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Markov-switching in target stocks during takeover bids

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ABSTRACT

This paper examines shifts in the market betas and the conditional volatility of stock prices of takeover targets. 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 regime-switches in all takeover deal-types (in cash bids, pure share-exchange bids, mixed bids). In particular, conditional 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.

1. Introduction

Within the last three decades, merger and acquisition attempts have substantially increased 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). 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 (DGP) by so-called *Markov-switching* (or *regime-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, the levels (market-beta) and the conditional volatility of target stock-price returns. Hence, our regime-switching framework constitutes an approach

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[1] Markov-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).

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that unifies and extends several results of earlier studies which have focused either on level or on volatility effects of corporate takeovers.

Intuitive economic motivation for expecting market-beta and volatility regime-switching in target stock-price returns during the post-announcement period will be presented in Section 2. We then proceed with our econometric analysis in which we specify two distinct regimes for the DGP 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 two-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 DGPs 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 regime-switching, and particularly volatility regime-switching, in target stock-price returns are statistically significant phenomena in the post-announcement period of a takeover bid. As we will argue in Section 5, regime-switching in the DGP of arbitrary underlying asset returns may have a great impact on option valuation. If ignored, regime-switching may generate considerable option-pricing errors. Consequently, our entire regime-switching framework should be useful to agents in derivative markets in valuing options on target stocks.

The remainder of the paper is organized as follows. Section 2 provides motivation for modelling the DGP of target stock-price returns as a 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 results of the paper and outlines the implications for the valuation of target stock options.

2. Features of target stock dynamics

Among the large number of studies examining the various aspects of target stock dynamics, a plethora of papers report 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 (regression) model of the form

$$R_t = \alpha + \beta R_t^m + \varepsilon_t, \tag{1}$$

where R_t is the target stock-price return, R_t^m is the return of the market portfolio (often represented by an appropriate stock-market index), ε_t is a classical disturbance term, and where the parameters α and β 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 (meaning that the parameter β in Eq. (1) decreases after the bid announcement). 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'.

For ease of notation let us denote, respectively, the date of the bid announcement by t_A and the date of the planned takeover deal by T. Putting together the stylized facts of a changing market-beta and changing conditional volatility, we summarize that the dynamics of target stock-price returns should typically be characterized by a high market-beta plus high conditional volatility before the bid announcement (i.e. for $t<t_A$) and a low market-beta plus low conditional volatility between the bid announcement and the completion of the takeover deal (i.e. for $t_A \leq t \leq T$).

However, the just described structural break from 'high-beta-high-volatility' to 'low-beta-low-volatility' target stock-price return dynamics at date t_A does not explicitly take into account the probability which market participants attach to a successful completion of the takeover deal. This subjective takeover probability comes into play at date t_A and can be expected to have an impact on target stock-price dynamics in the post-announcement period.[2] To illustrate, consider a cash bid in which the holders of the target stock are offered the future cash-bid price P^* (to be paid at date T) which lies significantly above the current target stock-price P_t, $t_A \leq t < T$. In this situation, the following two extreme scenarios may emerge:

1. If market participants are certain that the takeover deal will be completed successfully (i.e. if agents set the subjective takeover probability equal to 1) we would expect an instantaneous jump of the current target stock-price P_t towards P^* to ensure an arbitrage-free transition of the target stock-price to the (fixed) cash-bid price. This forward-looking approach of the target stock-price to the cash-bid price is likely to entail a decoupling of target stock-price returns from market-wide shocks (i.e. a lower market-beta) combined with lower volatility of target stock-price returns.

[2] An equivalent view is to interpret the subjective takeover probability to be equal to 0 for $t<t_A$.

2. If market participants are convinced that the deal will not be completed successfully (i.e. if the subjective takeover probability equals 0), then there is no need for any forward-looking arbitrage-removing transaction and the target stock-price P_t is likely to remain unaffected by the cash-bid offer. In this case, the market-beta as well as conditional volatility should remain as high as in the pre-announcement period.[3]

Next, it is important to recognize that the subjective takeover probability is rather unlikely to remain stable between t_A and T. Owing to the arrival of news concerning the conditions of the takeover deal, stock-market participants will revise their assessment of the takeover probability during the post-announcement period. Each news-induced revision of the takeover probability may imply a shift from a 'high-beta-high-volatility' to a 'low-beta-low-volatility' regime (or vice versa) of target stock-price returns. Since these probability revisions occur in a stochastic fashion due to the arrival of news, it appears appealing to model the sequence of the 'high-beta-high-volatility' and 'low-beta-low-volatility' states of the target stock-price returns as a two-state regime-switching process.

Finally, it is worth noting that a fully-fledged model for target stock-price dynamics should take into account that the subjective takeover probability can not only take on the two extreme values 0 and 1, but can (at least theoretically) range continuously in the interval [0,1]. Each of these intermediate takeover probabilities would then imply their own 'intermediate-beta-intermediate-volatility' regime. For reasons of econometric tractability we waive modelling such intermediate regimes and focus on the two extreme regimes in our subsequent empirical analysis.

3. Econometric methodology

3.1. Data

We now apply Markov-switching models to daily target stock-price returns which we define as

$$R_t = \log(P_t) - \log(P_{t-1}), \tag{2}$$

where, as above, P_t is the target stock price at date t. Our data set consists of the following target companies: *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.

For each takeover deal 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.[4] 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).
(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 June 2003 (646 observations).
Market index: DAX 30 performance (German stock-price index).
(d) Target: *Wella preferred stock*.
Sampling period: 1 July 2001–23 June 2003 (516 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).

