Switching volatility in target stocks during takeover bids

Sergey Gelman [a], Bernd Wilfling [b,*]

[a] *International College of Economics and Finance, Pokrovski Bulvar 11, Moscow 109028, Russia*

[b] *Westfälische Wilhelms-Universität Münster, Department of Economics (CAWM and CeNoS), Am Stadtgraben 9, 48143 Münster, Germany*

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Abstract. This paper examines movements in the conditional volatility of stock prices of takeover targets. Based on a continuous-time modelling framework, we provide theoretical justification for modelling the data-generating process of the target stock price as subject to volatility regime-switching. Using daily stock prices of five European and American targets, we find that adequately specified Markov-switching GARCH models are capable of detecting statistically significant volatility regime-switches in all takeover deal-types (in cash bids, pure share-exchange bids, mixed bids). Overall, volatility regime-switches are found to be most clear-cut for cash bids. Our econometric findings have implications for a broad range of financial applications such as the valuation of target stock options.

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*Corresponding author. Phone: +49 - 251 - 83 - 25040, Fax: +49 - 251 -83 - 25042, e-mail address: bernd.wilfling@wiwi.uni-muenster.de

1 Introduction

Within the last three decades, merger and acquisition attempts have experienced a substantial increase in number worldwide and have become a matter of vital interest to financial economists. Very often the process of a corporate takeover is characterized by strong price movements in the stock of the acquired firm (the target stock) which typically deviates from its *fundamental path*. Stylized facts on target stock price dynamics are well documented in the literature. Theoretical and empirical studies have focused on both, the *level* of target stock prices around the announcement of takeover offers as well as on the (conditional and unconditional) *volatility* of target stocks (see among others Bhagat et al., 1987; Schwert, 1996; Hutson and Kearney, 2001, 2005 and the literature cited there). As the starting point for our analysis we adopt an idea of Hutson and Kearney (2001, p. 274) who explain the *decline in conditional target stock-price volatility* after the announcement of the takeover bid by a *change in the price formation process* during the post-announcement period.

In this paper, we take this idea two steps further. (a) We argue that the price formation process may change discretely at any date during the post-announcement period and that each of these changes in the stock-price process reflects a revised market assessment of the ultimate takeover success. (b) We explicitly model these discrete shifts in the data-generating process by so-called *regime-switching* (or *Markov-switching*) models, a pure time-series approach which is in widespread use in various fields of financial economics.[1]

Hitherto, Markov-switching models have not yet been applied to data on target stock-price returns. As will become evident below, appropriately specified Markov-switching models are able to simultaneously capture switches in both, in levels (market-beta) and in conditional volatility of target stock-price returns. Hence, our regime-switching framework constitutes an approach that brings together and extends several results of earlier studies which have focused either on level or on volatility effects of corporate takeovers.

Deeper economic insight into market-beta and, in particular, into volatility regime-switching in target stock-price returns during the post-announcement period will be presented in Section 2. For this, we modify and extend an existing target stock-pricing model and derive explicit implications for the conditional variances of the stock-price returns in the time between the bid announcement and the conclusion of the takeover deal.

[1] Regime-switching models in their modern form were introduced by Hamilton (1988, 1989). For a recent state-of-the-art presentation see Hamilton and Raj (2002).

Being equipped with these theoretical results, we then proceed with the empirical investigation. To keep the econometric analysis tractable, we simplify by specifying two distinct regimes for the data-generating process of the target stock-price returns. (a) A *high-beta-high-volatility regime*, which is to represent the time during the post-announcement period when market participants consider the announced takeover to be highly improbable, and (b), a *low-beta-low-volatility regime*, in which market participants are almost certain that the takeover will finally be completed. We fit these 2-regime Markov-switching models to daily stock-price returns of five recent takeover targets. Along with the parameter estimates we provide estimation of the so-called *ex-ante* and *smoothed* regime-probabilities. These quantities allow us to make statistical inference about the regimes the respective data-generating processes were in at any arbitrary date from the sampling periods. Both, the *ex-ante* and the *smoothed* probability series reveal information about the stock market's assessment of the ultimate takeover success.

The key result of this study is that volatility regime-switching in target stock-price returns is a statistically significant phenomenon in the post-announcement period of a takeover bid. Consequently, regime-switches should be included in any econometric target stock-price model in order to avoid specification errors. Moreover, since regime-switching models contribute—via the *ex-ante* and *smoothed* regime-probabilities—to elucidating the stock market's assessment of the ultimate takeover success, an advisable procedure would be to sequentially fit such models to high-frequency stock-price data during a takeover deal. At least four groups of agents should benefit considerably from such a sequential analysis:

(a) The *ex-ante* and *smoothed* regime-probabilities can provide important information for the *bidder*. In addition to the bidder's potential knowledge about the portion of target stocks that have already been tendered, both probability series provide good forecasts on the stock markets' ultimate acceptance of the bid offer. Hence, the bidder can reconsider or even withdraw the offer if the stock market shows disapproval.[2]

(b) The regime-probabilities can be of value for the *regulation authorities* in detecting insider trades. Insider trades can be identified via suspicious changes in the regime-probabilities that are inconsistent with public information releases.

(c) Through the gain in information on the stock market's sentiments the regime-

[2]This reasoning is in line with Luo (2005) who demonstrates that stock markets indeed convey new relevant information to the decision-makers involved.

probabilities can support the *members of the managerial board* of the target company in better planning their protective actions in the case of a hostile takeover attempt.

(d) The entire regime-switching framework should be useful to *agents in derivative markets*. Since volatility regime-switching in target stock-price data turns out to be statistically significant, options on the target stock can be priced more adequately on knowing in which volatility regime the data-generating process is currently staying.

The remainder of the paper is organized as follows. Section 2 provides theoretical motivation for modelling the data-generating process of target stock-price returns as a volatility regime-switching process. Section 3 describes the data set and develops the econometric specification. Section 4 presents the estimation results and interprets the econometric findings in a target-specific context. The final section summarizes the main arguments of the paper and sketches possible lines of future research.

2 Theoretical aspects of target stock dynamics

Among the large number of studies examining the various aspects of target stock dynamics, a plethora of papers reports about the existence of so-called *abnormal returns*. Abnormal returns denote target stock-price returns during a takeover deal that systematically exceed the returns as predicted by the *market model*. Here, the market model is a reference model, whose parameters are estimated using data from a sampling period lying considerably before the first takeover announcement (see among others Jensen and Ruback, 1983; Jarrell et al., 1988).

An alternative interpretation of the concept of *abnormal returns* is that target stock-price returns change their mean process and become less responsive to market-wide shocks. Bhagat et al. (1987) provide a theoretical explanation of this phenomenon by representing the target stock during the tender period as a portfolio consisting of a hypothetical *fundamental target stock* plus a fractional put option. By invoking standard arguments of option-pricing theory, they demonstrate that the *market-beta* of this portfolio lies strictly below the *market-beta* of the fundamental target stock at every instant during the tender period.

A second important feature of target stock-price dynamics well-documented in the empirical literature is the *decreasing conditional volatility* in the period after the bid announcement. Hutson and Kearney (2001, p. 273) interpret this conditional volatility

reduction as a result of the 'convergence of trader opinion regarding the value of the target stock'.

In this section, we focus on conditional volatility. More precisely, we provide insight into conditional volatility dynamics of target stock-price returns. Our main objective is to present theoretical justification for the volatility regime-switching specifications which we use in our econometric analysis in Section 3.

For this purpose, we set up a continuous-time model which is in many respects similar to the target stock-pricing models presented in Brown and Raymond (1986) and Samuelson and Rosenthal (1986). We consider an arbitrary date t during the post-announcement period at which the stock market has already started to anticipate the potential takeover. As in the aforementioned papers, our model assumes that the current target stock-price $P(t)$ can be represented by a weighted average covering two components: (a) The price v_T that the bidder will pay at the conclusion date T of the bid offer,[3] and (b), the current fundamental price $P^*(t)$ of the target stock which would prevail in the case of no takeover (the *fallback price*):[4]

$$P(t) = \alpha \cdot v_T \cdot \mathrm{e}^{-r \cdot \tau} + (1 - \alpha) \cdot P^*(t). \tag{1}$$

In Eq. (1), α denotes the subjective probability that rational investors—based on their present date-t knowledge—attach to the ultimate success of the deal. Since offer periods frequently last for a significant time span, we account for the time-value of money according to the continuously compounded risk-free interest rate r with $\tau \equiv T - t$ denoting the time left until the conclusion of the deal.

As in a Black-Scholes-Merton world, we assume that the fundamental price-process $\{P^*(t)\}$ follows a geometric Brownian motion on $t \in [0, T]$ with stochastic differential representation

$$dP^*(t) = \mu P^*(t)dt + \sigma P^*(t)dW(t), \qquad P^*(0) = P_0^* > 0, \tag{2}$$

where $\mu \in \mathbb{R}$ and $\sigma > 0$ denote the process parameters and $dW(t)$ represents the increment of a standard Wiener process. The initial condition $P^*(0) = P_0^* > 0$ implies that the trajectories of $\{P^*(t)\}$ are positive on $t \in [0, T]$ (with probability 1).

