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GARCH Modeling of Austrian Stock Market Reactions on Dividend Announcement

Introduction

This paper examines the implications of announced changes in dividends on stock prices using data from the Austrian stock market[1]. We assess the market impacts of these announcements by measuring abnormal returns and the variability of returns. Thereby we infer the information content of a company's dividend policy.

To establish the impact of dividend announcements on stock prices, we conduct an event study analysis based on selected non-linear stochastic time-series models. This is different from most related studies that use simple linear regressions (based on the *Market Model*) to forecast stock returns.

Significant effects surrounding corporate announcements of changing dividend payouts are confirmed by several studies, mainly for the US market. One of the first is that of Aharony and Swary [1]. For a sample of 384 events, the authors report average significant excess returns on the day of announced dividend changes of +0.36% in case of dividend increases, and –1.13% for dividend decreases.

[1] The authors thank Christian Gutlederer (Reuters Austria) and Peter Ladreiter (Capital Bank) for supplying data, and Peter Steiner for helpful comments. All remaining errors are our own responsibility.

Asquith and Mullins [3] conduct a somewhat more rigorous study by limiting their investigation to firms that either initiate dividends after a long haul or pay dividends for the first time. From the nature of this sample, the authors assume announcements to be totally unexpected. To capture the entire impact of the announcement a two-day window is considered. For a sample of 160 firms they report an average two-day excess return of +3.7%.

Dyl and Weigand [12] add that dividend initiations not only lead to an increase in stock prices, but are also accompanied by an immediate downward shift in both total and systematic company risk. Furthermore they report a decline in earnings' volatility in the first years following the dividend initiation. The authors conclude that a management decision to initiate regular dividend payments brings new information to investors regarding the risk of a firm.

Dhillon and Johnson [11] not only find stock prices but also bond prices to change significantly in reaction to the announcement of changing dividends. Taking into consideration only large dividend changes this study supports the wealth redistribution hypothesis as bond prices move in the opposite direction to stock prices.

Lonie et al. [16] compute announcement effects for the UK stock market. They find statistically significant abnormal returns of +2.03% for a two-day window in case of dividend increases and –2.15% in case of dividend decreases. Interestingly, in contrast with most other studies, this study also reports a positive excess return of about +1.45% on the immediate day before the announcement of no change in dividends.

For 200 companies listed on the German stock market Amihud and Murgia [2] investigate the effects of changing dividends on shareholders' value during the period 1988 to 1992. In line with the studies mentioned above, they find a statistically significant cumulative abnormal return for the announcement day and the previous day of +0.96% for dividend increases and –1.73% for dividend decreases. The authors emphasize that due to less informative accounting rules in Germany (compared to the US), dividends convey valuable information to the market especially on current earnings.

Consistent with most theoretical models on corporate dividend policy these empirical results suggest that (*grosso modo*) higher dividends are good news to investors, whereas an announcement of decreases in dividend payouts is bad news to the market[2].

For the Austrian market our study is the first to quantify the reaction of stock prices on changing dividends. The Austrian stock market is very small compared to other Western European markets and is often stamped to be an insider market. Its aggregated turnover volume amounted to about 15 billion EUR in the ATX Market segment in 2001. This segment comprises the most liquid stocks in Austria (blue chips) and is the Austrian equivalent to the DAX

[2] A comprehensive overview of dividend policy theories can be found in Frankfurter and Wood Jr. BG (2002).

segment in Germany. The continuous trading of these stocks is conducted via the XETRA® Electronic Trading System of Deutsche Börse AG since 1999. Dividends are paid on a yearly basis in Austria.

