Institutional Investors and Stock Returns Volatility: Empirical Evidence from a Natural Experiment†

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Date of this version: September 18, 2007

Abstract: In this paper, we provide empirical evidence on the impact of institutional investors on stock market returns dynamics. The Polish pension system reform in 1999 and the associated increase in institutional ownership due to the investment activities of pension funds are used as a unique institutional characteristic. Performing a Markov-Switching-GARCH analysis we find empirical evidence that the increase of institutional ownership has temporarily changed the volatility structure of aggregate stock returns. The results are interpretable in favor of a stabilizing effect on index stock returns induced by institutional investors.

JEL-classification codes: C32, G14, G23

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†Earlier versions of this paper were presented at the Midwest Finance Association 54th Annual Meeting, Milwaukee, the Eastern Finance Association Annual Meeting 2005, Norfolk, the 12th Global Finance Conference, Trinity College Dublin and the International Conference on Finance, University of Copenhagen. Comments provided by Carol Alexander, Jerzy Gajdka, Steven Isberg, Mark Schaffer, seminar participants and an anonymous referee are gratefully acknowledged. The first two authors thank the Alexander von Humboldt Foundation for financial support.

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Abstract: In this paper, we provide empirical evidence on the impact of institutional investors on stock market returns dynamics. The Polish pension system reform in 1999 and the associated increase in institutional ownership due to the investment activities of pension funds are used as a unique institutional characteristic. Performing a Markov-Switching-GARCH analysis we find empirical evidence that the increase of institutional ownership has temporarily changed the volatility structure of aggregate stock returns. The results are interpretable in favor of a stabilizing effect on index stock returns induced by institutional investors.

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1 Introduction

The increase in the number of institutional investors trading on stock markets worldwide since the end of the 1980s has caused a rise in financial economists' interest in institutions' impact on stock prices. In particular, there is the suggestion that institutional traders destabilize stock prices due to their specific investment behavior and thereby induce autocorrelation and increase volatility of stock returns. Among others, herding and positive feedback trading are the two main arguments put forward for the destabilizing impact on stock prices induced by institutional investors. Consequently, empirical investigations have focused on the question of whether institutional traders exhibit these types of investment behavior.[1]

However, evidence in favor of herding and positive feedback trading does not necessarily imply that institutional traders destabilize stock prices. If institutions herd and all react to the same fundamental information in a timely manner, then institutional investors speed up the adjustment of stock prices to new information and thereby make the stock market more efficient. Moreover, institutional investors may stabilize stock prices, if they jointly counter irrational behavior in individual investors' sentiment. If institutional investors are better informed than individual investors, institutions will likely herd to undervalued stocks and away from overvalued stocks. Such herding can move stock prices towards rather than away from fundamental values. Similarly, positive feedback trading is stabilizing, if institutional traders underreact to news (Lakonishok, Shleifer and Vishny, 1992).

Consistent with the above arguments, Cohen, Gompers and Vuolteenaho (2002) find a stabilizing impact of institutions on US stock prices. Institutions respond to positive cash-flow news by buying stocks from individual investors, thus exploiting the less than one-for-one response of stock prices to cash-flow news. Moreover, in case of a price increase in the absence of any cash-flow news institutions sell stocks to individuals. The findings by Cohen, Gompers and Vuolteenaho indicate that institutional investors push stock prices to fundamental values and, hence, stabilize rather than destabilize stock prices. Barber and Odean (2005) find for the US that individual investors display attention-based buying behavior on days of abnormally high trading volume, on days of extremely negative and positive one-day returns and when stocks are in the news. In contrast, institutional investors do not exhibit attention-based buying. While the

[1] Evidence on institutions' trading behavior can be found in, for example, Lakonishok, Shleifer and Vishny (1992), Grinblatt, Titman and Wermers (1995), Sias and Starks (1997), Nofsinger and Sias (1999), Wermers (1999), Badrinath and Wahal (2002) and Griffin, Harris and Topaloglu (2003), Sias and Whidbee (2006) and Yan and Zhang (2007).

behavior of individual investors may contribute to stock returns autocorrelation and volatility, institutions may induce a stabilizing effect on stock price dynamics. Supporting evidence also comes from the literature on the trading behavior and the impact of foreign, predominantly institutional, investors. Choe, Kho and Stulz (1999) and Karolyi (2002) analyze data during crisis periods from Korea and Japan, respectively. Both investigations conclude that although foreign investors appear to follow positive feedback trading strategies their trading behavior does not destabilize the markets.

