RETURN BEHAVIOR IN AN
EMERGING STOCK MARKET:
THE CASE OF UKRAINE

by

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Abstract

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The paper investigates the nature and possible origins of return autocorrelation found in a Ukrainian stock market index. A simple model of stock market with rational and feedback traders, suggested by Sentana and Wadhwani [1992] is checked for consistency with the actual pattern of behavior of two out of three indices calculated after trading in the Ukrainian Over-the-counter Informational Trading System (PFTS), over a three-year period (from November 1997 till November 2001). The original empirical model by Sentana and Wadhwani had to be modified, which is taken to be an evidence of the Ukrainian stock market being much underdeveloped. EGARCH model introduced by Nelson [1991] was applied to daily PFTS and ProU50 returns. The model allowed us to capture the behavior of two types of investors in the market, which revealed itself in heteroscedasticity of returns and in an asymmetric market reaction to return shocks of different sign. The model proved consistent with the empirical data over the given period.

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GLOSSARY

Capital Asset Pricing Model (CAPM) – the model of asset pricing introduced by Sharpe [1962]. In CAPM, the return on each security is a linear function of this asset's beta (the ratio of the covariance of the return on the security with the return of the market to the variance of the return on the market). CAPM assumes traders to have rational expectations

Exponential Generalized Autoregressive Conditional Heteroscedasticity in Mean (EGARCH-M) models – a class of ARCH models introduced by Nelson [1991]. All ARCH models capture the serial correlation of the conditional volatility of a dependent variable. EGARCH-M model allows to test extensions of the CAPM model that imply autocorrelation of asset returns, volatility clustering (volatility shock persistence), the direct influence of volatility on the level of expected returns, the influence of volatility on the pattern of return autocorrelation, and the asymmetric reaction of the market to the volatility shocks of different sign

Efficient Market Hypothesis – the concept in financial economics which states that the capital markets correctly determine asset prices and utilize all relevant information for that purpose. The efficient market hypothesis implies impossibility to earn above-normal profits from a portfolio

Feedback traders – a type of stock market investors with adaptive expectations: they base their asset decisions on the past history of the market

Smart money traders – a type of stock market investors with rational expectations: they base their asset decisions on market fundamentals

Volatility clustering – the property of volatility of asset returns to be serially correlated, i.e. a tendency for large (small) values of volatility to be followed by large (small) values, of either sign

Securities and Stock Market State Commission (SSMSC) – a regulative authority over stock exchanges in Ukraine. It was established for regulating and control of the stock market in Ukraine

Chapter 1

INTRODUCTION

Emerging stock markets, in general, tend to be structurally and institutionally inefficient, characterized by thinness and low liquidity, low speed of information dissemination, imperfect organizational process, likely trading restrictions. Because of that, they, more than developed markets, are suspected to deviate from the predictions of the efficient market theory. Indeed, Barkoulas, Baum and Travlos [2000] discovered that the market index of the Greek stock market, an emerging one, exhibited a long-term persistence of shocks to daily returns, and gave a good prediction of the returns for over a year ahead (from November 1989 till December 1990).

In line with it, Dedov [2000], in his recent empirical investigation of *weekly* returns of some two Ukrainian stock market indices, rejected the joint hypothesis of the weak-form efficiency of stock prices and the random walk model of price behavior. Dedov found that *weekly* returns were autocorrelated, but failed to find a significant linear influence of return volatility on returns. Thus, for this thesis, a theoretical model was chosen explaining a related effect – a non-linear influence of return volatility on autocorrelation of returns (at a higher, daily, frequency).

A low correlation of returns in major financial markets with those in emerging markets may make the latter a potentially attractive place to trade in for international investors who seek to diversify their risks. A piece of information about the Ukrainian stock market might help attract foreign capital to the market. Thus, an empirical research, investigating the nature of the return behavior of the Ukrainian stock market, might be interesting both in the academic respect and from a practical viewpoint.

Early testing of the efficient market hypothesis, which was based on evidence from developed capital markets, confirmed the theory of efficient capital markets (Fama [1970]). Later empirical studies showed, however, that even in developed capital markets (Shiller [1981], De Bondt and Thaler [1985,1987]), return behavior did not always obey the predictions of the efficient capital markets theory. Returns exhibited autocorrelation and volatility clustering of returns, price bubbles, shock persistence. Extensive theoretical literature has emerged explaining some of these empirical phenomena. Nowadays, there are several classes of models that form two large groups, or approaches: "rational" approach, which is a development of the efficient market theory; and "behavioral" approach, which, along with economic theory, extensively incorporates psychological methodology and evidence into economic analysis.

Therefore, first part of the thesis is exploratory. There, the two major approaches of studying aggregate market return behavior are briefly reviewed, several specific models are described and compared. A simple model of stock market with rational and feedback traders, is described in detail.

In the second part of the thesis, an empirical investigation of returns in the Ukrainian Over-the-counter Informational Trading System (PFTS) is conducted, to discover a particular phenomenon of an aggregate daily stock index behavior – the influence of return volatility on the autocorrelation of returns[1].

The thesis is organized as follows. Chapter 2 explores major approaches of studying the behavior of aggregate stock market, and discusses several specific models. Chapter 3 presents a simple model of stock market with rational and feedback traders. Chapter 4 reviews methodology for empirical research, and

[1] Probably, the lengthier the time span, the fewer shocks must be expected to persist over it. Given that Dedov [2000] discovered autocorrelation of weekly returns in the market, daily series must also be suspected of autocorrelation. (This consideration is thus a pre-justification for the "daily" theoretical and empirical model employed in the study.)

discusses chosen model. Chapter 5 introduces relevant characteristics of the market under study. Chapter 6 summarizes and concludes.

Chapter 2

LITERATURE REVIEW

When there appeared increasing evidence of violations of random walk and market efficiency joint hypothesis (e.g., [include references]), the efficient market theory had to be re-considered to explain the new phenomena. New rational expectations models of aggregate stock market soon emerged. In some of them, homogeneity of agents in the market was assumed (as in the model discussed by Shiller [1981]), other ones proposed existence of heterogeneous types of traders (Grossman and Stiglitz [1980]) or traders possessing diverse information (Grossman [1976]). However, they retained the basic component of efficient capital markets theory - the assumption of agents maximizing their (expected) utility, and rationally using all the information available to achieve that.