Our results on the Austrian stock market are very similar to those of other markets in the sense that contrary to the market's reputation there is no indication of leakage of information prior to the announcement day. In addition, our findings provide evidence that the Austrian stock market digests news on dividends very fast, at least within one day, therefore having a high degree of semi-strong market efficiency. The well-known definition of Fama [14] states that under the semi-strong form of the efficient capital market hypothesis stock prices, at any time, reflect all publicly available information relevant to the valuation of the firm. Therefore, if an announced change in dividends is new information to the market (i.e. there is no insider trading), the speed of price reaction supplies information on the degree of market efficiency. The faster prices adjust to the news the more efficient the capital market. We also find that the price reactions on the announcement days are mostly unbiased since there are no subsequent abnormal price changes after that day. The validity of our results is supported by non-parametric rank test statistics.

The remainder of the paper is organized as follows: Section 2 describes our data and methodology to identify significant (excess) price effects surrounding announcement dates. Our empirical results are presented in Section 3. In Section 4 we apply various tests to check the robustness of the assumptions underlying our empirical model. Section 5 contains a discussion and concludes.

1. Reserch design

1.1. Sample selection

Our sample contains 22 companies listed on the Austrian stock market. The companies have been quoted in the Austrian Traded Index (ATX) between January 1992 and April 2002, although not all firms have been listed on the stock market for the whole period. The ATX comprises the most liquid stocks in Austria.

Daily closing prices for the sample firms are derived from *Bloomberg* and the *Vienna Stock Exchange* [17]. For the relevant period we filtered 175 dividend announcements from several thousands included in the Dow Jones and Reuters *Factiva* database.

We define the announcement (event) date as the occasion of the very first official statement on dividends of the executive board of the analyzed firm that can be identified in the *Factiva* database. This differs from most other studies that define the announcement date as the day the upcoming dividend is fixed [9]. In many cases the announcements under consideration are made several months before the end of the relevant fiscal year for which the dividend will be paid, and do not contain exact information on the level of dividends but only on the expected direction of dividend changes (increase; constant; decrease). Neither the ex-dividend day nor the day the dividend is paid is considered to be an announcement day. If the direction of dividend change is revised we consider this day of revision as an additional event date conveying new information to the market.

One major difficulty in assessing the information content of dividend announcements stems from the fact that most statements on dividends are combined with that of earnings. This makes it impossible to exactly isolate the impact of the dividend information on stock prices. Therefore even if we observe significant abnormal returns within the dividend announcement period we cannot be certain that this abnormality is solely caused by announced dividend changes. Although our data sample contains too little information for statistical tests we find support (in several cases of announcement) for the hypothesis that the market puts more emphasis on statements about dividends than on earnings, since when dividend forecasts move in the opposite direction as forecasts on earnings, stock price movements tend to be aligned with the former.

1.2. Abnormal returns methodology

We start our analysis by defining the dividend process to be a martingale, that is, agents expect future dividends to be unchanged.

$$\mathrm{E}[\Delta D_{i,y}] \equiv \mathrm{E}[D_{i,y}] - D_{i,y-1} = 0\,, \tag{1}$$

where $\mathrm{E}[\Delta D_{i,y}]$ denotes the expected change in dividend of firm i for year y, $\mathrm{E}[D_{i,y}]$ stands for the expected dividend of firm i for year y and $D_{i,y-1}$ is firm i's last year's dividend. A dividend announcement is considered a positive event if $D^a_{i,y} > \mathrm{E}[D_{i,y}]$, neutral if $D^a_{i,y} = \mathrm{E}[D_{i,y}]$ and a negative event if $D^a_{i,y} < \mathrm{E}[D_{i,y}]$, where $D^a_{i,y}$ denotes the announced dividend of company i for year y.

This dividend expectation model has its background in the *reluctance-to-change dividends hypothesis*, which assumes that managers are averse to change dividends unless they perceive substantial changes in the future economic situation of their firm. This statement is especially true in case of our study, since we consider announcements that often precede the actual dividend change by a substantial amount of time. Therefore managers will be cautious in their projections, especially in case of possible downward adjustments.

In a next step, we calculate log-returns $R_{i,t}$ for company i on date t. From daily stock prices at close we get

$$R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \tag{2}$$

where $P_{i,t}$ stands for the stock price of company i on date t, $P_{i,t-1}$ denotes the stock price of company i on date t–1, and *ln* denotes the natural logarithm.

