www.parkiet.com.pl.

All index time series end in December 30, 2003. Data for the indices for the emerging markets begin with the first complete month during which trading took place five days a week. To provide comparable empirical results, the sample relying on the stock index time series for the mature markets begin no earlier then January 2, 1994.

Table 1 contains information on the seven indices and the samples over which the model outlined above is estimated. Figure 1 provides a plot of the various indices considered in this paper.

Table 1 about here

Figure 1 about here

Table 2 reports the first order autocorrelation coefficient for each stock return index in our sample for the full sample (see Table 1) as well as for two sub-samples labeled “Tranquil” and “Volatile”. Our aim here is solely to illustrate whether the autocorrelation of stock returns may be a function of the level of risk in stock markets. Hence, we did not estimate dates at which there may have been a switch from “low” to “high” volatility. Rather the thresholds were simply imposed in an ad hoc fashion though, not surprisingly, high volatility periods in emerging stock markets tend to occur around the Asian and Russian crises of 1997 – 1998 while, for mature markets, high volatility consists essentially of the post 2000 bursting of the tech bubble.

Table 2 about here

The sign reversal in stock return autocorrelations is largely a phenomenon of mature markets save the DAX. In the case of emerging markets the first order autocorrelation coefficient rises in tranquil periods relative to volatile periods with the exception of the Polish market. Figures 2A and 2B plot a three-months rolling moving average of stock returns and the standard deviation of returns for the seven markets in our sample. The Figures highlight the Asian and Russian financial crises in emerging markets whereas the tech bubble and September 11th, 2001, are highlighted in the case of mature stock markets. Clearly, the Asian crisis figures prominently in explaining the evolution of the standard deviation of stock returns while there appear to be a few more episodes in mature markets when the standard deviation of returns flares up.

Figures 2A and 2B about here

Table 3 provides more stylized evidence about changing stock returns in the two market groups by showing regression results for a version of equation (5). A dummy variable to capture the Asian and Russian crises is used for the emerging markets. For the mature markets the period since the beginning of the bursting tech bubble serves as the dummy. It is clear from Table 3 that while the coefficients on lagged stock returns are positive in all markets they are several times higher in emerging markets than in their mature counterparts. Also, rising volatility tends to reduce the autocorrelation of stock returns in stock markets but the stock returns remain essentially positively autocorrelated in all emerging markets, except Poland (WIG), while they turn negative in mature markets except for the FTSE100. Hence, we have a little bit of preliminary evidence that positive feedback trading is particularly a phenomenon of mature markets.

Table 4 provides estimates of d in the PGARCH model (9). Estimates for mature markets are comparable to ones reported in Brooks et al. (2000). Estimates for emerging markets are considerably higher and these suggest that a TGARCH model might be more suitable for emerging market indices while the EGARCH variety might be more suitable for mature markets.

Table 4 about here

The estimation results for the chosen GARCH models are reported in Tables 5 and 6. Despite the many variants of GARCH type models estimated, including considerable differences found in the degree of persistence in the variances, the estimated coefficients shown were found to be remarkably robust across the specifications considered. Many studies that resort to the estimation of GARCH type models use a non-Gaussian likelihood relying on a *t* distribution to estimate standard errors. The results in Tables 5 and 6 rely on this distributional assumption. However, as shown in Newey and Steigerwald (1997), a Gaussian likelihood (typically a quasi maximum likelihood estimator) may be useful under certain conditions. Alternatively, some, such as Nelson (1991), have preferred to rely on a generalized error distribution. All our results are robust to the assumption of the chosen distribution for the ε_t. Hence, we generated estimates using both Gaussian and non-Gaussian likelihoods though we rely on the latter in reporting the results below.

