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

Martin T. Bohl*
European University Viadrina Frankfurt (Oder), Germany

Janusz Brzeszczyński
Hariot-Watt University Edinburgh, United Kingdom

Bernd Wilfling
University of Münster, Germany

Date of this version: February 15, 2005

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. However, the findings do not support the hypothesis that institutional investors have destabilized stock prices. The results are interpretable in favor of a stabilizing effect on index stock returns induced by institutional investors.

JEL-classification codes: C32, G14, G23

Keywords: Institutional Traders, Polish Stock Market, Pension Fund Investors, Stock Market Volatility, Markov-Switching-GARCH Model

*Corresponding author: Martin T. Bohl, Faculty of Economics, European University Viadrina, Frankfurt (Oder), Große Scharrnstraße 59, 15230 Frankfurt (Oder), Germany, Phone: ++ 49 335 5534 2984, Fax: ++ 49 335 5535 2959, E-mail: bohl@euv-frankfurt-o.de
Institutional Investors and Stock Returns Volatility: Empirical Evidence from a Natural Experiment

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. However, the findings do not support the hypothesis that institutional investors have destabilized stock prices. The results are interpretable in favor of a stabilizing effect on index stock returns induced by institutional investors.

JEL-classification codes: C32, G14, G23

Keywords: Institutional Traders, Polish Stock Market, Pension Fund Investors, Stock Market Volatility, Markov-Switching-GARCH Model
1 Introduction

The increase in the number of institutional investors trading on stock markets worldwide since the end of the 1980s has been associated with 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 institutions move stock prices away from fundamentals and thereby induce autocorrelation between and increases in the 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 on the stabilizing impact of institutions are the empirical findings for US data provided in Cohen, Gompers and Vuolteenaho (2002) on the relationship between institutional and individual investors. 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 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.

We can conclude from the short discussion above that empirical findings on institutional investors’ herding and positive feedback trading behavior are not necessarily

\(^1\) 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).
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. 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 when 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 May 19, 1999. The appearance of large institutional traders and the resulting increase in institutional ownership allows us to investigate the impact on stock returns volatility. Specifically, we use a modification of the Markov-switching-GARCH model put forward by Gray (1996a) to test whether the model’s key coefficients change after the entrance of institutional traders in the Polish stock market. The main advantage of 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 stochastic 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. Its capitalization is comparable to the ones of smaller mature European markets, like the Austrian stock market, and equals currently about 45 billion $-US.

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 Ubezpieczeń 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 May 19, 1999. This date changed the investors’ structure of the Polish stock market significantly. In 1999, about 20 % of the domestic institutional investors and 45 % of the domestic individual investors traded at the Warsaw Stock Exchange. This situation has nearly reversed until 2003 so that the number of institutional traders has approximately doubled over the 1999 – 2003 period. Constantly about 35 % of the investors on the Polish stock market adhere to the group of foreign investors.

While before May 19, 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 May 19, 1999 characterized mainly by non-institutional trading with the period after that date, where pension funds as institutional investors act on the stock market.

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 the smaller funds by the larger ones. By the end of 2003, 17 pension funds operated in the Polish stock market with about 8 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 3 billion $-US in stocks listed on the Warsaw Stock Exchange. Those funds account for about 17% of the daily turnover at 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 (Karpinski, 2002). Therefore, pension funds are important players on the Polish stock market, able to affect stock prices.

3 Econometric analysis

3.1 Data

Our data set consists of daily close prices of the Polish stock market index WIG20 and the U.S. index S&P500 covering the period between 1 November 1994 and 30 December 2003 (2391 trading days). Both indices were collected from Datastream. Figure 1 displays both index time series where the return is defined as \( R_t = 100 \times \ln(\text{index}_t/\text{index}_{t-1}) \). To test for a unit root in each of the return time series, we performed the usual battery of adequately specified Augmented Dickey-Fuller and Philips-Perron tests. The findings are not reported but are available upon request. All these tests reject the null hypothesis of a unit root at the 1%-level. Consequently, we will use both return time series in the subsequent econometric analysis without further differencing.

As can be seen in Figure 1, the Polish stock market experienced a bull market since the mid 1990s. Unlike the U.S. 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. Starting in April 2000 and ending in October 2001 Polish stock prices declined for a relatively long period. When looking at the graph for the stock returns, it is obvious that Polish index returns fluctuate in a narrower band after May 19, 1999 compared to the period before.