[3] For theoretical models of target stock-price dynamics taking into account the subjective takeover probability see Brown and Raymond (1986) and Samuelson and Rosenthal (1986). However, both papers do not elaborate the impact of changes in the takeover probability on target stock-price dynamics. By contrast, De Grauwe et al. (1999) and Wilfling and Maennig (2001) discuss a closely related problem. They analyze exchange-rate dynamics among those countries which participated in the first wave of the European Monetary Union (EMU). In their setting, the EMU exchange rates resemble our target stock-prices and the probability of a country's joining EMU can be viewed as the counterpart of the subjective takeover probability considered here.

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

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	7/03/2000[b]	01/04/2001
	Bid price:[a] 5/6 Sanofi shares plus 11.50 euro (Target management rejects)	Expected bid price:[a] ≈2/3 Deutsche Bank shares (Target management approves. Major shareholder [Allianz] rejects)	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 stock-buy-backs 12/03/2004–26/04/2004: 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 [+]
	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	18/03/2003	06/06/2003
	Bid price:[a] 90.25 euro (Majority of shareholders accept)	Bid price:[a] 61.50 euro	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 [+]

Notes:
(a) Bid price for 1 share of the target stock.
(b) The bid price was only vaguely specified.

Fig. 1 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 'stand-alone' 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.

Fig. 2 displays the daily target stock-price returns as defined in Eq. (2). 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 DGP of an economic variable is affected by a non-observable random variable S_t representing the state the DGP 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

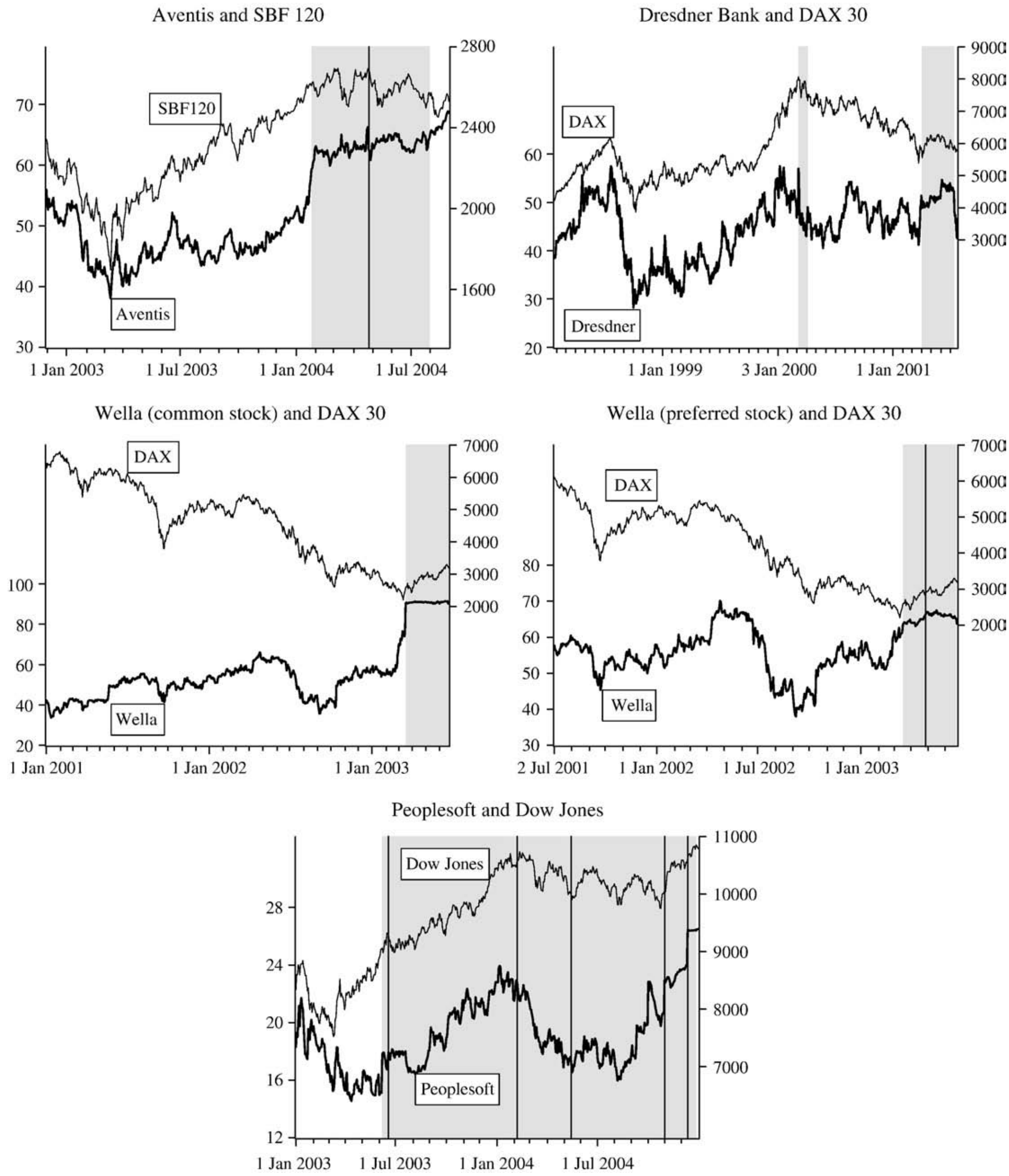

Fig. 1. Target stock-price series and market indices.

$t = 0,\ldots,T$. 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 sceptical about the ultimate deal success. Consequently, in line with our reasoning from Section 2, in this regime target stock-price returns should exhibit a *high market beta* plus *high conditional 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, regime 2 represents the 'low-beta-low-volatility' regime of target stock-price returns.

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.[5] Second, we combine Gray's framework with specific regime-dependent GARCH equations as proposed by Dueker (1997).[6]

[5] 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.

[6] For alternative modifications of Gray's (1996a) Markov-switching GARCH model see Klaassen (2002), Haas et al. (2004) and Bauwens et al. (2007).