Since we are interested in analyzing *target stock-price returns* rather than pure target

[3] In this section, we think of v_T as a cash-bid price. In our empirical analysis below, however, we also analyze data for mixed and pure share-exchange bids.

[4] For simplicity we assume that in the case of a takeover failure the target stock-price $P(t)$ reverts to its fundamental value $P^*(t)$ so that the fallback price equals the fundamental price. For an alternative scenario see Samuelson and Rosenthal (1986).

stock-prices, we derive the dynamics of the *natural logarithm* of the target stock-price. Making use of the Eqs. (1) and (2), the stochastic differential of

$$p(t) \equiv \log_{\mathrm{e}}[P(t)] = F(P^*(t), t) \tag{3}$$

can be obtained by direct application of Itô's lemma:

$$\begin{aligned} dp(t) &= \left[\frac{\alpha \cdot v_T \cdot r \cdot \mathrm{e}^{-r\cdot(T-t)} + (1-\alpha)\cdot\mu\cdot P^*(t)}{\alpha \cdot v_T \cdot \mathrm{e}^{-r\cdot(T-t)} + (1-\alpha)\cdot P^*(t)}\right. \\ &\quad \left. - \frac{1}{2}\cdot\frac{(1-\alpha)^2\cdot\sigma^2\cdot[P^*(t)]^2}{\left[\alpha \cdot v_T \cdot \mathrm{e}^{-r\cdot(T-t)} + (1-\alpha)\cdot P^*(t)\right]^2}\right]\cdot dt \\ &\quad + \frac{(1-\alpha)\cdot\sigma\cdot P^*(t)}{\alpha \cdot v_T \cdot \mathrm{e}^{-r\cdot(T-t)} + (1-\alpha)\cdot P^*(t)}\cdot dW(t). \end{aligned} \tag{4}$$

Next, we analyze the *infinitesimal variance* of the logarithmic target stock-price which we denote by $\sigma^2_{\{p(t)\}}(P^*(t), t)$. The relevance of the infinitesimal variance stems from the fact that for a small time increment $h > 0$ the conditional variance of the change $p(t+h) - p(t)$ can be represented as[5]

$$\mathrm{Var}[p(t+h) - p(t)|\phi(t)] = \sigma^2_{\{p(t)\}}(P^*(t), t)\cdot h + o(h), \tag{5}$$

where the variance on the left-hand side of Eq. (5) is conditioned upon the information set $\phi(t)$, which includes all information available to rational stock market participants at time t, while $o(h)$ represents a remainder term of order smaller than h. According to Eq. (5) the infinitesimal variance $\sigma^2_{\{p(t)\}}(P^*(t), t)$ may serve as an approximation of the conditional variance of *one-unit-ahead target stock-price returns*:

$$\begin{aligned} \sigma^2_{\{p(t)\}}(P^*(t), t) &\approx \mathrm{Var}[p(t+1) - p(t)|\phi(t)] \\ &= \mathrm{Var}\{\log_{\mathrm{e}}[P(t+1)] - \log_{\mathrm{e}}[P(t)]|\phi(t)\}. \end{aligned} \tag{6}$$

The explicit form of the infinitesimal variance follows directly from the stochastic differential (4):

$$\sigma^2_{\{p(t)\}}(P^*(t), t) = \frac{(1-\alpha)^2\cdot\sigma^2\cdot[P^*(t)]^2}{\left[\alpha \cdot v_T \cdot \mathrm{e}^{-r\cdot(T-t)} + (1-\alpha)\cdot P^*(t)\right]^2}. \tag{7}$$

[5] See Karlin and Taylor (1981, pp. 159).

Two special cases included in the variance-path (7) are worth mentioning:

(a) For $\alpha = 0$, that is if agents—based on their date-t information set—attach zero-probability to the ultimate takeover success, the infinitesimal variance reduces to the constant σ^2 which, by definition from Eq. (2), equals the infinitesimal variance of the *logarithmic fallback price*:

$$\sigma^2_{\{p(t)\}}(P^*(t), t) = \sigma^2 \equiv \sigma^2_{\{p^*(t)\}},$$

with $p^*(t) \equiv \log_{\mathrm{e}}[P^*(t)]$.

(b) For $\alpha = 1$, that is if agents are completely certain about the ultimate takeover success, the infinitesimal variance is constantly equal to zero:

$$\sigma^2_{\{p(t)\}}(P^*(t), t) = 0.$$

In order to quantify the effect of a *ceteris-paribus* change in the takeover probability α on $\sigma^2_{\{p(t)\}}(P^*(t), t)$, we consider the following partial derivative at a specifically chosen date t:

$$\frac{\partial\, \sigma^2_{\{p(t)\}}}{\partial\, \alpha} = -\frac{2 \cdot (1-\alpha) \cdot \mathrm{e}^{2r\cdot(T-t)}\sigma^2 \cdot [P^*(t)]^2 \cdot v_T}{\left[(1-\alpha) \cdot \mathrm{e}^{r\cdot(T-t)} \cdot P^*(t) + \alpha \cdot v_T\right]^3}. \tag{8}$$

The right-hand side of (8) is negative for all $\alpha \in [0, 1)$ implying that $\sigma^2_{\{p(t)\}}$ is strictly monotone decreasing in $\alpha \in [0, 1]$. Hence, the infinitesimal variance of the logarithmic target stock-price at date t becomes maximal for $\alpha = 0$ and minimal for $\alpha = 1$ while it ranges between 0 and σ^2 for intermediate α-values. Obviously, the opposite market assessments associated with $\alpha = 0$ and $\alpha = 1$ can be viewed as *extreme assessments* insofar as they envelop all other takeover probability assessments with regard to the $\sigma^2_{\{p(t)\}}$-levels which they entail.

In the derivation of the infinitesimal variance (7) we have treated the takeover probability α as constant. However, in the course of time stock-market participants will revise their assessments of the takeover probability at the arrival of news concerning the conditions of the takeover deal. Clearly, each news-induced revision of the α-value implies a shift between two alternative infinitesimal variance-paths both of which are of the form (7), but with distinct α-values. It follows from the partial derivative (8) that news-induced increases (decreases) in α lead to downward (upward) shifts of the infinitesimal variance-paths with the uniformly minimal and maximal (i.e. the *extreme*) variance-paths being achieved under the scenarios $\alpha = 1$ and $\alpha = 0$, respectively.

Figure 1 about here

Figure 1 sketches an exemplary evolution of the takeover probability α prior to the deal conclusion at date $T = 5$. As in many real-world scenarios, market participants are assumed to be uncertain about the ultimate takeover success at the beginning of the post-announcement period. This market uncertainty is reflected by frequent (irregularly spaced) revisions of the takeover probability α on the interval $[0.0, 2.5]$. In the course of time, market uncertainty is resolved due to increasingly precise information about the specific deal conditions so that the number of α-revisions decreases on the interval $(2.5, 5.0]$.

The frequent α-revisions at the beginning of the post-announcement period may explain an empirical finding which has been documented in various studies. The basic model equations (1) and (4) suggest a formal dependence of the target stock-price on the takeover probability α. It is very likely that frequent news-induced revisions of the α-values introduce an additional source of volatility into target stock-price dynamics. Hence, our theoretical model is consistent with the empirical finding of a temporary volatility increase in target stock-prices at the beginning of the post-announcement period.

However, the main implication of our theoretical target stock-price model is considerably more clear-cut. Each discrete change in the takeover probability α entails a shift in the infinitesimal variance-path $\sigma^2_{\{p(t)\}}(P^*(t), t)$ from Eq. (7). Owing to the approximation (6) qualitatively analogous shifts should appear in the conditional variances $\mathrm{Var}\{\log_{\mathrm{e}}[P(t+1)] - \log_{\mathrm{e}}[P(t)]|\phi(t]\}$. In econometric terms this amounts to modeling the data-generating process of (adequately defined) target stock-price returns as subject to volatility regime-switching where each volatility regime is associated with a specific α-level. Strictly speaking, the number of volatility regimes used in the specification of the data-generating process should equal the number of distinct α-values. However, since according to Eq. (8) the two variance-paths associated with the *extreme* takeover probabilities $\alpha = 0$ and $\alpha = 1$ envelop all other possible variance-paths, a 2-regime specification representing the *extreme* volatility states might yield statistically satisfactory results.

3 Econometric methodology

3.1 Data

In line with our theoretical considerations we now apply volatility regime-switching models to daily target stock-price returns of the form

$$R_t = \log_{\mathrm{e}}(P_t) - \log_{\mathrm{e}}(P_{t-1}). \tag{9}$$

Our data set consists of the following target firms: *Dresdner Bank* (a German bank), *Wella* (a German cosmetic-producing enterprise), *Aventis* (a French pharmaceutical enterprise), and *Peoplesoft* (a US software enterprise). For *Wella*, we analyze the *common* and the *preferred* stocks separately, since both types of stocks were subject to different bid offers. Overall, we consider the following six takeover attempts:

(a) The successful acquisition of *Aventis* by *Sanofi-Synthelabo*.