We can conclude from the short discussion above that empirical findings on institutional investors' herding and positive feedback trading behavior are not necessarily evidence in favor of a destabilizing effect on stock prices. Hence, these results provide only indirect empirical evidence on the destabilizing effects of institutional investors' trading behavior on stock prices. To our best knowledge no empirical evidence is available about the direct effect of institutional traders' destabilizing impact on stock prices. The existing literature on institutional trading behavior is predominantly forced to rely on quarterly ownership data to compute changes in institutional holdings and in turn draws conclusions about the behavior of institutional investors.[2] In contrast, under the condition that the entrance date of a large number of institutional investors in the stock market is known, a Markov-switching-GARCH model may provide direct empirical evidence of whether institutions change significantly the volatility structure of stock index returns. In a time series framework we are able to investigate empirically the consequences of a structural break in institutional ownership on stock returns volatility behavior.

The short history of the Polish stock market provides a unique institutional feature which allows us to contribute to the literature on the institutional investors' impact on stock prices. The special characteristic arises from the pension system reform in Poland. In 1999 privately managed pension funds were established and allowed to invest on the capital market. We focus on the volatility behavior of stock returns prior to and after the first transfer of money to the pension funds on 19 May 1999. The appearance of large institutional traders and the resulting increase in institutional ownership allows us to investigate the impact on stock returns volatility in the environment of a natural experiment. Specifically, we use a modification of the Markov-switching-GARCH model put forward by Gray (1996a) to study whether the model's key coefficients change after the entrance of institutional traders in the Polish stock market. The main advantage of

[2]Sias, Starks and Titman (2006) provide a solution to the problem that high-frequency institutional ownership data are not available. The estimates of higher frequency covariances between changes in institutional ownership and stock returns rely on the use of higher frequency stock returns data and the exploitation of covariance linearity.

this econometric method is that it does not require an exogenously predetermined date for the shift in stock returns volatility. Instead, Markov-switching-GARCH models allow for endogenous specifications of volatility regime shifts and thus let the data speak for themselves.

The remainder of the paper is organized as follows. Section 2 contains a brief description of the pension system reform and its consequences for the investors' structure on the stock market in Poland. In section 3, the time series methodology, data and the empirical results are outlined. Section 4 summarizes and concludes.

2 Pension System Reform and Investors' Structure on the Stock Market in Poland

Re-established in 1991 the Polish stock market has grown rapidly during the last decade in terms of the number of companies listed and the market capitalization. In comparison to the two other EU accession countries in the region, i.e. Czech Republic and Hungary, the capitalization of the Polish stock market is significantly higher. It is comparable to the ones of smaller mature European markets, like the Austrian stock market, and equalled about 60 billion $-US at the end of 2004 (Warsaw Stock Exchange, 2005).

The major change in the investors' structure on the Polish stock market has its origin in the pension system reform. In 1999, the public system was enriched by a private component, represented by open-end pension funds. Participation in this component is mandatory for the employees below certain age. They are obliged to transfer 7.3 % of their gross salary to the government-run social insurance institute called Zakład Ubezpieczen Społecznych (ZUS), which in turn transfers it to the pension funds. The first transfer of money from the ZUS to the pension funds took place on 19 May 1999. This date changed the investors' structure of the Polish stock market significantly. In 1999, about 20% domestic institutional investors and 45% domestic individual investors traded at the Warsaw Stock Exchange. Over time the proportion of domestic institutional traders has increased, whereas the relative importance of individual investors has decreased. In 2004, approximately one-third of the investors were domestic individuals, and about one-third were national institutions. Constantly about one-third of the investors on the Polish stock market adhere to the group of foreign investors. The growing importance of pension fund investors is also reflected by a gradual increase in annual ZUS transfers invested on the Warsaw Stock Exchange in relation to the average daily trading volume. This ratio increased from below 200%

in 1999 to about 1000% in 2002 and has remained approximately constant since then.

While before 19 May 1999 the majority of traders were small, private investors, after that date pension funds became important players on the stock market. There were also some mutual funds active in the market but they had relatively small amounts of capital under management. Moreover, the role of corporate investors was very marginal. It is this feature in the history of the Polish stock market which constitutes the major change in the investors' structure. This unique institutional characteristic allows us to compare the period before 19 May 1999 characterized mainly by non-institutional trading with the period after that date, where pension funds act as institutional investors on the stock market. For reasons of argument it is important to stress that around this date there were no other stock-market features which were of comparable importance as the market entrance of the Polish pension funds.