In an early stage of development of new models, there have been attempts to explain some new facts of stock market by minor extensions of classic 'rational' models without changing their basic framework. This did not enabled economists to plausibly explain the evidence. Shiller [1981] assessed capability of one classic model of rational expectations to explain the observed variability of Real Standard and Poor's Composite Stock Price Index, 1871-1979, and Real Modified Dow Jones Industrial Average, 1928-1979. That simple model (which nevertheless was widely used as describing the behavior of aggregate stock market indices by that time) stated that real stock prices equaled the present value of rationally expected future real dividends discounted by a constant real discount rate. It ascribed sudden movements in the stock price indices to "new information" about future dividends. Shiller presented a proof that those movements could not be attributed (at least solely) to any new information about future events, because movements in the price indices were too large relative to actual subsequent events. Still, Shiller proposed two ways of extending the model which might increase its validity. The first one was to attribute the movements in stock prices to changes in real interest rate, though again, this factor alone was shown to be unable to explain the extent of movements. The second qualification Shiller made was that true uncertainty about future dividends was actually much larger than the measure of that uncertainty - the sample standard deviation of real dividends from their long-run growth path. However, the power of both extentions, should they have been done, to explain the extent of the movements, would not be testable, as both were the unobservables.

Campbell and Cochrane [1999] present an example of much more recent 'rational' model. It was a consumption based explanation of aggregate stock market behavior. The authors retained the standard assumption of representative agent and consumption based asset pricing model. They assumed consumption to grow at some independently and identically distributed rate, to allow the model not to depend upon exogenous variation of probability distribution of consumption growth in the model's generation of asset price behavior.

The central component of the model was slowly moving external subsistence level that was added to the standard power utility function; this generated a slow counter-cyclical variation in risk premia, actually observed in stock markets. The model was capable of explaining also other asset pricing phenomena, such as procyclical variation of stock prices, the long-horizon predictability of excess stock returns, and the counter-cyclical variation of stock market volatility. It also explained the short- and long-run equity premium puzzles.

Together with rational expectations models, another major approach to explain stock market (as well as other financial markets) aggregate return behavior has been developing. It is so-called behavioral approach. It tries to widen the range of analytic tools with which to approach the processes of decision making and interaction between individuals in groups. This approach has partially adopted psychological methodology in studying mentioned problems, and it came up with interesting alternatives to conventional economic theories.

One such alternative was the prospect theory that extented its predecessor, the expected utility theory. Among other things, the prospect theory gave birth to a series of models explaining the behavior of financial markets in the aggregate. One such model was developed in Barberis, Huang and Santos [1999]. They proposed a new framework of asset pricing, partly derived from the traditional consumption based approach, but which also incorporated prospect theory and empirical evidence on how previous outcome influenced risky choices. It was assumed, after prospect theory, that an investor derived utility not only from consumption, but also from his wealth that s/he was much more sensitive to reductions in than to increases in.

The key component of the model apparently differs from that in Campbell and Cochrane [1999] model[2]. Barberis et. al. assumed that the (dis)utility the investor received from losses in the wealth (and hence the choices s/he would make now), depended upon the his/her *previous* investment outcomes. The worse were those outcomes, the more risk-averse would be the investor, that is, the agent's risk-aversion was changing over time with his/her prior investment performance. This made prices much more volatile than underlying dividends (observation which the early model discussed in Shiller [1981] could not justify). Moreover, this feature, together with risk aversion, implied large risk premia, which was also consistent with empirical observations. The model generated the high mean, volatility and predictability of stock returns, all being actually observed stock market phenomena.

[2] The two models' central ingredients only appear to be the two distinct phenomena. In the essence, they are realizations in the two different setups of the same factor - a changing risk aversion.

We did not review here a tiny fraction of the literature which, in that or the other respect, is relevant to the subject of our study. We only gave some recent examples of theoretical models within two main approaches to explaining the behavior of financial markets. Still, it can be concluded that behavioural approach in finance can successfully explain some stylised facts in financial markets. At the same time, traditional approach provides a rigorous conceptual foundation for the theoretical analysis.

Chapter 3

A SIMPLE MODEL OF STOCK MARKET WITH RATIONAL AND FEEDBACK TRADERS

In a recent empirical investigation of *weekly* returns of some two Ukrainian stock market indices, Dedov [2000] rejected the joint hypothesis of the weak-form efficiency of stock prices and the random walk model of price behavior. Specifically, Dedov found that *weekly* returns were autocorrelated, but failed to find a significant linear influence of return volatility on returns. The theoretical model of stock market with rational and feedback traders, applied in this thesis, explains, and suggests checking for, a related effect - the influence of return volatility on the pattern of autocorrelation of returns, at a higher (daily) frequency.

This model is proposed by Sentana and Wadhwani [1992][3]; though simple, it still can explain widely detected stock market phenomenon of return autocorrelation and asymmetry of market reaction to unexpected price changes of different sign (leverage effect). Apart from it, the model allows to draw inferences about:

- The presence of feedback traders in the market;
- The relative influence on the prices by the two groups of traders (which issue is relevant to that of the "fragility" of the market);
- The speed of price adjustment;
- The influence of previous trading schedule on the expected volatility;

[3] This model was applied later, for a number of developed and emerging stock markets, by Koutmos [1997], Koutmos and Saidi [2001], and Bohl and Reitz [2002].

- Whether the shocks in the market are persistent.

In case of more than one index analysed, the model allows to assess the relative liquidity of different market segments.

The model makes two main assumptions: that there are two types of traders in the market – rational and feedback traders; and that both types of traders have risk aversion that declines rapidly with their wealth.

The two groups of investors collectively form the total demand for stocks in the market. Rational investors ("smart money") demand the fraction Q_t of the market; feedback traders demand the fraction Y_t. Market equilibrium requires that total demand for stocks equal supply, i.e., that all stocks are held:

$$Q_t + Y_t = 1. \tag{1}$$

Smart money have rational expectations about value of stocks. Their proportionate demand for stocks in period t is given by:

$$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\mu_t} \tag{2}$$

where Q_t is the fraction of shares that they hold. Here, term $E_{t-1}(r_t)$ is the rational expectation of the period *t* return, which smart traders make in the period *t-1*. Term α is the return at which the demand for stocks by this type of traders is zero. The difference $\left(E_{t-1}(r_t) - \alpha\right)$ is the expected excess return. μ_t is defined as the risk premium needed for the smart money to hold all the shares.

The fraction of shares that smart money want to hold is the higher, the higher is the expected excess return $\left(E_{t-1}(r_t) - \alpha\right)$ compared to the μ_t. It is assumed that:

$$\mu_t = \mu\left(\sigma_t^2\right), \tag{3}$$

where σ_t^2 is the conditional variance of returns in period t (expected at time t-1). Smart money investors are assumed to be risk averse ($\mu'(\sigma_t^2)>0$). This means that a higher expected volatility (measured by σ_t^2) induces smart traders to hold less of stocks. Put another way, an increase in the expected volatility increases the risk premium needed by smart money if Q_t is to stay constant.