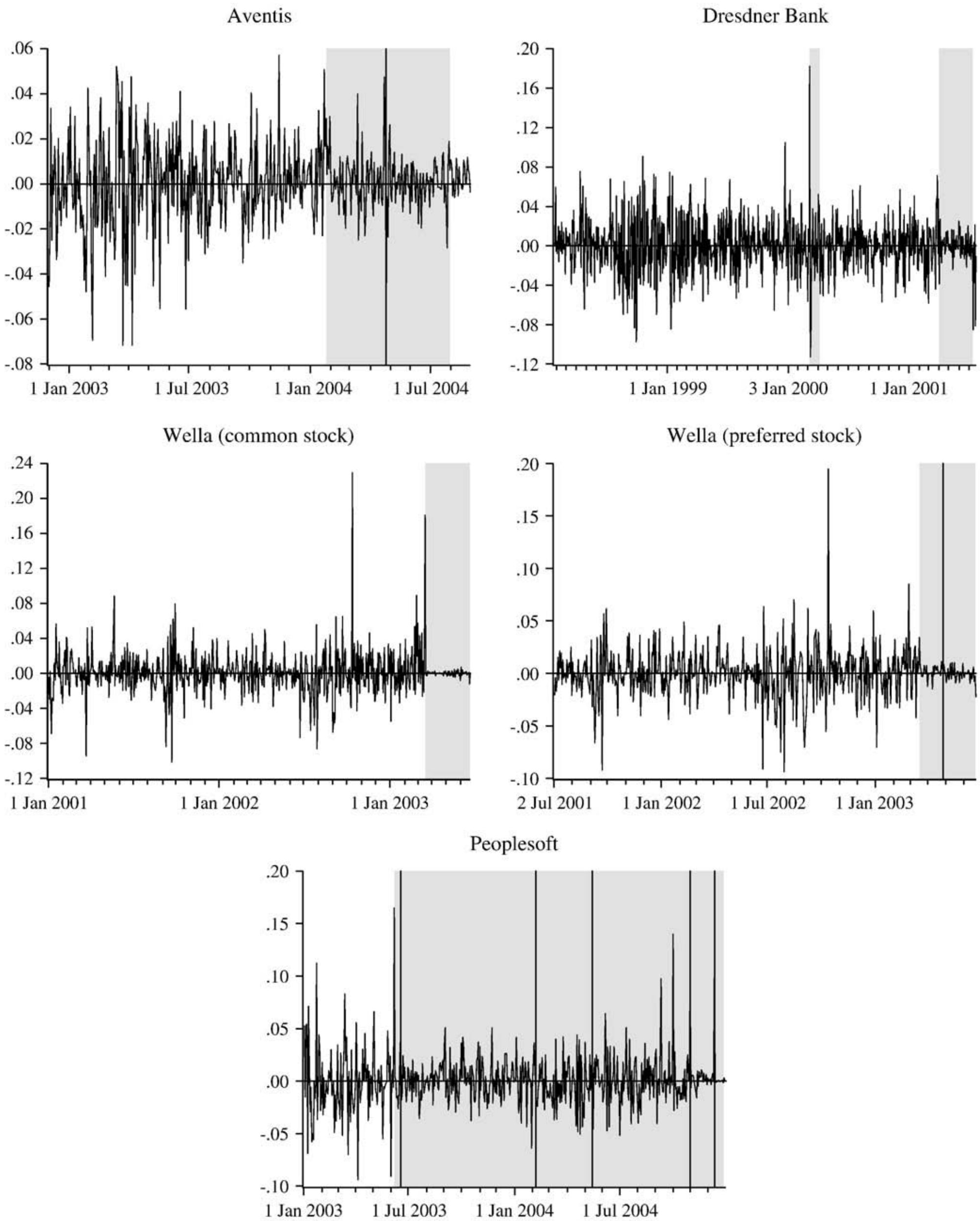

Fig. 2. Daily target stock-price returns.

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

$$t_{\nu,\mu,h}(x) = \frac{\Gamma[(\nu+1)/2]}{\Gamma[\nu/2]\cdot\sqrt{\pi\cdot(\nu-2)\cdot h}}\cdot\left[1+\frac{(x-\mu)^2}{h\cdot(\nu-2)}\right]^{-(\nu+1)/2}, \tag{3}$$

where $\Gamma(z)\equiv\int_0^\infty t^{z-1}\cdot e^{-t}dt$, $z>0$, 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 (location-shifted) t-distributions with v_i degrees of freedom in each regime, the conditional distribution of the return may be represented as a mixture of two distributions:

$$R_t\,|\,\phi_{t-1}\sim\begin{cases} t_{\nu_1,\mu_{1t},h_{1t}} & \text{with probability}\, p_{1t} \\ t_{\nu_2,\mu_{2t},h_{2t}} & \text{with probability}\,(1-p_{1t}) \end{cases}, \tag{4}$$

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)
$q_1=1/v_1$	0.2961	0.1321	0.3172	0.2743	0.0723
	(0.0757)	(0.0534)	(0.0402)	(0.0115)	(0.0010)
π_1	0.9981	0.9849	0.9749	0.9778	0.9740
	(0.0063)	(0.0221)	(0.0108)	(0.0065)	(0.0017)
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)
$q_2=1/v_2$	0.2477	0.2750	0.3599	0.0029	0.4072
	(0.0866)	(0.0410)	(0.0209)	(0.1006)	(0.0013)
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
$[\hat{p}^*(\hat{\tau})]$	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
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. (3)–(11). 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 *p*-values $\hat{p}^*(\hat{\tau})$ of the first LRT-statistic were estimated by a parametric bootstrap according to Eq. (13). The second LRT-statistic is asymptotically $\chi^2(4)$-distributed under the null hypothesis.