(b) The unsuccessful attempt of the *Deutsche Bank* to merge with the *Dresdner Bank* during March/April 2000.

(c) The successful acquisition of the *Dresdner Bank* by *Allianz* during April/June 2001.

(d) The successful takeover of *Wella common stock* by *Proctor & Gamble*.

(e) The partially successful acquisition of *Wella preferred stock* by *Proctor & Gamble*.

(f) The successful takeover of *Peoplesoft* by *Oracle*.

Table 1 summarizes the cornerstones of the respective takeover deals.

Table 1 about here

Table 1 continued about here

The sampling period for each takeover attempt should contain sufficient information on the fundamental process of the target stock. Therefore, we have chosen sampling periods starting at least 1.5 years before the first takeover attempt and ending at the date of the terminal bid offer expiration.[6] For our empirical analysis below, we also need values of appropriate stock-market indices. The following list describes our data that we obtained from *Datastream* (daily closing prices):

(a) Target: *Dresdner Bank*.
Sampling period: 23 January 1998 – 23 July 2001 (912 observations).
Market index: DAX 30 performance (German stock-price index).

[6]For some offers the exact expiration dates are not available. The sampling periods for these deals end slightly later.

(b) Target *Aventis*.
Sampling period: 29 November 2002 – 31 August 2004 (458 observations).
Market index: SBF 120 (French stock-price index).

(c) Target: *Wella common stock*.
Sampling period: 1 January 2001 – 23 Juny 2003 (646 observations).
Market index: DAX 30 performance (German stock-price index).

(d) Target: *Wella preferred stock*.
Sampling period: 1 January 2001 – 23 Juny 2003 (646 observations).
Market index: DAX 30 performance (German stock-price index).

(e) Target: *Peoplesoft*.
Sampling period: 1 January 2003 – 31 December 2004 (523 observations).
Market index: Dow Jones Industrial Average (US stock-price index).

Figure 2 about here

Figure 2 displays the five target stock-price series (left axis) along with the corresponding market indices (right axis). Each panel contains several time markers representing the most prominent dates of each deal (cf. Table 1). In particular, the shaded regions cover the time between the 'first official announcement' and the 'date of completion' while the vertical time markers within the shaded regions represent the dates at which 'bid-price revisions' occurred.

Obviously, the target stock-price series of the three cash bids (both Wella stocks and Peoplesoft) converge towards their bid prices rather directly. It is interesting to note that the Wella preferred stock approaches its offer price of 65.00 euro from above. Two lines of argument may explain this phenomenon. First, market participants may have assessed the fundamental value of the Wella preferred stock higher than the bid price of 65.00 euro, but could not avert the deal since the corporate control primarily depended on the common stock. Second, the market participants expected an upward bid-price revision until the last day of the deal completion.

Figure 3 about here

Figure 3 displays the daily target stock-price returns as defined in Eq. (9). All return series exhibit clear-cut heteroscedastic patterns with declining volatility towards

the end of the (successful) takeover negotiations. We now turn to analyzing these heteroscedastic structures within a Markov-switching framework.

3.2 A Markov model with switching mean and volatility

The idea of a univariate Markov-switching model is that the data-generating process of an economic variable is affected by a non-observable random variable S_t representing the state the data-generating process is in at time t. In this paper, our economic variable of interest is the target stock-price return R_t and we assume the two distinct regimes 1 and 2 at any point in time, that is, we assume either $S_t = 1$ or $S_t = 2$ for all $t = 0, \ldots, T$. Regime 1 is meant to represent the state in which the stock-market participants either are not aware of the intended future takeover, or are highly uncertain about the deal conditions and/or the credibility of the bidder and thus are highly sceptical about the ultimate deal success. Consequently, in line with our theoretical considerations from Section 2, in this regime target stock-price returns should exhibit a *high market beta* and *high volatility*. By contrast, regime 2 is meant to characterize the state in which market participants are certain that the takeover deal will ultimately succeed. Hence, the *market beta* and the *volatility* of target stock-price returns should be relatively *low*.

As a formal basis, we consider the type of Markov-switching GARCH models as presented in Gray (1996a). The Markov-switching volatility model developed in this paper modifies Gray's framework in two respects. First, we adapt Gray's model for t-distributed (instead of normally distributed) target stock-price returns within each regime.[7] Second, we combine Gray's framework with specific regime-dependent GARCH equations as proposed by Dueker (1997).

To set up the econometric model, we recall first the probability density function of a (non-central) t-distribution with ν degrees of freedom, mean μ and variance h:

$$t_{\nu,\mu,h}(x) = \frac{\Gamma[(\nu+1)/2]}{\Gamma[\nu/2] \cdot \sqrt{\pi \cdot (\nu-2) \cdot h}} \cdot \left[1 + \frac{(x-\mu)^2}{h \cdot (\nu-2)}\right]^{-(\nu+1)/2}, \tag{10}$$

where $\Gamma(z) \equiv \int_0^\infty t^{z-1} \cdot \mathrm{e}^{-t} dt, z > 0$, denotes the complete gamma function.

Next, we assume that each parameter specifying the conditional mean or the conditional variance of the return R_t may take on two distinct values depending on the regime indicator $S_t = i, i = 1, 2$. If we denote the mean and the variance in regime i by μ_{it} and h_{it}, respectively, and if we further assume (non-central) t-distributions with

[7] Owing to their *fatter tails*, the t-distribution often has greater descriptive validity than the Gaussian family in the modelling of financial time series such as stock-price returns.

ν_i degrees of freedom in each regime, the conditional distribution of the return may be represented as a mixture of two distributions:

$$R_t|\phi_{t-1} \sim \begin{cases} t_{\nu_1,\mu_{1t},h_{1t}} & \text{with probability } p_{1t} \\ t_{\nu_2,\mu_{2t},h_{2t}} & \text{with probability } (1-p_{1t}) \end{cases}, \tag{11}$$

where ϕ_{t-1} defines the information set as of date $t-1$ and $p_{it} \equiv \Pr\{S_t = 1|\phi_{t-1}\}$ denotes the so-called *ex-ante* probability of being in regime 1 at time t.

The first step in modelling the dynamics of target stock-price returns is to specify the conditional regime-specific mean μ_{it}. Generally, there are many possibilities of modelling this mean process. We only sketch three alternative specifications here:

(a) Campbell et al. (1997, pp. 66-74) suggest that stock-price returns may exhibit autocorrelation. In order to account for autocorrelation many applications make use of the parsimonious first-order autoregressive specification

$$\mu_{it} = a_{0i} + a_{1i} \cdot R_{t-1} \qquad \text{for } i = 1, 2. \tag{12}$$

(b) Alternatively, we can stay in line with the CAPM theory and model the mean process as a linear function of the current market returns R_t^m:

$$\mu_{it} = a_{0i} + a_{1i} \cdot R_t^m \qquad \text{for } i = 1, 2. \tag{13}$$

(c) Exploiting the findings of Hutson and Kearney (2005) on the interaction of bidder and target stock-price returns, we can model the mean process as a function of the current bidder stock-price return R_t^b:

$$\mu_{it} = a_{0i} + a_{1i} \cdot R_t^b \qquad \text{for } i = 1, 2. \tag{14}$$

Each of these three specifications has its own merits. However, we specify the conditional mean process of the target stock-price returns as in Eq. (13) and derive the current market returns from the three indices 'DAX 30', 'Dow Jones' and 'SBF 120' (see Figure 2).[8]

In contrast to mean-specification, the modelling of the conditional variance process is more problematic. This is due to a phenomenon known as *path dependence*, which, if not carefully handled, may entail severe estimation problems (see Cai, 1994; Hamilton

[8]It is interesting to note that our target stock-price return series do not reveal significant autocorrelation what justifies the rejection of the mean specification (12).

and Susmel, 1994). Gray (1996a) solves this problem by positing in Eq. (11) that the data-generating process, the process that determines which regime observation t comes from, in fact depends on the probability p_{it} as calculated from Eq. (20) below. From Eq. (11) the variance of the target stock-price return at time t is given by

$$\begin{aligned} h_t &= E\left[R_t^2|\phi_{t-1}\right] - \left\{E\left[R_t|\phi_{t-1}\right]\right\}^2 \\ &= p_{1t}\cdot\left(\mu_{1t}^2 + h_{1t}\right) + (1-p_{1t})\cdot\left(\mu_{2t}^2 + h_{2t}\right) - \left[p_{1t}\cdot\mu_{1t} + (1-p_{1t})\cdot\mu_{2t}\right]^2. \end{aligned} \tag{15}$$

The variance h_t represents an aggregate of conditional variances from both regimes and can now be used to specify the conditional variances h_{1t+1} and h_{2t+1} for each regime in a GARCH(1,1) model.[9]

However, instead of using a conventional GARCH(1,1) structure, we follow a proposition by Dueker (1997) and adopt a slightly modified GARCH process governing the so-called *dispersion*. For this GARCH dispersion specification, it is convenient first to parameterize the degrees of freedom from the t-distribution (10) by $q = 1/\nu$, so that $(1-2q) = (\nu-2)/\nu$, and second to define the GARCH equation as

$$h_{it} = b_{0i} + b_{1i}\cdot(1-2q_i)\cdot\epsilon_{t-1}^2 + b_{2i}\cdot h_{t-1}, \tag{16}$$

where h_{t-1} is given according to Eq. (15) and ϵ_{t-1} is obtained from

$$\begin{aligned} \epsilon_{t-1} &= R_{t-1} - E\left[R_{t-1}|\phi_{t-2}\right] \\ &= R_{t-1} - \left[p_{1t-1}\cdot\mu_{1t-1} + (1-p_{1t-1})\cdot\mu_{2t-1}\right]. \end{aligned} \tag{17}$$

An attractive feature of GARCH dispersion with switching degrees-of-freedom is that the lagged squared residuals endogenously downweight shocks from the fat-tailed state.