For each event (dividend announcement) in the sample we define an event-window and a pre-event window. The event window comprises 5 trading days, the announcement date ($t = 0$) plus the two days before ($t = -2$, $t = -1$) and the two days after the announcement ($t = +1$, $t = +2$). In contrast to many other studies examining the impact of corporate announcements on stock prices we choose a fairly short event window. This is justified by two facts: First, as is shown by Brown and Warner [6], the longer the event window the lower the power of the test statistic. This can lead to false inferences about the significance of an event. Second, by using a short event window we can better control for confounding effects (other news relevant for the stock price of the company). Since the announcement day can be detected exactly in the *Factiva* database and electronic trading makes possible immediate reactions on new information (buy or sell orders), this short event window seems to be justified.

The pre-event window covers the 50 trading days prior to the event window. For each day of the event window we compute the abnormal return *AR* as the difference between the actual ex-post return and the security's normal return that is predicted in the absence of the event.

Formally, for each announcement of the analyzed companies we compute

$$AR_{i,t} = R_{i,t} - E[R_{i,t} \mid X_i]\ , \qquad (3)$$

where $R_{i,t}$ stands for the actual return of firm i on date t in the event window and $\mathrm{E}[R_{i,t} \mid X_i]$ denotes the predicted return conditional on the information set X_i, where $X_i = (R_{i,-52},\ldots,R_{i,-3})$.

To model risk-adjusted expected returns $\mathrm{E}[R_{i,t} \mid X_i]$ we use GARCH time-series models. GARCH methodology (first introduced by Engle in [13] and refined and extended by Bollerslev in [4] and [5]) has proved to be an extremely popular class of non-linear stochastic processes for financial times series. To illustrate the model identification we consider general GARCH(p, q) model for a time series z_t:

$$z_t = \mu + \varepsilon_t$$

$$\sigma_t^2 = h_t = a_0 + \sum_{i=1}^{p} a_i \sigma_{t-i}^2 + \sum_{i=1}^{q} b_i \varepsilon_{t-i}^2 \qquad \varepsilon_t \sim N(0, h_t) \qquad (4)$$

where μ is the constant, ε_t is the error term, a_0 is the constant term, a_i are the parameters for the lagged conditional variance at lag i, b_i are the parameters for the lagged squared error at lag i. If sum of parameters a_i and b_i is less than one, the unconditional variance is constant (i.e., homoskedastic) and given by the formula

$$\sigma^2 = \frac{a_0}{1 - \sum_{i=1}^{p} a_i - \sum_{i=1}^{q} b_i}\ . \qquad (5)$$

The model identification refers to the methodology in identifying the required sample size (we choose n = 50 to be appropriate), proper orders p and q and order of integration when the original time series is nonstationary.

As a first step, we conduct unit root tests on the return series over the pre-event window. To define the appropriate models the following equation is estimated using ordinary least squares method (OLS):

$$\Delta R_{i,t} = \mu_i + \delta_i R_{i,t-1} + \sum_{j=1}^{k} a_{i,j} \Delta R_{i,t-j} + \varepsilon_{i,t} \ . \tag{6}$$

$\Delta R_{i,t}$ denotes the first differences of returns of firm i on day t, and μ_i, δ_i and $a_{i,j}$ are the parameters of firm i's model.

We formulate the null hypothesis of the time series $R_{i,t}$ to be integrated of order 1, i.e. $R_{i,t} \sim I(1)$. This means that

- the variance of $R_{i,t}$ goes to infinity as t goes to infinity,
- the random term $\varepsilon_{i,t}$ in the model has a permanent effect on the value of $R_{i,t}$ because $R_{i,t}$ is the sum of all previous random terms,
- the expected time between crossings of $R_{i,t}$ = 0 is infinite,
- the autocorrelations tend to 1 as t goes to infinity.