The findings for mature and emerging stock markets are reported in Tables 5 panel A and B, respectively. The coefficients describing the conditional variance process, $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$, are statistically significant in the vast majority of cases at the 1 % level. As is well known, volatility persistence is typically high in all financial markets. The stationarity conditions are violated in a few of the cases considered. In some instances we were able to obtain results without finding a unit root in the variance by adding an exogenous variable, namely the lagged mean stock return and conditional variance of stock returns. The asymmetry coefficient is statistically significant for all three mature capital market indices. Only the Russian stock market index does not exhibit asymmetry. Furthermore, with only two exceptions, the estimated parameters $\hat{\alpha}$ and $\hat{\mu}$ from the mean equation are statistically insignificant.

Tables 5 about here

Consistent with the theoretical model the $\hat{\gamma}_0$ parameters are significantly negative and the $\hat{\gamma}_1$ coefficients are significantly positive for one of three mature (S&P500) as well as three of four emerging markets indices (BUX, PX50, RTS). Also, note that the $\hat{\gamma}_0$ parameters are in absolute terms higher in emerging stock markets than in their counterpart mature markets. Hence, the empirical evidence is more supportive for negative feedback trading in emerging stock markets compared to mature ones. The same refers to positive feedback trading activities. Therefore, negative and positive feedback trading behavior seems to be more pronounced in emerging than in mature stock markets.

Finally, Table 6 in panel A and B considers the case where, in addition to the lagged return, the one-month deviation of the moving average of returns from the "long-run" average return, proxied by the sample mean of returns, is considered as an added determinant. The reason, as noted earlier, is that it is likely that feedback traders will act not on the lagged return but perhaps to a persistent deviation from some target or average return. The previously discussed results are indeed reinforced. Negative and positive feedback trading is enhanced by the addition of a proxy for “momentum” in the stock returns.

Table 6 about here

5. Summary and Conclusions

Within the framework of the market efficiency hypothesis (Fama, 1965) noise traders are unimportant in the stock price formation process because rational arbitrageurs’ trades drive prices close to their fundamental values. Continuing evidence of market anomalies, however, calls into question the notion that arbitrage can eliminate the difference between actual and fundamental stock prices. In this paper, we contribute to the behavioral finance literature by providing new empirical evidence on the presence of feedback traders in stock markets. More importantly, we compare the findings for developed markets with the results for emerging capital markets in Central Eastern European countries.

The theoretical basis for our empirical investigation is the Shiller-Sentana-Wadhwani noise trader model which has the attractive property that it yields to a testable hypothesis. If positive feedback traders are present in the stock market, the theoretical model predicts negatively autocorrelated returns during periods of high volatility. In contrast, negative feedback traders produce positively autocorrelated returns. This implication is investigated using several varieties of asymmetric GARCH models for three stock market indices in mature markets (Germany, the UK and the US) as well as four emerging stock markets in Central and Eastern Europe (Czech Republik, Hungary, Poland and Russia).

The empirical findings support the existence of positive and negative feedback trading strategies in stock markets. This result is generally robust across the different stock market indices as well as across models of conditional volatility that were estimated. Furthermore, the results show differences between the two types of groups of stock markets. To the extent that positive and negative feedback traders contribute to the stock price formation process, their impact is larger in emerging than in mature stock markets. Non-fundamental trading strategies seems to play a more important role in emerging stock markets compared to their mature counterparts.

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Table 1: Stock Market Indices Examined

Index	Stock Exchange, Country	Sample
DAX	Frankfurt/Main, Germany	January 2, 1994 – December 30, 2003
FTSE	London, United Kingdom	January 2, 1994 – December 30, 2003
S&P500	New York, United States	January 2, 1994 – December 30, 2003
BUX	Budapest, Hungary	January 3, 1995 – December 30, 2003
PX50	Prague, Czech Republic	October 3, 1994 – December 30, 2003
RTS	Moscow, Russia	September 1, 1995 – December 30, 2003
WIG	Warsaw, Poland	October 3, 1994 – December 30, 2003

Note: The stock market indices data were obtained are from http://www.parkiet.com.pl and represent daily close prices.