Finally, there remains the problem of specifying the probabilistic nature of the regime indicator S_t. To keep the analysis tractable, we model S_t as a first-order Markov process with constant transition probabilities π_1 and π_2:

[9] In many empirical studies parsimonious GARCH(1,1) specifications have been applied successfully in volatility models of financial variables (see Bollerslev et al., 1992, and the literature cited there). It is instructive to recall that the above-mentioned problem of path-dependence 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. Alternatively, Gray's (1996a) interpretation is that Eq. (16) from below, rather than the path-dependent formulation, represents a possible process for the conditional variance. In this sense, Gray's regime-switching GARCH framework may be viewed as a collapsing procedure which facilitates the evaluation of the likelihood function at the cost of introducing a negligible approximation error (see also Kim, 1994, and Dueker, 1997, for discussions of this issue).

$$\begin{aligned}
&\Pr\{S_t = 1|S_{t-1} = 1\} = \pi_1, \\
&\Pr\{S_t = 2|S_{t-1} = 1\} = 1 - \pi_1, \\
&\Pr\{S_t = 2|S_{t-1} = 2\} = \pi_2, \\
&\Pr\{S_t = 1|S_{t-1} = 2\} = 1 - \pi_2.
\end{aligned} \tag{18}$$

Now, when one performs similar calculations as in Gray (1996a), the specifications from the Eqs. (10) to (18) lead to the log-likelihood function

$$\begin{aligned}
\Lambda \;=\; \sum_{t=1}^{T} \log \Bigg\{ & p_{1t} \cdot \frac{\Gamma[(\nu_1+1)/2]}{\Gamma[\nu_1/2] \cdot \sqrt{\pi \cdot \nu_1 \cdot h_{1t}}} \cdot \left[1 + \frac{(R_t - \mu_{1t})^2}{h_{1t} \cdot \nu_1}\right]^{-(\nu_1+1)/2} \\
& + (1 - p_{1t}) \cdot \frac{\Gamma[(\nu_2+1)/2]}{\Gamma[\nu_2/2] \cdot \sqrt{\pi \cdot \nu_2 \cdot h_{2t}}} \cdot \left[1 + \frac{(R_t - \mu_{2t})^2}{h_{2t} \cdot \nu_2}\right]^{-(\nu_2+1)/2} \Bigg\}.
\end{aligned} \tag{19}$$

The whole series of *ex-ante* probabilities $p_{1t} \equiv \Pr\{S_t = 1|\phi_{t-1}\}$ can be estimated recursively by

$$p_{1t} = \pi_1 \cdot \frac{f_{1t-1} p_{1t-1}}{f_{1t-1} p_{1t-1} + f_{2t-1}\,(1 - p_{1t-1})} + (1 - \pi_2) \cdot \frac{f_{2t-1}\,(1 - p_{1t-1})}{f_{1t-1} p_{1t-1} + f_{2t-1}\,(1 - p_{1t-1})}, \tag{20}$$

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. (10), each evaluated at $x = R_t$.

Table 2 about here

4 Estimation results and target-specific discussion

4.1 Parameter estimates and specification issues

Table 2 displays the maximum-likelihood estimates of the Markov-switching GARCH dispersion models represented by the Eqs. (10) to (20). The log-likelihood functions from Eq. (19) were maximized by the use of the BFGS-algorithm as implemented in the MAXIMZE-routine of the software package RATS 6.01. Standard errors were computed from the diagonal of the heteroscedasticity-consistent (White-robust) covariance matrix. For each return series, the starting value p_{10} was chosen as the unconditional probability $(1 - \pi_2)/(2 - \pi_1 - \pi_2)$ of being in regime 1 for all $t = 1, \ldots, T$.[10]

The parameter estimates and standard errors given in Table 2 may be used to assess

[10]The explicit starting values for the respective target stocks are available upon request.

the significance of the model parameters on the basis of the t-statistics. Nonetheless, since the exact finite-sample distribution of the t-statistic is generally unknown under this model setup, the t-values can serve only as an informal significance guideline. However, the majority of the parameter estimates (across all targets) have t-values larger than 2 in absolute value (in 51 out of 70 cases).

For all five target stocks the parameters of the mean equations exhibit the typical features of a *market model*: the estimates $\hat{a}_{01}$ and $\hat{a}_{02}$ are close to zero while the market betas in regime 1, $\hat{a}_{11}$, are positive with t-values larger than 6 in all five cases. For the two cash-bid deals *Wella common stock* and *Wella preferred stock* the market betas in regime 2, $\hat{a}_{12}$, become insignificant as expected. However, for all five target stocks the market betas decrease substantially (in absolute value) in the second regime, a finding that is consistent with the theoretical considerations of Bhagat et al. (1987) and with earlier empirical studies (cf. Section 2).

An important statistical property of the variance equations concerns the *persistence of volatility shocks*. In a conventional single-regime GARCH(1,1)-equation of the form $h_t = b_0 + b_1 \cdot \epsilon_{t-1}^2 + b_2 \cdot h_{t-1}$, the persistence of volatility shocks is typically measured by the sum $b_1 + b_2$. The higher the value of $b_1 + b_2$, the more time it takes until a volatility shock dies out. The shock will die out in finite time if $b_1 + b_2 < 1$. For $b_1 + b_2 = 1$ (an *integrated* GARCH(1,1) or IGARCH(1,1) process) volatility shocks have a permanent effect and the *unconditional variance* of the process tends to infinity (see, for example, Verbeek, 2004, p. 299).

In our 2-state Markov-switching GARCH framework we may analyze the volatility persistence within each regime. According to our GARCH equation (16) a convenient persistence measure for regime i is given by $b_{1i} \cdot (1 - 2q_i) + b_{2i}$. These (estimated) persistence measures are displayed in Table 2. Obviously, the measures are less than one for all target stocks across both regimes.

The estimates of the degrees-of-freedom parameters $\nu_1 = 1/q_1$ and $\nu_2 = 1/q_2$ are all larger than 2, explicitly ranging between 2.4558 (Peoplesoft, regime 2) and 344.8276 (Wella preferred stock, regime 2). This is important since the variance of a t-distribution with density (10) only exists for $\nu > 2$. However, the t-distribution 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 convergence property suggests an intuitive test for normality within each regime by testing for (non-)significance of the q_i-parameters on the basis of their t-statistics. Bearing in mind that the exact finite-sample distribution of the t-statistic is unknown under our model setup, we find that 9 out of 10 t-values are considerably larger than 2 (the exception being the t-value for q_2-parameter of the

Wella preferred stock which is 0.0291). This provides some evidence that for all targets and across all regimes—except for regime 2 of the Wella preferred stock—the distributions of target stock-price returns differ significantly from the normal distribution.

The transition probabilties π_1 and π_2 represent the likelihood that no regime switch occurs between the dates $t-1$ and t. In all of our 5 cases, the estimates $\hat{\pi}_1$ and $\hat{\pi}_2$ exceed the value 0.97 indicating extreme persistence in both regimes for each of the five target stocks.

Next, we address several specification issues. As a first diagnostic check the lower part of Table 2 contains Ljung-Box-Q-statistics for serial correlation of the squared (standardized) residuals out the lags 1 and 5. For all target stocks, the null hypothesis of 'no autocorrelation out to lag i' cannot be rejected at the 5% level. Similarly, Ljung-Box-tests for serial correlation of the squared residuals out to various other lags were also performed (results not shown in Table 2). All these tests arrive at the same conclusion, namely that there is no statistical evidence of serial correlation.