To test the null hypothesis we apply the Dickey-Fuller (DF) test statistic which is defined as

$$DF = \frac{\hat{\delta}_i}{\hat{\sigma}_{\delta_i}} \ . \tag{7}$$

The numerator in equation (7) reflects the estimator of parameter δ of firm i's model, and the denominator shows standard error of parameter δ of firm i's model.

The number of time lags k is established by means of the method proposed by Cambell and Wasley [7], Cambell et al [8], Mills [18] and Phillips and Perron [19]. In this method a large initial value k is chosen (k = 8), and than this value will be gradually reduced by 1 until test statistic becomes significant (for $k \geq 1$). If the test statistic of the augmented DF is statistically significant, we should accept the alternative hypothesis that the time series $R_{i,t}$ is integrated of order zero, i.e. $R_{i,t} \sim I(0)$, so that

- the variance of $R_{i,t}$ is finite and does not depend on t,
- the random term has only a temporary effect on the value $R_{i,t}$,
- the vaules $R_{i,t}$ fluctuate around their mean of zero,
- the autocorrelations decrease steadily in magnitude for large enough time lags, so that their sum is finite.

The results of the augmented Dickey-Fuller (ADF) tests show that our sample returns are either integrated of order zero (in 170 cases) or order one (only in 5 cases).

In the next stage, we identify the orders p and q, based on the Akaike information criterion, and estimate six different models for the return series in the pre-event window: ARCH(1) (in 132 cases), ARCH(2), ARCH(3), ARCH(4), GARCH(1,1) and GARCH(2,1). We then use the appropriate time series models to predict event-window returns and calculate abnormal returns (the forecast errors).

We then divide our time series of stock returns into three clusters, one comprising announced dividend increases, one for dividend decreases and one for constant dividends. This distinction is based on equation (1). For each cluster, we compute average abnormal returns across sample members for day t as follows:

$$\overline{AR}_t = \frac{1}{N} \cdot \sum_{i=1}^{N} AR_{i,t} \ , \tag{8}$$

where N stands for the number of events in a cluster.

The sample standard deviation of $\overline{AR}_t$ $(= \hat{\sigma}\,[\,\overline{AR}_t\,])$ for the pre-event period is calculated from the time-series of mean abnormal returns for each cluster as

$$\hat{\sigma}\,[\,\overline{AR}_t\,] = \left[\frac{1}{49} \cdot \sum_{t=-52}^{-3} (\overline{AR}_t - \overline{AR}^*)^2 \right]^{1/2} . \tag{9}$$

Note that the statistic defined in (9) can be interpreted as a cross sectional – time series standard deviation.

$\overline{AR}^*$ in equation (9) defines the mean abnormal return (cross-sectional and time series) in the pre-event period:

$$\overline{AR}^* = \frac{1}{50} \cdot \sum_{t=-52}^{-3} \overline{AR}_t \ . \tag{10}$$

Finally, we wish to test the null hypothesis that the mean abnormal or excess return on day t of the event window is equal to zero. Our test statistic is the ratio of mean cross-sectional abnormal returns and the standard deviation given by (9).

$$t_{\text{stat}} = \overline{AR}_t \big/ \hat{\sigma}[\overline{AR}_t\,] . \tag{11}$$

Assuming that the $\overline{AR}_t$ are independent and identically distributed and normal, t_{stat} has a Student-t distribution under the null hypothesis with $(N-1)$ degrees of freedom (see Brown and Warner [6]). A necessary condition for this assumption is that the abnormal returns are not autocorrelated. Although daily excess returns are in general non-normal, by a standard central limit theorem (CLT), the cross sectional mean excess return converges to normality as the number of sample securities increases.

2. Empirical results

2.1. Abnormal returns

Our results for abnormal returns over the event window for each cluster are summarized in table 1. In order to prove significance by *t*-Student test we check the hypotheses that the time series of mean abnormal returns in the clusters considered are normally distributed. Using the Chi-square goodness-of-fit statistic, the Shapiro-Wilks *W* statistic and tests based on skewness and kurtosis, we cannot reject the mentioned hypotheses (*p*-value for all tests is greater than 0.05). Furthermore autocorrelations are not significant at the 5% level.