If all investors were smart money, then market equilibrium ($Q_t=1$) would yield the Capital Asset Pricing Model (Merton [1980]):

$$E_{t-1}(r_t) - \alpha = \mu(\sigma_t^2) \tag{4}$$

with α being the risk-free rate of return, and $\mu(\sigma_t^2)$, a measure of risk of the market return.[4]

Feedback traders are the second group of investors in the market. They form their part of stock demand based on realised price changes. Specifically, the model assumes that their proportion of demand Y_t linearly depends on their observation of the previous period return, r_{t-1}:

$$Y_t = \gamma r_{t-1}. \tag{5}$$

Parameter γ allows for two different types of feedback traders. $\gamma>0$ corresponds to the case of positive feedback traders, who buy (more) stocks after a price rise and sell (more) after a price fall. This behavior is claimed to be consistent with the portfolio insurance strategy and the behavior of traders using stop-loss orders. Also, positive feedback trading may occur right after significant market declines, when traders are likely to massively sell their

[4] Merton [1980] assumes that the variance of the market return is a sufficient statistic for its risk.

securities ("distress selling").[5] Bohl and Reitz [2002] add that this behavior may also originate in traders' using simple extrapolating expectations ("trend chasing").

It is also possible that some traders buy stocks after a price fall ($\gamma<0$); this is negative feedback trading. This behavior is claimed consistent with 'buy low, sell high' strategies, as well as with strategies that assign a constant share of wealth to a particular asset.[6]

Allowing the presence of both groups in the market yields:

$$\frac{E_{t-1}(r_t)-\alpha}{\mu_t} + \gamma r_{t-1} = 1, \tag{6}$$

which, after rearranging, gives the market equation:

$$E_{t-1}(r_t) - \alpha = \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)r_{t-1}. \tag{7}$$

Comparing (7) with the CAPM model in (4), we have an additional term, $(-\gamma\mu(\sigma_t^2)r_{t-1})$, that shows that stock returns exhibit autocorrelation in the presence of feedback traders in the market. Positive feedback trading ($\gamma>0$) induces negative return autocorrelation; negative feedback trading implies $\gamma<0$ and positive autocorrelation of returns.

Equation (7) also shows that the extent of return autocorrelation varies with volatility. As expected volatility rises, the model predicts returns to exhibit a larger autocorrelation. It is further assumed that γ itself varies over time with changes in volatility. Namely, it is expected that $\gamma'(\sigma_t^2) > 0$. To

5 Shiller [1987] found that, during the 19 of October 1987 stock market crash, the primary reason for the traders to sell their shares was that prices had fallen.

6 The rationale behind assigning a constant share of wealth to a given asset may be diversification by keeping the structure of incomes from respective portfolio assets constant.

justify this expectation, the authors make the assumption that a ceteris paribus rise in volatility, σ_t^2, lowers wealth of traders (which they have in the form of shares)[7]. This assumption, taken together with the assumption of risk aversion declining rapidly with wealth (as in the models in Black [1989], [1990], and Marcus [1989])[8], means that a rise in volatility makes traders more risk averse. As noted, those models also have a property that a higher risk aversion leads to more portfolio insurance trading. As was noted above, portfolio insurance is one of possible rationales behind positive feedback trading. Thus, it is argued that a rise in volatility induces more positive feedback trading (and hence, more negative autocorrelation in returns).

There is another consequence of traders' risk aversion declining rapidly with wealth; it is an asymmetry of their reaction to changes in the asset's value of the same magnitude but different sign. Namely, if the asset has increased in value, a trader becomes wealthier and thus has less risk aversion than before. If the asset price has decreased, the trader is more risk averse than initially. Since, as mentioned, more risk aversion leads to more positive feedback trading, large price declines must cause a larger positive feedback trading than equally large price rises. This effect is called "leverage effect".

At this point, we would like to present our intuition about the model, in particular about its mechanics, and make some important remarks. Larger volatility reduces traders' wealth; with a decrease in wealth, risk aversion of both types of traders rises rapidly. It is this increase in risk aversion that makes the traders change their behavior in view of a rise in volatility. Smart traders react to it by lowering their demand for shares, since the expected excess return, $\left(E_{t-1}(r_t)-\alpha\right)$, stays the same, while the "risk premium needed to induce them to hold all the shares" (the definition of $\mu(\sigma_t^2)$), as well as *any*

[7] To make this assumption valid for traders with different levels of wealth, Sentana and Wadhwani (after Marcus [1989]) take "wealth" to be assessed beyond some "subsistence wealth" which gradually increases with rise in prosperity.

[8] Campbell and Cochrane's [1999] model also has this property.

current Q_t , rises. Then, if smart traders are numerous in a market, or they have risk aversion declining *very* rapidly with wealth[9], it is plausible that smart traders, lowering their demand for shares in view of a rise in volatility, may exert a significant downward pressure on the market price. Likewise, in case of anticipated *fall* in volatility, smart money can be expected to push the price *up*.[10] Perhaps, of a particular interest is the fact that, in a given market, if it becomes well-documented that smart traders' reactions to changes in volatility significantly affect the market price, smart money will include this insight into their expectation of the next period return (r_t). This will further sharpen their reaction to a change in volatility. We, therefore, see that (in this model, at least) traders that have rational expectations, may *rationally* drive the market prices away from their fundamental value![11]

Feedback traders also change their behavior with the level of their risk aversion. While smart money do that by changing the amount of shares that they want to hold, feedback traders choose, between positive and negative feedback strategy, the one they find appropriate at a given volatility.[12] The higher the volatility, the more positive feedback trading is expected to be

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9 This property of risk aversion of smart traders may reflect the fact that they view the market as generally fragile. Thus, we may conjecture that the same investors can have different utility functions for different markets.

10 Perhaps because their empirical findings did not present evidence of this, Sentana and Wadhwani, in their interpretation of the model, only say that "intuitively, as expected volatility rises, smart money needs a higher expected return, and this allows a larger deviation of market price from its fundamental value…". They do not specify the direction of this deviation. (In chapter 4, this issue will be discussed again, in terms of the empirical specification of the model.)

11 In their interpretation of the model, Sentana and Wadhwani say only that "if preferences exhibit risk aversion that declines rapidly with wealth, … an exogenous reduction in the *values* of the shares (the risky asset) can lead to an even larger reduction in the demand for the risky asset".

12 In their paper, Sentana and Wadhwani do not say explicitly that positive feedback strategy is *safer* than negative. Though the way they show the link between volatility and appropriate feedback strategy, (it was presented above in this chapter), seems logical in every step. In general, the authors never say that one behavior is safer than another. The only statement they make about the link between risk and volatility, is that "…high volatility makes it more risky for smart money to take advantage of the predictable patterns in stock returns".

there.[13] (In particular, at high volatilities, positive feedback trading is expected to prevail.) Therefore, it is concluded that

$$\gamma = \gamma(\sigma_t^2) \tag{8}$$

and $\gamma'(\sigma_t^2)>0$.

