Kredit und Kapital, 42. Jahrgang, Heft 1, Seiten 55–91
Abhandlungen

Risk Effect versus Delayed Price Response: The Case of the Post-Earnings-Announcement Drift in Germany

By Hans-Peter Burghof and Matthias Johannsen, Stuttgart*

I. Introduction

Since the publication of *Fama's* (1970, 1991) works, his concept of three types of market efficiency has become a powerful theoretical framework. One of the well-known and well-documented anomalies within this framework is the post-earnings-announcement drift (PAD). It describes the phenomenon that firms which report positive (negative) unexpected earnings exhibit positive (negative) abnormal returns following the earnings announcement. A drift-based trading strategy taking a long position in shares with high unexpected earnings and a short position in shares with low unexpected earnings thus earns significant abnormal returns. *Ball/Brown* (1968: 169), using data from the US stock markets, were the first to verify empirically that stock prices react to earnings announcements only gradually. For the German market, *Brandi* (1977) reports evidence that most of the information contained in earnings disclosures is anticipated by capital markets. The study by *Foster/Olsen/Shevlin* (1984) was important in establishing the PAD as an anomaly beyond statistical doubt. In two widely recognized studies, *Bernard/Thomas* (1989, 1990) find that a large proportion of the drift occurs around the following earnings announcement and conclude that the drift is due to the market's failure to understand the information content of current earnings regarding future earnings. *Ball/Bartov* (1996) report evidence that the market correctly identifies the serial correlation inherent to earnings but underestimates this serial correlation by about 50 %. Further references are contained in *Kothari* (2001).

* We thank participants of the 2006 Annual Congress of the Midwest Finance Association, Chicago, the 2006 Annual Congress of the European Accounting Association, Dublin, the 2006 Annual Meetings of the Eastern Finance Association, Philadelphia, and an anonymous referee for helpful comments.

Attempts to explain the drift can be separated roughly into two groups. Authors within the first group argue that positive abnormal returns following earnings disclosures are a premium for some unidentified risk. Hence, these returns cannot be realized without risk, and their existence does not oppose the efficient market hypothesis. *Ball/Kothari/Watts* (1993) argue that unexpected earnings may cause shifts in the firm's beta which have the same sign as the unexpected earnings. *Francis* et al. (2003) argue that the abnormal returns following earnings disclosures are a risk premium for the information uncertainty involved in earnings disclosures. *Sadka/Sadka* (2003) show that systematic liquidity is an important determinant in explaining cross-sectional variations in unexpected earnings, and they interpret the PAD as a premium for liquidity risk. Finally, *Mendenhall* (2004) argues that investors are aware of the PAD and the resulting possibility to trade on it, but refrain from doing so due to arbitrage risk.

The second group of explanations interprets the post-earnings-announcement drift as a market inefficiency. Several effects which are likely to contribute to this inefficiency are identified. *Brennan/Jegadeesh/Swaminathan* (1993) show that the PAD decreases with an increasing number of analysts following a specific firm. Similarly *Chen/Wuh Lin/Sauer* (1997) present evidence that the PAD is smaller for firms for which more information and information of higher quality is available. *Sloan* (1996) reports evidence that markets do not fully recognize the different degrees of persistence of the cash flow and accrual components of earnings. *Mikhail/Walther/Willis* (2003) find that firms which are evaluated by analysts with longer experience in evaluating this specific firm display a PAD which is 18% lower than that of firms which are evaluated by less experienced analysts. In a study for the UK market, *Liu/Strong/Xu* (2003) come to the conclusion that the drift is robust to the *Fama/French* (1992, 1996) control variables size and book-to-market ratio.

This paper makes the following contributions. First, it tests for the existence of the drift on the German market, thereby producing out of sample evidence with respect to the works based on samples from the US or UK stock markets. Second, the incorporation of a wide range of risk-related variables not examined simultaneously in previous research allows for testing of their incremental explanatory power. The risk factor market beta and the risk-related variables size and book-to-market ratio from the *Fama/French* (1992, 1996) Three-Factor-Model are supplemented by a variable to capture a momentum effect. Additionally, it is tested whether the drift is related to a possible survivorship bias in the sample. Further, the use of an analysis of covariance in addition to significance tests of a drift-based trading strategy increases the robustness of the findings.

The main results of the data analysis support the existence of the drift taking into account the control variables. There is no systematic relationship between firm size or book-to-market ratio and cumulative abnormal returns. Subdividing the sample into terciles based on firm size and book-to-market ratio confirms that the drift is not generated by variations in these variables. The variable to control for a survivorship bias is significant, however, not in the event windows over which a significant drift can be observed. Strongly significant is the variable that controls for a momentum effect. These results suggest that there is a delayed or gradual reaction to earnings information on the German market.

The remainder of the paper is organized as follows. In section II the research design and the selection of the variables are outlined. Section III describes the data collection and the computation of the variables. The data analysis is contained in sections IV and V. Section VI finishes with the conclusions.

II. Research Design and Variable Selection

In this section the research design is described and the selection of the considered variables is discussed. Within the relevant literature, the methodology of event studies has emerged as the standard approach to investigating capital market responses to accounting disclosures. Good summaries of this approach are provided by *Schweitzer* (1989: 18 et seqq.), *Berry/Gallinger/Henderson* (1990: 78 et seqq.), *Kritzman* (1994: 17 et seqq.), and *McWilliams/Siegel* (1997: 628 et seqq.). To correct for a bias caused by possible measurement error, the sample firm years are sorted into 10 equally weighted portfolios according to their unexpected earnings. Then, cumulative abnormal returns are computed and averaged for these portfolios. Returns to buy-and-hold-strategies are calculated and compared over different periods prior to and following the earnings disclosure date.

Among more recent studies related to the post-earnings-announcement drift such as *Kim/Kim* (2003) or *Liu/Strong/Xu* (2003) it has become common to include the variables size and book-to-market ratio proposed by *Fama/French* (1992, 1996) as control variables. While *Fama/French* (1992, 1996) use the return difference between small and big firms and firms with a high book-to-market ratio and a low book-to-market ratio (*SMB, HML*), in this paper we use the levels of these variables. First, this allows for shorter estimation periods to obtain estimates for the market beta and simplifies the use of daily returns. Second, since these variables are used as control variables in an analysis of covariance where the dependent variables are cumulative daily abnormal returns summed over 10-day windows, there is no need to produce estimates for the factor loadings. Besides these commonly used risk-related variables, *Kim/Kim* (2003: 389) use a momentum factor developed by *Jegadeesh/Titman* (1993) as a control variable. *Jegadeesh/Titman* (1993: 88) show that the momentum effect is especially visible around earnings announcement dates, a result which is also confirmed by *Chan/Jegadeesh/Lakonishok* (1996: 1686 et seqq.). Hence, the momentum variable of *Jegadeesh/Titman* (1993) is included as a control variable. Finally, the possibility of a sample selection bias is investigated according to an approach taken by *Brown/Pope* (2000). This is done in an attempt to correct for the possibility of firms leaving the sample in a non-random way, thereby introducing a bias in the estimation results. To correct for such a bias, the two-stage estimator as proposed by *Heckman* (1979: 154 et seqq.) is used.

Two hypotheses are tested in the data analysis. First, in accordance with the previous literature it is expected that also on the German stock market firms with positive (negative) unexpected earnings will exhibit positive (negative) abnormal returns following the announcement on the German stock market as well. Second, if the drift is generated by different exposures to risk, the relationship between unexpected earnings and abnormal returns is expected to disappear once this risk is accounted for by control variables in the investigation.

III. Data Collection and Description

1. Sample Generation

The sample is constructed using the Worldscope and Datastream databases by Thomson Financial. The Worldscope database is screened for all public limited companies listed on the Frankfurt stock exchange with a market capitalization exceeding one million EUR as of May 7, 2004. This yields 927 companies. For these firms the relevant financial statement data is collected from the annual statements. Annual statements have to be used because quarterly data is available for few firms and for recent years only. The sample begins in 1990 because data availability is limited for earlier years in Worldscope. It finishes with the fiscal year 2003. Daily stock prices are taken from the Datastream database, which has data for 918 of the 927 firms. Since earnings are measured as net income available to common shares[1], preferred shares are eliminated from the sample. The final sample hence consists of 850 firms. This number is reduced by non-valid data points which vary across the years depending on the variables under consideration. Table 1 provides a brief year-by-year overview of the market with sample, missing, valid and non-valid observations as used in the analysis of Table 3.[2] Observations are part of the total market if they are listed on the Frankfurt stock exchange in the respective year. Observations are missing if they are part of the total market in the respective year but are not included in the sample.[3] These are mainly observations related to firms that were listed in the respective year and delisted before May 2004. To deal with the resulting possibility of a survivorship bias, inverse Mills ratios from the Heckman 2-step procedure are included as a control variable. Observations are non-valid if they are included in the sample but are not used in a specific statistical analysis due to lack of data for required variables. As can be seen in Table 1, the reduced number of observations is mostly due to the lack of data for specific variables of interest, rather than by excluding delisted firms.[4]

Financial Statement data is generally provided by Datastream based on the International Financial Reporting Standards (IFRS). The riskfree interest rate is taken as the monthly rate of return on German Treasury Bills.[5] The market portfolio is approximated by the portfolio containing all sample firms. Returns are computed based on daily closing prices, ad-

[1] This is the Worldscope item WC01751.

[2] Aggregated market values are not computed due to limited data availability. For foreign shares with a cross-listing in Germany, the Datastream database uses German price data and domestic number of shares, which causes a considerable distortion of market value.

[3] The price history in case of a merger continues under the code of the company taking-over. The company which is taken over is delisted. In case of a name change, the name of the stock is changed and there is no effect on prices. In case of bankruptcy, the stock is delisted.

[4] It is further noted that firm size is included as a control variable in the data analysis.

[5] This rate is taken from the IMF, Washington, Series YQM 134 60C.

Table 1: **Sample Size**

Year	Market and Sample Observations			Observations in Analysis of Covariance (as of Total Sample)			
		Total Sample	Missing	*SUE* Analysis		*SRM* Analysis $(y+1)$	
	Total Market	(CAR Days 0 to 9)	Observations	Valid	Non-valid	Valid	Non-valid
1990	362	342	20	0	342	0	342
1991	377	360	17	118	242	131	229
1992	388	370	18	89	281	99	271
1993	394	372	22	142	230	159	213
1994	408	385	23	148	237	160	225
1995	424	402	22	162	240	165	237
1996	456	423	33	156	267	167	256
1997	491	449	42	214	235	237	212
1998	580	511	69	248	263	255	256
1999	761	654	107	301	353	308	346
2000	974	796	178	431	365	446	350
2001	1,036	831	205	497	334	536	295
2002	1,095	846	249	431	415	0	846
2003	1,182	0	1,182	0	0	0	0
Sum	8,928	6,741	2,187	2,937	3,804	2,663	4,078

The table shows the number of market, sample and missing observations as well as valid and non-valid observations in the analysis of covariance in Table 3. Total Market is defined as the number of firms listed on the Frankfurt stock exchange in the respective year as provided by the Datastream database of Thomson Financial. Total Sample is defined as the number of firms in the sample. This is the number of firms with a market capitalization exceeding one million EUR as of May 7, 2004, for which abnormal return data over an event window of 10 days is available. Missing observations are the difference between market and sample observations. Observations are valid if they have data for all variables under consideration in the analysis of covariance in Table 3 performed over an event window of 10 days (SUE analysis) or an event window of 10 days starting in the following year (SRM analysis). The following year is chosen for the SRM analysis to account for the availability of the inverse Mills ratios. Non-valid observations are the difference between valid observations and total sample observations.