The number of pension funds in 1999 – 2003 varied between 15 and 21. The change in their number occurred mainly due to the acquisitions of smaller funds by larger ones. By the end of 2003, 17 pension funds operated in the Polish stock market with about 12 billion $-US under management. In comparison, Polish insurance companies and mutual funds had only 3 and 1 billion $-US of assets, respectively. In 2003, the pension funds invested about 4 billion $-US in stocks listed on the Warsaw Stock Exchange. Their stock holdings predominantly consist of large capitalization stocks that are listed in the blue-chip index WIG20 and usually belong to the Top 5 in their industries. Therefore, since May 1999 pension funds are important players on the Polish stock market, able to affect stock prices. In addition to their role as investors on the stock market, Polish pension funds gained significant control in companies quoted on the Warsaw Stock Exchange and executed their shareholder rights by appointing members of the supervisory boards.

Before May 1999, primarily individual private investors populated the Polish stock market. The stock market was re-opened in 1991 after being closed for nearly half a century. Thus, stock trading created a new investment opportunity for domestic private investors and attracted many individuals who, in a very short period of time, opened nearly 1 million brokerage accounts. While the level of the earliest available index WIG remained far below 2000 points in the period from September 1991 to beginning of May 1993, it jumped to 2027.7 on 6 May 1993 and reached the level of 20760.30 on 8 March 1994, an increase of 924% within 10 months. Anecdotal evidence indicates that trading decisions by Polish individual investors during this period often relied on non-professional information sources and gossips which, in turn, led to herding behavior. An indicator of lack of fundamentally relevant information on companies listed at the

Warsaw Stock Exchange is the limited access to information from professional data producers. The Reuters domestic news service for individual investors, Reuters Serwis Polski, was introduced in Poland in the late 1990s and Reuters' competitors followed with their products even later in the early 2000s.

3 Econometric analysis

3.1 Data

Our data set consists of daily close prices of the Polish stock market index WIG20 and the US index S&P500 covering the period between 1 November 1994 and 30 December 2003. The sample begins with the first complete month during which trading took place 5 days a week. Choosing 30 December 2003 as the end of the sample, we have the same number of months before and after the event in May 1999. Both indices were collected from *Datastream*. The WIG20 index is selected because it contains the 20 largest Polish stocks which are primarily held by the pension funds. Hence, using the WIG20 we approximate the pension funds' portfolio composition. Figure 1 displays both index time series where the stock return is defined as $R_t = 100 \times \ln(\text{index}_t/\text{index}_{t-1})$.

Figure 1 about here

As can be seen in Figure 1, the Polish stock market experienced a bull market since the mid 1990s. Unlike the US market, the Polish up market was interrupted by a downturn in the second half of 1998 but recovered quite quickly until the beginning of 2000. After the entrance of pension funds in May 1999 Polish stock prices increased moderately until mid July and decreased gradually until November 1999. Then stock prices increased drastically and reached their highest level in March 2000. Starting in April 2000 and ending in October 2001 Polish stock prices declined for a relatively long period. When looking at the graph for stock returns, Polish index returns show the well-known volatility clustering.

3.2 A Markov-Switching-GARCH model

An appropriate econometric technique for analyzing stochastic volatility shifts is provided by Markov-switching-GARCH models. Apart from some early methodological contributions to Markov-switching models scattered in the literature, their modern formal foundation is due to Hamilton (1988, 1989). In our analysis we make use of a

Markov-switching-GARCH model as developed in Gray (1996a), but modify his framework in two respects. First, we adapt Gray's model for t-distributed index returns within each regime and second, we incorporate a GARCH-dispersion specification as proposed by Dueker (1997).[3]

The idea of an univariate Markov-switching model is that the data generating process of the variable of interest—here of the daily stock returns of the WIG20 index—may be affected by a non-observable random variable S_t which represents the state the data generating process is in at date t. In our analysis, the state variable S_t differentiates between two volatility regimes and consequently takes on two distinct values. $S_t = 1$ indicates that the data generating process of the WIG20 index returns is in the high-volatility regime whereas for $S_t = 2$ the generating process is in the low volatility regime.