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). A collection of Markov-switching
applications in distinct areas of economics and finance is presented in Hamilton and Raj (2002). 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).\(^2\)

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 \( \nu \) degrees of freedom, mean \( \mu \) and variance \( h \):

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

where \( \Gamma(z) \equiv \int_0^\infty t^{z-1} e^{-t} dt, \; z > 0 \), denotes the complete gamma function. Next, we will specify stochastic processes for the mean and the variance in regime \( i \) (\( \mu_{it} \) 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:

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

where \( \phi_t \) represents the usual time-\( t \) information set and \( p_{1t} \equiv \Pr \{ S_t = 1 | \phi_{t-1} \} \) denotes the so-called "\textit{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 \( R_{t-1}^{SP} \) as a control variable in

---

\(^2\)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).
the mean equation (Jochum et al., 1999; Tse et al., 2003; Voronkova, 2004):

\[ \mu_{it} = a_{0i} + a_{1i} \cdot R_{t-1} + a_{2i} \cdot R_{t-1}^{sp} \quad \text{for } i = 1, 2. \]  

(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:

\[ h_t = E \left[ R_t^2 | \phi_{t-1} \right] - \{ E \left[ R_t | \phi_{t-1} \right] \}^2 = p_{1t} \cdot (\mu_{1t}^2 + h_{1t}) + (1 - p_{1t}) \cdot (\mu_{2t}^2 + h_{2t}) - [p_{1t} \cdot \mu_{1t} + (1 - p_{1t}) \cdot \mu_{2t}]^2. \]  

(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:

\[ h_t = b_{0i} + b_{1i} \cdot (1 - 2q_i) \cdot \epsilon_{t-1}^2 + b_{2i} \cdot h_{t-1} \]  

(5)

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

\[ \epsilon_{t-1} = R_{t-1} - E \left[ R_{t-1} | \phi_{t-2} \right] = R_{t-1} - [p_{1t-1} \cdot \mu_{1t-1} + (1 - p_{1t-1}) \cdot \mu_{2t-1}] \]  

(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:

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

(7)

Now, invoking similar arguments as Gray (1996a), we obtain the log-likelihood function $\Lambda$ of our Markov-switching-GARCH(1,1) model:

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

(8)

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

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

(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 $x = R_t$.

### 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 and, for robustness checking, a shortened dataset consisting of 392 trading days between 1 September 1998 and 1 March 2000. Maximization of the log-likelihood function was performed by the 'MAXIMIZE'-routine within the software package RATS 5.02 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. Three statistical aspects are worth being mentioned. First, the estimates of the degree-of-freedom parameters $\nu_1 = 1/q_1$ and $\nu_2 = 1/q_2$ are all larger than 2.0, explicitly ranging between 4.9334 and 22.0751. This is an important stipulation for the existence of the variance of a $t$-distribution (Hamilton, 1994, p. 662). However, 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 $\nu$. Obviously, invoking the Chebyshev inequality, all $q$-parameters, except $q_1$ of the shortened dataset, are larger than zero at any conventional significance level. This implies significant deviations from the normal distribution for these 3 regimes. Second, the constant transition probabilities $\pi_1$ and $\pi_2$ 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. Third, 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. This provides some econometric evidence in favour of our Markov-switching-GARCH specification.

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 \textit{ex-ante} probabilities $p_{1t} = \Pr\{S_t = 1|\phi_{t-1}\}, t = 2, \ldots, T$, which can be estimated recursively via Eq. (9), and second, the so-called \textit{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.$^3$

The \textit{ex-ante} probabilities are useful in forecasting one-step-ahead regimes based on an information set which evolves over time. In our context, the \textit{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 \textit{smoothed} probabilities are based on the full sample-information set $\phi_T$ and thus provide a basis for inferring \textit{ex post} if and when volatility regime switches have occurred in the sample.

The majority of the estimated coefficients of the mean and GARCH equations (3) and (5) are statistically significant at the 1 % level. Exceptions are the autoregressive coefficients $a_{11}$ and $a_{12}$ which are either statistically insignificant or statistically

$^3$The \textit{smoothed} probabilities for the WIG20 index returns were computed on the basis of a filter algorithm provided by Gray (1996b).
significant and negative. This is contradictory to the results often found 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 and positive in both regimes revealing the strong interdependence between U.S. 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. However, the sum of the coefficients \( b_{11} + b_{21} \) for the full dataset exceeds 1 indicating a unit root in the conditional volatility process in regime 1.

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 \textit{ex-ante} probabilities are represented by the full lines while the dashed lines depict the \textit{smoothed} regime-1 probabilities. Since the \textit{ex-ante} probabilities are determined by an evolving (and thus smaller) information set, they exhibit a more erratic dynamic behaviour than the \textit{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.