justed for subsequent capital actions[6]. For each variable the upper and lower extreme 0.5 % of the distribution are replaced by the value of the upper and lower 99.5 % percentile.[7]

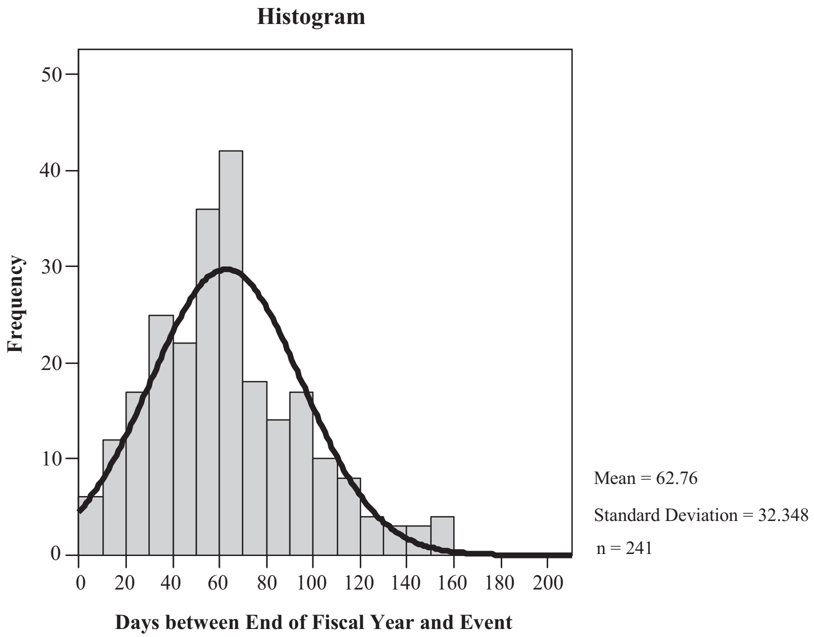
The identification of the event date[8] poses difficulties. This date is defined as the date on which earnings information is disclosed to the market. The disclosure does not have to take place in the form of an annual meeting, but can also occur in an earnings announcement (e. g. in an adhoc message) or in a presentation of financial statements at a press conference. Since identifying individual dates of earnings disclosures would be prohibitively cumbersome, this study follows the approach taken by *Francis* et al. (2003: 12), who assume that the relevant earnings information is known to the market 80 trading days after the end of the fiscal year.[9] This approach assumes that individual earnings are generally disclosed within a period of 80 trading days after the end of the fiscal year. To verify the applicability of this assumption to a German sample, the individual earnings announcement dates are obtained for a random subsample of firms from the LexisNexis database. For 241 of the 250 randomly selected firms, dates for the earnings announcements and the end of the fiscal year are available. On average, earnings announcements take place 63 trading days after the end of the fiscal year, and about 74 % of all firms disclose their earnings numbers within the assumed period of 80 trading days. Figure 1 shows the histogram of earnings announcement dates in the random sub-sample. For firms that disclose their earnings earlier than 80 trading days, the drift is underestimated. Since this underestimation reduces the magnitude of a possible drift, it does not reduce the relevance of the obtained results. To further check whether the results are affected by the 26 % of the cases in which the earnings disclosure takes place after the assumed period of 80 trading days, the significance test for the post-earnings-announcement drift is repeated for the sub-sample with individual event dates. Results are contained in Panel B of Table 2 below and indicate that the results are not

[6] Prices are adjusted for splits, consolidations, scrips/bonuses, rights, and stock dividends.

[7] Data trimming is performed since these extreme values are very likely to contain errors such as wrong decimal places, wrong sign etc. resulting from manual data input or system breaks. The qualitative information content that the particular observation is extreme is preserved by this methodology. The choice of the 99.5 % percentile as the threshold is very prudent.

[8] This date is called earnings announcement or earnings disclosure date.

[9] 80 trading days correspond to the four-month dissemination period used by *Francis* et al. (2003: 12).



The graph contains the histogram of the earnings announcement dates measured in days from the end of the corresponding fiscal year as obtained in a random sub-sample of 241 observations. The curved line represents a normal distribution.

Figure 1: Distribution of Event Dates in Random Sub-sample

affected by setting the event date to the 80th trading day after the end of the fiscal year. These results support the applicability of the assumption of *Francis* et al. (2003) that earnings information is known to market participants 80 trading days after the end of the fiscal year. The data analysis is performed in event time[10], that is, adjusted for the end of the fiscal year.[11] Since in the present sample most of the firms use the calendar year as their fiscal year, the use of event time does not inhibit the implementation of the tested trading strategy.

[10] Market betas are estimated in calendar time using the three calendar years before the most recent event.

[11] If the end of the fiscal year is not December 31, the fiscal year is associated with the calendar year, in which it ends. In 2.3 % of all cases, the end of the fiscal year falls between January 1 and May 31.

2. *Variable Computation*

a) Computation of Unexpected Earnings

Unexpected earnings serve as the explanatory variable. Three main approaches exist to compute unexpected earnings: an analyst forecast method, a time series regression method and a price-based approach. A good overview over these three techniques is contained in *Liu/Strong/Xu* (2003: 92 et seqq.). Analyst forecasts are obtained from the JCF Quant database of JCF Group; however the German dataset causes the problem that both *EBIT* and *EPS* forecasts are available only for a small fraction of the sample firms. Therefore, the last two approaches seem suitable for the present study. Earnings are represented by consolidated net income before extraordinary items and after preferred dividends. Considering the time series regression approach, several annual specifications of earnings are tested and the one with the highest R^2 is chosen. It is an AR(1) specification amended by a firm-specific effect:

$$E\left[X_{i,t}\right] = c + \phi X_{i,t-1} + \gamma_{i,\, i \neq 1} \tag{1}$$

where

$X_{i,t}$ = earnings for firm i in period t,

γ_i = firm-specific effect of firm i.

To model the expectation formation process, Formula (1) is estimated successively over the sample period starting with 280 observations for the year 1990 and then using additional data for each year as it becomes available. Standardized unexpected earnings are then given by:

$$SUE = \frac{\left(X_{i,t} - E\left[X_{i,t}\right]\right)}{\sigma_{\left(X_i - E\left[X_i\right]\right)}} \tag{2}$$

where

$X_{i,t} - E\left[X_{i,t}\right]$ = unexpected earnings for firm i in period t,

$\sigma_{\left(X_i - E\left[X_i\right]\right)}$ = standard deviation of the time series of unexpected earnings for firm i as given by Formula (1)

Since Formula (1) produces only one unique regression error in each time period, this error is unsuitable for standardizing unexpected earnings. Therefore, the standard deviation of the time series of unexpected earnings generated by iterative estimation of Formula (1) is used instead.

The results suffer from the introduced imprecision. Firms are then placed into 10 decile portfolios of equal size based on their *SUE*.

In accordance with the terminology used by *Bernard/Thomas* (1989: 4) the price-based measure of unexpected earnings is labeled security return model *(SRM)*. To compute this measure, the present study employs the cumulative abnormal returns over an estimation period before the event rather than the excess return around the event. This is done to reduce measurement error due to the imprecise identification of the event date.[12] Abnormal returns are computed using the CAPM:

$$E(R_i) - R_f = \beta_i\big(E[R_m] - R_f\big) \tag{3}$$

where

$\beta_i = \frac{\sigma_{i,m}}{\sigma_m^2}$ = the market beta of the share,

$\sigma_{i,m}$ = covariance of share *i's* return and the market return,

σ_m^2 = variance of the market return,

$R_i,\ R_f,\ R_m$ = return of share i, the risk-free rate and return of the market portfolio, respectively.

Abnormal returns are summed over the 40 trading days prior to the earnings announcement date. The 40-day period is chosen to reduce the influence of confounding events. Cumulative abnormal returns represent the price-based measure of unexpected earnings (*SRM*) and are given by:

$$SRM_{i,t} = \sum_{t=-40}^{t=-1} A_{i,t} \tag{4}$$

where $A_{i,t}$ = abnormal return of stock i at day t given by Formula (3).

In order to model the expectation formation process, Formula (3) is estimated successively over the sample period starting with 3835 monthly observations in 1990. For subsequent years, monthly data for the three most recent calendar years of data are used as the estimation sample.[13] The estimation period ends on December 31 of the calendar year preceding the earnings announcement date. Firms are allocated to 10 decile portfolios of equal size according to their *SRM*.

[12] Using cumulative abnormal returns, a mismeasurement of – say – 5 trading days only changes 5 of the 40 individual returns in the summation. The same mismeasurement changes all used daily returns under the excess return approach.

[13] The estimation period of 36 months is chosen as a trade-off between the estimation period sample size and the problems of long estimation periods.

The existing literature differs in the reported duration of the drift. *Liu/Strong/Xu* (2003: 94 et seqq.) find evidence for the drift for durations of up to 12 months, while *Defeo* (1986: 354 et seqq.) reports that the price adjustment to earnings news on average begins 5.1 days before the event and finishes 12 days after the event. Therefore, to best suit the data, abnormal returns are computed beginning 40 trading days prior to the event and extending up to 319 trading days after the event. Cumulative abnormal returns are computed for 32 different 10-day windows over this period.

b) Computation of Risk-related Variables

This section is concerned with the computation of the selected risk-related variables. The discussion in section 2 led to the consideration of the following variables: market beta, size and book-to-market ratio. Additionally, a variable to control for the momentum effect and the inverse Mills ratio from the Heckman 2-step procedure to correct for the possibility of a survivorship bias are included.

The market beta is obtained from an estimation of Formula (3) using the three most recent, complete calendar years before each event. The size effect is measured by the market value of the common shareholders' equity at the end of the fiscal year. The book-to-market ratio is computed as the ratio of the book value of common equity to the market value of common equity at fiscal year end. The computation of the momentum factor is based on the methodology of *Jegadeesh/Titman* (1993: 68), modifying it for the present purpose. These authors use the returns over the past 3, 6, 9 and 12 months as indicators for the momentum effect. Here, the returns over the 80 trading days or 4 months before the event are taken as the momentum variable. To avoid the undue influence of confounding events or of the previous year's drift a comparably short period is chosen. As with the computation of the price-based measure of unexpected earnings, the error resulting from an imprecise identification of the event date is reduced by using the cumulative returns. The momentum variable hence is:

(5) $$MOMENTUM_i = \sum_{t=-80}^{t=-1} r_{i,t}$$

where $r_{i,t}$ = share return of firm i on day t.

The inverse Mills ratios are computed according to the methodology outlined in *Heckman* (1979: 154 et seqq.) and *Wooldridge* (2003: 560 et seqq.). While no detailed information about the missing observations is available, it is reasonable to assume that observations are missing due to the delisting of the respective firm before May 2004. Therefore, sample membership is seen to be highly dependent on the financial strength of the respective firm. It is defined as a function of income, size and leverage. The probit model takes the following form:

$$P(s = 1 \mid \mathbf{z}) = G\left(\beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3\right) \tag{6}$$

where

$G(\mathbf{z}) = \Phi(\mathbf{z}) = \int\limits_{-\infty}^{z} \phi(v)dv$, the standard normal cumulative distribution function,

$\phi(\mathbf{z}) = (2\pi)^{-0.5} \exp\left(\frac{-z^2}{2}\right)$, the standard normal density function,

z = vector of explanatory variables which are:

$z_1 = \frac{OI}{AT}$ = ratio of operating income to total assets,

$z_2 = CSE$ = size measured by book value of common equity,

$z_3 = \frac{DT}{AT}$ = leverage measured by the debt-assets ratio.