Table 2: First Order Autocorrelations

Stock Index	Full Sample	Tranquil	Volatile
BUX	0.063	0.092	0.014
PX50	0.123	0.213	0.073
RTS	0.117	0.140	0.092
WIG	0.140	0.116	0.160
DAX	– 0.014	– 0.050	– 0.010
FTSE	0.012	0.027	– 0.041
S&P500	– 0.016	0.015	– 0.043

Note: “Volatile” is defined as a 3 months moving standard deviation that exceeds 2.0 for BUX, 1.2 for PX50, 3.0 for RTS, 2.0 for WIG, 1.4 for DAX, 1.4 for FTSE and 1.2 for SP500. Otherwise, the sample is treated as “Tranquil”. “Full Sample” is as shown in Table 1. Also, see Figures 2A and 2B.

Table 3: Stylized Facts from Emerging and Mature Markets

Stock Index	$\hat{\alpha}$	$\hat{\gamma}_0$	$\hat{\gamma}_1$
BUX	0.07 (0.04)*	0.11 (0.03)*	– 0.09 (0.04)*
PX50	0.01 (0.03)	0.11 (0.02)*	0.11 (0.05)*
RTS	0.05 (0.07)	0.15 (0.03)*	– 0.08 (0.05)*
WIG	0.01 (0.04)	0.08 (0.02)*	– 0.20 (0.04)*
DAX	0.02 (0.03)	0.02 (0.03)	– 0.09 (0.04)*
FTSE	0.01 (0.02)	0.05 (0.03)	– 0.11 (0.04)*
S&P500	0.04 (0.02)*	0.002 (0.02)	– 0.07 (0.04)[#]

Note: Coefficients are based on estimate of (5) where $I_t = [0,1]$ and is set to 1 for the Asian crisis, namely July 1, 1997 to December 31, 1998 in the case of emerging markets. In the case of mature markets, $I_t = 1$ from June 3, 2000 to 31 December 2003. Standard errors are in parenthesis. * indicates statistically significant coefficients at the 5 % level and [#] that the parameter is significant at the 12 % level.

Table 4: Estimates of the Power Parameter in PGARCH Models

Stock Index	*d*	
BUX		1.73
		1.44 (0.23)
PX50		2.82
		2.97 (0.09)
RTS		2.07
		0.09(0.76)
WIG		1.77
		0.37 (0.54)
DAX	0.91	1.29
	– *0.46*	*1.42* (0.23)
FTSE	1.44	1.38
	1.23	*3.28* (0.07)
S&P500	1.21	1.06
	0.69	*0.31* (0.58)

Note: d is the estimate of the power parameter in (9). Estimates based on the samples shown in Table 1 are given in column 3. Column 2 shows estimates of d reported in Brooks et al. (2000). *t*-statistics for the null hypothesis $H_0 : d = 2$ for emerging markets and $H_0 : d = 1$ for mature markets are italicized. p-values are shown in parenthesis.

Table 5: GARCH Model Estimation Results

A. Mature Stock Markets

	DAX: TGARCH	FTSE100: EGARCH	S&P500: EGARCH
$\hat{\alpha}$	0.04 (0.02)	– 0.04 (0.10)	0.02 (0.02)
$\hat{\gamma}_0$	0.08 (0.03)**	– 0.08 (0.05)*	– 0.09 (0.03)***
$\hat{\gamma}_1$	0.01 (0.01)	0.04 (0.04)	0.05 (0.02)***
$\hat{\mu}$	0.001 (0.02)	0.04 (0.09)	0.01 (0.02)
$\hat{\gamma}_0^{'}$	0.23 (0.03)***		
$\hat{\omega}$	– 0.18 (0.09)**	– 0.12 (0.05)***	– 0.10 (0.01)***
$\hat{\beta}_0$	0.04 (0.01)***	0.20 (0.05)***	0.12 (0.02)***
$\hat{\beta}_1$	0.07 (0.02)***	– 0.07 (0.03)**	– 0.12 (0.01)***
$\hat{\beta}_2$	0.90 (0.01)***	0.36 (0.15)***	0.98 (0.01)***
$\hat{\beta}_2^{'}$	0.22 (0.09)***		
Log Likelihood	– 3888.74	– 3490.12	– 3207.50