Another specification issue concerns the number of the Markov regimes modelled in the regime-switching representation (10) to (20). Unfortunately, testing the significance of the second regime on the basis of a conventional likelihood ratio test (LRT) is statistically improper. The reason is that under this model setting the χ^2-approximation to the LRT statistic does not hold since there are six parameters which are unidentified under the null hypothesis of a single regime (i.e. when $\pi_1 = 1$ and $\pi_2 = 0$). Hansen (1992) suggests a standardized LRT procedure that, in principle, can overcome this difficulty by performing a series of optimizations over a (fine) grid of the nuisance parameters. However, owing to the large number of parameters in the representation of each of the regime-switching models fitted in this paper, an application of Hansen's test procedure is practically unfeasible here.[11]

In view of the numerical problems with the Hansen procedure, several authors simply report the results of the conventional LR test and explicitly emphasize its statistical dubiousness because of the identification problem (see, among others, Hamilton and Susmel, 1994; Gray, 1996a, Bollen et al., 2000). Following this approach, we fitted single-regime GARCH dispersion models to the five target stock-price return series. The LRT statistics were computed as twice the difference in the log-likelihoods under the respective hypotheses and are shown in Table 2 (row 'H_0 : Single Regime'). The critical values of the conventional LR test are derived from the quantiles of the χ^2-distribtuion with degrees of freedom equal to the difference in the number of parameters

[11] Garcia (1998) describes the computational limitation of Hansen's (1992) LRT procedure even for moderately parameterized Markov-switching models.

between the alternative and the null hypothesis. For our Markov-switching model specification, this difference amounts to 8 parameters and the critical values at the 1%, 5%, and 10% levels are given by 20.0902, 15.5073, and 13.3616. Obviously, the LRT statistics for all five targets exceed the critical value at the 1% level considerably. Thus, this informal test does provide a certain amount of confidence in the existence of a second regime for each of the five target stocks.

It is clear that the statistical testing for the existence of more than two regimes becomes more and more difficult as the number of Markov-regimes increases. Owing to the large number of optimizations, the Hansen (1992) LRT procedure is already unfeasible when testing for the existence of a second regime within our highly parameterized specification and hence, *a fortiori*, is unfeasible when testing for a higher number of Markov-regimes. But even the implementation of the conventional LRT—apart from being statistically problematic—becomes increasingly difficult. For example, to test for the existence of a third regime, the Markov-switching GARCH dispersion specification (10) to (20) would have to be expanded to cover 27 parameters (18 parameters for the regime-specific mean and GARCH equations plus 9 transition probabilities). Even when taking account of the three restrictions $\sum_{j=1}^{3} \Pr\{S_t = j | S_{t-1} = i\} = 1$ for $i = 1, 2, 3$, there still remain 24 (independent) parameters to be estimated in order to compute the LRT statistic. Unfortunately, it proves impossible to numerically maximize the 3-regime log-likelihood function for any of our five target stock-price return series.

Owing to the lack of a statistically rigorous testing for the exact number of Markov regimes, there appears no other alternative but to appeal to the economic significance of the two enveloping volatility regimes described in Section 2 (the *extreme high-* and the *extreme low-volatility regime*). Recall that additional *intermediate* volatility regimes come into play if agents revise their assessment of the takeover probability due to relevant news, a situation that is likely to happen at the beginning of the post-announcement period (cf. Figure 1). In this case, however, it will be difficult (if not impossible) anyway to trace the sequence of α-revisions and hence to determine the exact number of *intermediate* volatility regimes. Consequently, the only feasible approach is to restrict the econometric modelling to the two *extreme* volatility regimes. Whenever an *intermediate* volatility regime becomes effective, our 2-regime volatility switching model is likely to have difficulties in discriminating between the two *extreme* volatility regimes.

In contrast to the methodological problems just discussed, it is straightforward to test for statistically significant switching in the regime-specific parameters governing

the mean and/or the volatility equations once the number of Markov regimes has been fixed. Since the focus of our study is on volatility dynamics, we only document the significant switching in the volatility parameters.[12]

To be more explicit, consider the 2-regime specification (10) to (20) in which—due to our GARCH equation (16)—the parameters governing the regime-dependent conditional volatility are b_{0i}, b_{1i}, b_{2i} and q_i. Hence, a statistical test of the null hypothesis of 'no volatility regime-switching between the regimes' ($H_0 : b_{01} = b_{02}, b_{11} = b_{12}, b_{21} = b_{22}, q_1 = q_2$) versus the alternative of a 'switching volatility structure' is provided by the conventional LRT. For this test, the above-mentioned identification problem does not arise, since the respective Markov-switching models under the null and the alternative are nested. Owing to the number of restrictions under the null hypothesis, the conventional LRT statistic is approximately distributed χ^2 with 4 degrees of freedom.

The last two rows of Table 2 display these LRT statistics along with their p-values for the five target stocks. Within our 2-regime framework, volatility regime-switching in target stock-price returns is statistically significant at the 5%-level for all five targets, and additionally, for the three cash-bid deals (*Wella common stock*, *Wella preferred stock* and *Peoplesoft*) volatility-regime switching is even significant at the 1%-level.

4.2 Target-specific discussion

Besides the volatility regime-switching evidence provided by the likelihood ratio tests, two conditional probabilities are relevant to forecasting and to making statistical inference about regimes. The series of *ex-ante* probabilities $\Pr\{S_t = 1|\phi_{t-1}\}$ is estimated recursively via Eq. (20), while the *smoothed* probabilities $\Pr\{S_t = 1|\phi_T\}$ are computed by the use of filter techniques after the model estimation has been carried out.[13] Based on an information set that evolves over time, the *ex-ante* probabilities are of interest in forecasting the one-step-ahead regime. As these probabilities reflect today's stock-market perceptions of tomorrow's regime, they represent a natural measure of how markets assess the ultimate success of the respective takeover deals. Unlike the *ex-ante* probabilities, the *smoothed* probabilities rest on the information from the full sample. These probabilities are of interest in inferring *ex post* 'if and when' regime switches have occurred during the sampling period.

Figure 4 about here

[12]However, completely analogous statistical results do hold with respect to switching in the mean parameters (i.e. in the market betas). Econometric details are available upon request.

[13]This study uses a filter algorithm provided by Gray (1996b).

Figure 5 about here

Figure 4 depicts the *ex-ante* and the *smoothed* regime-1 probabilities for the five target stock-price return series. Owing to the smaller information set on which they are defined, the *ex-ante* probabilities exhibit a more erratic behaviour than their *smoothed* counterparts. Evidently, all regime-1 probability series ultimately decline from one towards zero within the shaded regions (i.e. between the 'first official announcement' and the 'date of completion') tracing the target-specific switches from *high-beta-high-volatility* to *low-beta-low-volatility* regimes. Figure 5 focuses on volatility dynamics by depicting the target-specific *conditional variances* which were estimated recursively according to our Markov-switching GARCH specification.

Among our five targets the most clear-cut regime switches are to be noted for the two Wella stocks. Their regime-1 probability series exhibit sharp declines towards zero exactly at the (common) official announcement date on March 18, 2003 (see Figure 4). Figure 5 indicates that both target-specific regime switches were accompanied by clear-cut decreases in the conditional variances. Obviously, both cash-bid deals were perceived as credible by the market although the Wella preferred stock was subject to a bid-price revision from 61.50 to 65.00 euro on April 28, 2003 (cf. Table 1). However, none of the deals seems to have been disturbed by protective actions providing additional explanation for the clear-cut and irreversible regime-switches.

Our third cash-bid deal concerns the takeover of Peoplesoft by Oracle. For this target the shaded regions in the figures are interspersed with five bid-price revisions (cf. Table 1). In conjunction with the protective action (the antitrust trial against Oracle between June 7, 2004 and September 9, 2004) this large number of bid-price revisions give rise to the conjecture that in the aftermath of the first official announcement on June 6, 2003 market participants were highly uncertain about the ultimate success of the takeover deal. The regime-1 probabilities in Figure 4 seem to support this view econometrically. Both series exhibit massive fluctuations between zero and one and it is no earlier than on November 1, 2004 (the fourth bid-price revision) that the regime-1 probabilities eventually drop towards zero.

The Peoplesoft-stock provides an appealing example for the interplay between our theoretical model from Section 2 and our Markov-switching specification from Section 3. The market uncertainty between June 6, 2003 and November 1, 2004 entailed frequent revisions of the takeover probability α during this period. Each α-revision induced an *intermediate* regime in the true data-generating process of the stock-price returns. But our econometric specification is restricted to modelling the two *enveloping* regimes

associated with the *extreme* assessments $\alpha = 0$ and $\alpha = 1$. A direct consequence of this specification gap is that the estimation procedure has difficulties in discriminating between the two *extreme* regimes. It is exactly this discrimination problem that causes the massive fluctuations of the regime-1 probabilities during this period.