Formula (6) is estimated separately for both measures of unexpected earnings, i.e. the *SUE* and *SRM* specification, and the different event windows. Based on the fitted values of Formula (6), the inverse Mills ratios are computed as:

$$\hat{\lambda}(c) = \frac{\phi(c)}{\Phi(c)} \tag{7}$$

where

$\hat{\lambda}(c)$ = Estimated inverse Mills ratio at c,

$\phi(c)$, $\Phi(c)$ = the standard normal density function and the standard normal cumulative distribution function, respectively,

$c = \hat{\beta}_o + \hat{\beta}_1 z_1 + \hat{\beta}_2 z_2 + \hat{\beta}_3 z_3$ = the fitted values from Formula (6).

The estimated inverse Mills ratios from Formula (7) serve as the control variable for a possible selection bias in the analysis of covariance.

c) Computation of Abnormal Returns

Abnormal returns finally serve as the dependent variable and are calculated using the CAPM as given in Formula (3). The CAPM is estimated using monthly firm-specific return data of the three most recent calendar years before the event.[14] The obtained firm-specific market betas are used to compute expected returns given as the fitted values and abnormal returns given as the forecast errors. Cumulative abnormal returns are computed for the range between the earnings announcement date up to 319 trading days after the event. There are 32 different return windows, which begin at the announcement date and always extend 10 more days than the previous one.[15] To simplify the execution of the drift-based trading strategy, it is assumed that equal amounts of money are invested in each share. Hence, the cumulative abnormal returns are added and averaged over all firm-years belonging to the same unexpected earnings decile portfolio:

$$CAR_j \; days \; 0 \; to \; \tau = \frac{1}{n_j} \sum_{i=1}^{i=n} \sum_{t=0}^{t=\tau} A_{i,t} \tag{8}$$

where

$CAR_j \; days \; 0 \; to \; \tau$ = average cumulative abnormal returns of the unexpected earnings decile portfolio j and $j \in \{1, 2, 3, ..., 10\}$,

n_j = number of firm years in the decile portfolio j,

τ = range of the return event window: return windows begin at event day 0 and end at trading day τ after the event, where $\tau \in \{9, 19, 29, 39, ..., 319\}$,

$A_{i,t}$ = abnormal return of firm year i at trading day t.

---

[14] The results suffer from the fact that unexpected earnings are computed for fiscal years, and market betas are estimated using calendar years. Since in most cases the fiscal year coincides with the calendar year, and since changes in the market beta are driven mainly by changes in the nature of the firm's business occurring over longer periods of time, this deviation is regarded as ineffectual. Also, *Bernard/Thomas* (1989) show that current earnings only have a small effect on the firm's beta.

[15] The results suffer from the fact that the market betas are estimated using monthly data and CAPM-based abnormal returns are computed daily. Monthly data are used to estimate betas since the relationship between firm-specific returns and market returns is assumed to be shaped by underlying firm characteristics. Daily market and firm-specific returns are seen to be dominated by idiosyncratic factors, and hence a monthly data frequency is considered suitable. Abnormal returns are computed daily to allow comparison of obtained results with the existing literature, such as *Defeo* (1986). Since changes in the market beta are generally thought to occur over longer periods of time, the imprecision introduced by using betas computed on a monthly basis to calculate daily abnormal returns is considered ineffectual.

Additionally, 4 event windows of cumulative abnormal returns are computed for the 40 trading days before the event. Each event window begins one day before the event and extends 10 more days back in time. The cumulative abnormal returns of the unexpected earnings decile portfolios and serve as the dependent variable in the data analysis.

IV. First Hypothesis: Post-Earnings-Announcement Drift in Germany

In this section the results of the significance tests for the existence of the post-earnings-announcement drift are presented. These tests are designed to investigate the hypothesis that stocks with positive (negative) surprise earnings exhibit positive (negative) abnormal returns following the earnings announcement. In section V the relationship between the considered risk-related variables and cumulative abnormal returns is examined. The nature of this hypothesis is to test whether unexpected earnings convey new information to the stock market. This approach differs from the one pursued in association studies, which test to what degree earnings numbers reflect factors that affect stock prices. In an important work, *Beaver/Lambert/Morse* (1980) develop the concept that prices reflect more information than earnings. In an efficient market, price changes incorporate the present value of the market's revision of the expected future earnings (or cash flow) stream of the firm. By comparison, due to the realization and expense matching principles, accounting earnings are a measure of the economic success generated over the historic reporting period. Hence, accounting earnings incorporate information contained in prices with a lag ("prices lead earnings"). To take this effect into account, in this study only the unexpected component of earnings is related to (abnormal) share returns.

Significance tests for the cumulative abnormal returns are conducted for the different unexpected earnings deciles and the difference between deciles 10 and 1. The results of the tests for the individual deciles are only reported for the two extreme deciles 1 and 10 but the relationship between unexpected earnings and cumulative abnormal returns for the remaining deciles 2 to 9 is accounted for in the analysis of covariance which covers all deciles. *Kritzman* (1994: 17 et seq.) points out that *CAR* are a linear combination of a random variable and computes their standard deviation using the standard deviation of abnormal returns measured over the 90 trading days preceding the event. However, a more timely measure of the standard deviation can be obtained using the decile sorting mechanism. This is the cross-sectional standard deviation of cumulative abnormal returns of the stocks within each decile. *CAR* are measured over 10-day periods, and at the end of such a period both the *CAR* and their cross-sectional standard deviation are known to market participants. Therefore, the cross-sectional standard deviation of cumulative abnormal returns will be used for the *T*-tests. *T*-ratios for the significance tests are computed in the usual way as given by *Bortz* (2005: 134 et seqq.), for example.

The test for insignificant differences of the *CAR* between deciles 10 and 1 is aimed at testing the profitability of the trading strategy of buying stocks with the most positive unexpected earnings and shortselling stocks with the most negative unexpected earnings. In the presence of the post-earnings-announcement drift this strategy is expected to yield a profit. *Bortz* (2005: 141) notes that *T*-tests for the difference of sample means assume equal population variances of the two tested samples and also suggests a correction of the degrees of freedom if this is not the case. Since equality of variance among the deciles cannot be assumed, this adjustment is applied here. Table 2 illustrates the results of the *T*-tests. The event windows are chosen up to a duration of 179 trading days. While such event windows cause the previously mentioned methodological difficulties, this approach is chosen in accordance with *Bernard/Thomas* (1989: 11) who find little evidence for a significant effect beyond this time. Panel A contains the results setting the event date to the 80^{th} trading day after the end of the fiscal year, and Panel B displays the results for the sub-sample with individual event dates.

Turning to Panel A of Table 2, the results show that the drift produces significantly positive abnormal returns for the highest decile of both sorting methods. Inconsistent with respect to this effect are the insignificant or negatively significant abnormal returns of deciles 10 over the first trading days after the event date. A likely reason for this may be a mis-specification of the event date. These low abnormal returns just after the event cause the considered trading strategy of a long position in decile 10 and a short position in decile 1 to earn insignificant returns over the first 9 days after the event for the *SUE* deciles and over the first 29 days for the *SRM* deciles. From there on, the strategy earns highly significant, positive abnormal returns, producing strong evidence for the presence of the post-earnings drift on the German market as well. In terms of statistical significance' the drift is driven by the positive abnor-

Table 2: ***T*-tests for *CAR* and *CAR* Differences of the *SUE* and *SRM* Deciles**

Panel A: Event Date 80 Trading Days after the End of the Fiscal Year

Event Window	Standardized Unexpected Earnings (*SUE*)						Security Return Model (*SRM*)					
	SUE Decile 10	*SUE* Decile 1	Avg. Diff. (10-1)	*T*-ratios of Diff.	Adjusted df	F (Linear Trend)	*SRM* Decile 10	*SRM* Decile 1	Avg. Diff. (10-1)	*T*-ratios of Diff.	Adjusted df	F (Linear Trend)
CAR Days –40 to –1	5.2147***	–2.4262**	0.0602	4.9234***	954	31.4192***						
CAR Days –30 to –1	5.4111***	–0.773	0.0398	3.6548***	950	12.1654***						
CAR Days –20 to –1	5.3606***	–2.4028**	0.0435	5.0674***	983	19.7877***						
CAR Days –10 to –1	2.29*	–1.7099*	0.0172	2.6729**	929	2.1126						
CAR Days 0 to 9	1.167	–0.6001	0.0072	1.0813	796	1.7966	–2.4318**	–0.7223	–0.008	–0.856	1218	1.5272
CAR Days 0 to 19	3.5436***	0.1071	0.0161	1.7044*	831	4.2063	–0.1581	–1.6307	0.0145	1.1766	1265	3.5836
CAR Days 0 to 29	4.6448***	–1.3357	0.0406	3.7017***	900	13.5138***	0.8187	–1.3452	0.0226	1.5579	1286	7.4236**
CAR Days 0 to 39	3.8298***	–0.8176	0.0363	2.668**	842	9.761**	1.3936	–2.4643**	0.0483	2.7834**	1290	14.5101***
CAR Days 0 to 49	4.1514***	–0.6685	0.0404	2.6734**	830	8.6804**	1.9778*	–0.7087	0.0351	1.8149*	1290	6.808**
CAR Days 0 to 59	2.9537**	–0.2916	0.0287	1.7148*	817	5.5059	2.7418**	–1.1023	0.0575	2.606**	1289	13.6202***
CAR Days 0 to 69	2.4479**	–0.2643	0.0269	1.4382	815	2.1546	3.4778***	–1.3816	0.0778	3.3326***	1306	19.2372***
CAR Days 0 to 79	2.9021**	–0.1579	0.0302	1.5562	809	3.2176	3.3008***	–0.9119	0.0682	2.8312**	1294	15.7052***
CAR Days 0 to 89	2.2867*	–0.1845	0.0266	1.3002	821	1.9207	2.8934**	–1.2133	0.0721	2.8059**	1299	15.4725***
CAR Days 0 to 99	1.9688*	–0.2545	0.0253	1.1924	815	1.0997	2.7017**	–1.0797	0.0719	2.5523**	1282	14.5428***
CAR Days 0 to 109	1.3703	0.4529	0.0068	0.2925	819	0.5864	4.1287***	0.8667	0.0641	2.0526*	1303	9.9905**
CAR Days 0 to 119	1.6639*	–0.0883	0.0219	0.8849	804	0.0727	3.6097***	1.4183	0.0411	1.2313	1289	3.8257
CAR Days 0 to 129	1.8397*	–0.2534	0.0271	1.1284	816	0.1982	3.8831***	1.5101	0.0423	1.2238	1261	4.0502
CAR Days 0 to 139	2.1919*	–0.3434	0.0338	1.3607	803	0.7734	3.2131***	1.3714	0.0327	0.9207	1262	2.7532
CAR Days 0 to 149	2.4288**	–0.4975	0.041	1.5988	797	1.4769	2.7172**	1.7732*	0.0059	0.1547	1209	0.4737
CAR Days 0 to 159	2.6591**	–0.5846	0.0472	1.8366*	825	1.9268	2.7936**	2.1139*	–0.0059	–0.1469	1182	0.0005
CAR Days 0 to 169	2.3505**	–0.847	0.051	1.9246*	838	2.477	2.6996**	1.8072*	0.0021	0.0511	1182	0.0004
CAR Days 0 to 179	2.9524**	–0.9374	0.0643	2.3119*	839	4.6806	2.9026**	1.7328*	0.0097	0.222	1179	0.0245
CAR Days $(y+1)$ 0 to 9	–0.2653	–0.023	–0.0008	–0.1006	553	0.1044	–1.1412	–3.3864***	0.0174	1.9739*	1009	3.8534
CAR Days $(y+1)$ 0 to 19	1.6279	–0.7142	0.0162	1.5302	671	0.2578	–0.179	–2.6446**	0.0226	1.9964*	1001	3.3619
CAR Days $(y+1)$ 0 to 29	2.122*	–1.7841*	0.0335	2.7046**	666	3.3504	–0.8131	–1.5694	0.0104	0.7332	1013	0.5016
CAR Days $(y+1)$ 0 to 39	1.8151*	–0.8017	0.0255	1.6522*	618	1.0024	–0.3083	–0.3177	0.001	0.0566	1018	0.1106
CAR Days $(y+1)$ 0 to 49	1.277	–0.0844	0.0125	0.7173	596	0.1874	0.2416	0.5374	–0.005	–0.2575	1038	0.5721
CAR Days $(y+1)$ 0 to 59	0.8509	0.544	–0.0025	–0.1241	540	1.851	0.0424	0.7667	–0.0135	–0.5908	989	1.213