At this point, one might become suspicious about the consistency of the model, namely about the real attitude of feedback traders to risk. On the one hand, the model says that feedback traders respond to, e.g., an increase in volatility by an increase in their γ, i.e. by a proportionate shifting to more positive feedback strategy, which was indirectly shown by Sentana and Wadhwani to be a *safer* strategy than negative feedback trading. On the other hand, equation (5) tells us that γ is proportionate to Y_t, the share of the market that feedback traders want to hold. That is, at a given r_{t-1}, feedback traders want to hold more shares in a more volatile market, which says that they must be *risk seekers*![14]

An explanation of this apparent inconsistency is simple, however. At a higher volatility, feedback traders choose more positive trading, each trying to maximize his or her *own* utility. Indeed, this switch, taken apart from other's actions, reduces the trader's risk. In the aggregate, though, at higher volatilities, feedback traders *together* increase their demand for stocks. Thus,

[13] Sentana and Wadhwani do not specify that, at low volatilities, negative feedback strategy must prevail. Equation (4) shows that negative feedback strategy implies a *negative share* of the market held by feedback traders. A justification for this may be that traders in a given market are allowed to sell shares short. (In the Ukrainian stock market, traders *are* allowed to sell short.)

[14] In fact, Sentana and Wadhwani do not say that traders are risk averse, only that the degree of their risk aversion declines with wealth. But from what they say about the smart money (as quoted in footnote 10), it is clear that they assume the traders to be risk averse.

feedback traders create a general negative externality for one another by raising the risk of an explosion of the price "bubble".[15]

This seems to explain that feedback traders are indeed risk averse. Importantly, the fact that together they create a general negative externality for further positive feedback trading, probably can explain one (apparently) confusing feature of the Sentana and Wadhwani model. It is that positive feedback trading induces negative autocorrelation in returns (and negative feedback trading, positive autocorrelation). Intuitively, if traders are chasing trends, an increase in price (positive return) generates more buying and consequently more increases. Such a situation would normally induce positive autocorrelation in returns. However, if feedback traders can, if imprecisely, assess the fundamental value of prices (e.g., they could view the previous low-volatility period price to be close to fundamental, because then it was determined largely by rational traders), then they must perceive the growing risk of an explosion of the speculative bubble, as positive feedback trading drives the price ever father from the fundamental. At some point, risk of the explosion grows so high that it may become *safer* for feedback traders to eliminate uncertainty (and take advantage of current high prices) by selling shares, i.e. by shifting from positive to negative feedback trading. When a growing trend is broken[16], the risk of the explosion is eliminated (because it has happened already!), and high volatility suggests feedback traders to follow positive feedback strategy again. Hence, here, we assume an additional determinant of the behavior of feedback traders, as compared to the model's assumption expressed in equation (8), that feedbask traders react to changes in their wealth (induced by changes in volatility) only.

[15] Simultaneous switching to positive feedback trading is one manifestation of a well-documented phenomenon of "herding" behavior in financial markets. This kind of behavior tends to drive the prices away from the fundamentals (create price bubbles). Other factors that can explain deviations from the fundamentals, include information costliness, transaction costs, non-synchronous trading, market trading rules.

[16] To break the growing trend, it must be enough that slightly more than a half of feedback traders switch to negative trading.

There is one more important consideration about the reaction of feedback traders to volatility. Sentana and Wadhwani clearly state that smart money react to changes in *expected* volatility. About feedback traders, it is assumed that $\gamma=\gamma(\sigma_t^2)$ (equation (8)), which is a logical inference from the models by Black [1989], [1990], and Marcus [1989]. However, it is not specified *what* volatility σ_t^2 is: expected or realized. Apparently, by this formula, it is meant that feedback traders observe the *realized* volatility. Otherwise they would be not different from rational traders, because, in our model, smart traders collapse a large part of their information about future market risk into σ_t^2. Thus, the "right" functional form for γ may be $\gamma=\gamma(\sigma_{t-1}^2)$ if feedback traders cannot determine *current* volatility in the market within a trading day.

In a market with continuous trading, it can be expected that traders *are* able to observe current volatility (i.e. how the prices develop from the beginning of the trading day); thus the assumption in equation (8) must be valid for the United Kingdom stock market, which Sentana and Wadhwani empirically studied[17]. However, for call markets, of which the Ukrainian is the one, this ability of traders is to be questioned.[18]

[17] Empirically, however, the volatility expected by smart money, and actual volatility from the beginning of the trading day, as perceived by feedback traders, must not coincide. (These two volatilities correspond to two places where σ_t^2 enters the empirical specification by Sentana and Wadhwani, as presented in Chapter 4.)

[18] In accordance with the supposition that the "right" version of equation (8) may be $\gamma=\gamma(\sigma_{t-1}^2)$ for the Ukrainian stock market, we empirically estimated an alternative specification, in addition to one proposed by Sentana and Wadhwani. The results are very similar to those in the original specification.

Chapter 4

EMPIRICAL MODEL

Sentana and Wadhwani [1992] propose the empirical specification presented below. Equation (9) is called "the mean equation", and is a linearized version of the market equation (7):

$$r_t = \alpha + \rho\sigma_t^2 + \left(\gamma_0 + \gamma_1\sigma_t^2\right)r_{t-1} + \varepsilon_t \qquad (9)$$

The authors interpret the coefficients in equation (9) as follows:

r_t – the realized return in period t;

r_{t-1} – the realized return in period t-1;

σ_t^2 – the conditional variance of returns based on information about its past values. It is used as a measure of volatility of returns expected by rational traders;

ε_t – the residual. It must be white noise, to stress that r_t is rational-expectations return, i.e. that, on average, it is predicted correctly);

α – the measure of return consistent with smart traders holding no shares.

Again, in accordance with our intuition about the theoretical model, as presented in Chapter 3, some additional remarks seem relevant about the meanings of the variables and coefficients in the mean equation.

We saw in Chapter 3 that as expected volatility rises (falls), smart money can, in principle, exert a downward (upward) pressure on the price. If they indeed do this in a given market, we observe it as a negative ρ coefficient. We then can interpret ρ as a measure of the influence of smart traders on the market price. As such a measure, ρ coefficient tells us about the sum (or, possibly, a synergy) of two factors: the relative share of assets held by smart traders in the market (Q_t), and a measure of how *actively* smart traders react to changes in the expected volatility (i.e. how sensitive Q_t is to changes in σ_t^2). The ρ coefficient thus can be called a measure of "fragility" of the market with respect to new information, "new information" being collapsed into the expected volatility[19].

If we accept that feedback traders can observe how volatility develops within the trading day, then we can use *expected* by smart money σ_t^2 as the best approximation to volatility *observed* by feedback traders. If not, we must adopt the alternative version of equation (8), namely that $\gamma = \gamma(\sigma_{t-1}^2)$.