Finally, it remains to address the non-cash-bid deals which are not (fully) covered by our theoretical model from Section 2. Interestingly, the dynamics of the Aventis regime-1 probabilities (a mixed bid) resembles the case of a pure cash bid under market uncertainty about the deal success. The *ex-ante* regime-1 probabilities began to leave the unity-baseline immediately after the first official announcement on January 26, 2004, but it was no earlier than at the beginning of May 2004 that they reached the zero-baseline. This extended period of intermediate regime-1 probabilities coincides with public discussions about stock-buy-backs and a rival bid of *Novartis* that was unsuccessfully negotiated between March 12 and April 26, 2004 (see Table 1).

Similar patterns appear in the regime-1 probabilities of the Dresdner Bank. The sampling period contains two important takeover attempts: (a) the failed merger attempt by the Deutsche Bank between March 7, 2000 and April 5, 2000, and (b), the successful takeover by Allianz between April 1, 2001 and July 12, 2001. The Dresdner-Bank regime-1 probabilities initially drop from one towards zero prior to the official announcement of the (ultimately unsuccessfull) merger attempt by the Deutsche Bank (a pure share-exchange bid), then increase again towards one in the aftermath of this event and eventually drop towards zero prior to official announcement of the (finally successful) takeover by Allianz (a mixed bid). Overall, it is remarkable that our regime-switching structures seem to be empirically robust under all kind of deal-types.

5 Summary and conclusions

The main finding of this paper is that market-beta and volatility regime-switching in target stock-price data is an empirically important phenomenon. In summary, three conclusions can be drawn from our econometric analysis covering data on four European and one American target stocks:

(a) A first likelihood ratio test (although econometrically informal) on the number of Markov-regimes provides evidence of the existence of at least two distinct Markov-regimes.

(b) A second (econometrically valid) likelihood ratio test documents statistically significant volatility regime-switching for all target stocks in our sample.

(c) Although volatility regime-switching is statistically significant for all takeover deal-types, cash-bid deals tend to exhibit 'more distinct' volatility regime-switching than mixed-bid and pure share-exchange deals.[14]

However, irrespective of the deal-type, estimation equations for target stock-price data should account for regime-switching in market-betas as well as in conditional volatility in order to avoid econometric misspecification.

Our theoretical modelling framework in Section 2 extends earlier models by transferring economic ideas into a continuous-time setting. This enables us to derive explicit implications for the conditional volatility dynamics of the target stock by means of stochastic calculus. Our model accounts for stock-market uncertainty about the ultimate deal success as well as for news which entail revisions of the market assessment. In the end, it is these revisions that inject volatility regime-switching structures into the dynamics of the target stock.

It may seem desirable to estimate our structural model equations (1) and (2) on the basis of discretely sampled target stock-prices and to make use of the estimation results in financial applications.[15] Unfortunately, a direct estimation of the model parameters turns out to be difficult for two reasons. First, the takeover probability α changes unpredictably due to news. Second, the fundamental target stock-price P^* cannot be observed in the market rendering a direct estimation of the parameters μ and σ impossible. These estimation problems seem to pose severe problems in evaluating our theoretical framework econometrically. However, since our empirical analysis documents the statistical significance of volatility regime-switching, we have demonstrated that at least the most important implication of our theoretical model is reflected by real-world data.

A possible line of future research may start from the observation that our Markov-switching GARCH specifications perform well in capturing the volatility of target stock-price returns. A well-documented property of several related Markov-switching models is their good performance in forecasting volatility out-of-sample (see Gray, 1996a; Bollen et al., 2000). In the likely case that our Markov-switching specifications yield accurate variance-forecasts, too, they should be plugged into valuation models for target stock-options during takeover bids and may thus provide empirical complement to theoretical option-pricing models such as those developed in Subramanian (2004).

[14] In our sample volatility regime-switching is statistically significant in cash-bid data at levels far below 1% and significant in the data of the other deal-types at levels between 2% and 5%.

[15] Econometric methods for estimating continuous-time diffusion processes by discretely sampled observations have been proposed, among others, by Elerian et al. (2001) and Ait-Sahalia (2002). See also Trede and Wilfling (2007) for empirical implementations of these techniques.