Panel B: Case-Specific Individual Event Dates

Event Window	Standardized Unexpected Earnings (*SUE*)						Security Return Model (*SRM*)					
	SUE Tercile 3	*SUE* Tercile 1	Avg. Diff. (3-1)	*T*-ratios of Diff.	Adjusted df	P-value of *T* (Diff.)	*SRM* Tercile 3	*SRM* Tercile 1	Avg. Diff. (3-1)	*T*-ratios of Diff.	Adjusted df	P-value of *T* (Diff.)
CAR Days –40 to –1	0.5353	–1.8243*	0.0937	1.8132*	57	0.0375						
CAR Days –30 to –1	–0.121	–0.4924	0.0224	0.3859	48	0.3506						
CAR Days –20 to –1	–0.6653	–1.0404	0.0189	0.4946	58	0.3114						
CAR Days –10 to –1	–0.3763	–1.5652	0.0244	0.927	66	0.1786						
CAR Days 0 to 9	1.1284	–0.8731	0.0452	1.3709	58	0.0878	–0.7591	0.3776	–0.0251	–0.7333	58	0.2332
CAR Days 0 to 19	0.9372	–0.1816	0.0291	0.6012	48	0.2753	–0.9348	0.2915	–0.0371	–0.6752	49	0.2514
CAR Days 0 to 29	0.8757	–0.1943	0.0309	0.6298	53	0.2658	–0.983	0.2061	–0.0393	–0.6704	54	0.2527
CAR Days 0 to 39	0.6601	–0.6045	0.0465	0.862	53	0.1963	–1.2921	–0.7624	0.0062	0.0977	50	0.4613
CAR Days 0 to 49	0.9298	–0.9159	0.0775	1.2851	57	0.102	–1.0514	–0.5671	0.0024	0.0358	50	0.4858
CAR Days 0 to 59	1.3761	–1.308	0.1294	1.772*	45	0.0416	–0.9126	–1.2041	0.0664	0.7847	44	0.2184
CAR Days 0 to 69	2.3204*	–1.3254	0.1597	2.2785*	49	0.0135	–0.2789	–0.7886	0.05	0.6199	46	0.2692
CAR Days 0 to 79	2.2411*	–1.5632	0.1898	2.4081*	47	0.01	–0.8622	–1.0696	0.0529	0.6042	48	0.2743
CAR Days 0 to 89	2.0913*	–1.3137	0.194	2.1945*	51	0.0164	–0.5668	–0.8628	0.0579	0.6424	41	0.2621
CAR Days 0 to 99	1.8879*	–2.1937*	0.2715	2.8203**	48	0.0035	–1.1094	–1.5864	0.0983	1.0056	47	0.1599
CAR Days 0 to 109	1.873*	–1.9607*	0.2516	2.6494**	52	0.0053	–0.5221	–1.3799	0.1021	1.0724	46	0.1446
CAR Days 0 to 119	1.9012*	–1.6308	0.2578	2.3894*	53	0.0102	0.4851	–1.1125	0.1325	1.2238	42	0.1139
CAR Days 0 to 129	2.2697*	–1.7	0.2845	2.6504**	54	0.0053	0.4866	–1.0564	0.1279	1.1714	42	0.124
CAR Days 0 to 139	1.6266	–1.6028	0.2505	2.2469*	57	0.0143	0.0477	–0.8153	0.0886	0.7906	42	0.2168
CAR Days 0 to 149	1.1812	–0.9768	0.1661	1.4939	59	0.0703	–0.7881	–0.0845	–0.021	–0.1904	42	0.425
CAR Days 0 to 159	0.8891	–0.3415	0.0935	0.7966	58	0.2145	–1.5618	0.5797	–0.1272	–1.0882	42	0.1414
CAR Days 0 to 169	1.5439	–0.3054	0.1373	1.0737	53	0.1439	–1.7645*	0.4083	–0.1313	–1.0117	43	0.1587
CAR Days 0 to 179	1.2546	–0.4249	0.1408	1.0382	54	0.1519	–1.2426	0.1619	–0.091	–0.651	46	0.2591
CAR Days $(y+1)$ 0 to 9	–0.2426	0.2411	–0.0119	–0.3421	54	0.3668	1.9531*	0.6312	0.0266	0.7499	59	0.2282
CAR Days $(y+1)$ 0 to 19	–0.1318	0.6736	–0.027	–0.6044	52	0.2741	0.5058	1.3999	–0.0318	–0.7172	60	0.238
CAR Days $(y+1)$ 0 to 29	–0.5436	–0.1151	–0.0158	–0.3093	54	0.3791	1.8943*	0.5058	0.0372	0.8354	59	0.2034
CAR Days $(y+1)$ 0 to 39	–0.8551	–0.2948	–0.0226	–0.356	54	0.3616	1.1603	–0.2293	0.0492	0.8783	57	0.1917
CAR Days $(y+1)$ 0 to 49	–1.029	–0.7137	–0.0216	–0.3023	54	0.3818	1.1488	–1.2651	0.1093	1.6861	55	0.0487
CAR Days $(y+1)$ 0 to 59	–1.7054	–0.8931	–0.0709	–0.8375	51	0.2031	0.3047	–1.0778	0.0824	1.0676	51	0.1454

Continue page 72

Table 2: Continued

Panel A contains the results with the event date set at the 80th trading day after the end of the fiscal year. Panel B contains the results for the random sub-sample with individually obtained event dates. In Panel A, The first 6 columns present the results for the standardized unexpected earnings (SUE) deciles. The remaining 6 columns contain the results for the security return model *(SRM)*. Under the *SRM* method, no tests over the anticipation period are performed, since the *SRM* method sorts firm years according to their cumulative abnormal returns *(CAR)* over this period. For each sorting method, the first 2 columns contain T-ratios of the H_0: average *CAR* of the respective deciles (*SUE* or *SRM*) are zero over the indicated event windows. The standard deviation of the *CAR* is obtained using the cross-sectional standard deviation of cumulative abnormal returns within each decile measured over the corresponding event window. The next 3 columns contain test results of the H_0: average *CAR* of the respective decile (*SUE* or *SRM*) 10 equal those of decile 1 over the indicated event windows. The H_1 is that the *CAR* of decile 10 exceed those of decile 1. The last columns in each section display the F-statistic from an univariate analysis of variance with the *CAR* of the respective event period as the dependent variable and the *SUE* or *SRM* deciles as the explanatory variable. The F-statistics refer to the significance of a linear trend over all deciles as an a-priori contrast.

The first group of rows displays the test results over the 40 days before the event, the second groups of rows shows the results of tests performed over the 179 days after the event and the third group of rows contains the test results for the 59 trading days starting after the following earnings announcement, which takes place about 260 trading days after the current event. The population standard deviation of cumulative abnormal returns over each event window is estimated as a weighted average of the observed standard deviations of abnormal returns within deciles 10 and 1:

$$\hat{\sigma}_{CAR} = \sqrt{\frac{(n_{10}-1)s_{10}^2 + (n_1-1)s_1^2}{(n_{10}-1)+(n_1-1)}}$$

where s_{10}^2, s_1^2 are the cross-sectional variances of cumulative abnormal returns of deciles 10 and 1 measured over the respective event window and n_10, n_1 are the sizes of deciles 10 and 1. The standard deviation of the *CAR* difference between deciles 10 and 1 for the respective event window is obtained by

$$\hat{\sigma}_{\overline{CAR}_{10}-\overline{CAR}_1} = \sqrt{\hat{\sigma}_{CAR}^2} \cdot \sqrt{\frac{1}{n_{10}} + \frac{1}{n_1}}.$$

Significance is indicated as follows: (***) = significant at 0.1 %, (**) = significant at 1 %; (*) = significant at 5 %. To account for the possibility of different treatment group variances in the analysis of variance, the critical significance level is lowered to 1 % for the F-test of the linear trend.

Panel B repeats the analysis for the random sub-sample of 241 observations for which individual event dates are available. The analysis is repeated in order to investigate whether the findings in Panel A are affected by the fact that within the sub-sample about 26 % of firms do not disclose their earnings within 80 trading days after the end of the fiscal year. To provide a sufficient number of observations in order to allow the application of the central limit theorem, observations are grouped into terciles rather than deciles. The adjusted degrees of freedom are given and the test for a linear trend is omitted.

mal returns of deciles 10 rather than by the negative returns of deciles 1. A reason for this may be found in shortselling restrictions making it difficult to execute the short position of the trading strategy. The data confirm a strong anticipation effect. Across the 40 days prior to the event the trading strategy earns highly significant abnormal returns. Indeed, the highest cumulative abnormal returns occur over the total of the 40 days before the event. This is consistent with numerous studies starting with *Ball/Brown* (1968) which come to the conclusion that a large part of the total drift occurs over the anticipation period. It further corresponds with the notion of "prices leading earnings" mentioned above.

The duration of the drift is difficult to infer from Table 2. For the *SUE* deciles the strategy ends earning significant abnormal returns after 59 trading days following the event. For the *SRM* deciles the trading strategy stops being profitable 109 trading days after the event. Finally, the significance of the linear trend within the analysis of variance strongly supports the findings. This supports the result obtained by *Beaver/Clarke/Wright* (1979: 327 et seqq.) that an increase in unexpected earnings implies an increase in cumulative abnormal returns. Regarding the succeeding earnings announcement, the results in Table 2 produce no support for the result of *Bernard/Thomas* (1990: 315 et seq.) that a reversal of returns can be seen one year after the initial event. After the succeeding event the returns to the trading strategy are close to zero and most of them are insignificant. The few significant abnormal returns are actually positive. The linear trend remains insignificant indicating that there is no linear relationship between unexpected earnings decile membership and cumulative abnormal returns. Hence, the finding of *Bernard/Thomas* (1990, 315 et seq.) can neither be rejected nor confirmed using annual German data.

To verify whether these results are affected by the definition of the event date as the 80^{th} trading day after the end of the fiscal year, the significance tests for the *CAR* are repeated using the sub-sample for which individual earnings announcement dates are obtained. Panel B contains these results. For 121 of the 241 cases with earnings announcement date information, cumulative abnormal returns are available. The Panel illustrates that the drift can also be verified using individual event dates. Standardized unexpected earnings (*SUE*) produce positive and highly significant differences between terciles 3 and 1 for 59 to 139 trading days after the event. For the *SRM* measure, the differences remain positive and lie right at the margin of significance, with *p*-values of 11.4% and

12.4 % for 119 and 129 days after the event. These high p-values are likely to be caused by the small number of observations available. Using individual announcement dates, it takes somewhat longer until the *SUE* terciles display significant abnormal returns than using the fixed event date. This supports the result of Figure 1 that in the majority of cases, earnings are disclosed earlier than 80 trading days after the end of the fiscal year.