Equation (9) also allows some 'natural' rate of return aurocorrelation (term $\gamma_0 r_{t-1}$), which may arise due to non-synchronous price quotes (non-trading problem). This non-trading effect is well known (Lo and Mackinlay [1989] quoted in Sentana and Wadhwani [1992]; Cohen et. al. [1980]). If stock A is traded less frequently than B, the return on B will respond with a lag to the return on A, i.e., there will be positive autocorrelation. A large number of positive cross-autocorrelations will result in a positive autocorrelation in the whole index. Hence, non-synchronous trading must cause positive autocorrelation in returns of the market index.

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[19] As is shown in Table 1, ρ is significant and negative, implying that rational traders do indeed exert a downward (upward) pressure on the price in anticipation of a larger (smaller) volatility in the Ukrainian stock market. For comparison, Sentana and Wadhwani, who analysed the U.K. stock market, found ρ to be negative, but very close to zero, and insignificant. This difference in our empirical findings may be due to the fact that the Ukrainian stock market is a call market, whereas the U.K. stock market is one with a continuous trading, which means that the price must adjust to new information much more quickly in the latter market. In fact, we suspect that Sentana and Wadhwani would receive a significantly negative ρ (i.e. a significant influence of rational traders on the price) if they studies the returns over much shorter periods than one day – may be hourly returns, or bi-hourly.

To allow conditionally heteroscedastic variances (implying varying volatility), equation (9) is estimated in the context of the Exponential General Conditional Heteroscedasticity (EGARCH) model, which includes equation ("variance equation") for conditional variance of the form:

$$\ln\sigma_t^2 = \omega + \pi N_t + \beta \ln\sigma_{t-1}^2 + \left(\varphi\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \psi\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \tag{10}$$

The variance equation contains the following terms:

$\ln(\sigma_t^2)$ – logarithmic volatility (to ensure non-negativeness of σ_t^2);

ω – the intercept (average logarithmic volatility);

N_t – the quantity of non-trading days before day t (there is a view that preceding days when there were no trade, may increase expected volatility);

$\ln(\sigma_{t-1}^2)$ – the previous day volatility (smart traders are assumed to include it into their forecast of σ_t^2);

the two ratio terms that allow an asymmetric reaction of the expected volatility to return surprises of different sign ("leverage effect"). Leverage effect exists when volatility tends to rise more in response to a negative than to a positive return surprise of the same magnitude (i.e. when φ>0 and ψ<0).

Chapter 5

DESCRIPTION OF THE UKRAINIAN CONTEXT

Emerging from the Soviet system, newly independent states inherited inefficient, state owned economies that needed restructuring. The first task was to introduce private ownership, which was naturally conducted through privatisation of the economy's fixed assets. Each country in Central and Eastern Europe was in a different initial position, which, to an extent, pre-determined the length and peculiarities of their transition paths.

After some ten years of market reforms, it appears that the countries comprise a spectrum of the extent of reforms. Ukraine (together with Russia) is in the worst end of the spectrum of outcomes (Bokros [2001]). The middle part of the spectrum is represented by Slovakia and Croatia. The most advances reformers, so far, are Poland and Hungary. Some indicators of financial market development in transition economies are shown in Appendix A. Market capitalization levels are especially low in the countries of the former Soviet Union.

The stock market in each of these sovereign countries has emerged due to privatisation, the major means of reforming the structure of the country's ownership. Ukraine represents an example of country where stock market development was not defined by the state as an independent goal but rather followed the needs of the evolving privatisation program in the country.

Absence of a stock market in the early years of Ukrainian independence left the government with a single possible way to privatise enterprises: give them away to insiders (managers and employees)[20]. In 1991-1994 the market

20 In early years of the independence, buy outs by foreigners were not allowed, perhaps primarily because of underdevelopment of the legislation, and also for political reasons. Now foreigners are allowed to trade shares of Ukrainian issuers, though they may be represented in the market only by custodians. (Among some 800 traders and banks, only 84

capitalisation and volumes of trade were minimal; the only traders in the market were the securities issuers themselves.

Mass privatisation was launched in 1995, which demanded a better-developed stock market. In anticipation of this, supervision over the market was transferred from the Ministry of Finance to a newly created specialized authority - the Securities and Stock Market State Commission (SSMSC). Despite this, regulation in the market remained quite imperfect. In particular, ownership rights of shareholders were not secured. On the other side, injudicious management of enterprises under a very severe macroeconomic instability, led to mass bankruptcies. As a result, with non-secured rights, a major part of shareholders lost their invested money. This made participating in mass privatisation a highly risky venture for small investors, especially for individuals. This hindered mass privatisation[21]. Until mid 1997, privatisation remained slow and stock-market capitalization small.

Since then, the state tightened control over stock market participants. In particular, the SSMSC provided basic regulations governing transactions between participants. Issues of new packages of shares by joint-stock firms increased. Starting in 1998, the primary way of privatisation, instead of certificate auctions, became offerings of new packages of shares in stock market, and international commercial tenders (Dedov [2000])[22]. The market grew in terms of the number of traded securities and active traders. This

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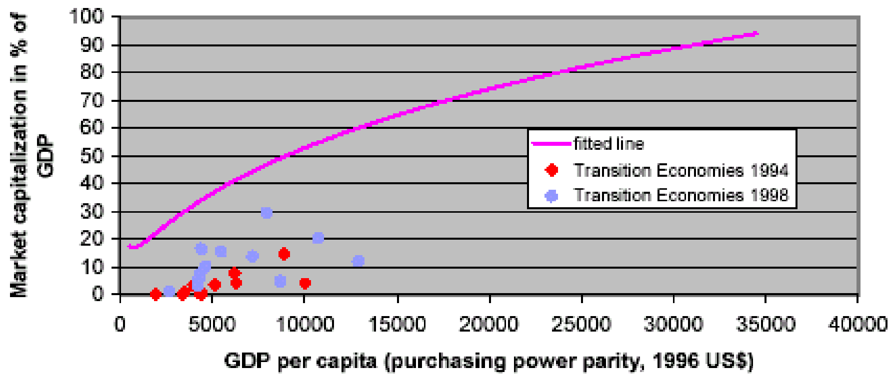
hold a custodian licence and can work with non-residents.) The access of foreigners to the Ukrainian stock market is stipulated by a directive "On registering the ownership rights of non-residents to securities issued by Ukrainian entities" (dated 20 April 2001) by the State Securities and Stock Exchange Commission.

[21] To actually involve the public in the privatisation, all the citizens were given privatisation and compensation certificates that could be exchanged for a corresponding amount of shares of a chosen enterprise. However, many people preferred to sell the certificates for low prices to half-legal buyers in the streets. Eventually, those certificates were used in privatisation, but having already been gathered into large packages.