To set up our Markov-switching-GARCH model, recall first the probability density function of a (displaced) t-distribution with ν degrees of freedom, mean μ and variance h:

$$t_{\nu,\mu,h}(x) = \frac{\Gamma[(\nu+1)/2]}{\Gamma[\nu/2] \cdot \sqrt{\pi \cdot (\nu-2) \cdot h}} \cdot \left[1 + \frac{(x-\mu)^2}{h \cdot (\nu-2)}\right]^{-(\nu+1)/2}, \tag{1}$$

where $\Gamma(z) \equiv \int_0^\infty t^{z-1} \cdot \mathrm{e}^{-t}\, dt,\ z > 0$, denotes the complete gamma function. Next, we will specify stochastic processes for the mean and the variance in regime i (μ_{it} and h_{it}, respectively) according to which the return at date t (denoted by R_t) is generated conditional upon the regime indicator $S_t = i, i = 1, 2$. Following Gray's (1996a) Markov-switching framework, the conditional distribution of the returns can be represented as a mixture of two displaced t-distributions:

$$R_t|\phi_{t-1} \sim \begin{cases} t_{\nu_1,\mu_{1t},h_{1t}} & \text{with probability } p_{1t} \\ t_{\nu_2,\mu_{2t},h_{2t}} & \text{with probability } (1-p_{1t}) \end{cases}, \tag{2}$$

where ϕ_t represents the usual time-t information set and $p_{1t} \equiv \Pr\{S_t = 1|\phi_{t-1}\}$ denotes the so-called *"ex-ante probability"* of being in regime 1 at time t.

In our regime-dependent mean equations we explicitly take into account the possibility of first order autocorrelation in stock returns (by including R_{t-1}) and the interdependence of the Polish stock market with the international stock market. For this latter aspect we include the lagged S&P500 index returns R^{SP}_{t-1} as a control variable in

[3] The use of t-distributed rather than normally distributed returns within each regime is motivated by the 'fat-tail'-property of stock index returns (Bollerslev, 1987). Alternatively, any other heavy-tailed parametric distribution like the *Generalized Error Distribution* (GED) suggested by Nelson (1991) could be specified to govern the tail thickness of the index returns. However, as will be argued below, the t-distribution constitutes a good empirical model for our dataset.

the mean equation:

$$\mu_{it} = a_{0i} + a_{1i} \cdot R_{t-1} + a_{2i} \cdot R^{\mathrm{SP}}_{t-1} \qquad \text{for } i = 1, 2. \tag{3}$$

In contrast to the mean equation (3) the specification of an adequate GARCH-process for the regime-specific variance h_{it} is more problematic. Technically, this complication is phrased as *"path dependence"* and stems from the GARCH lag structure which causes the regime-specific conditional variance to depend on the entire history $\{S_t, S_{t-1}, \ldots, S_0\}$ of the regime-indicator S_t. We will circumvent this problem by applying the same collapsing procedure as Gray (1996a). For this we have posited in Eq. (2) that the data generating process that determines which regime observation t comes from in fact depends on the probability p_{it} as calculated from Eq. (9) below. From Eq. (2) the variance of the stock return at date t can be expressed as:

$$\begin{aligned} h_t &= E\left[R_t^2|\phi_{t-1}\right] - \{E\left[R_t|\phi_{t-1}\right]\}^2 \\ &= p_{1t} \cdot \left(\mu_{1t}^2 + h_{1t}\right) + (1 - p_{1t}) \cdot \left(\mu_{2t}^2 + h_{2t}\right) - \left[p_{1t} \cdot \mu_{1t} + (1 - p_{1t}) \cdot \mu_{2t}\right]^2. \end{aligned} \tag{4}$$

The quantity h_t can be thought of as an aggregate of conditional variances from both regimes and now provides the basis for the specification of the regime-specific conditional variances $h_{it+1}, i = 1, 2$ in the form of parsimonious GARCH(1,1) models. However, instead of using a conventional GARCH(1,1) structure, we follow the econometric motivation by Dueker (1997) and adopt a slightly modified GARCH equation. For this, it is convenient to parameterize the degrees of freedom from the t-distribution (1) by $q = 1/\nu$, so that $(1 - 2q) = (\nu - 2)/\nu$, and to specify the alternative GARCH equation as:

$$h_{it} = b_{0i} + b_{1i} \cdot (1 - 2q_i) \cdot \epsilon_{t-1}^2 + b_{2i} \cdot h_{t-1} \tag{5}$$

with h_{t-1} as given according to Eq. (4), while ϵ_{t-1} is obtained from:

$$\begin{aligned} \epsilon_{t-1} &= R_{t-1} - E\left[R_{t-1}|\phi_{t-2}\right] \\ &= R_{t-1} - \left[p_{1t-1} \cdot \mu_{1t-1} + (1 - p_{1t-1}) \cdot \mu_{2t-1}\right]. \end{aligned} \tag{6}$$