Table 5 (Continued): GARCH Model Estimation Results

B. Emerging Stock Markets

	BUX: TGARCH	PX50: TGARCH	RTS: TGARCH	WIG: TGARCH
$\hat{\alpha}$	– 0.07 (0.02)***	0.003 (0.09)	0.16 (0.07)***	– 0.01 (0.04)
$\hat{\gamma}_0$	– 0.12 (0.03)***	– 0.27 (0.05)***	– 0.20 (0.03)***	– 0.19 (0.02)***
$\hat{\gamma}_1$	0.01 (0.00)***	0.04 (0.01)***	0.004 (0.001)***	0.001 (0.003)
$\hat{\mu}$	0.04 (0.03)	– 0.01 (0.05)	– 0.01 (0.01)	0.006 (0.013)
$\hat{\gamma}_0^{'}$	– 0.06 (0.02)***			
$\hat{\omega}$	2.34 (0.25)***	1.03 (0.09)***	0.24 (0.06)***	0.10 (0.02)***
$\hat{\beta}_0$	0.07 (0.03)***	0.13(0.03)***	0.19 (0.03)***	0.12 (0.02)***
$\hat{\beta}_1$	0.14 (0.05)***	0.08 (0.05)*	0.004 (0.04)	0.04 (0.03)*
$\hat{\beta}_2$	0.31 (0.06)***	0.47 (0.05)***	0.81 (0.02)***	0.84 (0.02)***
$\hat{\beta}_2^{'}$	– 0.28 (0.03)***	– 0.37 (0.02)***		
Log Likelihood	– 4357.19	– 3612.50	– 5073.05	– 4484.35

Note: Equations (5) and (6) or, alternatively, (8) are jointly estimated via maximum likelihood. $\hat{\beta}_2^{'}$ is the coefficient for one period lagged S&P500 for the BUX and one period lagged FTSE100 for the PX50 in the variance equation. $\hat{\gamma}_0^{'}$ is the coefficient for one period lagged S&P500 in the mean equation for the BUX, and lagged FTSE100 in the mean equation for the DAX. Standard errors are in parentheses and ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Table 6: Further GARCH Model Estimation Results

A. Mature Stock Markets

	DAX: TGARCH	FTSE100: EGARCH	S&P500: EGARCH
$\hat{\alpha}$	0.04 (0.02)*	– 0.002 (0.02)	0.03 (0.02)*
$\hat{\gamma}_0$	– 0.01 (0.03)	– 0.18 (0.07)***	– 0.09 (0.03)***
$\hat{\gamma}_1$	0.01 (0.01)	0.11 (0.05)**	0.05 (0.02)***
$\hat{\gamma}_0^*$	– 0.10 (0.02)***	– 0.05 (0.02)***	– 0.03 (0.02)*
$\hat{\omega}$	0.02 (0.01)***	– 0.08 (0.01)***	– 0.08 (0.01)***
$\hat{\beta}_0$	0.04 (0.01)***	0.10 (0.02)***	0.10 (0.02)***
$\hat{\beta}_1$	0.08 (0.02)***	– 0.10 (0.01)***	– 0.12 (0.01)***
$\hat{\beta}_2$	0.91 (0.01)***	0.99 (0.003)***	0.98 (0.003)***
$\hat{\beta}_2'$			
Log Likelihood	– 3877.71	– 3210.82	– 3191.60