[22] As a step towards making the market more attractive for international commercial investors, the SSMSC is moving the market regulation closer to international standards. Since May 1, 2002, the Commission registers primary and secondary issues of only those stocks (and other securities) which have been assigned international codes.

naturally raised market liquidity. Still, the market remained very small compared to other transition countries (Figure 1). Old problems, though mitigated, were not resolved. Ownership rights of shareholders were not fully secured[23]. Regulation of issuing entities is yet not good enough to make the market transparent. Improving market transparency is still on the agenda.

Figure 1: Market capitalization in transition economies relative to a market benchmark, 1994 and 1998



"Note: The fitted line is estimated from a cross-country regression over 132 market economies of private credit/GDP against GDP per capita (in US dollars at purchasing power parities) and its squared value. The regression was run on data for 1996, obtained from the International Financial Statistics. See Transition Report 1998 for details. The data for the transition economies is reported in Appendix A" (Pistor, Raiser and Gelfer [2000]).

Currently in Ukraine, stocks are traded on six stock exchanges and two informational-trading systems:

- The Ukrainian Inter-bank Foreign Exchange;
- The Ukrainian Stock Exchange;

[23] They are still not fully secured. It is believed that the protection of property rights will be improved with the approval of the laws "On joint-stock companies" and "On the stock market of Ukraine"(ICPS [2001]). On the other hand, there is evidence that some three quarters of firms in Ukraine (as well as in Russia and several other CIS countries) do not trust the legal system to really protect their property rights and enforce their contracts (Pistor, Raiser and Gelfer [2000]).

- The Kyiv International Stock Exchange;
- The Donetsk Stock Exchange;
- The Prydniprovska Stock Exchange;
- The Crimean Stock Exchange;
- The Over-the-counter Information and Trading System;
- The Over-the-counter Stock Trading System (PFTS).

These trading floors are largely separate segments of the overall market with different supply and demand conditions and trade prices (Dedov [2000]). Their operations are regulated by the (SSMSC)[24]. Among the stock exchanges, only the Ukrainian Inter-bank Foreign Exchange has large overall asset trading volumes. Other stock exchanges usually have low trading volumes; there, mostly primary placements of stocks of newly privatised enterprises are traded, and occasional large-volume trades are conducted to redistribute ownership.

The largest trading floor in Ukraine has been the Ukrainian over-the-counter informational trading system ('PFTS'). More than 73% of all secondary stock market transactions took place at the PFTS in 1999 (94% - in the third quarter of 2000).

24 "[The SSMSC] structures its activity mainly on the basis of the 1991 "The law on securities and stock exchange", the 1996 "The law on state regulation of the securities market", the 1994 "The law on investment funds and companies", and the 1998 "The law on the National Depository System and the peculiarities of electronic circulation of securities in Ukraine" (Dedov [2000], p.22 fn.14).

Chapter 6

DISCUSSION OF DATA

As was shown in Chapter 3, non-synchronous trading in the market must induce positive autocorrelation of returns, which is expected to interfere with the empirical results. This suggests choosing among the existing stock market indices the one that is expected to suffer least from the non-synchronous trading. That is, the best index to analyse would be the one that includes the most heavily traded stocks in the market. On the other hand, the index chosen must be representative of the market, in other words, it must be inclusive.

It turns out that if one would want to incorporate the behavior of stock market indices into an analysis of the Ukrainian stock market, one would face a trade-off between an index' inclusiveness and its exposure to non-synchronous trading. Three indices, being calculated nowadays in the Ukrainian stock market, all have in the top of their listings most heavily traded stocks in the market, and then include less and less liquid stocks. Hence, under this principle of forming an index, the least inclusive (and hence, least representative) index is also the one that suffers least from the non-synchronous trading. In Ukraine, there are three indices currently calculated: ProU10, ProU50, and PFTS.

ProU10 includes stocks of 10 "blue chips" – the largest and most stable strategic enterprises of Ukraine. These stocks are the most heavily traded and ProU10 is expected not to suffer from the non-synchronous trading. However, this index is very unrepresentative of the whole market that is characterized by a huge non-synchronous trading and even by whole periods of non-trading some securities.

Slightly more inclusive is PFTS index. The index is based on the PFTS quotes of shares of the most liquid companies that must satisfy several additional conditions put forward by the PFTS. On the average, the index includes about 15 stocks. The conditions for the inclusion concern the company's performance. Like ProU10, PFTS is expected not to suffer from non-synchronous trading.

Considerably more inclusive is ProU50. It includes shares of 50 largest privatised enterprises from leading Ukrainian industries: energy, metallurgy, oil and gas, chemical, machine-building industries – and several enterprises from other industries. This index might turn out to be inclusive enough to suffer from the non-synchronous trading.[25]

There is an additional consideration about the best index to analyse. Sentana and Wadhwani [1992] point out that a relevant characteristic of an index is how it is calculated. Ceteris paribus, the preference must be given to indices based on (or close to) the mid-market prices. Such indices are guaranteed against exhibiting a spurious serial correlation of index returns arising when a large number of stocks close at either the bid or ask at the same time. With this respect, PFTS is a much safer index than the ProU's. To mitigate the contamination from this side, PFTS is calculated on the latest deal price that has been between the best (i.e. the highest) bid price and the best (the lowest) ask price during the corresponding day. If there were not a single deal during the day, then a 'smoothing' rule would be applied by taking the average between the two best prices of the *previous* trading day. This calculation procedure makes the value of the index close to the mid-market price. In contrast, the ProU's are calculated based on the prices of the constituent shares, which prices are the best (i.e. the highest) *bid* prices of the shares during the day.

25 Indeed, the results of testing of the feedback trader model for ProU50 show that it must suffer severely from the non-synchronous trading.

Making an overall comparison of these three indices, we concluded that the most preferable two to analyse are PFTS and ProU50. PFTS, though not very representative of the Ukrainian stock market, is much more 'pure' than the more inclusive ProU50, and hence is the best (second best, after ProU10) to test the model's validity *in principle*. On the other hand, one may not derive very meaningful policy implications for the whole market, on the basis of the analysis of PFTS only. For that purpose, ProU50 was analysed as well.

The list of companies that are included in PFTS, is revised monthly (also, for comparison of the representativeness, note that ProU's had their constituents revised only few times since July 1997). The full sample of daily stock returns computed from PFTS, consists of 1012 observations (1102 for ProU50).

Possible problems of the empirical testing of the feedback trader model are discussed below. First, strictly speaking, $\ln(P_t / P_{t-1})$, used in the empirical test, are capital gains, not returns that the model uses. Returns include the dividends term: $\ln(P_t + DI_t / P_{t-})$. However, dividend data are not accessible, if calculated.