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

The first step in modelling the dynamics of target stock-price returns is to specify the conditional regime-specific mean μ_{it}. To stay in line with the market model from Eq. (1), we specify the mean process as a linear function of the current market returns R_t^m,

$$\mu_{it} = a_{0i} + a_{1i}\cdot R_t^m \quad \text{for } i = 1,2, \tag{5}$$

where we derive the (approximate) current market returns from the three indices 'DAX 30', 'Dow Jones' and 'SBF 120' (see Fig. 1).

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 and Susmel, 1994). Gray (1996a) solves these problems by positing in Eq. (4) that the DGP that determines which regime observation *t* comes from, in fact depends on the probability p_{1t} as calculated from Eq. (11) below. From Eq. (4) the variance of the target stock-price return at time *t* is given by

$$\begin{aligned} h_t &= E[R_t^2|\phi_{t-1}]-\{E[R_t|\phi_{t-1}]\}^2 \\ &= p_{1t}\cdot(\mu_{1t}^2 + h_{1t}) + (1-p_{1t})\cdot(\mu_{2t}^2 + h_{2t})-[p_{1t}\cdot\mu_{1t} + (1-p_{1t})\cdot\mu_{2t}]^2. \end{aligned} \tag{6}$$

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.[7]

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 in Eq. (3) by $q=1/v$, so that $(1-2q)=(v-2)/v$, and second to define the GARCH equation as

$$h_{it} = b_{0i} + b_{1i}\cdot(1-2q_i)\cdot\varepsilon_{t-1}^2 + b_{2i}\cdot h_{t-1}, \tag{7}$$

where h_{t-1} is given according to Eq. (6) and ε_{t-1} is obtained from

$$\begin{aligned}\varepsilon_{t-1} &= R_{t-1}-E[R_{t-1}|\phi_{t-2}]\\ &= R_{t-1}-[p_{1t-1}\cdot\mu_{1t-1} + (1-p_{1t-1})\cdot\mu_{2t-1}].\end{aligned} \tag{8}$$

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, to close the model, we have to specify 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:

$$\begin{aligned}\Pr\{S_t=1|S_{t-1}=1\} &= \pi_1,\\ \Pr\{S_t=2|S_{t-1}=1\} &= 1-\pi_1,\\ \Pr\{S_t=2|S_{t-1}=2\} &= \pi_2,\\ \Pr\{S_t=1|S_{t-1}=2\} &= 1-\pi_2.\end{aligned} \tag{9}$$

Now, when one performs similar calculations as in Gray (1996a), the specifications from the Eqs. (3)–(9) lead to the log–likelihood function

$$\begin{aligned}\Lambda = \sum_{t=1}^{T}\log\Bigg\{ & p_{1t}\cdot\frac{\Gamma[(v_1+1)/2]}{\Gamma[v_1/2]\cdot\sqrt{\pi\cdot v_1\cdot h_{1t}}}\cdot\left[1+\frac{(R_t-\mu_{1t})^2}{h_{1t}\cdot v_1}\right]^{-(v_1+1)/2}\\ & + (1-p_{1t})\cdot\frac{\Gamma[(v_2+1)/2]}{\Gamma[v_2/2]\cdot\sqrt{\pi\cdot v_2\cdot h_{2t}}}\cdot\left[1+\frac{(R_t-\mu_{2t})^2}{h_{2t}\cdot v_2}\right]^{-(v_2+1)/2}\Bigg\}.\end{aligned} \tag{10}$$

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

$$p_{1t} = \pi_1\cdot\frac{f_{1t-1}p_{1t-1}}{f_{1t-1}p_{1t-1}+f_{2t-1}(1-p_{1t-1})} + (1-\pi_2)\cdot\frac{f_{2t-1}(1-p_{1t-1})}{f_{1t-1}p_{1t-1}+f_{2t-1}(1-p_{1t-1})}, \tag{11}$$

where f_{1t} and f_{2t} denote the $t_{v_1,\mu_{1t},h_{1t}}$- and $t_{v_2,\mu_{2t},h_{2t}}$-density functions from Eq. (3), each evaluated at $x=R_t$.

4. Estimation results and target-specific discussion

4.1. Parameter estimates and specification issues

Table 2 displays the maximum–likelihood (ML) estimates of the Markov-switching GARCH dispersion models represented by the Eqs. (3)–(11). The log–likelihood functions from Eq. (10) 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. Our estimation results are robust to different starting values.

The parameter estimates and standard errors given in Table 2 may be used to assess the significance of the model parameters on the basis of the t-statistics. Although the exact finite-sample distribution of the t-statistic is generally unknown under our model setup, we can make use of some asymptotic distribution results concerning the t-statistics. For this, it is worth calling attention to the following two aspects: First, our ML approach satisfies the well-known regularity conditions so that our ML estimators are asymptotically normally distributed (see Greene, 2008, Chapter 16). Second, our standard errors are (weakly) consistent estimates of the true standard deviations of the ML estimators. As a result, under the null hypothesis of a single parameter being equal to 0,

[7] In many empirical studies parsimonious GARCH(1,1) specifications have been applied successfully in volatility models of financial variables. 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. (7) 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 (see also Kim, 1994; Dueker, 1997, for discussions of this issue).

our t-statistics should converge in distribution towards a standard normal variate implying a critical value of 1.96 at the 5%-level for the absolute value of the t-statistic (see Greene 2008, Appendix D). In our dataset, the majority of the parameter estimates (across all targets) have t-values larger than 1.96 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 0 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 $h_t = b_0 + b_1 \cdot \varepsilon^2_{t-1} + b_2 \cdot h_{t-1}$, 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) 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 two-state Markov-switching GARCH framework we may analyze the volatility persistence within each regime. According to our GARCH equation (7) 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 1 for all target stocks across both regimes.