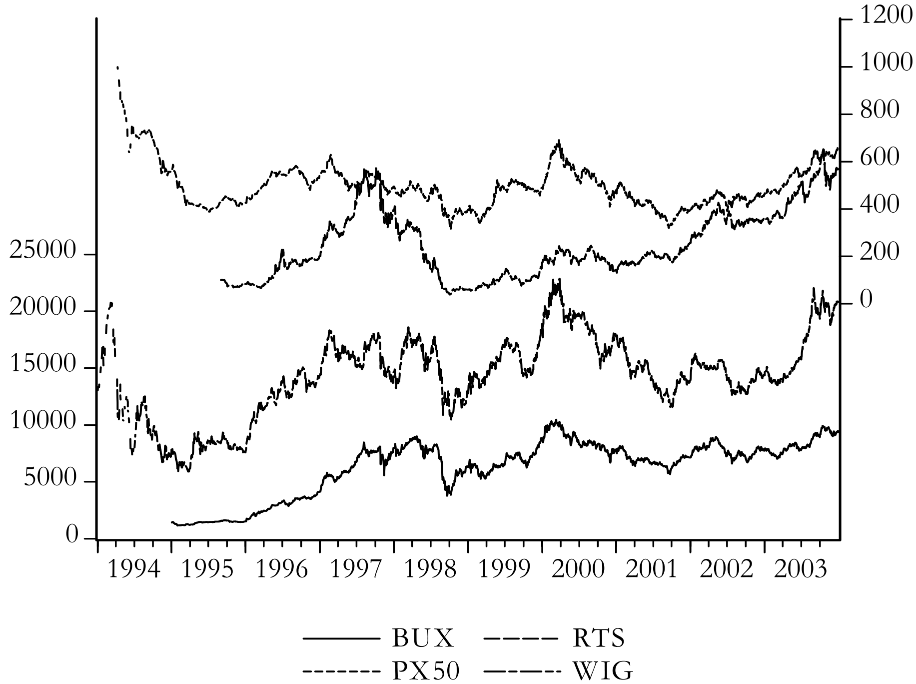
Table 6 (Continued): Further GARCH Model Estimation Results