Combined, the cumulative abnormal returns of the *SUE* and *SRM* deciles indicate that the data contain strong evidence for the presence of the post-earnings-announcement drift with a duration of about 59 to 109 trading days after the (fixed) earnings announcement date. In Panel A, both the *SUE* and *SRM* sorting of firm years produce a drift of similar duration and magnitude. For the *SUE* sorting, the differences stop being significant 59 trading days after the event, reaching about 3 %. Similarly, for the *SRM* deciles, the differences are no longer significant 109 trading days after the event, amounting to about 6 %. This evidence confirms results of previous studies. *Foster/Olsen/Shevlin* (1984) as well as *Bernard/Thomas* (1989) conclude that the majority of the drift occurs within 60 trading days after the event, with *Bernard/Thomas* (1989) finding only very little evidence for the drift after 180 trading days.

V. Second Hypothesis: Explanatory Power of Risk-Related Variables

In this section the test results regarding the second hypothesis are presented and discussed. This hypothesis postulates that the previously established relationship between unexpected earnings and abnormal returns disappears once the risk-related variables and the control variables are included in the investigation. The hypothesis is investigated in the following way. First, an analysis of covariance is used to control for the effects of the variables size, book-to-market ratio, momentum and the inverse Mills ratio. Then, the returns of the trading strategy of a long position in the stocks within the highest unexpected earnings decile and a short position in the stocks within the lowest unexpected earning decile are recomputed for sub-samples of the variables size and book-to-market ratio.

1. Analysis of Covariance

The analysis of covariance is used to examine the relationship between the membership of an unexpected earnings decile and the cumulative abnormal returns after controlling for the risk-related variables size and book-to-market ratio, the momentum effect and the possibility of a survivorship bias. Under the second hypothesis it is expected that the relationships between these variables and the cumulative abnormal returns are significant, and the relationship between the unexpected earnings and the cumulative abnormal returns becomes insignificant when controlling for these variables. Table 3 below contains the key results of the analysis of covariance. To account for the possibility of non-linear relationships between risk-related variables and cumulative abnormal returns, multiplicative dummy variables are included that take the value of one if the respective observation has a value below the median.

Prior to the data interpretation it is noted that results for the inverse Mills ratios in panel B are only given for event windows following the succeeding event. This is done since there are no firms leaving the sample used for the *SRM* deciles over the 179 trading days following the current event. The linear trend is repeated here from Table 2 to compare the results with the case when no control variables are included.

Considering the risk-related variables size and book-to-market ratio, a significant relation with abnormal returns can only be seen for the *SUE* deciles and for the book-to-market ratio. Over the 40 days preceding the event, the book-to-market ratio has explanatory power with respect to abnormal returns. However, the influence of unexpected earnings is robust to this effect. Over the time periods following the event, only the multiplicative dummy variable produces significant coefficients, suggesting that an effect of the risk-related variable book-to-market ratio can only be identified for the sub-sample with low unexpected earnings. It is reasonable to assume that the unexpected low earnings performance has changed the firm's exposure to the risk factor underlying the book-to-market ratio and hence the risk premia that the market demands.

No significant results are obtained for the *SRM* deciles and for the risk-related variable size. One exception is the event window of 109 days, over which a significant effect of the market value of equity is obtained for the *SRM* deciles. However, this one significant F-ratio is unlikely to point to a systematic influence of the variable size since the variable size produces no significant effect for all other event windows over which the *SRM* dec-

Table 3: **Analysis of Covariance of Cumulative Abnormal Returns**

Panel A: Standardized Unexpected Earnings (SUE)

Event Window	Linear Trend	Size	D_Size	BE/ME	D_BE/ME	Momentum	Inverse Mills Ratio	*SUE* Decile
CAR Days –40 to –1	31.4192***	0.5112	1.2248	7.7689**	0.9594	18.0573***		2.7648**
CAR Days –30 to –1	12.1654***	0.1574	0.3181	6.572	2.5286	18.6028***		2.4792**
CAR Days –20 to –1	19.7877***	2.591	1.2382	10.1381**	1.0346	2.2031		2.9496**
CAR Days –10 to –1	2.1126	0.0395	0.3295	10.0368**	0.9068	26.7027***		1.0398
CAR Days 0 to 9	1.7966	3.0569	0.0226	0.0065	3.1306	14.2863***	2.305	1.8022
CAR Days 0 to 19	4.2063	3.5004	0.0009	0.1486	1.7985	4.0963	0.8438	1.5428
CAR Days 0 to 29	13.5138***	2.423	0.0526	1.2939	1.7067	0.8987	0.7139	2.0287
CAR Days 0 to 39	9.761**	1.9658	0.6258	2.7517	7.1931**	7.9091**	3.2804	1.844
CAR Days 0 to 49	8.6804**	0.1842	0.2347	1.7942	8.5489**	7.7725**	0.5244	1.8838
CAR Days 0 to 59	5.5059	0.3497	0.1471	0.4384	4.5809	11.1775***	0.0072	1.2935
CAR Days 0 to 69	2.1546	0.1309	0.5426	0.736	6.8955**	12.3524***	0.9945	1.3358
CAR Days 0 to 79	3.2176	0.2001	0.559	0.2934	1.602	7.6961**	1.3499	1.2925
CAR Days 0 to 89	1.9207	0.3017	1.214	0.4461	5.5047	6.0982	0.261	1.0154
CAR Days 0 to 99	1.0997	0.1772	1.2383	0.5738	3.9386	7.0243**	0.986	1.0861
CAR Days 0 to 109	0.5864	0.0867	1.2376	2.1638	2.9678	13.4173***	3.384	1.5119
CAR Days 0 to 119	0.0727	0.5204	2.1038	1.5853	4.0997	8.1282**	5.4188	1.3376
CAR Days 0 to 129	0.1982	1.5075	0.6057	4.7086	6.7673**	9.1633**	6.4001	1.2422
CAR Days 0 to 139	0.7734	1.8174	0.612	4.542	7.9075**	8.9751**	5.8786	1.1667
CAR Days 0 to 149	1.4769	2.9065	0.2764	2.2671	7.2643**	6.7578**	6.5754	1.4428
CAR Days 0 to 159	1.9268	3.1851	0.0383	3.6822	8.3801**	7.9493**	7.4239**	1.6945
CAR Days 0 to 169	2.477	2.974	0.004	2.9938	7.057**	5.8066	8.158**	1.8113
CAR Days 0 to 179	4.6806	5.2403	0.1559	2.8867	5.7277	7.2738**	8.3985**	1.8028
CAR Days $(y+1)$ 0 to 9	0.1044	2.3531	0.0292	0.0195	0.193	14.2908***	0.6409	1.4007
CAR Days $(y+1)$ 0 to 19	0.2578	2.2234	0.0009	0.7928	2.8084	6.0359	0.0981	1.4355
CAR Days $(y+1)$ 0 to 29	3.3504	4.6183	0.0012	0.2134	1.6885	1.3851	1.5221	2.0084

Panel A: Standardized Unexpected Earnings (SUE)

Event Window	Linear Trend	Size	D_Size	BE/ME	D_BE/ME	Momentum	Inverse Mills Ratio	*SUE* Decile
CAR Days $(y+1)$ 0 to 39	1.0024	3.1815	0.0014	0.7718	1.7708	2.3298	1.4831	1.6416
CAR Days $(y+1)$ 0 to 49	0.1874	1.3489	0.0115	0.0096	0.6419	1.8106	0.5692	1.9163
CAR Days $(y+1)$ 0 to 59	1.851	0.1439	0.0306	0.2964	0.032	4.4262	0.5919	1.1544

Panel B: Security Return Model (SRM)

Event Window	Linear Trend	Size	D_Size	BE/ME	D_BE/ME	Momentum	Inverse Mills Ratio	*SUE* Decile
CAR Days –40 to –1								
CAR Days –30 to –1								
CAR Days –20 to –1								
CAR Days 0 to 9	1.5272	1.9603	0.4248	6.5835	1.4657	14.4095***		3.2173***
CAR Days 0 to 19	3.5836	2.2124	0.0989	1.5599	0.2039	1.7951		1.2155
CAR Days 0 to 29	7.4236**	2.3285	0.9906	0.4063	0.9631	0.1845		1.5234
CAR Days 0 to 39	14.5101***	3.0337	2.66	1.6798	0.5196	6.5046		1.5513
CAR Days 0 to 49	6.808**	0.4523	0.769	3.0677	0.3055	5.548		1.2455
CAR Days 0 to 59	13.6202***	0.0762	1.6109	1.0626	0.2913	7.4163**		2.6736**
CAR Days 0 to 69	19.2372***	1.6157	2.3573	3.729	0.2536	9.2591**		1.7461
CAR Days 0 to 79	15.7052***	0.8929	1.0542	2.848	0.0943	6.6244		1.8561
CAR Days 0 to 89	15.4725***	0.4193	0.7707	0.6435	1.3197	3.6945		2.1338
CAR Days 0 to 99	14.5428***	2.0733	2.2048	0.0012	2.6124	4.3959		2.3218
CAR Days 0 to 109	9.9905**	6.6774**	1.8836	0.9677	2.7286	11.701***		2.9165**
CAR Days 0 to 119	3.8257	3.0504	1.7903	0.0444	0.3194	7.293**		1.8341

Continue page 78

Table 3: Continued

Panel B: Security Return Model (SRM)

Event Window	Linear Trend	Size	D_Size	BE/ME	D_BE/ME	Momentum	Inverse Mills Ratio	*SUE* Decile
CAR Days 0 to 129	4.0502	0.7564	1.1688	0.1812	0.2634	7.7182**		2.4272**
CAR Days 0 to 139	2.7532	0.5083	1.3465	0.1598	0.3416	7.7558**		1.7405
CAR Days 0 to 149	0.4737	0.0619	1.3459	0.1221	0.2716	5.7586		1.1341
CAR Days 0 to 159	0.0005	0.0148	0.6048	0.0199	0.5218	7.9524**		1.1471
CAR Days 0 to 169	0.0004	0.0131	1.1526	0.0201	0.8367	5.8703		1.2973
CAR Days 0 to 179	0.0245	0.0729	1.5069	0.2772	1.1258	7.8992**		1.7451
CAR Days $(y+1)$ 0 to 9	3.8534	0.6809	0.8055	2.5494	1.6561	13.6034***	0.0259	0.751
CAR Days $(y+1)$ 0 to 19	3.3619	0.9912	0.4512	0.3196	0.0193	4.8229	0.011	1.3311
CAR Days $(y+1)$ 0 to 29	0.5016	1.0234	0.6412	0.0046	2.2817	2.5043	0.0093	1.4526
CAR Days $(y+1)$ 0 to 39	0.1106	0.1917	1.167	0.001	0.5206	4.411	0.1216	1.2827
CAR Days $(y+1)$ 0 to 49	0.5721	0.0112	0.9241	1.0491	0.2877	3.3946	0.3546	0.6519
CAR Days $(y+1)$ 0 to 59	1.213	0.1105	0.8662	0.0133	0.304	6.1334	0.0001	0.4652

Panel A contains the test results for the standardized unexpected earnings *(SUE)*, and panel B contains the results for the security return model *(SRM)*. For the *SRM*, no test results are obtained for the pre-event period since the *SRM* methodology consists of sorting observations according to their abnormal returns over this period. The first column in each panel repeats the F-statistic of the significance test of a linear trend between the unexpected earnings portfolio membership and the cumulative abnormal returns *(CAR)* without the control variables as contained in Table 2. The following 4 columns display the results of the significance tests of the risk-related variables size and book-to-market ratio. Size is the market value of common equity at fiscal year end and BE/ME is the ratio of the book value of common equity to the market value of common equity at fiscal year end. For both of these variables a slope dummy variable is used to model possible nonlinearity. The dummy variable is equal to 1 for the lower half of the unexpected earnings sample. The following two columns contain the F-statistics regarding the momentum and the survivorship bias control variables. Finally, the last column displays the F-statistics for the *SUE* or *SRM* deciles as the ordinal explanatory variable after including the control variables. The event date is 80 trading days after the end of the fiscal year. Significance is indicated as follows: (***) = significant at 0.1%, (**) = significant at 1%. To account for the possibility of different treatment group variances in the analysis of covariance, the critical significance level is lowered to 1% and significance at the 5% level is not reported.

iles remain significant. An explanation of the insignificant F-statistics of the book-to-market ratio for the *SRM* deciles in comparison with the significant results for the *SUE* deciles can be seen in the computation of the unexpected earnings according to the security return model. Since this model is based on market returns, it has a higher correlation with the demanded risk premia. This causes difficulties in identifying changes in the exposure to the risk factor represented by the book-to-market ratio as the consequence of poor earnings performance.