The estimates of the degrees-of-freedom parameters $v_1 = 1/q_1$ and $v_2 = 1/q_2$ are all larger than 2, explicitly ranging from 2.4558 (Peoplesoft, regime 2) to 344.8276 (Wella preferred stock, regime 2). This is important since the variance of a t-distribution with density (3) only exists for $v > 2$. However, the t-distribution converges to the normal distribution for $q = 1/v \to 0$, but has fatter tails than the corresponding normal distribution for any finite v. 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. Invoking the aforementioned asymptotic distribution result for the t-statistics once more, we find that 9 out of 10 t-values are considerably larger than 1.96 (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 conditional distributions of target stock-price returns differ significantly from the normal distribution.

The transition probabilities 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 to 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 (3)–(11). 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, Garcia (1998) points out two shortcomings of Hansen's (1992) LRT procedure. First, Hansen's test procedure is computationally burdensome and practically unfeasible even for moderately parameterized Markov-switching models. Second, Garcia (1998) argues that 'Hansen's (1992) method provides a bound for the LRT statistic and not a critical value, which means that the test may be conservative'.

In view of these problems with the Hansen procedure, we decided to implement a bootstrap hypothesis-testing approach to assess the finite-sample distribution of the LRT statistic. The statistical validity of our bootstrap procedure is established, among others, by Davidson and MacKinnon (2004, Chapter 4.6) and MacKinnon (2007). Interestingly, Davidson and MacKinnon (2004, p. 165) also emphasize that there are strong theoretical reasons to believe that bootstrap tests like those implemented below generally perform better than tests based on approximate asymptotic distributions.[8]

To formally describe our bootstrap test, let us formulate our testing problem by H_0:'Single Regime' versus H_1:'Two Regimes' meaning that under the null hypothesis the DGP follows a single-regime GARCH dispersion model according to the specifications from the Eqs. (3)–(8) (with non-switching parameters) whereas under the alternative the DGP follows the fully specified two-regime Markov-switching GARCH dispersion model from the Eqs. (3)–(11). We denote the LRT statistic, which is defined as twice the difference in the log–likelihoods under the respective hypotheses, by τ.

We approximated the finite-sample distribution of the LRT statistic τ under H_0 by a parametric bootstrap. For this, we fitted single-regime GARCH dispersion models to our five target stock-price return series. Using the target-specific point estimates $\hat{a}_0, \hat{a}_1, \hat{b}_0, \hat{b}_1, \hat{b}_2, \hat{q}$, we then simulated $B = 1000$ synthetic stock-return series for each of our five target firms where the size n of each simulated stock-return series was set equal to the number of observations of the corresponding original target stock-return series as given in Section 3.1.

[8] See Beran (1988) for the fundamental theoretical result on this issue. Additional strong support for this proposition is provided by the results of a series of Monte Carlo studies (see, for example, Davidson and MacKinnon, 2004, p. 165, and the literature cited there).

In what follows, we denote the LRT statistic computed from an original target stock-return series by $\hat{\tau}$ and the corresponding target-specific LRT statistics bootstrapped under the null hypothesis by τ_j^*, $j=1,\ldots,B$. The empirical distribution function (EDF) $\hat{F}^*$ of the τ_j^* can be constructed by

$$\hat{F}^*(x) = \frac{1}{B}\sum_{j=1}^{B} I(\tau_j^* \leq x), \tag{12}$$

where $I(\cdot)$ is the indicator function, which is equal to 1 when its argument is true and 0 otherwise. Following MacKinnon (2007), we estimate the true p-value of our LR test based on $\hat{\tau}$ by

$$\hat{p}^*(\hat{\tau}) = 1 - \hat{F}^*(\hat{\tau}) = \frac{1}{B}\sum_{j=1}^{B} I(\tau_j^* > \hat{\tau}). \tag{13}$$

Fig. 3 displays the EDFs $\hat{F}^*(x)$ (bold lines) of the LRT statistics τ_j^* bootstrapped under the null hypothesis for the five target firms. In each panel we compare the EDF against the cumulative distribution function (CDF) of a χ^2 distribution with 8 degrees of freedom (thin line) which represented the asymptotic distribution under H_0 if the identification problem for the conventional LR test did not arise. Obviously, all EDFs are fairly similar to the $\chi^2(8)$ CDF. Table 2 shows the bootstrapped p-values (row '$[\hat{p}^*(\hat{\tau})]$') estimated according to Eq. (13). All bootstrapped p-values are virtually 0 leading to the rejection of the null hypothesis. Thus, our bootstrap LR tests overwhelmingly endorse regime-switching for all five target firms.

In contrast to the methodological complication 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. Because of space constraints, we only document the significant switching in the volatility parameters although completely analogous significance results do hold with respect to switching in the market-beta parameters a_{11} and a_{12}.[9]

To be more explicit, consider the two-regime specification (3)–(11) in which—due to our GARCH Eq. (7)—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 two-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 LR 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. (11), 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.[10] 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 may serve as 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.

Fig. 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 1 towards 0 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. Fig. 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 can be noted for the two Wella stocks. Their regime-1 probability series exhibit sharp declines towards 0 exactly at the common official announcement date on March 18, 2003 (see Fig. 4). Fig. 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

[9] Econometric details are available upon request.
[10] This study uses a filter algorithm provided by Gray (1996b).