To close the model, it remains to specify the transition probabilities of the regime indicator S_t. For simplicity we consider a first order Markov process with constant transition probabilities, i.e. for $\pi_1, \pi_2 \in [0,1]$ we define:

$$\begin{aligned}
\Pr\{S_t = 1|S_{t-1} = 1\} &= \pi_1, \\
\Pr\{S_t = 2|S_{t-1} = 1\} &= 1 - \pi_1, \\
\Pr\{S_t = 2|S_{t-1} = 2\} &= \pi_2, \\
\Pr\{S_t = 1|S_{t-1} = 2\} &= 1 - \pi_2.
\end{aligned} \tag{7}$$

Now, following Wilfling (2007), we obtain the log-likelihood function Λ of our Markov-switching-GARCH(1,1) model:

$$\begin{aligned}
\Lambda = \sum_{t=1}^{T} \log \Bigg\{ & p_{1t} \cdot \frac{\Gamma[(\nu_1+1)/2]}{\Gamma[\nu_1/2] \cdot \sqrt{\pi \cdot \nu_1 \cdot h_{1t}}} \cdot \left[1 + \frac{(R_t - \mu_{1t})^2}{h_{1t} \cdot \nu_1}\right]^{-(\nu_1+1)/2} \\
& + (1 - p_{1t}) \cdot \frac{\Gamma[(\nu_2+1)/2]}{\Gamma[\nu_2/2] \cdot \sqrt{\pi \cdot \nu_2 \cdot h_{2t}}} \cdot \left[1 + \frac{(R_t - \mu_{2t})^2}{h_{2t} \cdot \nu_2}\right]^{-(\nu_2+1)/2} \Bigg\}.
\end{aligned} \tag{8}$$

The log-likelihood function (8) contains the *ex-ante* probabilities $p_{1i} = \Pr\{S_t = 1|\phi_{t-1}\}$. The whole series of *ex-ante* probabilities can be estimated recursively by

$$p_{1t} = \pi_1 \cdot \frac{f_{1t-1} p_{1t-1}}{f_{1t-1} p_{1t-1} + f_{2t-1}(1 - p_{1t-1})} + (1 - \pi_2) \cdot \frac{f_{2t-1}(1 - p_{1t-1})}{f_{1t-1} p_{1t-1} + f_{2t-1}(1 - p_{1t-1})}, \tag{9}$$

where f_{1t} and f_{2t} denote the $t_{\nu_1,\mu_{1t},h_{1t}}$- and $t_{\nu_2,\mu_{2t},h_{2t}}$-density functions from Eq. (1), each evaluated at $x = R_t$.

Table I about here

3.3 Empirical results

Table I presents the maximum-likelihood estimates of the Markov-switching-GARCH model from the Eqs. (1) to (9) for the WIG20 index returns. The model was estimated using the full dataset covering 2391 trading days between 1 November 1994 and 30 December 2003 as described above. Furthermore, we investigated a shortened dataset consisting of 392 trading days between 1 September 1998 and 1 March 2000 to take into account the effect of major financial crises on Polish stock returns. The short sample starts after the Asian and Russian crisis and ends before the world-wide collaps of stock markets in early 2000. Hence, we exclude the possibility that financial crises before May 1999 are responsible for the relative lower volatility in stock returns after the entrance of pension funds investors in the stock market. Maximization of the log-likelihood function was performed by the 'MAXIMIZE'-routine within the software package RATS 6.01 using the BFGS-algorithm, heteroscedasticity-consistent estimates of standard errors and suitably chosen starting values for all parameters involved.

The estimates in Table I can be analyzed and interpreted economically. Before analyzing the coefficients of the mean and GARCH equations (3) and (5), four aspects of model specification and model diagnostics are worth mentioning.

(a) The first specification issue concerns the functional form of the GARCH equation (5). Finance theory and empiricism suggest a positive relationship between the perceived risk of an asset and its return on average. Within a single-regime time-series framework this and other asymmetry considerations have led to various refined and mostly nonlinear GARCH specifications such as the GARCH-M model (Engle et al., 1987), the EGARCH model (Nelson, 1991) and the TGARCH specification (Glosten et al., 1993; Zakoian, 1994). Within a Markov-switching framework with two (or even more) regimes, however, at least parts of these asymmetries and relationships may be captured by ordinary linear autoregressive and GARCH specifications of the distinct regime-specific mean- and volatility equations. For example, the two regime-specific mean equations given by Eq. (3) in conjunction with the two regime-specific volatility equations from Eq. (5) are well-suited to capture the empirically frequently-encountered finding that higher perceived risk should pay a higher return on average. In such a situation the high-volatility (low-volatility) regime would be linked with that mean equation which generates the higher (lower) mean returns. However, in some situations it might appear appropriate to specify nonlinear GARCH equations (like EGARCH or TGARCH) for each individual regime. In principle, our Markov-switching framework can be extended to accommodate these and even more general asymmetric GARCH specifications (e.g. those examined by Hentschel, 1995) in each regime. Unfortunately, up to now the econometric properties of the resulting Markov-switching GARCH-M, EGARCH or TGARCH models have not yet been explored. Since a rigorous mathematical analysis with respect to estimation, hypothesis-testing and specification issues for these new model classes is beyond the scope of this paper, we stick to safe econometric ground and use the linear GARCH specification (5) in our Markov-switching framework.