The control variables momentum and survivorship bias are significant. Significant F-statistics of the inverse Mills ratios indicate the presence of a survivorship bias over the respective event windows. This is only the case for the *SUE* deciles and for longer event windows with a duration of 160 trading days or more. It is intuitively reasonable to assume that the statistical effect of firms leaving the sample in a non-random way increases with increasing length of the event windows. In opposition to this interpretation, the inverse Mills ratios over the time periods after the following event remain insignificant. It should be noted here that for the event windows following the succeeding event, the inverse Mills ratios were computed over the entire period beginning with the current year. The cumulative abnormal returns following the next earnings announcement are measured over a different time period and hence are not associated with the likelihood of leaving the sample over the time period before the succeeding event. To verify this explanation, additional tests are computed in which the cumulative abnormal returns are also measured over the complete time period starting from the current event. For the sake of brevity, these results are omitted here and show that the inverse Mills ratios are highly significant for the cumulative abnormal returns over these event windows.

The fact that there is no significant survivorship bias for the *SRM* deciles can be attributed to the different data requirements of the two approaches. The *SRM* approach only requires stock return data, whereas the *SUE* approach also requires financial statement data. This higher data requirement causes a higher likelihood of missing observations. When assessing the importance of the survivorship bias, the results from Table 2 should be kept in mind. The table demonstrates that the duration over which the drift is significant ranges from 59 trading days for the *SUE* deciles to 109 trading days for the *SRM* deciles; in other words, the duration of the drift remains below the time period over which the survivorship bias starts being significant. This casts doubt on the interpretation of the drift as a result of the bias introduced in the sample due to missing observations. The explanatory effect of the momentum effect for the post-earnings-announcement drift shows that firms with positive past returns tend to have positive unexpected earnings and firms with negative past returns tend to have negative unexpected earnings.

The combined effect of the inclusion of the risk-related variable size and book-to-market ratio as well as the control variables for the momentum effect and the survivorship bias is presented in the last columns of Panels A and B, which contain the F-ratios for the unexpected earnings deciles. For the *SUE* deciles in Panel A, it can be seen that the combined effect does indeed cause the unexpected earnings decile membership to become insignificant in explaining the variation of cumulative abnormal returns. These F-statistics show that there are no significant differences in the cumulative abnormal returns across the 10 unexpected earnings deciles. For the *SRM* deciles in Panel B the explanatory effect is lower. The drift remains significant here, but the significance decreases considerably compared to that of the linear trend without control variables.

Concluding the examination it can be summarized that the results contained in Table 3 do not support a risk-based explanation for the post-earnings-announcement drift. Only for firm years with low standardized unexpected earnings does the book-to-market ratio have explanatory power for the cross-sectional differences in cumulative abnormal returns. Insignificant results are obtained for the variable size and for the security return model of unexpected earnings. The inverse Mills ratios do not indicate a strong survivorship bias over the relevant event windows of up to 109 trading days after the event. Finally, the momentum variable is highly significant for most of the event windows for both the *SUE* and the *SRM* deciles. It can even be identified after the succeeding earnings announcement. This means that the performance before the earnings announcement is significant in explaining the variation of cumulative abnormal returns following the earnings announcement. *Jegadeesh/Titman* (1993: 86 et seqq.) find that the earnings announcement date returns of the high return firms exceed those of the low return firms by 0.7% on average and further find that that the returns measured over the 3 trading days around earnings announcements account for 25% of the total return of a six-month buy-and-hold strategy within stocks with extreme high and extreme low past returns. They explain this with a systematic underreaction of stock prices to information about future earnings. The results obtained in Table 3 also agree with the conclusions drawn by *Chan/Jegadeesh/Lakonishok* (1996: 1705 et seqq.). Their results indicate that the momentum and unexpected earnings variables have a high explanatory power with respect to the drift, and the portfolio variables *SMB* and *HML* mimicking *Fama/French* (1996) remain insignificant.

All these findings suggest that market participants do not fully recognize the implications of current earnings for future earnings, as *Bernard/ Thomas* (1990) conclude. Further, they support the conjecture that markets fail to recognize fully the implications of other information used to forecast future earnings. From this follows that not only after an earnings announcement is there a gradual incorporation of the information conveyed to the market by the earnings disclosure, but also that markets only gradually or partially incorporate information useful for forecasting earnings before that disclosure.

2. Sub-Samples Based on Size and Book-to-Market Ratio

A drawback of the analysis of covariance is that it cannot be used to compute the abnormal returns for the trading strategy of a long position in the highest unexpected earnings decile and a short position in the lowest unexpected earnings decile after inclusion of the risk-related variables and control variables. The reason for this is that the cumulative abnormal returns adjusted for the control variables can be interpreted as being statistically independent of these variables but are unobtainable in capital markets. In Table 3 it was found that the variables size and book-to-market ratio have no systematic explanatory power regarding cumulative abnormal returns. In order to investigate whether this also holds for the returns to the arbitrage portfolio of a long position in decile 10 and a short position in decile 1, the returns to the trading strategy are computed for sub-samples based on these two variables. If the differences with respect to size and book-to-market ratio influenced the returns to the trading strategy, then the returns computed within sub-samples should be lower than those computed using the entire sample. This is so since in the sub-samples one particular variable that contributes to the returns of the strategy under the null hypothesis is kept constant, or at least its variation is reduced considerably. The sample is therefore divided in three size-based sub-samples (small, medium, large) and three book-to-market-based sub-samples (low, medium, and high). Returns to the trading strategy of a long position in the stocks within the highest unexpected earnings decile and a short position in the stocks within the lowest unexpected earning decile are computed as in section IV and reported for different event windows. The results are summarized below in Table 4.

Table 4: **Trading Strategy Returns for Size and Book-to-Market Sub-samples**

Panel A:	ME = small		ME = medium		ME = large		BE/ME = low		BE/ME = medium		BE/ME = high	
SUE Deciles Event Window	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.
CAR Days –40 to –1	0.062	2.2362*	0.079	3.3272***	0.020	1.2059	0.062	2.447**	0.037	1.9179*	0.100	4.2033***
CAR Days –30 to –1	0.053	2.207*	0.047	2.1559*	0.007	0.438	0.027	1.2505	0.035	1.9141*	0.075	3.5074***
CAR Days –20 to –1	0.042	2.1579*	0.064	3.6518***	0.020	1.7623*	0.051	2.9335**	0.025	1.8587*	0.074	4.4054***
CAR Days –10 to –1	0.010	0.71	0.031	2.391**	0.005	0.5435	0.015	1.1233	0.024	2.3884**	0.025	1.9743*
CAR Days 0 to 9	0.012	0.8113	0.016	1.2331	0.006	0.6634	0.009	0.9512	0.014	1.3308	0.002	0.1621
CAR Days 0 to 19	0.000	–0.0011	0.046	2.464**	0.016	1.3966	0.038	2.6771**	0.033	2.1567*	–0.017	–0.8493
CAR Days 0 to 29	0.029	1.2347	0.064	3.0177**	0.041	2.918**	0.070	3.9913***	0.052	3.0851**	0.000	–0.0148
CAR Days 0 to 39	0.021	0.6864	0.068	2.6257**	0.046	2.7362**	0.081	3.6939***	0.051	2.4899**	–0.013	–0.4567
CAR Days 0 to 49	0.009	0.2733	0.095	3.4432***	0.039	2.0904*	0.086	3.6181***	0.059	2.5165**	–0.020	–0.6318
CAR Days 0 to 59	–0.026	–0.7417	0.092	2.8162**	0.019	0.945	0.065	2.3137*	0.050	2.0589*	–0.033	–0.9768
CAR Days 0 to 69	–0.037	–0.9242	0.104	2.9515**	0.023	0.9362	0.071	2.2531*	0.030	1.1218	–0.028	–0.7378
CAR Days 0 to 79	–0.037	–0.9119	0.127	3.3769***	0.013	0.537	0.086	2.6559**	0.019	0.6517	–0.013	–0.3341
CAR Days 0 to 89	–0.033	–0.7733	0.106	2.6573**	0.017	0.6458	0.081	2.3758**	0.005	0.151	–0.015	–0.3667
CAR Days 0 to 99	–0.059	–1.3104	0.115	2.8698**	0.026	0.934	0.092	2.5634**	–0.004	–0.1313	–0.033	–0.7791
CAR Days 0 to 109	–0.081	–1.6887*	0.105	2.304*	0.018	0.5491	0.061	1.5122	–0.001	–0.0399	–0.053	–1.1299
CAR Days 0 to 119	–0.108	–2.1118*	0.133	2.8199**	0.068	1.9998*	0.106	2.4253**	0.020	0.5367	–0.060	–1.2024
CAR Days 0 to 129	–0.075	–1.4932	0.106	2.3282*	0.061	1.7642*	0.106	2.5065**	0.016	0.448	–0.036	–0.7548
CAR Days 0 to 139	–0.069	–1.3325	0.122	2.5417**	0.046	1.3602	0.112	2.6216**	0.021	0.5567	–0.039	–0.769
CAR Days 0 to 149	–0.076	–1.4158	0.144	2.9361**	0.064	1.8731*	0.117	2.6717**	0.044	1.16	–0.034	–0.6403
CAR Days 0 to 159	–0.054	–0.9953	0.135	2.8183**	0.068	1.9146*	0.117	2.6728**	0.049	1.2528	–0.016	–0.302
CAR Days 0 to 169	–0.041	–0.7241	0.141	2.9077**	0.069	1.86*	0.106	2.3159*	0.056	1.3961	0.002	0.0388
CAR Days 0 to 179	–0.035	–0.6115	0.155	2.9781**	0.080	2.0217*	0.122	2.5138**	0.075	1.7624*	0.005	0.0846
CAR Days $(y+1)$ 0 to 9	–0.006	–0.3642	–0.012	–0.6782	0.010	1.1002	–0.027	–1.8353*	0.007	0.4961	0.003	0.1616
CAR Days $(y+1)$ 0 to 19	0.002	0.1192	0.015	0.6469	0.015	1.0942	–0.002	–0.1058	0.004	0.1596	0.024	1.2397
CAR Days $(y+1)$ 0 to 29	0.033	1.3522	0.034	1.2808	0.030	1.722*	0.010	0.45	0.028	1.1269	0.051	2.3072*
CAR Days $(y+1)$ 0 to 39	0.040	1.1267	0.027	0.9281	0.025	1.3306	–0.001	–0.0225	0.018	0.6447	0.054	1.8948*
CAR Days $(y+1)$ 0 to 49	0.035	0.9625	0.020	0.5994	0.009	0.4367	–0.017	–0.5622	0.011	0.3644	0.056	1.8226*
CAR Days $(y+1)$ 0 to 59	0.014	0.2995	0.005	0.1392	–0.007	–0.3136	–0.030	–0.8765	0.010	0.3139	0.032	0.7789
avg. Diff. to total Sample	*–0.043*		*0.0488*		*0.001*		*0.028*		*–0.001*		*–0.026*	