Table 1. Average daily abnormal returns for the event window in three clusters

	Dividend increases Sample size: 74		Constant dividends Sample size: 74		Dividend decreases Sample size: 27	
Event period day *t*	$\overline{AR}$ (%)	t_{stat}	$\overline{AR}$ (%)	t_{stat}	$\overline{AR}$ (%)	t_{stat}
–2	+ 0.456*	+ 2.026	– 0.189	– 0.938	– 0.077	– 0.160
–1	+ 0.262	+ 1.165	– 0.179	– 0.886	– 0.251	– 0.523
0	+ 0.652**	+ 2.900	– 0.007	– 0.035	– 1.287**	– 2.678
+1	+ 0.059	+ 0.263	– 0.002	– 0.012	+ 0.045	+ 0.093
+2	+ 0.596*	+ 2.652	– 0.244	– 1.212	+ 0.073	+ 0.152

* significant at the 5% level
** significant at the 1% level

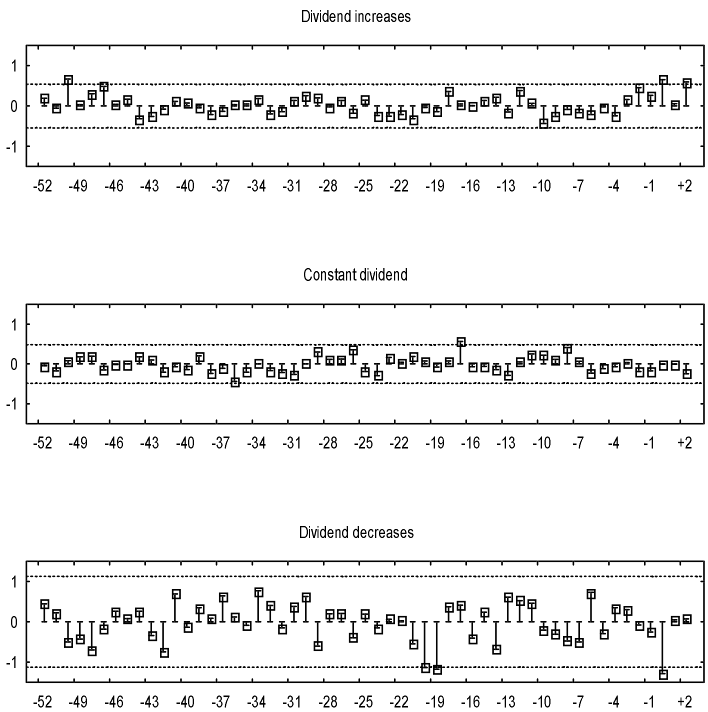
For the 74 announced dividend increases the average abnormal return on the announcement day is +0.65% (significant at the 1% level) and +0.46% (+0.60%) on day t = –2 (t = +2) (significant at the 5% level). We also find that all average abnormal returns in the event window are positive for this cluster (although not all are significantly different from zero). This result corroborates the findings of other studies that examine whether dividend increases are interpreted as positive signals by investors.

In case of constant dividends (sample size: 74), the average abnormal returns are not statistically different from zero on any day of the event window. This supports the hypothesis that companies that leave their dividends unchanged communicate no significant new information to the market.

In the cluster of announced dividend decreases we find a statistically significant average abnormal daily return of –1.29% on day $t = 0$. This result is intuitive and supports empirical findings for other markets that a cut in dividend payments conveys negative information to the public. In comparison to the abnormal returns induced by increasing dividends the reported negative return due to an announced contraction in dividends is much higher in absolute terms. This confirms the general observation on financial markets that bad news has a greater impact on stock returns than good news. This can be seen as an indication that analysts revise their forecasts for future earnings of companies much more strongly in case of dividend decreases than increases.