However, there is no obvious reason to expect that dividends on shares are correlated with capital gains on them. Therefore, the use of capital gains instead of dividends is deemed not to reduce the significance of the empirical test. Indeed, Nelson [1991] fitted a simple EGARCH model for CRSP stock market *returns* for July 1962 - December 1987. Then he repeated his estimation with *capital gains* instead of returns, ignoring both dividends and the riskless interest rate. It made virtually no difference in the estimated parameters.

Another problem is that of estimating a risk-free rate of return (though monthly T-bill returns might be used under the assumption that they were constant for each calendar day within a given month, as Nelson [1991] assumed). In fact, Sentana and Wadhwani [1992], and then all the authors who consequently empirically applied their model (as mentioned in footnote 3), did not impose this restriction on the risk-free rate of return. They received significantly positive values for α. In this thesis, we follow their approach: the risk-free return appears as a 'free' intercept in the adopted specification of the mean equation.

Speaking about the bid-ask problem, it seems unlikely that it does much harm to the empirical results for PFTS, because it is close to the mid-market price. The problem is more severe for ProU, because it is based only on the best *bid* price, and does not have the smoothing rule of reverting to the previous-day price, which PFTS has. However, it is unlikely that days when (for a large number of stocks simultaneously!) the last deal prices are close to the best ask prices, exactly interchange with days when the last deal prices (again, of a large number of stocks) are close to the respective best bid prices. This seems true even for short sequences of trading days. Hence, no significant contamination is expected from this side.

Chapter 7

EMPIRICAL RESULTS

The empirical model, introduced in Chapter 5, is estimated with ARMA(1,1) conditional variance equation. This specification completely allowed for heterocsedasticity and for aurocorrelations in the conditional variance: ARMA(1,1) specification of conditional variance equation gives white noise residuals in the variance equation. However, the mean equation, when estimated according to the original model, has residual autocorrelation (ACF significant at lags 2 and 3). That is why, the model is re-estimated with the mean equation having additional lag term $(\gamma_0 + \gamma_1 \sigma_t^2)r_{t-2}$, and again, with the two terms, $(\gamma_2 + \gamma_3 \sigma_t^2)r_{t-2}$ and $(\gamma_4 + \gamma_5 \sigma_t^2)r_{t-3}$. Only the last specification gave white noise residuals. The new specification is presented here for convenience:

$$r_t = \alpha + \rho\sigma_t^2 + (\gamma_0 + \lambda_1\sigma_t^2)r_{t-1} + (\gamma_2 + \gamma_3\sigma_t^2)r_{t-2} + (\gamma_4 + \gamma_5\sigma_t^2)r_{t-3} + \varepsilon_t \quad (9')$$

$$\ln\sigma_t^2 = \omega + \pi N_t + \beta\ln\sigma_{t-1}^2 + \left(\varphi\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \psi\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right). \quad (10)$$

This specification implies a modification of the theoretical model where the feedback traders base their asset decisions upon the three latest returns rather than upon the single last return This modification seems logical, since the Ukrainian stock market is characterized by much less active trade than, say, the United Kingdom stock market. In Ukraine, shares are traded only once a day, after all negotiations about the price has been made; in the United Kingdom, there is a continuous trading process in the market. Hence, the implied speed of price adjustment to new information is much slower in the Ukrainian stock market. The empirical results are given below in Table 1:

Table 1. Estimation results of EGARCH-M(1,1) model for PFTS

Mean Equation	**PFTS**		**ProU50**	
Regressor	Coefficient	P-value	Coefficient	P-value
Risk-free return	**0.0013**24	0.0175	**-0.000**283	**0.69**69
Volatility-return coeff.	**-4.06**5628	**0.01**95	**-1.73**6795	**0.34**35
γ_0	**0.16**0174	0.0008	**0.14**0151	0.0107
γ_2	**0.14**5966	0.0047	**0.07**8872	0.0635
γ_4	**0.15**6653	0.0017	**0.18**8293	0.0000
γ_1	**-178.**7986	0.0000	**-20.**96540	**0.34**07
γ_3	**-94.**78500	0.0054	**-14.**90082	**0.41**47
γ_5	**-54.**71790	**0.079**7	**-17.**81930	**0.32**07
Variance Equation	**PFTS**		**ProU50**	
Regressor	Coefficient	P-value	Coefficient	P-value
Mean log volatility	-0.315609	0.0043	-1.028877	0.0000
Non-trading days	0.015866	**0.70**80	0.112714	**0.10**76
Latest past volatility	0.982236	0.0000	0.912493	0.0000
Surprise: Level effect	0.227639	0.0000	0.419611	0.0000
Surprise: Sign effect	**-0.05**5524	**0.09**03	**-0.14**2315	**0.00**35

The empirical results fully agree with the predictions of the theoretical model. Moreover, as we hypothesized, the results for a "clearer" index (PFTS) are more supportive of the model. The adjustment of the price to news in the market is much slower than in the United Kingdom stock market.

In particular, the results are consistent with the hypothesis that in the Ukrainian stock market, there are feedback traders that shift to more positive feedback strategy as return volatility rises. This is reflected by *negative* "high-volatility" autocorrelation coefficients, as opposed to *positive* "low-volatility" coefficients. (For ProU50, feedback traders fail to significantly influence the pattern of autocorrelation at higher volatilities, probably because of a large-scale non-synchronous trading in the lower part of the index, causing positive autocorrelation.)

A negative ρ coefficient, statistically significant for PFTS index, implies that smart traders can exert an essential pressure on the prices, and do this at times of changing volatilities. Hence, the active segment market of the market can be viewed as fragile[26]. Again, for ProU50, the coefficient is negative but insignificant, which confirms our conclusion about a large contamination of ProU50. Indeed, it looks like the index can be relatively well described by a model of simple 3-day autocorrelation, as "low-volatility" (or "simple") autocorrelation coefficients are the only significant in the mean equation for the index.

Interestingly, this model was applied also by Koutmos [1997], Koutmos and Saidi [2001], and Bohl and Reitz [2002], for a number of developed and emerging stock markets. In more than a half of those markets, the ρ coefficient was found to be negative, though for all the markets it was statistically insignificantly different from zero. This must be viewed as more justified for developed markets, which are less fragile than emerging ones.

It was necessary to include three lags into the mean equation, to obtain white noise residuals. This may reflect the fact of a slow adjustment of prices to new information, under the conditions of a call stock market with significant non-synchronous trading.

Intercept in the mean equation for PFTS, is positive, which complies with the model in that traders (smart traders, at least) has a positive opportunity cost of investing in stocks. For ProU50, it is insignificant.

The previous volatility , σ_{t-1}^2, ("latest past volatility" in the table) is very close to unity for *both* indices, suggesting shock persistence in the market. Again, shocks are less persistent for ProU50 than for PFTS.

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[26] The fact that In the Ukrainian stock market, traders are allowed to sell shares short, must be relevant to the issue of the market fragility. However, it is not clear if it tends to reduce "fragility" as it is defined in this thesis, or contribute to it.