Figures 2 and 3 about here

More importantly, Figures 2 and 3 demonstrate the effect of the change in the investors’ structure in the Polish stock market on May 19, 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 \textit{ex-ante} and the \textit{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 high volatility regime in 2000 can be explained by the bear market, the evidence around the May 19, 1999 date 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. 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 May 19, 1999 result in a change in the volatility structure of stock index returns? Did Polish pension fund investors destabilize or stabilize stock prices?

Relying on the framework outlined above 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. However, in contrast to the often mentioned belief 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. 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.
References


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

<table>
<thead>
<tr>
<th>Regime 1:</th>
<th>Estimate</th>
<th>Std. error</th>
<th>Estimate</th>
<th>Std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$a_{01}$</td>
<td>-0.0080</td>
<td>0.0386</td>
<td>0.6127**</td>
<td>0.1236</td>
</tr>
<tr>
<td>$a_{11}$</td>
<td>0.0239</td>
<td>0.0282</td>
<td>-0.2163**</td>
<td>0.0609</td>
</tr>
<tr>
<td>$a_{21}$</td>
<td>0.4260**</td>
<td>0.0306</td>
<td>0.8267**</td>
<td>0.1060</td>
</tr>
<tr>
<td>$b_{01}$</td>
<td>0.2336**</td>
<td>0.0202</td>
<td>0.3512**</td>
<td>0.0166</td>
</tr>
<tr>
<td>$b_{11}$</td>
<td>0.2267**</td>
<td>0.0058</td>
<td>0.1599**</td>
<td>0.0349</td>
</tr>
<tr>
<td>$b_{21}$</td>
<td>0.7958**</td>
<td>0.0119</td>
<td>0.7933**</td>
<td>0.0139</td>
</tr>
<tr>
<td>$q_1 = 1/\nu_1$</td>
<td>0.1501**</td>
<td>0.0128</td>
<td>0.0453</td>
<td>0.0475</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regime 2:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$a_{02}$</td>
<td>0.0312</td>
<td>0.0327</td>
<td>0.0342</td>
<td>0.0919</td>
</tr>
<tr>
<td>$a_{12}$</td>
<td>-0.0298*</td>
<td>0.0128</td>
<td>0.0314</td>
<td>0.0507</td>
</tr>
<tr>
<td>$a_{22}$</td>
<td>0.1519**</td>
<td>0.0389</td>
<td>0.1550**</td>
<td>0.0533</td>
</tr>
<tr>
<td>$b_{02}$</td>
<td>0.0397**</td>
<td>0.0056</td>
<td>0.1523**</td>
<td>0.0505</td>
</tr>
<tr>
<td>$b_{12}$</td>
<td>0.0694**</td>
<td>0.0033</td>
<td>0.0275*</td>
<td>0.0136</td>
</tr>
<tr>
<td>$b_{22}$</td>
<td>0.9170**</td>
<td>0.0030</td>
<td>0.8836**</td>
<td>0.0111</td>
</tr>
<tr>
<td>$q_2 = 1/\nu_2$</td>
<td>0.1890**</td>
<td>0.0114</td>
<td>0.2027**</td>
<td>0.0136</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transition probabilities:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_1$</td>
<td>0.9973**</td>
<td>0.0052</td>
<td>0.9803**</td>
<td>0.0247</td>
</tr>
<tr>
<td>$\pi_2$</td>
<td>0.9932**</td>
<td>0.0037</td>
<td>0.9929**</td>
<td>0.0123</td>
</tr>
</tbody>
</table>

#### Residual analysis

<table>
<thead>
<tr>
<th></th>
<th>Test statistic</th>
<th>p-value</th>
<th></th>
<th>Test statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$LB_1^2$</td>
<td>1.1034</td>
<td>0.2935</td>
<td>0.3924</td>
<td>0.5310</td>
<td></td>
</tr>
<tr>
<td>$LB_2^2$</td>
<td>1.6371</td>
<td>0.4411</td>
<td>0.3960</td>
<td>0.8204</td>
<td></td>
</tr>
<tr>
<td>$LB_3^2$</td>
<td>2.0383</td>
<td>0.5645</td>
<td>0.6753</td>
<td>0.8790</td>
<td></td>
</tr>
<tr>
<td>$LB_5^2$</td>
<td>4.6763</td>
<td>0.4566</td>
<td>1.0324</td>
<td>0.9599</td>
<td></td>
</tr>
<tr>
<td>$LB_{10}^2$</td>
<td>13.3144</td>
<td>0.2066</td>
<td>4.8182</td>
<td>0.9030</td>
<td></td>
</tr>
</tbody>
</table>

*Note:* Estimates for parameters from the Eqs. (1) to (9). Standard errors are in parenthesis. $LB_i^2$ 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)