A graphical illustration of our results is given in figure 1, which shows average abnormal returns with 99% confidence sets for the three clusters from $t = -52$ to $t = +2$ relative to the announcement date.

Figure 1. Cross-sectional abnormal returns with 99% confidence regions for three clusters over the preevent and event period



The effect of dividend announcements on stock prices is less pronounced when we consider cumulative abnormal returns (CAR) for the event window. For constant dividends and dividend decreases the CAR are 0.62% and –1.05%, respectively, and not significant. For dividend increases the CAR is 2.03% and significantly different from zero at the 5% level.

In order to check the relevance of using GARCH time series models to replicate the return generating process of stocks in our sample we test the model assumptions. To analyze whether the residuals (abnormal returns) in the pre-event window are white noise, we first test the mean values of abnormal returns for significance in each pre-event window by *t*-Student test. In all cases the mean value of residuals is not significantly different from 0 at the 5%. In a next step we test homogeneity of residuals by using Engle's ARCH test. Only in four cases (out of 175) the GARCH effects (i.e. heteroscedasticity) is statistically significant at the 5% level.

Finally we compute the sample ACF (autocorrelation function) and sample PACF (partial autocorrelation function) of residuals for each pre-event window to see whether they do not form any pattern and are statistically insignificant. In addition, we test the autocorrelation of residuals by using portmanteau lack of fit test. This test uses all the residual sample ACFs as a unit to check the joint null hypothesis that the first k autocorrelations are not significant (we chose k = 15). We apply Q test statistic (portmanteau statistic) which approximately follows the chi-square (k–m) distribution where m is the number of parameters estimated in the model. Our finding is that in twenty two cases Q slightly exhibits the critical value at the 5% significance level (i.e. in twenty two cases residuals are significantly autocorrelated). Testing results of mean residuals, homoscedasticity of variance and autocorrelation of residuals does not deliver significant evidence against the null hypothesis of residuals to be white noise.

2.2. Volatility

Besides the level of abnormal returns, we are also interested in their second moments, since variance is an indicator of the level of uncertainty, as well as the relative importance of new information to the market, and affects the accuracy of our statistical inferences on the levels.

We start by analyzing the time series of cross-sectional variances of abnormal returns over the entire time-horizon (pre-event and event window) to test whether the variances from the pre-event period differ from those of the event period. An illustration is given in figure 2 which shows cross-sectional variances of abnormal returns for the three clusters from t = –52 to t = +2 relative to the announcement date.

Figure 2 shows a significant increase in variances in the event window for the constant dividend and dividend decrease cluster. The fact that variances tend to increase in the event window justifies the restriction of the model fitting to the pre-event window. From figure 2 one can also see that pre-event variances in the dividend decrease cluster are in most cases on a substantially higher level than in the other clusters. This can be seen as an indicator of rumors about upcoming negative information that increase uncertainty and hence the variance of excess returns. A consequence of the larger variance in the pre-event window is that *t*-statistics for abnormal returns are generally smaller in this cluster than for dividend increases (see table 1).

Table 2 presents the cross sectional variances of excess returns in the event window for each cluster. While the variances for dividend increases stay relatively constant over time, the variances for constant dividends and dividend decreases increase by a factor of more than 2 and more than 4, respectively, on the announcement day (relative to the day before).

Figure 2. Cross-sectional variances of abnormal returns for three clusters over the pre-event and event period