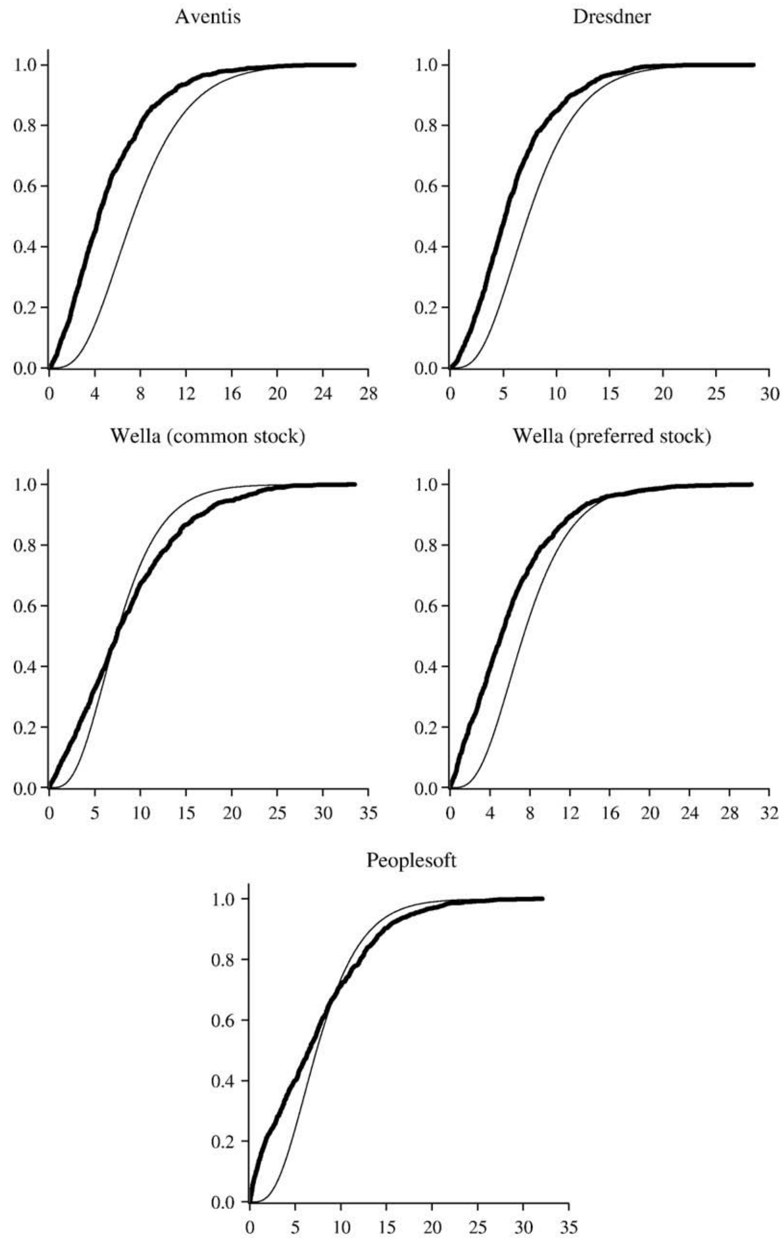

Fig. 3. Empirical distribution functions $\hat{F}^{*}(x)$ of the LRT statistics τ_j^{*} bootstrapped under H_0 (bold line) compared to the $\chi^2(8)$ cumulative distribution function (thin line).

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 Fig. 4 seem to support this view econometrically. Both series exhibit massive fluctuations between 0 and 1 and it is no earlier than on November 1, 2004 (the fourth bid-price revision) that the regime-1 probabilities eventually drop towards 0.

Finally, it remains to address the non-cash-bid deals. 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