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Figures and Tables

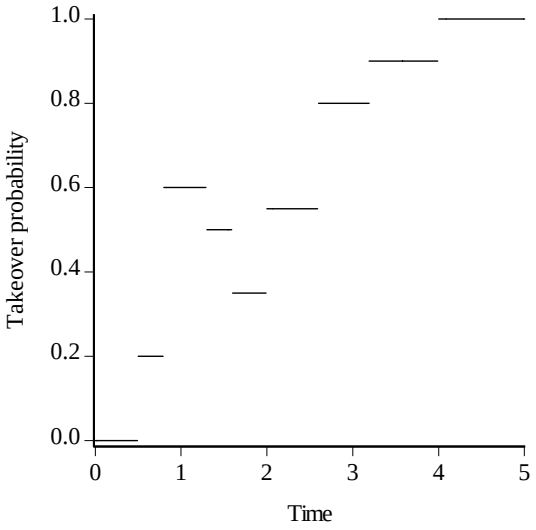

Figure 1: Typical post-announcement revisions of the takeover probability α

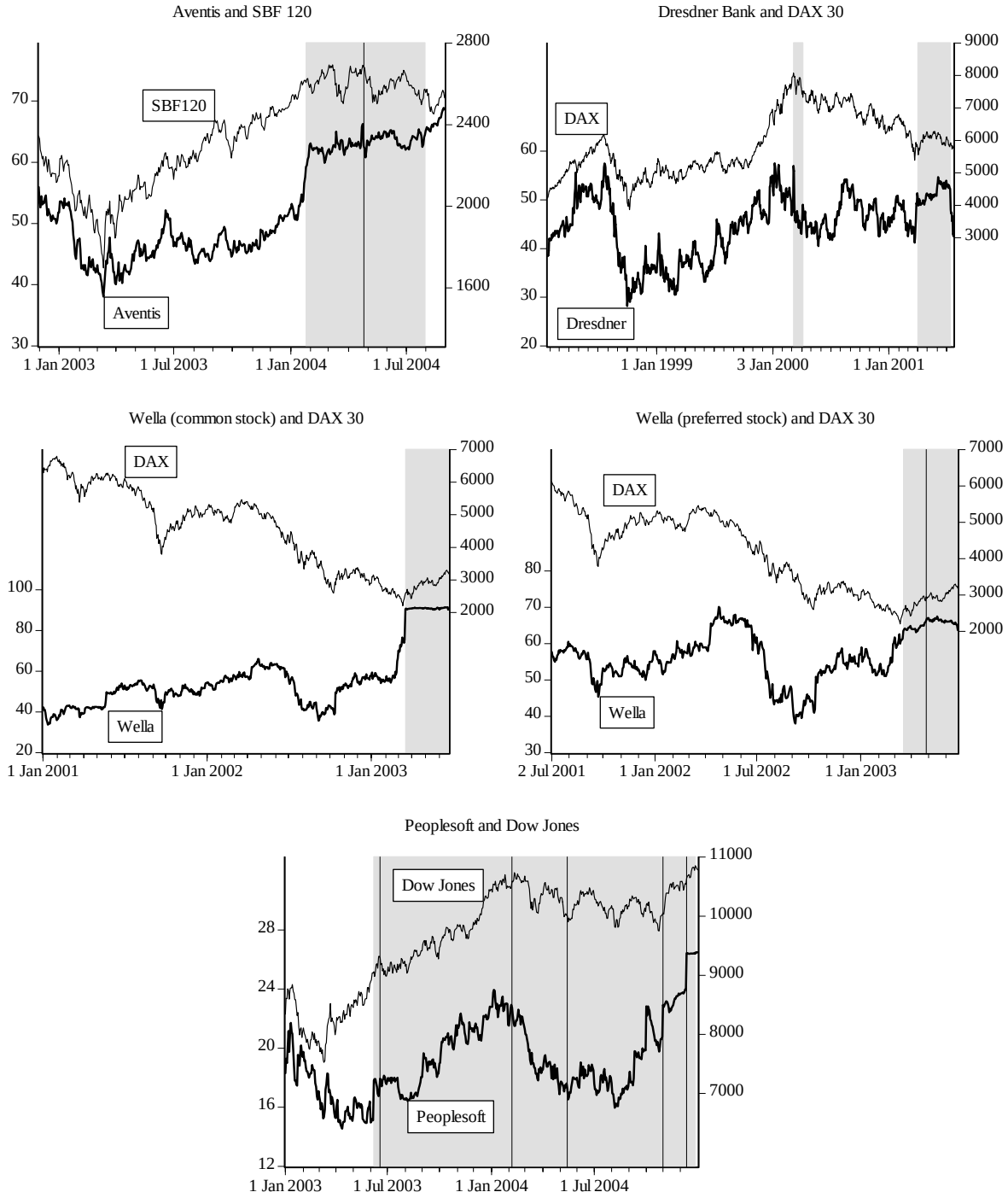

Figure 2: Target stock-price series and market indices

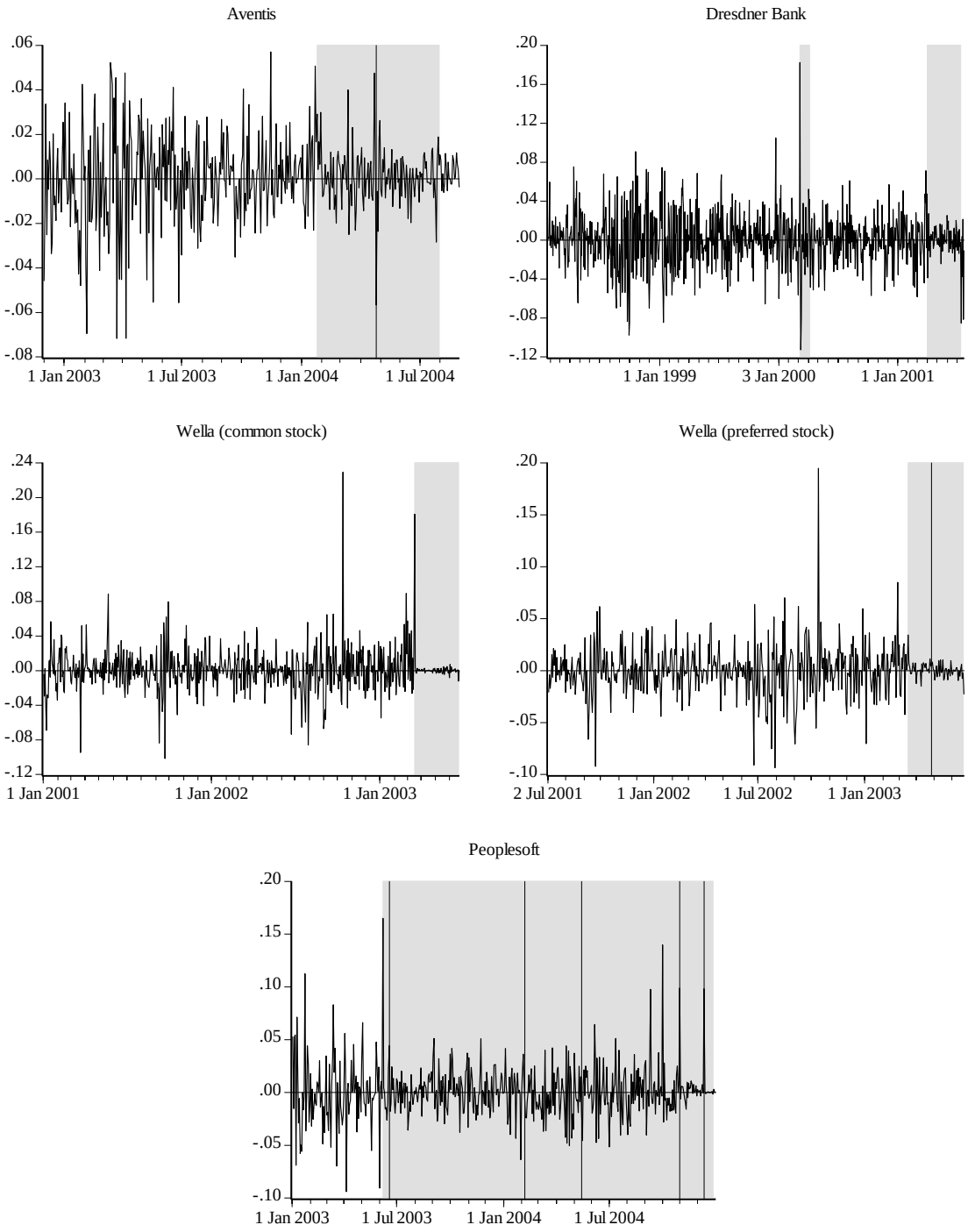

Figure 3: Daily target stock-price returns

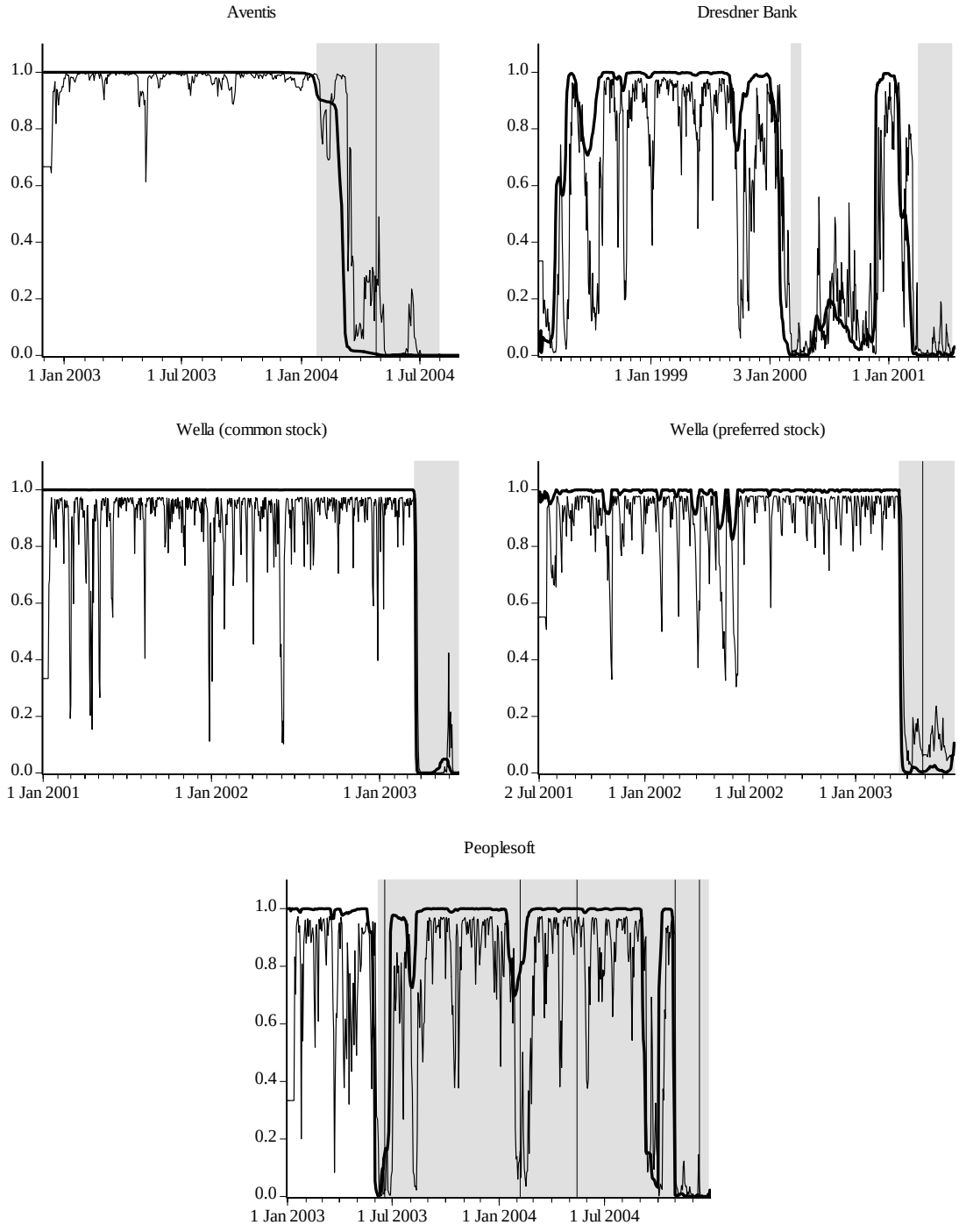

Figure 4: *Ex-ante* (thin lines) and *smoothed* regime-1 probabilities (bold lines) of target stock-price returns