(b) Another specification issue concerns the statistical significance of the second Markov regime as opposed to a single-regime GARCH specification. Unfortunately, a conventional likelihood ratio test (LRT) for testing the significance of the second regime turns out to be statistically improper, since under our model setup there are seven parameters which remain unidentified under the null hypothesis of a single regime (i.e. when $\pi_1 = 1$ and $\pi_2 = 0$). However, bearing in mind the statistical dubiousness of the LRT, we follow a frequently encountered approach and report the values of the conventional LRT-statistics here.[4] For this purpose, we fitted single-regime models with mean and GARCH specifications analogous to our equations (3) and (5) whose log-likelihood values are given in Table I (row 'Log-Likelihood: One-regime model'). In conjunction with the log-likelihood values of our Markov-switching-GARCH model (row 'Log-Likelihood: Two-regime model' in Table I) we computed the LRT statistics for both datasets as twice the difference between the log-likelihood values of the respective specifications (row 'LRT' in Table I). If the LRT were statistically valid, we would have had to compare the LRT statistics against the critical values derived from the quantiles of a χ^2-distribution with nine degrees of freedom (since the 'two-regime' specification has 9 additional parameters as opposed to the 'single-regime' model). Now, the critical value of a $\chi^2(9)$-distribution at the 1% level is 21.6660. Obviously, the LRT statistics for both datasets clearly exceed this critical value providing at least some (statistically informal) confidence in the existence of a second regime.[5]

(c) All q-parameters except for q_1 (i.e. for Regime 1) of the shortened dataset are larger than zero at any conventional significance level. It is well-known that the t-distribution (1) converges to the normal distribution for $q = 1/\nu \to 0$, but has 'fatter tails' than the corresponding normal distribution for any finite ν. This implies significant deviations from the normal distribution for the Regimes 1 and 2 of the full dataset and for Regime 2 of the shortened dataset. Moreover, the estimates of the degree-of-freedom parameters $\nu_1 = 1/q_1$ and $\nu_2 = 1/q_2$ are all larger than 4.0, explicitly ranging between 6.5359 and 344.8276. This result has two important implications for all regime-specific (time-varying) t-

[4]This simplifying approach has been adopted among others by Hamilton and Susmel (1994) and Gray (1996a). Ang and Bekaert (2002) provide a statistically more stringent justification for this approach.

[5]The modelling of only two Markov regimes, namely a low- and a high-volatility regime, might appear unrealistic at first glance. The consideration of at least one additional intermediate volatility regime seems natural. Unfortunately, the estimation of Markov-switching models with three or even more regimes becomes numerically unfeasible due to an exploding number of parameters arising from each additional Markov regime included in the econometric specification (see Wilfling, 2007, for statistical details). However, since we are merely interested in testing for an overall-effect on stock-return volatility (i.e. either for an overall-volatility increase or for an overall-volatility decrease) caused by the institutional investors' entrance into the Polish stock market, a two-regime Markov-switching model—apart from being numerically estimable—also appears to represent a factually well-grounded specification.

distributions estimated on the basis of our dataset. First, all t-distributions have finite variances (Hamilton, 1994). Second, all t-distributions have finite kurtosis (Mood et al., 1974). Obviously, the t-distribution constitutes a highly adequate empirical specification to capture the 'fat-tail' property of stock-index returns for our dataset.

(d) The lower part of Table I contains a diagnostic check of the model fit by providing Ljung-Box statistics for serial correlation of the squared (standardized) residuals out to the lags 1, 2, 3, 5, 10. Obviously, the null hypothesis of no autocorrelation cannot be rejected out to all lags at any conventional significance level providing further econometric evidence in favour of our two-regime Markov-switching-GARCH specification.