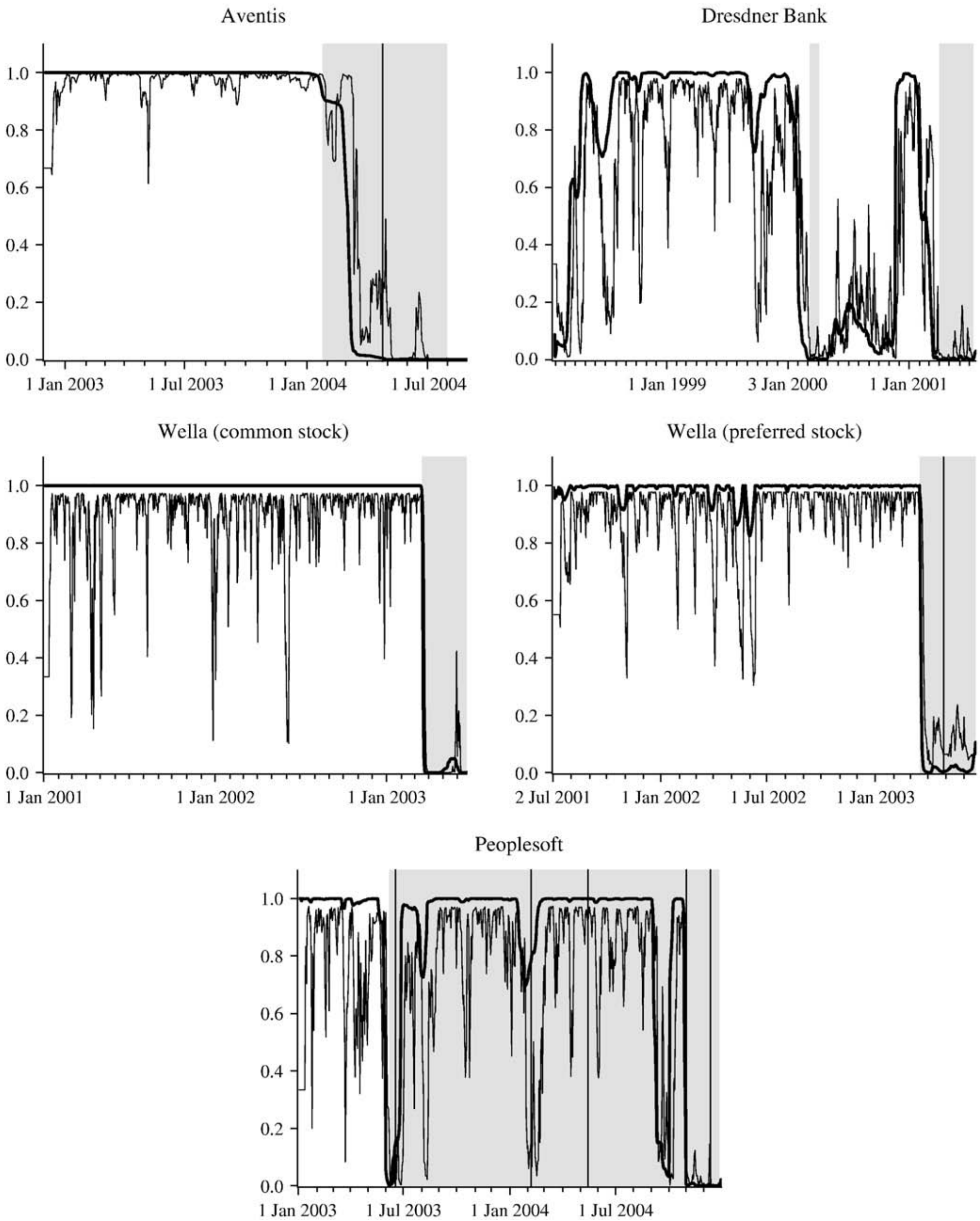

Fig. 4. *Ex-ante* (thin lines) and *smoothed* regime-1 probabilities (bold lines) of target stock-price returns.

from 1 towards 0 prior to the official announcement of the (ultimately unsuccessful) merger attempt by the Deutsche Bank (a pure share-exchange bid), then increase again towards 1 in the aftermath of this event and eventually drop towards 0 prior to the official announcement of the (finally successful) takeover by Allianz (a mixed bid). Overall, it is remarkable that our regime-switching structures are 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 are empirically significant phenomena. In summary, three conclusions can be drawn from our econometric analysis covering data on four European and one American target stocks:

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

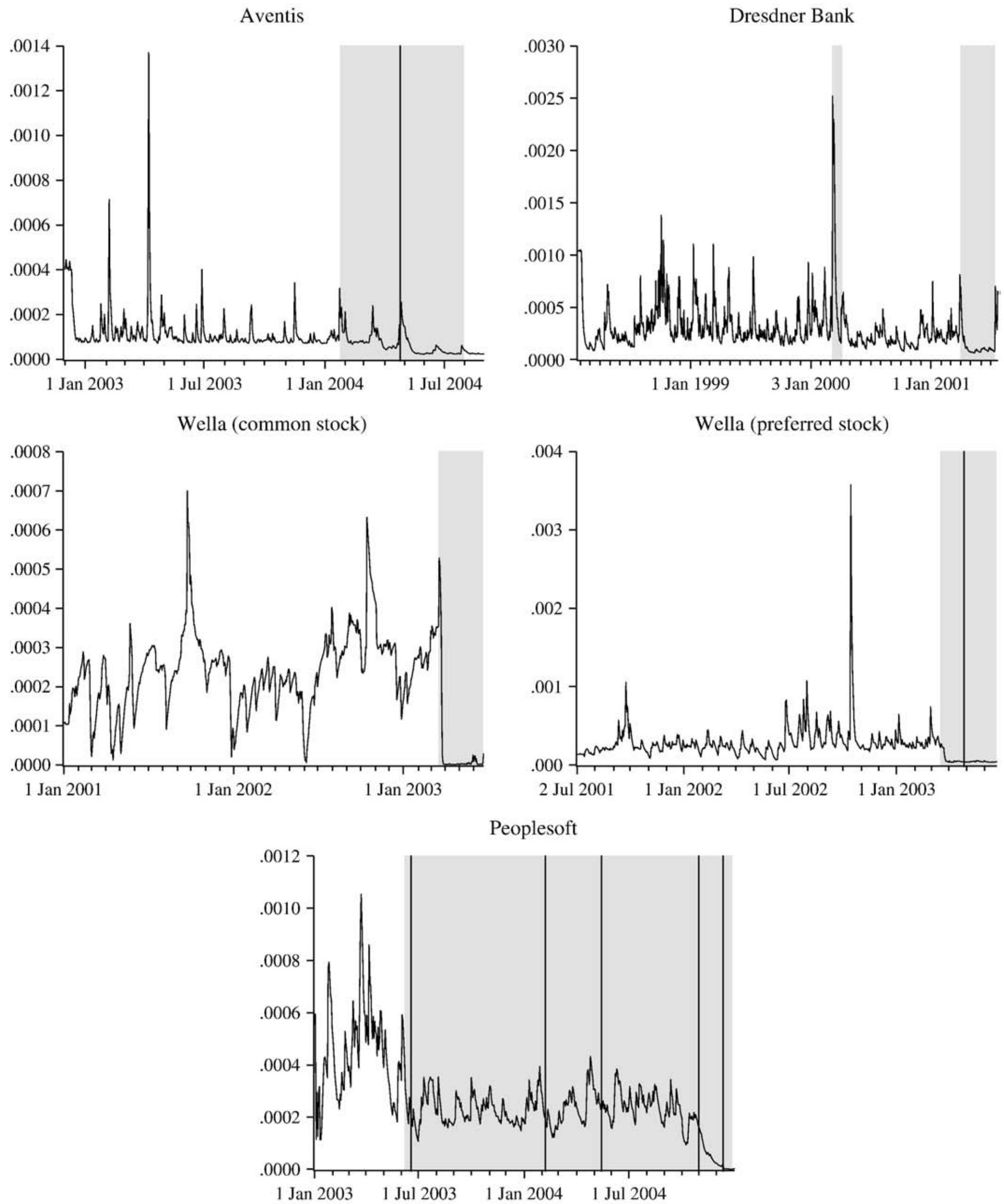

Fig. 5. Conditional variances of target stock-price returns.