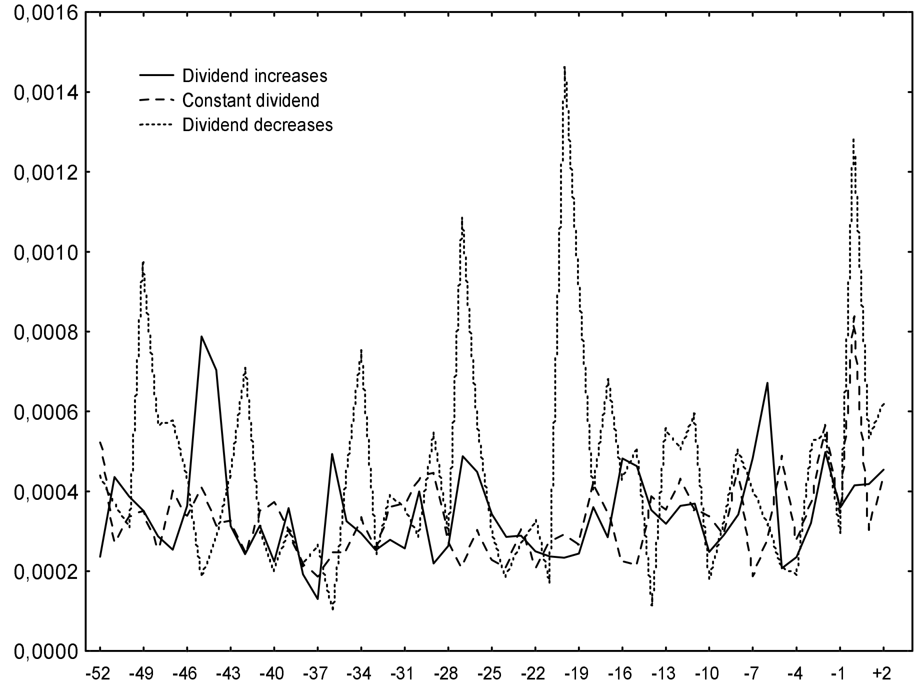


Table 2. Variances of abnormal returns over the event window for three clusters

	Dividend increases Sample size: 74	Constant dividends Sample size: 74	Dividend decreases Sample size: 27
Event period day t	Variance	Variance	Variance
–2	$4.989 \cdot 10^{-5}$	$5.650 \cdot 10^{-5}$	$5.441 \cdot 10^{-5}$
–1	$3.590 \cdot 10^{-5}$	$3.451 \cdot 10^{-5}$	$2.968 \cdot 10^{-5}$

0	$4.150 \cdot 10^{-5}$	$8.386 \cdot 10^{-5}$	$12.840 \cdot 10^{-5}$
+1	$4.185 \cdot 10^{-5}$	$3.035 \cdot 10^{-5}$	$5.332 \cdot 10^{-5}$
+2	$4.542 \cdot 10^{-5}$	$4.430 \cdot 10^{-5}$	$6.262 \cdot 10^{-5}$

We apply several tests (Cochran's C, Bartlett's, Hartley's and Levene's tests statistics) to check the null hypothesis that cross sectional variances in each cluster are the same for each day in the event window against the alternative hypothesis of heteroscedasticity along the time dimension. The results of these tests are presented in table 3 and confirm our earlier impression from table 2 that the cross sectional variances are stable in case of dividend increases but not for constant or decreasing dividends.

Table 3. Variance check of abnormal returns over the event window for three clusters

	Dividend increases Sample size: 74		Constant dividends Sample size: 74		Dividend decreases Sample size: 27	
Test	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Cochrane C	0.2325	0.685	0.3361	0.000	0.3910	0.002
Bartlett	1.0059	0.710	1.0708	0.000	1.1205	0.006
Hartley	1.3897	-	2.7628	-	4.3267	-
Levene	0.3637	0.835	1.6085	0.172	0.7311	0.572

These observations allow two possible conclusions. First, they confirm the usual hypothesis that bad news have a stronger impact on volatility than good news. In this sense constant dividends cannot (in mean) be interpreted as good news. Second, the fact that for some clusters cross sectional variances fluctuate over consecutive days points towards a *clientele effect* since investors of different companies react differently towards similar information. In line with theoretical predictions from behavioral models (see e.g. Frankfurter/Wood [15]) our results confirm that investors mainly prefer regular and higher payments to capital gains. If a company announces higher dividends, its clientele does not change as this meets the preferences of the investors. In case of dividend decreases as well as constant dividends, these announcements imply a change in the clienteles of these companies, as the distribution of corporate payouts does not correspond with the distribution of investors' preferences for payouts. Therefore variances of abnormal returns change in these clusters.