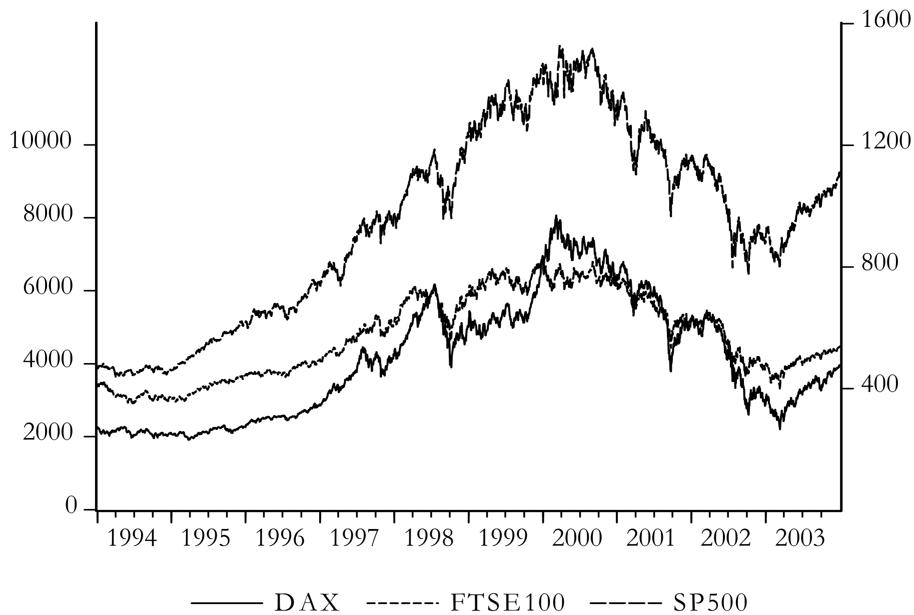
B. Emerging Stock Markets

	BUX: TGARCH	PX50: TGARCH	RTS: TGARCH	WIG: TGARCH
$\hat{\alpha}$	0.08 (0.02)***	0.01 (0.02)	0.13 (0.04)***	– 0.003 (0.03)
$\hat{\gamma}_0$	– 0.11 (0.03)***	– 0.31 (0.03)***	– 0.19 (0.03)***	– 0.19 (0.03)***
$\hat{\gamma}_1$	0.01 (0.004)***	0.06 (0.01)***	0.004 (0.001)***	0.01 (0.003)***
$\hat{\gamma}_0^*$	– 0.06 (0.02)***	– 0.04 (0.02)***	– 0.15 (0.04)***	– 0.09 (0.03)***
$\hat{\omega}$	0.06 (0.02)***	– 0.07 (0.04)*	0.24 (0.06)***	0.10 (0.02)***
$\hat{\beta}_0$	0.09 (0.02)***	0.14 (0.03)***	0.19 (0.03)***	0.11 (0.02)***
$\hat{\beta}_1$	0.05 (0.02)***	0.07 (0.03)**	– 0.01 (0.04)	0.06 (0.03)**
$\hat{\beta}_2$	0.86 (0.02)***	0.83 (0.02)***	0.81 (0.02)***	0.84 (0.02)***
$\hat{\beta}_2^{'}$	0.02 (0.01)*	0.10 (0.04)**		
Log Likelihood	– 4107.38	– 3359.37	– 5029.72	– 4420.78

Note: The equations (5) and (6) or, alternatively, (8) are jointly estimated via maximum likelihood. $\hat{\gamma}_0^*$ is the coefficient estimate for the variable $\tilde{\tilde{R}}_{t-1} - (\overline{R}_{t-1} - \varepsilon_t)$, where the first term is the one month (i.e., 20 day) moving average of returns less the differential between the sample mean return and a random variable with mean 0 and standard deviation of 1. $\hat{\beta}_2^{'}$ is the coefficient for one period lagged S&P500 for the BUX and one period lagged FTSE100 for the PX50. The GARCH term ($\hat{\mu}$) is constrained to zero as it was found to be highly insignificant in all cases.Standard errors are in parantheses and ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Figure 1: Daily Stock Market Indices in Emerging and Mature Markets