Panel B:	ME = small		ME = medium		ME = large		BE/ME = low		BE/ME = medium		BE/ME = high	
SRM Deciles Event Window	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.	Avg. Diff. (10–1)	*T*–ratios of Diff.
CAR Days –40 to –1												
CAR Days –30 to –1												
CAR Days –20 to –1												
CAR Days –10 to –1												
CAR Days 0 to 9	–0.034	–2.1676*	–0.022	–1.3616	0.060	3.0376**	0.018	0.9977	–0.029	–1.459	–0.024	–1.6568*
CAR Days 0 to 19	–0.018	–0.9062	–0.010	–0.4408	0.083	3.2183***	0.054	2.2927*	–0.038	–1.5542	–0.017	–0.8432
CAR Days 0 to 29	–0.011	–0.4574	0.019	0.7176	0.054	2.1187*	0.045	1.8218*	–0.001	–0.0276	–0.005	–0.2315
CAR Days 0 to 39	0.010	0.3448	0.044	1.4581	0.148	4.5294***	0.106	3.4336***	0.007	0.2327	0.023	0.8147
CAR Days 0 to 49	0.003	0.1055	0.074	2.3088*	0.060	1.5357	0.065	1.8721*	0.035	0.9698	0.025	0.7963
CAR Days 0 to 59	0.026	0.7184	0.122	3.2914***	0.065	1.466	0.079	1.9765*	0.084	2.0609*	0.051	1.4324
CAR Days 0 to 69	0.053	1.3141	0.125	3.1995***	0.134	3.2651***	0.137	3.3805***	0.075	1.7056*	0.062	1.6344
CAR Days 0 to 79	0.042	1.0046	0.127	3.2095***	0.110	2.4802**	0.115	2.6259**	0.074	1.6043	0.063	1.6238
CAR Days 0 to 89	0.022	0.4823	0.130	3.0522**	0.168	3.7488***	0.146	3.1484***	0.067	1.3498	0.053	1.2765
CAR Days 0 to 99	0.009	0.1772	0.123	2.7956**	0.241	4.4647***	0.206	4.0447***	0.042	0.817	0.042	0.9414
CAR Days 0 to 109	–0.002	–0.0282	0.183	3.5904***	0.110	1.716*	0.130	2.2578*	0.086	1.4737	0.060	1.2159
CAR Days 0 to 119	–0.008	–0.1485	0.147	2.7673**	0.044	0.6332	0.078	1.277	0.045	0.7208	0.064	1.2345
CAR Days 0 to 129	0.027	0.5052	0.153	2.9869**	–0.036	–0.4475	0.021	0.3102	0.065	1.0832	0.107	2.1451*
CAR Days 0 to 139	0.004	0.0617	0.138	2.62**	0.002	0.0283	0.034	0.5078	0.065	1.043	0.081	1.5025
CAR Days 0 to 149	–0.012	–0.1994	0.141	2.6226**	–0.104	–1.1151	–0.033	–0.4335	0.075	1.1643	0.072	1.3269
CAR Days 0 to 159	–0.007	–0.109	0.139	2.6287**	–0.173	–1.6423	–0.071	–0.8283	0.093	1.4722	0.071	1.2906
CAR Days 0 to 169	–0.023	–0.374	0.165	3.0903**	–0.149	–1.3841	–0.077	–0.881	0.124	1.9188*	0.072	1.3011
CAR Days 0 to 179	–0.005	–0.0775	0.192	3.2833***	–0.188	–1.5523	–0.083	–0.8592	0.168	2.388**	0.078	1.3679
CAR Days $(y+1)$ 0 to 9	0.007	0.4456	0.006	0.3802	0.038	2.2347*	0.008	0.5095	0.022	1.3376	0.005	0.3186
CAR Days $(y+1)$ 0 to 19	0.013	0.6661	0.023	0.9678	0.027	1.297	0.008	0.418	0.011	0.4328	0.032	1.5395
CAR Days $(y+1)$ 0 to 29	0.009	0.3972	0.014	0.4773	–0.007	–0.2911	–0.023	–0.9259	–0.013	–0.406	0.038	1.6188
CAR Days $(y+1)$ 0 to 39	0.003	0.0959	0.001	0.0257	–0.011	–0.3684	–0.024	–0.8375	0.002	0.0473	–0.002	–0.0735
CAR Days $(y+1)$ 0 to 49	–0.007	–0.2029	–0.001	–0.0141	–0.027	–0.809	–0.028	–0.843	0.005	0.1173	–0.031	–0.8607
CAR Days $(y+1)$ 0 to 59	–0.016	–0.3781	–0.034	–0.7824	–0.026	–0.6854	–0.047	–1.1728	0.001	0.0293	–0.050	–1.1108
avg. Diff. to total Sample	*–0.025*		*0.055*		*–0.003*		*0.008*		*0.016*		*0.008*	

Continue page 84

Table 4: Continued

Panel A contains the results for the standardized unexpected earnings *(SUE)* deciles and Panel B contains the results for the security return model *(SRM)*. Under the *SRM* method, no tests over the anticipation period are performed since the *SRM* method sorts firm years according to their cumulative abnormal returns *(CAR)* over this period. ME is the market value of common equity and BE/ME is the ratio of the book value of common equity to the market value of common equity. In each panel the first 6 columns contain the results for the small firm tercile, medium firm tercile and large firm tercile. The remaining 6 columns contain the results for the tercile with the low book-to-market firms, the tercile with the medium book-to-market firms and the tercile with the high book-to-market firms. For each sub-sample the differences of cumulative abnormal returns between the highest and the lowest unexpected earnings decile over the respective event windows are reported. The T-ratios correspond to the H_0: average *CAR* of the respective decile *(SUE* or *SRM)* 10 equal those of decile 1 over the indicated event windows. The H_1 is that the average *CAR* of decile 10 exceed those of decile 1. The standard deviation of the *CAR* is obtained using the cross-sectional standard deviation of cumulative abnormal returns within each decile measured over the corresponding event window. The population standard deviation of cumulative abnormal returns over that period is estimated as a weighted average of the observed standard deviations of abnormal returns within deciles 10 and 1:

$$\hat{\sigma}_{CAR} = \sqrt{\frac{(n_{10}-1)s_{10}^2 + (n_1-1)s_1^2}{(n_{10}-1)+(n_1-1)}}$$

where s_{10}^2, s_1^2 are the cross-sectional variances of cumulative abnormal returns of deciles 10 and 1 measured over the respective event window and n_{10}, n_1 are the sizes of deciles 10 and 1. The standard deviation of the *CAR* differences between deciles 10 and 1 for the respective event window is obtained by

$$\hat{\sigma}_{\overline{CAR}_{10}-\overline{CAR}_1} = \sqrt{\hat{\sigma}_{CAR}^2} \cdot \sqrt{\frac{1}{n_{10}} + \frac{1}{n_1}}.$$

The event date is 80 trading days after the end of the fiscal year. Significance is indicated as follows: (***) = significant at 0.1 %, (**) = significant at 1 %; (*) = significant at 5 %.

The results in both panels of Table 4 oppose the hypothesis that the drift is generated by differences in the variables size and book-to-market ratio. For most sub-samples the returns are at least of similar size compared to the total sample. Only within the sub-samples containing small firms and, for the *SUE* variable, firms with a high book-to-market ratio, are the returns of the considered trading strategy lower than in the entire sample. *Liu/Strong/Xu* (2003: 99 et seq.) come to similar conclusions. These authors also find varying magnitudes of the drift across different sub-samples with some sub-samples actually displaying a stronger drift than the whole sample generates. Additionally, they also find a lower intensity of the drift for small firms and firms with a high book-to-market ratio. Regarding the firms with a high book-to-market ratio, they interpret the smaller drift with a result obtained by *Daniel/Hirshleifer/Subrahmanyam* (1998: 1841 et seqq.) who demonstrate that mis-pricing is smaller for value stocks, i. e. for stocks with a comparably high book-to-market ratio. For such stocks the book value represents a larger proportion of the total value. Thus, for such stocks the valuation requires less judgment and forecasting.

The finding of a smaller drift for smaller firms is inconsistent with previous studies like *Bernard/Thomas* (1989: 12) who find a larger drift for smaller firms. This result can be attributed to the size of the firms as an indicator for the market and information environment. For such an interpretation it is helpful to look at the actual averages of the firm size within the size-based subgroups. This is done for quintiles and terciles based on the market value of common equity. Supplemented by the general descriptive statistics the results are contained below in Table 5.

Table 5 illustrates that the frequency distribution of the firm size is highly skewed. This property is also reflected in the large difference between the mean and the median. There are by far more small firms in the sample. The quintile and tercile averages of the market value reveal that quintile 1 and tercile 1 contain very small firms. The average size of firms in quintile 1 (tercile 1) is only about 0.7 % (1.2 %) compared to the average firm size and about 10 % (18 %) compared to the median firm size. Hence, the results in Table 4 show that there is no significant evidence of the post-earnings-announcement drift when only firms with a market value of less than 1.2 % of the average firm size or 18 % of the median firm size are considered. This result can be interpreted by the market and information environment of these firms. It is reasonable to assume that for such small firms there is a low level of liquidity, which makes such stocks

Table 5

Descriptive Statistics and Average Firm Size within Sub-samples

Descriptive Statistics, Market Value of Common Equity in Million € (based on trimmed values)		Market Value of Common Equity as for			
		Quintile	ME in Million €	Tercile	ME in Million €
Mean	1162	1	8	1	14
Median	79	2	29	2	90
σ	4801	3	83	3	3383
Skewness	7.2388	4	258		
Kurtosis	60.1513	5	5434		
Minimum	0.041				
Maximum	51513	Average	1162	Average	1162

unattractive to professional or institutional investors. Market participants who do trade in these stocks can be assumed to have more precise information regarding the respective firm. Therefore, it is reasonable to assume that for these stocks there is a higher proportion of insider trading. This line of reasoning offers a possible explanation for the finding that the drift is insignificant for the small firm tercile. Support for this argument can also be seen in the average size of the firms within middle quintile 3 and middle tercile 2. Table 4 documents the strongest drift for these firms. And the average firm size within these groups still remains less than 10% of the total mean. In other words, compared to the total sample, firms in quintile 3 and in tercile 2 are still rather small. Hence, finding a strong drift for these firms is consistent with *Bernard/Thomas* (1989: 12) and most previous studies. However, a final explanation of this finding remains open to a more detailed investigation.

To conclude the investigation of the size and book-to-market sub-samples, it can be stated that there are variations in the intensity of the drift across these sub-samples. But contrary to the hypothesis that the intensity decreases with the reduction of the variation in these variables, some of the sub-samples actually show a stronger drift. A lower intensity of the drift can be seen for the small firms and the firms with a high book-to-market ratio. Both effects can be related to arguments other than the risk exposure of the concerning firms. Therefore, the analysis of the sub-samples produces opposing evidence to the hypothesis that the drift is caused by variations of the variables size and book-to-market ratio.

VI. Conclusions

This study is concerned with verifying and interpreting the post-earnings-announcement drift in Germany. Using annual financial statement data for 850 public limited companies covering the years 1990 to 2003, it is shown that the post-earnings drift can also be identified on the German stock market. The trading strategy of a long position in the decile of the firms with the highest unexpected earnings and a short position in the decile of the firms with the lowest unexpected earnings generates significant cumulative abnormal returns of about 3 to 6% over a period of up to about 59 to 109 trading days after the earnings announcement date.

In an analysis of covariance, the significance and explanatory power of the risk-related variables size and book-to-market ratio and the two control variables for the momentum effect and survivorship bias effect are then tested.[16] It can be seen that a significant relation with cumulative abnormal returns is detected only for low standardized unexpected earnings firm years and the book-to-market ratio. Insignificant results are obtained in the other cases. Consequently, these variables cannot account for the complete post-earnings-announcement drift.