The applied tests indicate that the variances of abnormal returns are not homogeneous over the event window in the cases of constant and decreasing dividends. The most widely applied test in this case is Bartlett's test; *p*-values of this test are much lower than 1% in these two clusters. It is common practice in statistics to reject the hypothesis of homogeneity of variances in consecutive days if at least one test rejects this hypothesis.

3. Non-parametric test statistic

The validity of our results based on GARCH-modeling of stock returns and the parametric test statistic is supported by application of a nonparametric rank test developed by Corrado [10]. This test is based on the transformation of each security's time series of excess returns into their respective rank, i.e. $K_{i,t} = \text{rank}(AR_{i,t})$, $t = -52,\ldots,+2$.

For each day in the event window, we compute the test statistic

$$T(u) = \frac{1}{N_k} \cdot \frac{\sum_{i=1}^{N_k} \left(K_{i,u} - 28\right)}{\hat{\sigma}(K)} \ , \qquad (12)$$

where N_k denotes the number of events in a cluster, $u = -2,\ldots,+2$, and $T(u)$ is asymptotically unit normal. The estimator for the standard deviation of the ranks $\sigma(K)$ is given by

$$\hat{\sigma}(K) = \left(\frac{1}{55} \sum_{t=-52}^{2} \left(\frac{1}{N_k} \sum_{i=1}^{N_k} \left(K_{i,t} - 28\right) \right)^2 \right)^{1/2} . \qquad (13)$$

The results of this test are summarized in table 4.

Table 4. Testing average daily abnormal returns for the event window in three clusters by Corrado rank test

	Dividend increases Sample size: 74		Constant dividends Sample size: 74		Dividend decreases Sample size: 27	
Event period day t	$\overline{AR}$ (%)	$T(u)$	$\overline{AR}$ (%)	$T(u)$	$\overline{AR}$ (%)	$T(u)$
–2	+ 0.456*	+ 1.272	– 0.189	– 0.909	– 0.077	– 0.992
–1	+ 0.262	+ 1.200	– 0.179	– 0.696	– 0.251	– 1.030
0	+ 0.652**	+ 2.383**	– 0.007	– 0.972	– 1.287**	– 1.689*
+1	+ 0.059	+ 0.364	– 0.002	– 0.857	+ 0.045	+ 0.869
+2	+ 0.596*	+ 2.078**	– 0.244	– 0.421	+ 0.073	+ 0.804

* significant at the 10% level
** significant at the 5% level

In line with the *t*-statistics we find abnormal returns in the event window to be highly significant on day $t = 0$ and $t = +2$ in the dividend increase cluster. The abnormal return on $t = 0$ in the dividend decrease cluster is also significant at the 10% level. All other abnormal returns are not statistically significant. The results of this nonparametric rank test support our earlier findings of market reactions on dividend changes and support the validity of using GARCH-models to generate normal stock returns in our study.

4. Conclusions

The findings of this research show that dividend policy is an important source of information for investors on the Austrian stock market. In line with most related studies on other markets we find that dividend increases induce a significant positive reaction in stock prices, whereas announced dividend decreases lead to a fall in stock prices. Constant dividends leave stock prices unaltered.

In case of dividend decreases the variance of abnormal returns experiences a sharp hike on the announcement day, which we interpret as evidence for the often-quoted fact that bad news has a stronger impact on financial markets than good news. Furthermore we find that pre-event variances in the dividend decrease cluster are on a substantially higher level than in the other clusters. This can be seen as an indicator of rumors about upcoming negative information that increase uncertainty and hence the variance of excess returns.

We compute non-parametric rank test statistics to confirm the robustness of our *t*-statistics and find that they lead to very similar conclusions.

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