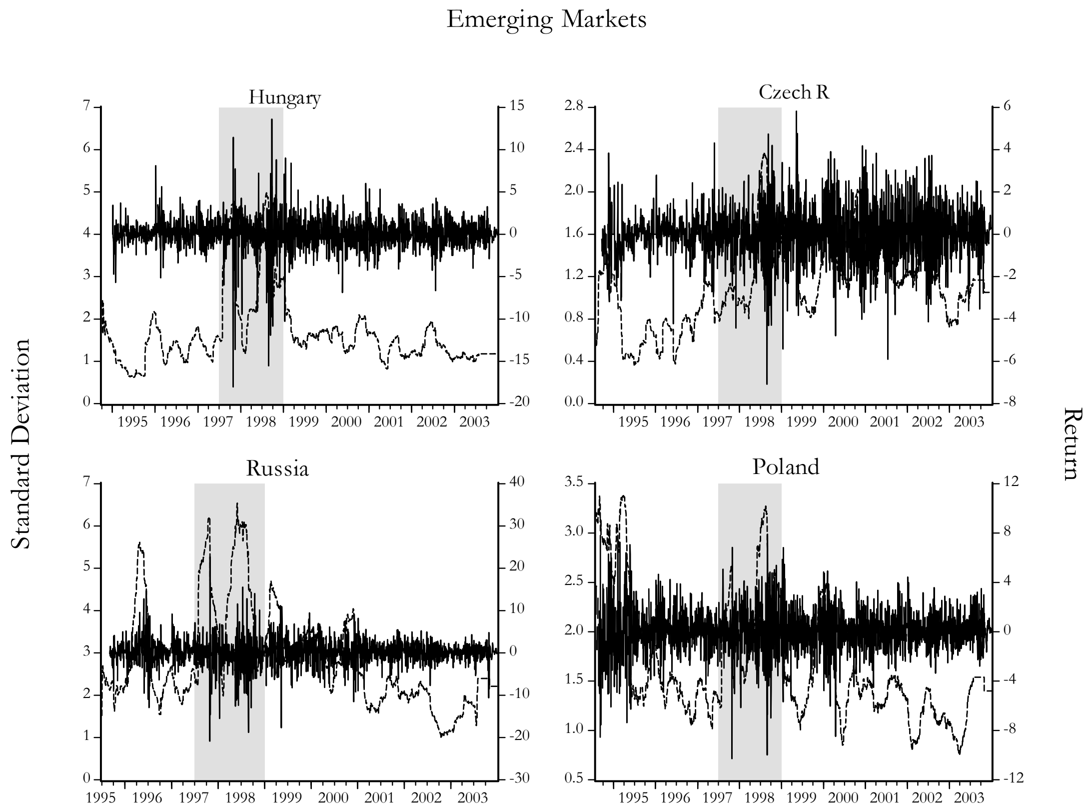




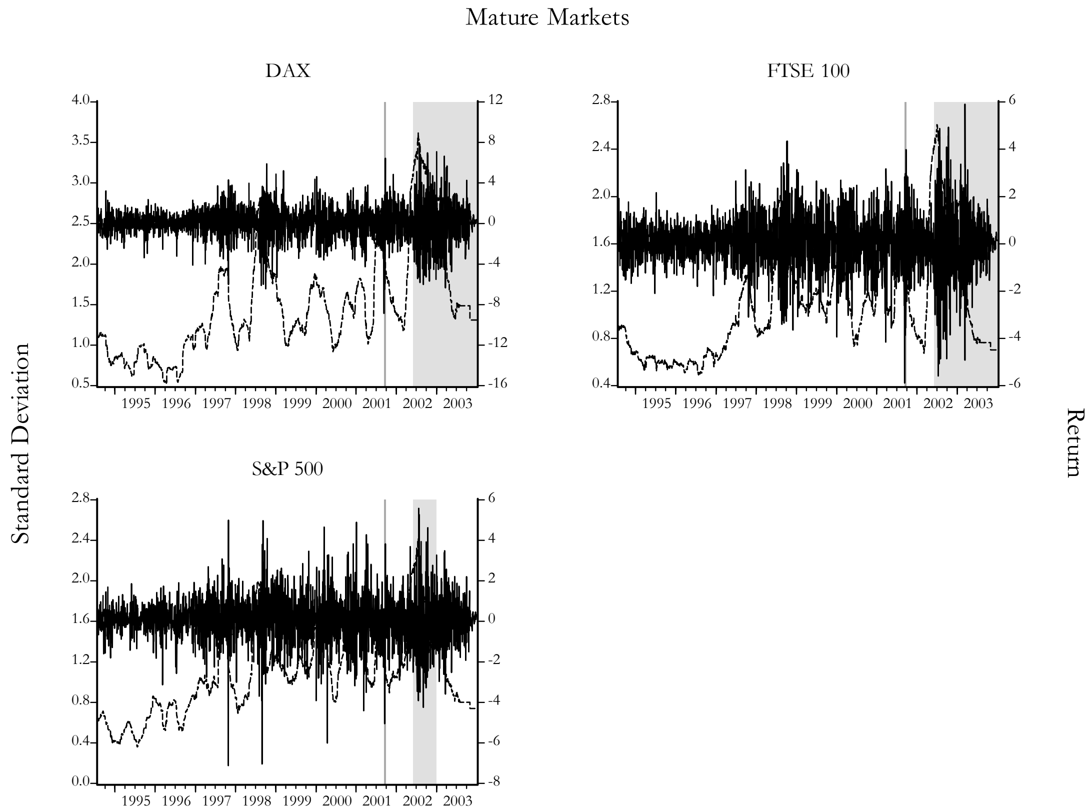
Source: www.parkiet.com.pl. Figures for the RTS and PX50 are plotted on the right hand scale; BUX and WIG figures are plotted on the left hand scale. Data for the DAX and the FTSE100 are plotted on the left hand scale while those for the SP500 are plotted on the right hand scale.

Figure 2: Rolling Moving Average and Standard Deviation of Stock Returns

A. Emerging Markets



B. Mature Markets



Note: Returns are the daily rates of change in the index levels plotted in Figure 1. A three-month moving average was calculated as well as a three month moving standard deviation of stock returns. Each value was then "rolled" on a daily basis to obtain the figures plotted above. Sources of data and samples are as in Table 1. The highlighted areas represent the Asian crisis (1997 – 1998), September 11th, the US recession, or the collapse of the tech bubble beginning in 2002.