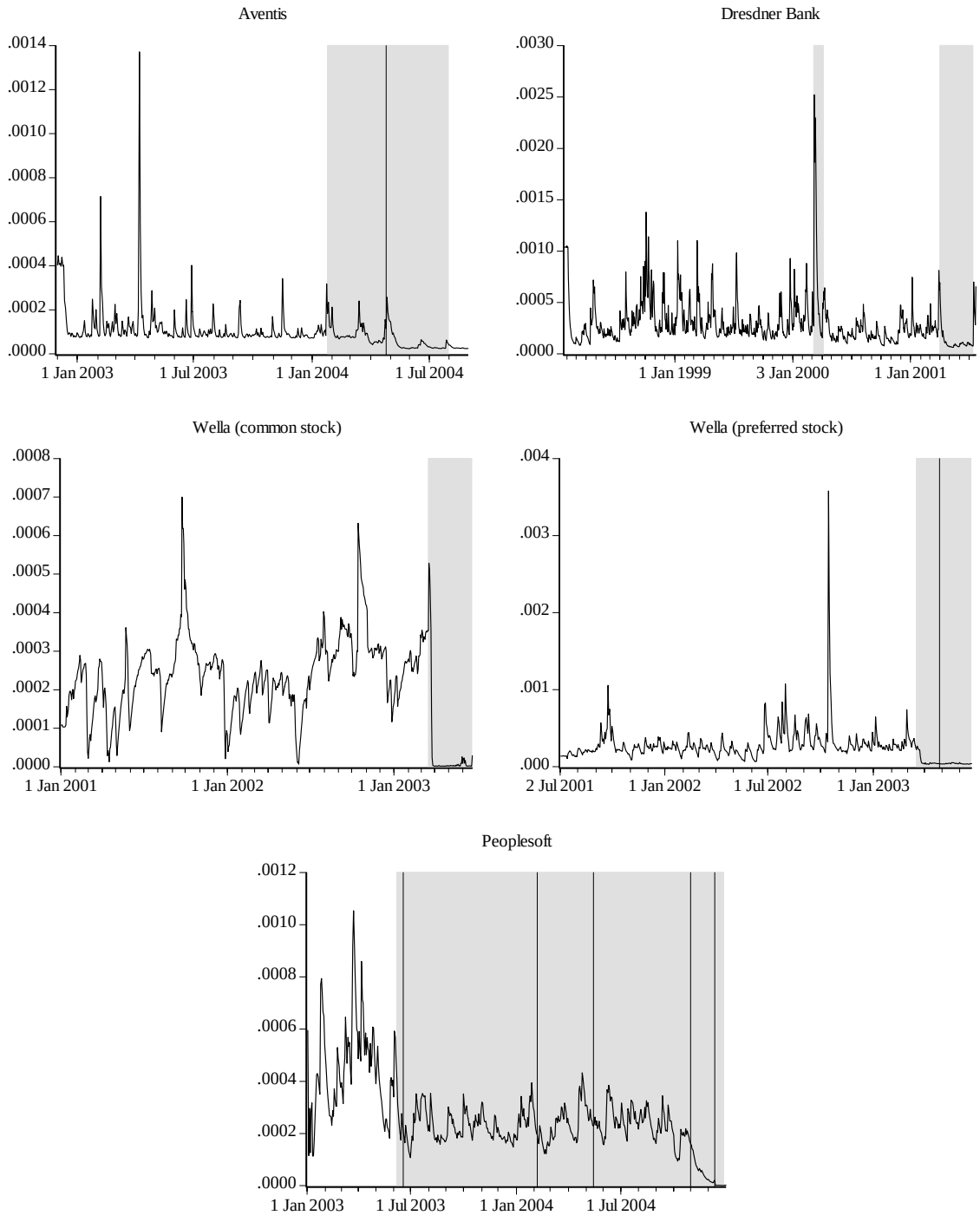

Figure 5: Conditional variances of target stock-price returns

Table 1

Cornerstones of takeover deals

	Aventis	Dresdner	Dresdner
Bidder	Sanofi-Synthelabo	Deutsche Bank	Allianz
Deal-type	Mixed bid	Share swap	Mixed bid
First official announcement	26/01/2004 Bid price:[a] 5/6 Sanofi shares plus 11.50 euro (Target management rejects)	07/03/2000[b] Expected bid price:[a] $\approx$ 2/3 Deutsche Bank shares (Target management approves. Major shareholder [Allianz] rejects)	01/04/2001 Bid price:[a] 1/10 Allianz shares plus 20.00 euro (Target management and major shareholder [Allianz] approve)
Protective actions	05/02/2004: Discussion about a stock-buy-backs 12/03/ – 26/04/2004: Takeover negotiations with *Novartis*	None	None
Bid-price revisions	25/04/2004: Bid raised to 5/6 Sanofi shares plus 20.00 euro	None	None
Date of completion (success [+], failure [−])	30/07/2004 [+]	05/04/2000 [−]	12/07/2001 [+]

Notes:

(a) Bid price for 1 share of the target stock.

(b) The bid price was only vaguely specified.

Table 1 (continued)

Cornerstones of takeover deals

	Wella (common stock)	Wella (preferred stock)	Peoplesoft
Bidder	Proctor & Gamble	Proctor & Gamble	Oracle
Deal-type	Cash bid	Cash bid	Cash bid
First official announcement	18/03/2003 Bid price:[(a)] 90.25 euro (Majority of shareholders accept)	18/03/2003 Bid price:[(a)] 61.50 euro	06/06/2003 Bid price:[(a)] 16.00 US-$ (Target management rejects)
Protective actions	None	None	07/06/2004: Antitrust trial against Oracle 09/09/2004: Dismissal of Oracle-trial
Bid-price revisions	None	28/04/2003: Bid price raised to 65.00 euro	18/06/2003: Bid price raised to 19.50 US-$ 06/02/2004: Bid price raised to 26.00 US-$ 14/05/2004: Bid price reduced to 21.00 US-$ 01/11/2004: Bid price raised to 24.00 US-$ 13/12/2004: Bid price raised to 26.50 US-$
Date of completion (success [+], failure [−])	20/06/2003 [+]	20/06/2003 [+]	28/12/2004 [+]

Note:

(a) Bid price for 1 share of the target stock.

Table 2

Estimates and statistics of the Markov-switching GARCH dispersion models

	Mixed bids		Cash bids		
	Aventis	Dresdner	Wella (com.)	Wella (pref.)	Peoplesoft
Regime 1:					
a_{01}	−0.0003	−0.0014	0.0006	0.0006	−0.0014
	(0.0007)	(0.0011)	(0.0008)	(0.0012)	(0.0001)
a_{11}	1.0012	1.2476	0.2077	0.2583	1.5033
	(0.0834)	(0.1301)	(0.0278)	(0.0414)	(0.0272)
b_{01}	0.0000	0.0001	0.0000	0.0001	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_{11}	0.2770	0.2669	0.0031	0.1838	0.0734
	(0.3514)	(0.0922)	(0.0166)	(0.0354)	(0.0076)
b_{21}	0.3235	0.4901	0.9374	0.5767	0.7554
	(0.2707)	(0.1390)	(0.0288)	(0.0192)	(0.0039)
$q_1 = 1/\nu_1$	0.2961	0.1321	0.3172	0.2743	0.0723
	(0.0757)	(0.0534)	(0.0402)	(0.0115)	(0.0010)
Regime 2:					
a_{02}	0.0015	0.0005	0.0003	0.0002	0.0004
	(0.0006)	(0.0010)	(0.0002)	(0.0008)	(0.0000)
a_{12}	0.4419	0.6952	0.0027	0.0272	−0.0386
	(0.0913)	(0.0736)	(0.0090)	(0.0405)	(0.0001)
b_{02}	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b_{12}	0.0674	0.1684	0.6356	0.0151	0.0102
	(0.2424)	(0.0944)	(0.0897)	(0.0162)	(0.0000)
b_{22}	0.6990	0.7308	0.0681	0.0372	0.8631
	(0.1591)	(0.0886)	(0.0533)	(0.0609)	(0.0017)
$q_2 = 1/\nu_2$	0.2477	0.2750	0.3599	0.0029	0.4072
	(0.0866)	(0.0410)	(0.0209)	(0.1006)	(0.0013)
Transition Probabilities:					
π_1	0.9981	0.9849	0.9749	0.9778	0.9740
	(0.0063)	(0.0221)	(0.0108)	(0.0065)	(0.0017)
π_2	0.9999	0.9969	0.9999	0.9795	0.9976
	(0.0002)	(0.0070)	(0.0001)	(0.0284)	(0.0002)
Log-likelihood	1348.7812	2299.9431	1708.6723	1309.3918	1341.7101
$\hat{b}_{11} \cdot (1 - 2\hat{q}_1) + \hat{b}_{21}$	0.4365	0.6865	0.9385	0.6597	0.8182
$\hat{b}_{12} \cdot (1 - 2\hat{q}_2) + \hat{b}_{22}$	0.7330	0.8066	0.2462	0.0522	0.8650
LB_1^2	0.0159	0.7208	0.1703	0.2683	0.0314
	[0.8997]	[0.3959]	[0.6798]	[0.6044]	[0.8593]
LB_5^2	0.8634	4.6857	0.6323	3.8290	0.0880
	[0.9728]	[0.4554]	[0.9865]	[0.5743]	[0.9999]
Likelihood Ratio Tests:					
H_0 : Single Regime	43.8594	47.6400	128.0342	36.7630	88.0106
$H_0 : b_{01} = b_{02}, b_{11} = b_{12},$	10.8310	9.5564	102.9650	16.6228	67.0146
$b_{21} = b_{22}, q_1 = q_2$	[0.0285]	[0.0486]	[0.0000]	[0.0023]	[0.0000]

Note: Estimates for parameters from the Eqs. (10) to (20). Standard errors are in parentheses, p-values in square brackets. LB_i^2 denotes the *Ljung-Box-Q*-statistic for serial correlation of the squared standardized residuals out to lag i. The null distribution of the first LRT-statistic is unknown. The second LRT-statistic is asymptotically $\chi^2(4)$-distributed under the null hypothesis.