The majority of the estimated coefficients of the mean and GARCH equations (3) and (5) are statistically significant at the 1% level. The autoregressive coefficients a_{11} for regime 1 are statistically significant and negative for both datasets while the coefficients a_{12} for regime 2 are positive for both datasets. It is informative to note that the negative autoregressive coefficients a_{11} are contradictory to a result often reported in the literature finding a positive autoregressive structure of order one in stock index returns due to non-synchronous trading (Lo and MacKinlay, 1990), time-varying expected returns (Conrad and Kaul, 1988) and transaction costs (Mech, 1993). The coefficients of the control variable R_{t-1}^{SP} are statistically significant (at least at the 5% level) and positive in both regimes revealing the strong interdependence between US and Polish stock returns dynamics.

When looking at the estimated parameters describing the conditional volatility process we find the well-established result of volatility persistence for both datasets and in both regimes (except for regime 2 in the shortened dataset). However, none of the four coefficient sums $\hat{b}_{1i} \cdot (1 - 2\hat{q}_i) + \hat{b}_{2i}, i = 1, 2$, for both datasets exceeds 1 providing some evidence for stationary conditional volatility processes in all regimes.

The constant transition probabilities π_1 and π_2 are close to one in both estimations. Since both quantities represent the probability of the data generating process remaining in the same volatility regime during the transition from date $t-1$ to t, both volatility regimes reveal a high degree of persistence.

Next, we address two conditional probabilities which are of inferential relevance for detecting how often and at which dates the Polish stock market switched between the high and the low volatility regimes. First, the *ex-ante* probabilities $p_{1t} \equiv \Pr\{S_t = 1|\phi_{t-1}\}, t = 2, \ldots, T$, which can be estimated recursively via Eq. (9), and second, the so-called *smoothed* probabilities $\Pr\{S_t = 1|\phi_T\}, t = 1, \ldots, T$, which can be computed after model estimation by the use of filter techniques.[6]

The *ex-ante* probabilities are useful in forecasting one-step-ahead regimes based on an information set which evolves over time. In our context, the *ex-ante* probabilities reflect current market perceptions of the one-step-ahead volatility regime, thus representing an adequate measure of stock market volatility sentiments. In contrast to this, the *smoothed* probabilities are based on the full sample-information set ϕ_T and thus provide a basis for inferring *ex post* if and when volatility regime switches have occurred in the sample.

Figures 2 and 3 about here

Figures 2 and 3 display both regime-1 probabilities (upper panels) along with the conditional variance processes (lower panels) estimated for the Markov-switching-GARCH model on the basis of the full and the shortened datasets, respectively. The *ex-ante* probabilities are represented by the thin lines while the bold lines depict the *smoothed* regime-1 probabilities. Since the *ex-ante* probabilities are determined by an evolving (and thus smaller) information set, they exhibit a more erratic dynamic behaviour than the *smoothed* regime-1 probabilities. As a visual support, all panels contain a marker for the 19 May 1999, the crucial date of the Polish pension system reform.

As can be seen in Figure 2, after a period of low conditional volatility we observe a jump to a high volatility regime around February 1997 when all blue chip stocks contained in the WIG20 became continuously traded. High conditional variances at the end of 1997, mid 1998 and at the beginning of 1999 are associated with the Asian (October/November 1997), the Russian (August/September 1998) and the Brazilian (January 1999) crises, respectively. More importantly, Figures 2 and 3 demonstrate the effect of the change in the investors' structure in the Polish stock market on 19 May 1999. The conditional volatility process exhibits a structural break around this date. While the conditional variances are higher before May 1999, they are significantly lower afterwards in both Figures. Further econometric evidence is provided by the *ex-ante* and the *smoothed* probabilities in the upper panels which show a clear-cut transition from a high to a low volatility regime around the date of the entrance of pension fund investors. In 2000 the low volatility regime switches again to the high volatility regime. We can conclude that the entrance of institutional investors on the Polish stock market reduced at least temporarily the volatility of stock returns. While the

[6]The *smoothed* probabilities for the WIG20 index returns were computed on the basis of a filter algorithm provided by Gray (1996b).

high volatility regime in 2000 can be explained by the bear market, the evidence around 19 May 1999 convincingly demonstrates the stabilizing effect of institutional investors on Polish stock price dynamics.