Leverage effect is statistically significant for both indices, suggesting more positive feedback trading after negative return shocks than after positive ones with the same magnitude. The quantity of previous days of non-trading can be taken not to affect the volatility.

Chapter 8

CONCLUSIONS

The purposes of this thesis were:

- to explore the theoretical development in explanation of behavior of stock market at an aggregated level;
- to make a step to determine, and theoretically justify, the nature of the return behavior in Ukrainian stock market, an emerging one, following Dedov [2000] conclusion that it violated (the weakest form of) the EMH;
- to identify implications of the findings.

Making large qualifications for the limited scope of the author in the relevant theoretical literature, it still can be concluded that behavioural approach in finance can successfully explain some stylised facts in financial markets. At the same time, traditional approach provides a rigorous conceptual foundation for the theoretical analysis.

It was found that a simple theoretical model of stock market with feedback traders is consistent with the evidence on the behavior of the Ukrainian stock market indices allowing for worsening liquidity of shares in more inclusive ProU50. This suggests existence of feedback traders of both types in the market. It must be mentioned, however, that the market being very much underdeveloped required a corresponding adjustment of the model suggested by Sentana and Wadhwani [1992].

The empirical results also confirm that liquidity of stocks in the market falls rapidly as one goes down the listings of shares. The "top" part of the market, comprised by actively traded securities, behaves quite differently from the next part of the market where the securities are much less liquid. It is so already for the index of *50* most heavily traded securities. Perhaps, the market can be viewed as "segmented".

Overall, Dedov's conclusion of violation of the weakest form of the Efficient Market Hypothesis by the Ukrainian stock market was confirmed and extended. Returns in the market are, technically, rather predictable during periods of high volatility, the predictions being based only on the information about the past returns and volatilities. At low volatilities, returns are positively autocorrelated, while at large volatilities they exhibit negative autocorrelation. Informational shocks tend to persist in the market. Overall, it is no doubt that there is a large room for further development of the market.

LIST OF WORKS CITED

Barberis, N., M. Huang, and T. Santos, 1999. Prospect theory and asset prices. NBER working paper 7220.

Barkoulas, J.T., C.F. Baum, and N. Travlos, 2000. Long memory in the greek stock market. Applied Financial Economics, vol. 10, 177-184.

Black, F., 1988. An equilibrium model of the crash. NBER Macroeconomics Annual, 269-276.

Black, F., 1989. Mean reversion and consumption smoothing. NBER working paper 2946.

Bohl, M.T., and S. Reitz, 2002. The influence of positive feedback trading on return autocorrelation: evidence for the German stock market. Postgraduate Research Programme "Capital Markets and Finance in the Enlarged Europe" working paper 1/2002.

Bokros, L., 2001. Experience and perspectives of financial sector development in Central and Eastern Europe. CASE-CEU working paper 38.

Campbell, J.Y., and J.H. Cochrane, 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. Journal of Political Economy, vol. 107, 205-251.

Cohen, K.J., G.A. Hawawini, S.F. Maier, R.A. Schwartz, and D.K. Whitcomb, 1980. Implications of microstructure theory for empirical research on stock price behavior. Journal of Finance, vol. 35, part 2, 249-257.

De Bondt, W., and R. Thaler, 1985. Does the stock market overreact? Journal of Finance, vol. 40, 793-805.

De Bondt, W., and R. Thaler, 1987. Further evidence on investor overreaction and stock market seasonality. Journal of Finance, vol. 42, 557-581.

Dedov, M., 2000. The efficient stock market hypothesis and the Ukrainian stock market. MA thesis, Economics Education and Research Consortium, National University of Kiyv-Mohyla Academy.

Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. Journal of Finance, vol. 25, 383-417.

Fama, E.F., 1991. Efficient capital markets: II. Journal of Finance, vol. 46, 1575-1617.

Grossman, S.J., 1976. On the efficiency of competitive stock markets where traders have diverse information. Journal of Finance, vol. 31, 573-585.

Grossman, S.J., and J.E. Stiglitz, 1980. On the impossibility of informationally efficient markets. American Economic Review, vol. 70, 393-408.

ICPS, 2001. Quarterly predictions: Ukrainian economic survey. [what month?] Pekotoff-print.

Koutmos, G., 1997. Feedback trading and the autocorrelation pattern of stock returns: Further empirical evidence. Journal of International Money and Finance, vol. 16, 625-636.

Koutmos, G., and R. Saidi, 2001. Positive feedback trading in emerging capital markets. Applied Financial Economics, vol. 11, 291-297.

Lo, A.W., and A.C. Mackinlay, 1989. An econometric analysis of non-synchronous trading. NBER working paper 2960.

Marcus, A.J., 1989. An equilibrium theory of excess volatility and mean reversion in stock market prices. NBER working paper 3106.

Merton, R.C., 1980. On estimating the expected returns on the market. Journal of Financial Economics, vol. 8, 323-361.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: a new approach. Econometrica, vol. 59, 347-370.

Pistor, K., M. Raiser, and S. Gelfer, 2000. Law and finance in transition economies. CID working paper 49.

Sentana, E., and S. Wadhwani, 1992. Feedback traders and stock return autocorrelations: evidence from a century of daily data. Economic Journal, vol. 102, 415-425.

Shiller, R.J., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? American Economic Review, vol. 71, 421-436.

Shiller, R.J., 1984. Investor behavior around the October 1987 stock market crash: survey evidence. NBER working paper 2446.

APPENDIX A

Some financial market development indicators for transition economies

Country	Market capitalization/ GDP, 1994	Market capitalization/ GDP, 1998	Stock market turnover/ GDP, 1998
A	1	2	3
Albania	NA	NA	NA
Armenia	0,10	0,97	0,00*
Azerbaijan	NA	0,08	0,00
Belarus	NA	NA	NA
Bulgaria	0,66	7,65	0,00
Croatia	3,31	15,46	0,51
Czech Republic	14,64	20,36	0,00
Estonia	NA	9,46	18,02
FYR Macedonia	NA	0,25	0,00
Georgia	NA	NA	NA
Hungary	4,16	29,49	33,79
Kazakhstan	NA	7,99	0,14
Kyrgyzstan	NA	NA	0,08
Latvia	0,23	5,78	1,34
Lithuania	0,98	10,21	2,12
Moldova	NA	4,56	4,43
Poland	3,54	13,77	5,97
Romania	0,36	3,29	1,59
Russia	0,08	16,54	2,55
Slovakia	7,76	4,88	5,10
Slovenia	4,08	12,12	3,57
Ukraine	NA	1,87	0,20

"Source: International Financial Statistics, IFC Emerging Markets Handbook

* Data for Armenia are from 1996" (Pistor, Raiser and Gelfer [2000]).