Highly significant are the control variables for the momentum effect and the survivorship bias. However, the inverse Mills ratios only become significant for longer event windows starting from about 160 days, that is, for event windows beyond those over which the drift is significant. This makes the survivorship bias an unlikely source of the drift. The explanatory power of the momentum variable and the inverse Mills ratio is reflected by the insignificance of the *SUE* deciles which means that after the inclusion of these variables there are no longer significant differences in the cumulative abnormal returns over the *SUE* deciles. For the *SRM* deciles, the significance of the differences in cumulative abnormal returns is reduced considerably.

To further investigate the influence of the variables size and book-to-market ratio on the trading strategy returns, these returns are computed separately for tercile sub-samples based on these variables. The results do not support the hypothesis that the drift is driven by these variables. In the majority of the sub-samples the magnitude of the trading strategy returns remains at least in the same proportion compared to the whole sample.

[16] The influence of the variable market beta is already accounted for by using the CAPM to compute abnormal returns.

Altogether, the results presented in this paper cannot confirm the hypothesis that the post-earnings-announcement drift is generated by the risk associated with the variables size and book-to-market ratio. The significant momentum effect in explaining the trading strategy returns supports the hypothesis of delayed incorporation of information into prices. *Jegadeesh/Titman* (1993: 86 et seq.) conclude that stock prices systematically underreact to information regarding future earnings. The finding that firms with positive past returns tend to have positive unexpected earnings and firms with negative past returns tend to have negative unexpected earnings suggests a similar interpretation. The persistence of past returns indicates that market participants form expectations regarding future earnings but seem to underestimate these future earnings. This conclusion is supported by the strong anticipation effect before the event date. Likewise, the post-earnings-announcement drift suggests that market participants use the earnings information to update their expectation of the firm's future performance but seem to underestimate the information content of the earnings announcement.

References

Ball, R./*Bartov,* E. (1996): How naive is the stock market's use of earnings information? Journal of Accounting & Economics, 21, 319–337. – *Ball,* R./*Brown,* P. (1968): An Empirical Evaluation of Accounting Income Numbers. Journal of Accounting Research, 16, 159–177. – *Ball,* R./*Kothari,* S. P./*Watts,* R. L. (1993): The Economics of the Relation between Earnings Changes and Stock Returns. Accounting Review, 68-3, 622–638. – *Beaver,* W. H./*Clarke,* R./*Wright,* W. F. (1979): The Association between Unsystematic Security Returns and the Magnitude of Earnings Forecast Errors. Journal of Accounting Research, 17, 316–340. – *Beaver,* W./*Lambert,* R./*Morse,* D. (1980): The information content of security prices, Journal of Accounting & Economics, 2, 3–28. – *Bernard,* V. L./*Thomas,* J. K. (1989): Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? Journal of Accounting Research, 27, supplement, 1–36. – *Bernard,* V. L./*Thomas,* J. K. (1990): Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting & Economics, 13, 305–340. – *Berry,* M. A./*Gallinger,* G. W./*Henderson Jr.,* G. V. (1990): Using Daily Stock Returns in Event Studies and the Choice of Parametric Versus Nonparametric Test Statistics. Quarterly Journal of Business & Economics, 29-21, 70–85. – *Bortz,* J. (2005): Statistik für Human- und Sozialwissenschaftler. Berlin: Springer. – *Brandi,* E. H. (1977): Informationswirkungen der Jahresabschlussveröffentlichung auf Entscheidungen am Aktienmarkt. Augsburg: Univ. Diss. – *Brennan,* M. J./*Jegadeesh,* N./*Swaminathan,* B. (1993): Investment Analysis and the Adjustment of Stock Prices to Common Information. Review of Financial Studies, 6-4, 799–824. – *Brown,* S. J./*Pope,* P. F. (2000): Post-Earnings Announcement Drift? New York University Stern School of Business working paper. – *Chan,* L. K. C./*Jegadeesh,* N./*Lakonishok,* J. (1996): Momentum Strategies. Journal of Finance, 51-5, 1681–1713. – *Chen,* C. R./*Wuh Lin,* J./*Sauer,* D. A. (1997): Earnings Announcements, Quality and Quantity of Information and Stock Price Changes. Journal of Financial Research, 20-4, 483–502. – *Daniel,* K./*Hirshleifer,* D./*Subrahmanyam,* A. (1998): Investor Psychology and Security Market Under- and Overreaction. Journal of Finance, 53-6, 1839–1885. – *Defeo,* V. J. (1986): An Empirical Investigation of the Speed of the Market Reaction to Earnings Announcements. Journal of Accounting Research, 24, 349–363. – *Fama,* E. F. (1970): Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance, 25-2, 383–417. – *Fama,* E. F. (1991): Efficient Capital Markets: II. Journal of Finance, 46-5, 1575–1617. – *Fama,* E. F./*French,* K. R. (1992): The Cross-Section of Expected Stock Returns. Journal of Finance, 47-2, 427–465. – *Fama,* E. F./*French,* K. R. (1996): Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance, 51-1, 55–84. – *Foster,* G./*Olsen,* C./*Shevlin,* T. (1984): Earnings Releases, Anomalies and the Behaviour of Security Returns. Accounting Review, 59, 574–603. – *Francis,* J./*LaFond,* R./*Olsson,* P./*Schipper,* K. (2003): Accounting Anomalies and Information Uncertainty. Duke University Fuqua School of Business working paper. – *Heckman,* J. J. (1979): Sample Selection Bias as a Specification Error. Econometrica, 47-1, 153–161. – *Jegadeesh,* N./*Titman,* S. (1993): Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance, 48- 1, 65–91. – *Kim,* D./*Kim,* M. (2003): A Multifactor Explanation of Post-Earnings-Announcement Drift. Journal of Financial and Quantitative Analysis, 38-2, 383–398. – *Kothari,* S. P. (2001): Capital Market research in accounting. Journal of Accounting & Economics, 38, 1–3, 105–231. – *Kritzman,* M. P. (1994): What Practitioners Need to Know about Event Studies. Financial Analysts Journal, 50-6, 17–20. – *Liu,* W./*Strong,* N./*Xu,* X. (2003): Post-earnings-announcement Drift in the UK. European Financial Management, 9-1, 89–116. – *McWilliams,* A./*Siegel,* D. (1997): Event Studies in Management Research: Theoretical and Empirical Issues. Academy of Management Journal, 40-3, 626–657. – *Mendenhall,* R. R. (2004): Arbitrage Risk and Post-Earnings-Announcement Drift. Journal of Business, 77-4, 875–894. – *Mikhail,* M. B./*Walther,* B. R./*Willis,* R. H. (2003): Security Analyst Experience and Post-Earnings-Announcement Drift. Journal of Accounting, Auditing and Finance, 18-4, 529–550. – *Sadka,* G./*Sadka,* R. (2003): The Post-Earnings-Announcement Drift and Liquidity Risk. University of Chicago Graduate School of Business working paper. – *Schweitzer,* R. (1989): How Do Stock Returns React to Special Events? Business Review – Federal Reserve Bank of Philadelphia, 17–29. – *Sloan,* R. G. (1996): Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings? Accounting Review, 71-3, 289–315. – *Wooldridge,* J. M. (2003): Introductory Econometrics: A Modern Approach. Cincinnati, Ohio: South-Western College Publishing.

Summary

Risk Effect versus Delayed Price Response: the Case of the Post-Earnings-Announcement Drift in Germany

This paper presents supporting evidence for the post-earnings-announcement drift using annual data on 850 firms listed on the Frankfurt stock exchange for the years 1990 to 2003. Standardized unexpected earnings and unexpected earnings based on the security return model yield significant abnormal returns to the drift trading strategy of about 3% to 6% over 59 to 109 days. In an analysis of covariance the variables size and book-to-market ratio are insignificant in explaining the drift. Further, a control variable for a momentum effect is highly significant, and the inverse Mills ratios to control for a survivorship bias are significant for periods starting from about 160 days. All variables combined cause the drift to become insignificant for the standardized unexpected earnings model and reduce the significance of the drift given by the security return model. The insignificance of the variables size and book-to-market ratio is confirmed by repeating the analysis within sub-samples. The results suggest that there is a delayed response to earnings-related information on the German stock market. (JEL G14, M41)

Zusammenfassung

Risikoeffekt oder verzögerte Preisreaktion: Die Post-Earnings-Announcement-Drift in Deutschland

Dieses Paper untersucht die Reaktion von Kapitalmarktteilnehmern auf Gewinninformationen deutscher Aktiengesellschaften. Fundamentale Unternehmensbewertungen, die Rolle von Jahresabschlussinformationen in Verträgen und im politischen Prozess sowie Tests der Kapitalmarkteffizienz stellen zentrale Quellen der Nachfrage nach dieser Art der Kapitalmarktforschung dar. Eine von *Kothari* (2001) gelieferte Zusammenfassung der Literatur zur empirischen Kapitalmarktforschung nennt eine Reihe von Studien, die belegen, dass im Widerspruch zu *Famas* (1970) Definition eines effizienten Marktes als einem Markt, auf dem „Wertpapierpreise alle zugänglichen Informationen beinhalten", Aktienkurse nur graduell auf neue Gewinninformationen reagieren. Dieses Phänomen ist unter dem Namen „Post-Earnings-Announcement Drift" bekannt geworden. Das Paper überprüft die Existenz der Drift auf dem deutschen Kapitalmarkt und testet die Signifikanz einer Reihe von risikobezogenen Variablen.

Unter Verwendung einer Stichprobe bestehend aus Jahresabschlussdaten von 850 in Frankfurt gelisteten Aktiengesellschaften für die Jahre 1990 bis 2003 lässt sich die Existenz der Drift auch auf dem deutschen Markt zeigen. Mithilfe zweier Maße zur Bestimmung des vom Markt unerwarteten Gewinnanteils wird die Rentabilität einer Handelsstrategie geprüft, die eine Long-Position in Werten mit positiver Gewinnüberraschung und eine Short-Position in Werten mit negativer Ge-

winnüberraschung aufbaut. Diese Handelsstrategie liefert marktrisikobereinigte und statistisch signifikante Überrenditen von etwa 3% bis 6% innerhalb von 59 bis 109 Handelstagen ab dem Datum der angenommenen Gewinnmitteilung. Da die Handelsstrategie auf bekannten Informationen basiert, stellt ihre Profitabilität, soweit sie risikolos realisiert werden kann, eine Marktanomalie dar. Studien wie jene von *Francis* et al. (2003) und *Kim/Kim* (2003) versuchen daher, die Renditen der Handelsstrategie in Bezug zu risikobezogenen Variablen zu setzen.

In einer Kovarianzanalyse bleiben die risikobezogenen Variablen Größe und Buchwert-Marktwert-Quotient insignifikant. Inverse Mills-Quotienten zur Kontrolle eines möglichen Survivorship Bias werden erst ab etwa 160 Handelstagen nach dem Ereignis signifikant. Eine Kontrollvariable für den Momentum-Effekt ist hochsignifikant. In einer Unterteilung der gesamten Stichprobe anhand der Variablen Größe und Buchwert-Marktwert-Quotient in je drei gleichgroße Gruppen wird geprüft, ob die festgestellten abnormalen Renditen der genannten Handelsstrategie von diesen Variablen abhängen. Die Ergebnisse bestätigen die Insignifikanz dieser Variablen. Zusammenfassend deuten die Ergebnisse darauf hin, dass auf dem deutschen Markt eine verzögerte Reaktion des Aktienkurses auf Gewinninformationen existiert.