4 Summary and Conclusions

One of the most prominent changes in financial markets during the recent decades is the surge of institutional investors. Concerning their specific investment behavior numerous studies indicate that institutional investors engage in herding and tend to exhibit positive feedback trading strategies and thus contribute to stock returns autocorrelation and volatility. In this paper, we challenge this view and provide empirical evidence on the influence of institutional investors on stock returns dynamics. The Polish pension reform in 1999 is used as an institutional peculiarity to implement a Markow-switching-GARCH model. Before and after 19 May 1999 there were no other features of the Polish stock market which were of comparable relevance as the market entrance of pension funds. Therefore, it is this institutional feature of the Polish emerging stock market together with the econometric technique that allows us to answer the following questions: Did the increase of institutional ownership after the appearance of Polish pension funds on 19 May 1999 result in a change in the volatility structure of stock index returns? Did Polish pension fund investors destabilize or stabilize stock prices?

We provide empirical evidence in favor of a change in the conditional volatility process due to the increased importance of institutional investors on the Polish stock market. In contrast to the often mentioned suggestion that institutional investors increase stock returns volatility, our findings support the hypothesis that the pension fund investors in Poland reduced stock market volatility. Hence, our empirical evidence is in favor of a stabilizing rather than a destabilizing effect induced by pension funds investors in Poland.

In a broader perspective our findings are supportive of the view that institutional investors can be characterized as informed investors who speed up the adjustment of stock prices to new information thereby making the stock market more efficient. Institutions can create an informational advantage by exploiting economies of scale in information acquisition and processing. The marginal costs of gathering and processing are lower than for individual traders. In this sense our findings are consistent with the evidence in Dennis and Weston (2001) for the US. If individual investors contribute to stock returns volatility, a significant decrease in trades by individuals relative to institutions might provide an explanation for the stabilizing effect. Moreover, institutional investors may stabilize stock prices and counter irrational behavior in individual investors' sentiment. Gabaix et al. (2006) provide a theoretical model in which trades by large institutional investors in relatively illiquid markets generate excess stock market volatility. Our empirical findings do not support this theoretical prediction.

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Table I
Estimates and related statistics for Markov-switching-GARCH models

	Full dataset		Shortened dataset	
	Estimate	Std. error	Estimate	Std. error
Regime 1:				
a_{01}	−0.0643	0.0623	0.2120	0.1830
a_{11}	−0.0952**	0.0316	−0.2234**	0.0523
a_{21}	0.5300**	0.0400	0.9648**	0.1438
b_{01}	0.1439	0.0819	3.0571**	0.1174
b_{11}	0.1317**	0.0272	0.1101**	0.0023
b_{21}	0.8282**	0.0410	0.8502**	0.0550
$q_1 = 1/\nu_1$	0.1333**	0.0218	0.0029	0.0550
$[\hat{b}_{11} \cdot (1 - 2\hat{q}_1) + \hat{b}_{21}]$	[0.9248]		[0.9597]	
Regime 2:				
a_{02}	0.0395	0.0356	0.0572	0.1011
a_{12}	0.0909**	0.0291	0.0143	0.0675
a_{22}	0.1689**	0.0304	0.1672*	0.0729
b_{02}	0.0764*	0.0355	1.3128**	0.2562
b_{12}	0.0882**	0.0197	0.1188*	0.0481
b_{22}	0.8692**	0.0348	0.0614	0.1259
$q_2 = 1/\nu_2$	0.1530**	0.0282	0.1278**	0.0403
$[\hat{b}_{12} \cdot (1 - 2\hat{q}_2) + \hat{b}_{22}]$	[0.9304]		[0.1498]	
Transition probabilities:				
π_1	0.9982**	0.0023	0.9826**	0.0045
π_2	0.9991**	0.0006	0.9963**	0.0018
Log-Likelihood:				
Two-regime model	−4721.6049		−781.9689	
One-regime model	−4739.8082		−794.8619	
LRT	36.4066		25.7860	
Residual analysis	Test statistic	p-value	Test statistic	p-value
LB_1^2	0.6602	0.4165	0.0801	0.7771
LB_2^2	0.9398	0.6251	0.2341	0.8895
LB_3^2	1.5727	0.6656	0.3556	0.9492
LB_5^2	3.7951	0.5793	0.4368	0.9943
LB_{10}^2	12.4444	0.2564	5.8881	0.8246

Note: Estimates for parameters from the Eqs. (1) to (9). LB_i^2 denotes the *Ljung-Box-Q*-statistic for serial correlation of the squared standardized residuals out to lag i. ** and * denote statistical significance at the 1 % and 5 % levels, respectively.

Figure 1: Stock market indexes and returns

Figure 2: Regime-1 probabilities and conditional variances (full dataset)

Figure 3: Regime-1 probabilities and conditional variances (shortened dataset)