(b) Within a two-state Markov-switching GARCH framework an (asymptotically 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.[11]

However, irrespective of the deal type, estimation procedures for target stock-price data should generally take into account switching market-betas and conditional volatility. The main reason is that regime-switching structures in the data-generating process of arbitrary asset returns are highly relevant to option-pricing. A seminal paper in this context is Bollen (1998) who presents a lattice-based method for option valuation under regime-switching and demonstrates that conventional option-pricing models typically 'generate significant pricing errors when a regime-switching process governs underlying asset returns'. In a

[11] 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%.

follow-up study, Bollen et al. (2000) show that in the context of currency options regime-switching models may have practical implications for investors since trading strategies that use regime-switching option valuation have the potential to generate higher profits than strategies that do not apply this technique.

Bollen's (1998) lattice-based option-pricing technique under regime-switching is derived on the basis of two assumptions. First, it only allows for switching *unconditional variances* between the regimes, but does not take into account switching GARCH structures. Second, it assumes normal distributions within both regimes. By contrast, our empirical analysis from Section 4 clearly reveals that target stock-price returns are (a) subject to significantly switching GARCH-structures, and (b) typically follow regime-specific *t*-distributions which differ significantly from their normal counterparts. Consequently, Bollen's (1998) option-pricing technique is not directly applicable here. One possible line of future research could be the adaptation of his technique to our empirical regime-switching results for target stock-price returns. Such an adaptation will then provide an empirical complement to theoretical option-pricing models such as those developed in Subramanian (2004).

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References

Bauwens, L., Preminger, A., Rombouts, J., 2007. Theory and inference for a Markov-switching GARCH model. CORE Discussion paper 2007-33. Université catholique de Louvain, Belgium.
Beran, R., 1988. Prepivoting test statistics: a bootstrap view of asymptotic refinements. Journal of the American Statistical Association 83, 687–697.
Bhagat, S., Brickley, J.A., Loewenstein, U., 1987. The pricing effects of interfirm cash tender offers. Journal of Finance 42, 965–986.
Bollen, N.P.B., 1998. Valuing options in regime switching models. Journal of Derivatives 6, 38–49.
Bollen, N.P.B., Gray, S.F., Whaley, R.F., 2000. Regime switching in foreign exchange rates: evidence from currency option prices. Journal of Econometrics 94, 239–276.
Brown, K.C., Raymond, M.V., 1986. Risk arbitrage and the prediction of successful corporate takeovers. Financial Management 54–63.
Cai, J., 1994. A Markov model of switching-regime ARCH. Journal of Business & Economic Statistics 12, 309–316.
Davidson, R., MacKinnon, J.G., 2004. Econometric theory and methods. Oxford University Press, New York.
De Grauwe, P., Dewachter, H., Veestraeten, D., 1999. Price dynamics under stochastic process switching: some extensions and an application to EMU. Journal of International Money and Finance 18, 195–224.
Dueker, M.J., 1997. Markov switching in GARCH processes and mean-reverting stock market volatility. Journal of Business and Economic Statistics 15, 26–34.
Garcia, R., 1998. Asymptotic null distribution of the likelihood ratio test in Markov switching models. International Economic Review 39, 763–788.
Gray, S.F., 1996a. Modeling the conditional distribution of interest rates as a regime-switching process. Journal of Financial Economics 42, 27–62.
Gray, S.F., 1996b. An analysis of conditional regime-switching models. Working paper, Fuqua School of Business. Duke University, Durham NC.
Greene, W.H., 2008. Econometric analysis, 6th edition. Pearson Education, New Jersey, USA.
Haas, M., Mittnik, S., Paolella, M., 2004. A new approach to Markov-switching GARCH models. Journal of Financial Econometrics 2, 493–530.
Hamilton, J.D., 1988. Rational-expectations econometric analysis of changes in regime: an investigation of the term structure of interest rates. Journal of Economic Dynamics and Control 12, 385–423.
Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57, 357–384.
Hamilton, J.D., Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime. Journal of Econometrics 64, 307–333.
Hamilton, J.D., Raj, B., 2002. Advances in Markov-switching models. Springer-Verlag, Berlin.
Hansen, B.E., 1992. The likelihood ratio test under non-standard conditions: testing the Markov switching model of GNP. Journal of Applied Econometrics 7, S61–S82.
Hutson, E., Kearney, C., 2001. Volatility in stocks subject to takeover bids: Australian evidence using daily data. Journal of Empirical Finance 8, 273–296.
Hutson, E., Kearney, C., 2005. Stock price interaction between target and bidder stocks during takeover bids. Research in International Business and Finance 19, 1–26.
Jarrell, G., Brickley, J., Netter, J., 1988. The market for corporate control: the empirical evidence. Journal of Economic Perspectives 2, 29–68.
Jensen, M., Ruback, R.S., 1983. The market for corporate control: the scientific evidence. Journal of Financial Economics 11, 5–50.
Kim, C.-J., 1994. Dynamic linear models with Markov-switching. Journal of Econometrics 60, 1–22.
Klaassen, F., 2002. Improving GARCH volatility forecasts with regime-switching GARCH. Empirical Economics 27, 363–394.
MacKinnon, J.G., 2007. Bootstrap hypothesis testing. Queen's Economics Department Working Paper No. 1127. Queen's University, Ontario, Canada.
Samuelson, W., Rosenthal, L., 1986. Price movements as indicators of tender offer success. Journal of Finance 41, 481–499.
Schwert, G.W., 1996. Markup pricing in mergers and acquisitions. Journal of Financial Economics 41, 153–192.
Subramanian, A., 2004. Option pricing on stocks in mergers and acquisitions. Journal of Finance 59, 795–829.
Verbeek, M., 2004. A guide to modern econometrics, 2nd Edition. John Wiley & Sons, Chichester.
Wilfling, B., Maennig, W., 2001. Exchange rate dynamics in anticipation of time-contingent regime switching: modelling the effects of a possible delay. Journal of International Money and Finance 20, 91–113.